The Role of Primary Healthcare Provider in Caring for the Elderly in Jeddah City using Artificial Intelligence "A proposed vision"

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***Abstract*:** The current study aimed to investigate the role of primary health care providers in caring for the elderly in Jeddah using artificial intelligence as a proposed vision. Research on the integration of artificial intelligence into community primary health care has highlighted several advantages and disadvantages in practice, for example, in facilitating diagnosis and disease management, as well as doubts about unintended harmful effects of such integration. However, there is a lack of evidence on a comprehensive synthesis of knowledge that could shed light on AI systems that have been tested or implemented in community primary health care.

Keywords: Primary Healthcare - Elderly - Jeddah City - Artificial Intelligence - proposed vision.

I. Introduction

Population aging is a global issue; 703 million people aged 65 and up are expected to rise to 1.5 billion by 2050 [1]. One in six persons worldwide will be over 65 by 2050, based on the most recent population projections and estimates of the United Nations Population Division Department of Economic and Social Affairs (DESA) [2]. Ensuring older people can fully engage in all facets of communal life is a pressing requirement. However, older persons are often subjected to discrimination, neglect, agism, exclusion, and other violations [3]. It presents a growing need for effective Elderly in Jeddah Citycare solutions that can provide adequate support and maintain the independence and well-being of older adults. Artificial intelligence (AI) and robotics offer innovative approaches to address these challenges as technology advances. These technologies are revolutionizing many areas, including public health, medicine, physiotherapy, and other allied health services for older people, where they can help predict health risks and events, enable drug development, and support individualization of treatments [4]. The COVID-19 pandemic has placed a heavy burden on older people, especially those in long-term care facilities, reinforcing the demand for new strategies to help older adults. In this article, we tried to explore the importance of AI and robotics in improving the independence and quality of life among the Elderly in Jeddah City population.

AI in Elderly in Jeddah City care:

Promoting Independence:

AI-powered systems can assist older adults in performing daily activities, such as medication management, fall detection, and navigation, enabling them to live independently for longer [5]. Innovative home technologies with AI algorithms can detect deviations from standard behavior patterns and provide timely emergency alerts. In the context of aging, AI may also be used to support a more sophisticated level of decision-making in the home by older adults who are living independently or desire to do so. This includes the use of AI to automate home safety risk prevention and the capability to respond to emergencies in real time. The system can send a real-time alarm to the family, care facility, or medical agent without human assistance if it determines that something odd might occur (broadly) or something is wrong with the user's health practices or medical recommendations. In addition, AI-driven wearable devices can monitor vital signs and activity levels, promoting a healthier and more independent lifestyle.

Geriatric Population and Mental Health:

Recent studies have shown that loneliness is a significant issue for older adults, contributing to cognitive impairments, depression, and frailty [6]. To help the lonely elderly, there is a need to create "Circle of Friends" programs adopting AI. In addition, there is a need for programs to lessen caretaker discomfort and for a greater understanding of carer stress employing AI.

Monitoring of Chronic Diseases:

AI algorithms have the potential to revolutionize health monitoring for older adults. By analyzing data from wearable devices, electronic health records, and other sources, AI can provide real-time data analysis, detect early warning signs of diseases, and provide personalized treatment plans and recommendations. AI-enabled telemedicine platforms also enable remote monitoring and virtual consultations, improving access to healthcare for older adults in remote or underserved areas [7]. In addition to a diagnostic and management algorithm, humankind has created an iPad software with Reshma Merchant in Singapore for geriatric syndromes (RGA). It has been demonstrated that AI can read retinal scans like doctors [8]. AI will also be crucial in the deprescription process. These methods will be used often in medicine over the next 10 years. Other possible applications include the ongoing development of virtual medicine and improved assessment of osteoporosis and fracture risk concerning age, frailty, and life expectancy.

Robotics in Elderly in Jeddah City care:

Assistive Robots:

Robotic systems equipped with sensors and actuators can provide physical assistance to older adults with mobility support, personal hygiene, and household chores. These robots can be programmed to adapt to individual needs, providing personalized and responsive care [9]. Robotic exoskeletons and mobility aids enable older adults with mobility impairments to regain independence and perform activities they would otherwise struggle with. Robots with a mind are being created to help Elderly in Jeddah Citypatients in hospitals with their therapy. By physically touching humans, these robots can affect their emotional, physical, and social well-being. With this addition, older adults' spirits were seen to improve.

Social Robots:

Social interaction is vital in combating social isolation and promoting mental well-being among older adults. Social robots offer companionship and engagement, providing emotional support and cognitive stimulation. These robots can engage in conversations, play games, and even assist in reminiscence therapy, improving older adults' overall quality of life. The robot's acceptance among older people is greatly influenced by its physical appearance. When dementia-stricken seniors were given companion animal robots, positive outcomes were discovered. Studies reveal that companion animal robots of the right size, weight, and shape can stimulate the brains of older people with dementia.

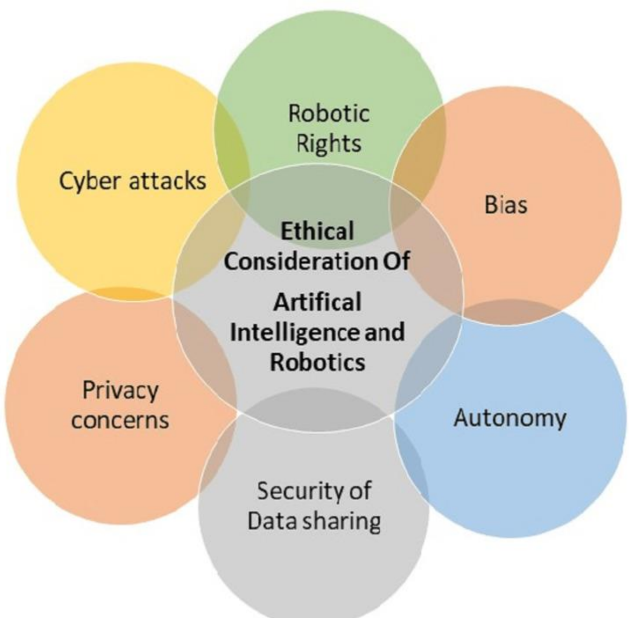
Geriatric rehabilitation and AI:

Robots, exoskeletons, smart homes, wearable, voice-activated technology, and virtual reality applications are all AI technologies. One or more of these strategies might be very helpful regarding rehabilitation, offering emotional, practical, or material assistance and encouraging social and interpersonal interactions. A method for applying AI as a nursing care-support tool is based on its capacity to create robotic technology, which would lessen the labor of nursing staff in long-term care facilities. Aside from providing more alternatives for movement and living space, it is also predicted to offer psychological advantages [10].

Ethical considerations and challenges:

The integration of AI and robotics in Elderly in Jeddah Citycare raises critical ethical considerations. Privacy concerns regarding collecting and using personal health data must be addressed through robust security measures and clear consent procedures [11]. However, cloud technologies that allow for real-time data analytics from numerous sources across integrated organizations and data sharing need to be carefully evaluated, information security needs to be maintained, and the threat of cyberattacks needs to be minimized. In addition, the issue of autonomy arises when older adults rely heavily on AI and robotic systems, raising questions about decision-making and the potential loss of human connection. Developing guidelines and regulations that ensure these technologies' responsible and ethical use is crucial. The employment of robots by older persons may increase the danger of dishonesty, infantilization, and confusion among them as to why their human caretakers are using technology rather than face-to-face consultations (Figure 1).

Figure 1. Ethical consideration of artificial intelligence and robotics.



Future directions and conclusion:

The escalating global challenge of population aging necessitates urgent and innovative solutions to support older adults' independence and well-being. AI and robotics offer promising technologies to address the healthcare needs of the rapidly aging senior population. This review explored various applications of AI and robotics in Elderly in Jeddah Citycare, emphasizing their pivotal roles in promoting independence, monitoring health, facilitating social interaction, and aiding in geriatric rehabilitation. AI-powered systems enable personalized assistance, allowing older adults to live autonomously for extended periods. Innovative home technologies with AI algorithms swiftly detect emergencies and deviations in behavior patterns, ensuring prompt responses and heightened safety. AI-driven wearable devices monitor vital signs, foster healthier lifestyles among older people, and predict health risks, offering individualized treatment plans through telemedicine platforms. Integrating robotics complements AI, providing invaluable physical assistance and companionship, effectively combating social isolation, and enhancing mental well-being among older adults. However, ethical considerations are essential in implementing AI and robotics in Elderly in Jeddah City care, ensuring privacy and data security, and preserving human connection and autonomy.

By thoughtfully regulating and embracing these technologies, we can empower older adults to lead fulfilling lives and improve the quality of Elderly in Jeddah Citycare globally.

The use of artificial intelligence (AI) in primary health care has been widely recommended [1]. AI systems have been increasingly used in health care, in general [2], given the hope that such systems may help develop and augment the capacity of humans in such areas as diagnostics, therapeutics, and management of patient-care and health care systems [2]. AI systems have the capability to transform primary health care by, for example, improving risk prediction, supporting clinical decision making, increasing the accuracy and timeliness of diagnosis, facilitating chart review and documentation, augmenting patient–physician relationships, and optimizing operations and resource allocation [3].

Community-based primary health care (CBPHC) is a society-wide approach to primary health care that involves a broad range of prevention measures and care services within communities, including health promotion, disease prevention and management, home care, and end-of-life care [4]. CBPHC incorporates health service delivery from personal to community levels and is the first and most frequent point of contact for the patients with health care systems for patients in many countries, including Canada [4]. In addition to providing comprehensive health care and its importance within healthcare systems, CBPHC has also been identified as essential in formulating evidence-informed public health policies [5]. Given the growing role of primary health care and CBPHC in our society [6], it is important to develop strategies that address the limitations of the existing health care system and enhance the overall quality of care delivered alongside all other aspects of CBPHC. This includes efforts for reducing the growing health care burden of CBPHC providers as well as the burden of chronic diseases, decreasing rates of misclassification and misdiagnosis, reducing cases of mismanaged diseases, and increasing accessibility to care [7-17].

Indeed, integration of AI into CBPHC could help in a variety of ways, including identifying patterns, optimizing operations, and gaining insights from clinical big data and community-level data that are beyond the capabilities of humans. Over time, using AI in CBPHC could lessen the excessive workload for health care providers by integrating large quantities of data and knowledge into clinical practice and analyzing these data in ways humans cannot, thus yielding insights that could not otherwise be obtained. This will allow health care providers to devote their time and energy to the more human aspects of health care [18]. Several studies have reported early successes of AI systems for facilitating diagnosis and disease management in different fields, including radiology [19], ophthalmology [20], cardiology [21], orthopedics [22], and pathology [23]. However, the literature also raises doubts about using and implementing AI in health care [24,25]. Aspects including privacy and consent, explainability of the algorithms, workflow disruption, and the

"Frame Problem" that is defined as unintended harmful effects from issues not directly addressed for patient care [26].

Despite the potential advantages, disadvantages, and doubts, there is no comprehensive knowledge synthesis that clearly identifies and evaluates AI systems that have been tested or implemented in CBPHC.

Thus, we performed a systematic scoping review aiming to (1) summarize existing studies that have tested or implemented AI methods in CBPHC; (2) report evidence regarding the effects of different AI systems' outcomes on patients, health care providers, or health care systems, and (3) critically evaluate current studies and provide future directions for AI-CBPHC researchers.

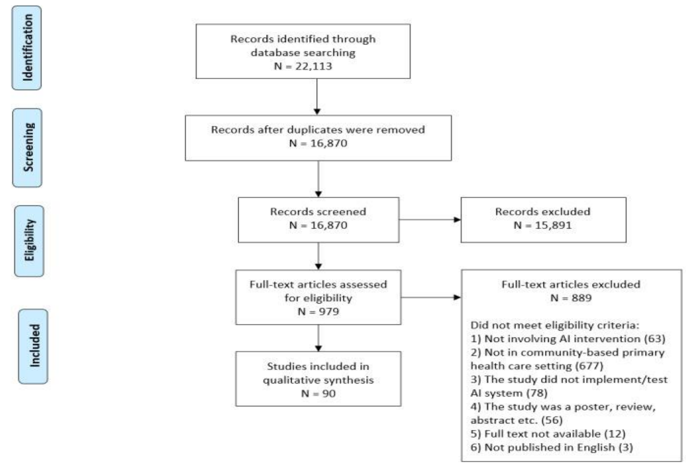
Methods:

Study Design:

Based on the scoping review methodological framework proposed by Levac et al [27], and the Joanna Briggs Institute (JBI) methodological guidance for scoping reviews [28], we developed a protocol with the following steps: (1) clarifying the purpose of the review and linking it to a research question, (2) identifying relevant studies and balancing feasibility with breadth and comprehensiveness, (3) working in a team to iteratively select studies and extract their data, (4) charting the extracted data, incorporating a numerical summary, (5) collating, summarizing, and reporting the results, and (6) consulting the results regularly with stakeholders throughout regarding emerging and final results. This protocol is registered and available on the JBI website and the Open Science Framework (OSF) websites. We completed this review as per the published protocol.

We formed a multidisciplinary committee of experts in public health, primary health care, AI and data science, knowledge translation, and implementation science, as well as a patient partner and an industry partner (with expertise in the AI-health domain) with whom we consulted during all the steps of the scoping review. This helped us to interpret the results. The screening process is shown in Figure 1. Our review is reported according to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analysis-Scoping Reviews) reporting guideline for reporting the study [29] (see Multimedia Appendix 1). Studies that did not report their study design are categorized by methodology according to the classification outlined by the National Institute for Health and Care Excellence [30].

Figure 1.



PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart of the selection procedure. AI: artificial intelligence.

We used the Prediction Model Risk of Bias Assessment Tool (PROBAST) tool for assessing the risk of bias, which includes 20 signaling questions to facilitate structured judgment of risk of bias organized in four domains of potential biases related to the following: (1) participants (covers potential sources of bias related to participant selection methods and data sources); (2) predictor variables (covers potential sources of bias related to the definition and measurement of predictors evaluated for inclusion in the model); (3) outcomes (covers potential sources of bias related to the definition and measurement of the outcomes predicted by the model); and (4) analyses (covers potential sources of bias in the statistical analysis methods) [31]. Risk of bias was judged as low, high, or unclear. If one or more domains were judged as having high risk of bias, the overall judgment was "high risk" [31].

Eligibility Criteria:

We defined our bibliographic database search strategy for peer-reviewed publications in English or French using the Population, Intervention, Comparison, Outcomes, Setting and Study (PICOS) design components [32].

Population:

Studies about any population that provides health care services, including nurses, social workers, pharmacists, dietitians, public health practitioners, physicians, and community-based workers (an unregulated type of provider) were included, as were those about any populations who receive CBPHC services. We adhered to the definition of CBPHC provided by the Canadian Institutes of Health Research (CIHR) (ie, the broad range of primary prevention measures including public health, and primary care services within the community, including health promotion and disease prevention; the diagnosis, treatment, and management of chronic and episodic illness; rehabilitation support; and end-of-life care) [4]. Studies that took place in any CBPHC points of care, including community health centers, primary care networks, clinics, and outpatient departments of hospitals, were also included. Studies conducted in emergency departments were excluded.

Intervention:

Only studies that "tested" or "implemented" or "tested and implemented" AI methods, such as computer heuristics, expert systems, fuzzy logic, knowledge representation, automated reasoning, data mining, and machine learning (eg, support vector machines, neural networks, and Bayesian networks) were included. Studies related to robot-assisted care were excluded.

Comparison:

No inclusion or exclusion criteria were considered.

Outcomes:

The primary outcomes of interest were those related to individuals receiving care (eg, cognitive outcomes, health outcomes, behavioral outcomes), providers of care (eg, cognitive outcomes, health outcomes, behavioral outcomes), and health care systems (eg, process outcomes). Moreover, we analyzed the outcomes of the AI systems for their accuracy and impact on the outcomes of care.

Analysis Methods:

All study designs using qualitative, quantitative, or mixed methods were eligible for inclusion. In particular, we included experimental and quasi-experimental studies (randomized controlled trials, quasi-randomized controlled trials, nonrandomized clinical trials, interrupted time series, and controlled before-and-after studies), and observational (cohort, case control, cross- sectional, and case series), qualitative (ethnography, narrative, phenomenological, grounded theory, and case studies), and mixed methods studies (sequential, convergent).

Information Sources and Search Criteria:

An information specialist with an epidemiologist, an AI-healthcare researcher, and a family doctor developed a comprehensive search strategy and Medical Subject Headings (MeSH) mediated by the National Library of Medicine. The systematic search was conducted from inception until February 2020 in seven bibliographic databases: Cochrane Library, MEDLINE, EMBASE, Web of Science, Cumulative Index to Nursing and Allied Health Literature (CINAHL), ScienceDirect, and IEEE Xplore. Retrieved records were managed with EndNote X9.2 (Clarivate) and imported into the DistillerSR review software (Evidence Partners, Ottawa, ON) to facilitate the selection process (see Multimedia Appendix 2 for the search strategies used on each database).

Study Selection Process

Title and Abstract Screening (Level 1)

Using Distillers, two independent reviewers conducted a pilot screening session using a questionnaire based on our eligibility criteria to test the screening tool and to reach a common understanding. Then, the two reviewers independently screened the titles and abstracts of the remaining records. A third reviewer resolved disagreements between the two reviewers.

Full-Text Screening (Level 2)

Using DistillerSR and the abovementioned questionnaire, the same two reviewers independently assessed the full texts selected at level 1 for their eligibility to be included in the review. A third reviewer resolved conflicting decisions. For those references for which we did not have full-text access, we attempted to obtain access through the interlibrary loan mechanism at the McGill University Library. Studies that met the eligibly criteria were included for full data extraction.

Data Collection

We used a data extraction form, approved by our consultative committee, that we designed based on the Cochrane Effective Practice and Organisation of Care Review Group (EPOC) data collection checklist [33]. Specifically, we extracted study characteristics (eg, design and country of the corresponding author); population characteristics (eg, number of participants and type of disease or treatment); intervention characteristics (eg, AI methods used); and outcome characteristics, including outcomes related to the patients (eg, cognitive outcomes, health outcomes, behavioral outcomes), providers of care (eg, cognitive outcomes, health outcomes, behavioral outcomes), and health care systems (eg, process outcomes).

Assessment of Risk of Bias in the Included Studies:

Two reviewers independently appraised the included studies using the criteria outlined in PROBAST to evaluate the risk of bias in each included study that was eligible for evaluation using PROBAST [31]. A third reviewer verified their appraisals.

Synthesis:

We performed a descriptive synthesis [34] to describe the studies in terms of their population (patient, primary care providers), interventions (AI systems, evaluated parameters), and outcomes. The results were arranged according to the PICOS format. The tools and techniques for developing a preliminary synthesis included textual descriptions of the studies, grouping and clustering, and tabulation.

Consultation:

Throughout the steps of the review, we regularly updated all members of the research team and requested their feedback. We also presented our preliminary results during a workshop at Université Laval, Québec, Canada, with a multidisciplinary group of experts (in public health, primary care, AI and data science, knowledge translation, implementation science, as well as a patient partner, and an industry partner) and collected their comments and feedback.

Patient Involvement:

Using a patient-centered approach, our team co-developed the protocol, conducted the review, and reported the results of this study. We integrated patients' priorities within our research questions, search strategy terms, and outcomes of interest. Our patient partner was involved in each step of the research process, including the definition of the objectives, main analysis, descriptive synthesis, interpretation of preliminary and final results, and dissemination of the results obtained in this study.

In spite of substantial improvements in the Saudi Arabian health services sector in the past few decades, the country is facing critical challenges in its primary health care system. These challenges include increased demand because of rapid population growth, high costs of health care services, inequitable access, concerns about the quality and safety of care, a growing burden of chronic diseases, a less than effective electronic health system (eHealth), poor cooperation and coordination between other sectors of care, and a highly centralized structure (1–5). The government has developed and implemented a number of initiatives which include the Strategic Plan of the Ministry of Health 2010–2020 to effectively tackle these challenges (6). These initiatives resulted in the replacement of seven ministers of health in just one year, which indicates the serious administrative and practical difficulties in tackling these challenges in the health care system.

Most review papers in Saudi Arabia have focused on hospital-based medical services and have neglected primary health care services, which are the first point of access to health care in the Saudi Arabian health care system. The primary health care sector provides essential health care services to Saudi Arabians and to expatriates working in the public sector (7). No reform of the Saudi Arabian health care system can be complete without first considering the primary health care services at the heart of the health care system.

This narrative review aimed to explore the challenges facing the Saudi Arabian health care system with a focus on primary health care services. It further discusses and analyses the barriers to and drivers of health sector reforms, including the effect of demographic and economic factors on the health care system. The review also recommends mechanisms for effective reform of primary health care services as the nucleus of overall health care system.

Methods:

Data relating to the Saudi Arabian health care system were extracted from published literature in the following databases: PubMed, MEDLINE, CINAHL, Saudi Medical Journal, Eastern Mediterranean Health Journal, and the portal of the Ministry of Health in Saudi Arabia. A further search using Google Scholar search engine was carried out to identify other relevant papers and documents, government reports and information published in Arabic. All the studies and documents were analysed for their content and the relevant information was synthesized and reported.

Results and Discussion:

Saudi Arabia is a country with a culture and traditions rooted in Islamic teachings and Arab customs (8). Saudi Arabia is a kingdom with an integrated system of government based on the principles of justice, consultation and equality in accordance with Islamic law (9). Therefore, to some extent, the principles of Islam and Saudi Arabian traditions influence the culture of organizations within the country. The centralized tradition of Saudi Arabian society is also embodied in the health care service (10,11). In other words, the structure and functioning of the health care organizations, including primary health care, are strongly influenced by the society's norms and traditions.

Demographic impacts:

The population of Saudi Arabia was estimated to be about 30 million in 2014 with expatriates comprising about 31% of the total population (7).

The population growth rate was 2.81% from 2010 to 2015 (12), which has driven demand for more health care. Although increased financial resources have been allocated to the health sector, the population is growing faster than the health services made available. This indicates an urgent need to tackle this important challenge (Table 1) (13–17).

Economic impacts:

Saudi Arabia is a leading oil exporter; oil exports account for almost 69% of the country's exports (18). According to the World Bank, Saudi Arabia is classified as a high-income country (19). The strong oil-based economy has facilitated the development of local public and private organizations, creating new jobs and raising the socioeconomic status of Saudi Arabian citizens (20). The Saudi Arabian government provides free public services including health care to its population (21). However, the global instability of oil prices in the past few years has affected public and private services and forced the Saudi Arabian Government to explore alternate sources for revenue. The 2030 National Vision for Saudi Arabia seeks long-term sustainability of living standards by diversifying the country's income sources in the future, rather than relying only on oil revenue (22).

Saudi health care system:

The Ministry of Health is responsible for public health care services (23). A number of semi-independent bodies, the private sector and nongovernmental organizations also provide health care services. The Ministry of Health provides 60% of health services while the private sector provides 23% and other government health sectors provide 17% (17).

Levels of care in the Saudi health care system:

There are three levels of health care services in Saudi Arabia: primary, secondary and tertiary. However, in reality, there are four levels of care as shown in Figure 1. The primary health care services are the focus of the following discussion.

Primary health care in Saudi Arabia:

Primary health care is the first level of health care service (6). It is provided by the Ministry of Health through a network of primary health care centres. However, primary health care services face many challenges in terms of the patterns of disease, workforce, information systems, financial support and accessibility.

Historical issues of primary health care:

In accordance with the Alma-Ata declaration, Saudi Arabia has committed to develop its primary health care services (24). The Ministry of Health integrated both preventive and basic curative health care services in 1984. These services targeted individuals, families and the community, and provided a range of health care services including maternal and child health, immunization for communicable diseases, follow-up for patients with chronic diseases, dental care services, health education and essential drugs (24,25).

Primary health care services have improved considerably in the past four decades which has resulted in better health outcomes, for example a lower infant mortality rate, lower incidence of communicable diseases and an increase in average life expectancy (6). According to the Ministry of Health, there were 2281 public primary health care centres across the country in 2014 (17).

Saudi Arabia has seen changes in disease patterns with a shift away from communicable diseases to chronic diseases which are becoming more prevalent (6). These diseases place an increased burden on existing health care services (1,6,26–28). This change in disease pattern suggests that primary health care services, including patient follow-up strategies and preventive and health education activities, are insufficient. Recent data from the Saudi Health Information Survey show high rates of diabetes – 14.8% for males and 11.7% for females. Diabetes prevalence was 19.9%, almost double in those who were obese in comparison with non-obese (28). There is a real need to develop primary health care services directed to patients with chronic diseases and people who are most at high risk of these diseases.

Health system financing and expenditure:

Saudi Arabian citizens have free access to all levels of public health care services available in the country, which is funded by the central government. The Ministry of Health expenditure per capita has increased substantially by 0.41% (17), which is equivalent to US$ 299 per capita (13–17,29–32). However, Saudi Arabia still spends less per capita on health than a number of industrialized nations (Figure 2) (33).

Ministry of Health planners and leaders focus primarily on hospitals rather than primary health care centres. According to one report, more than 90% of the Ministry of Health budget allocated for infrastructure and development projects was spent on hospitals (21). Low expenditure on primary health care centres has resulted in 80% of primary health care buildings being rented; as such they are not specifically designed to provide health care services and they lack the necessary structural features to provide primary care (21,34).

According to government regulations, the budget for the Ministry of Health is released after approval of the Ministry of Finance. This practice may influence the performance and efficiency of the Ministry of Health and delay its work in all sectors including the primary health care services.

A comparison of the primary health care systems in Saudi Arabia and Cuba shows that health leaders and the government in Cuba saw primary health care as the cornerstone of successful health care together with a focus on the social determinants of health. Cuba's approach has contributed to making its primary health care among the best in the world (35). The Saudi Arabian Ministry of Health should shift the focus of the health system from hospital-based health care services to the primary preventive and promotive health care services to deal effectively and efficiently with the increasing burden of chronic diseases.

Workforce of primary health care:

Shortage of health care professionals is a global concern (36). The Saudi Arabian health care system is not immune to this challenge, and most health care professionals in Saudi Arabia are expatriates (1). In 2014, the primary health care workforce included 9304 physicians and dentists (3 per 10 000 inhabitants), 18 136 nurses (5.9 per 10 000 inhabitants), and 9690 allied health workers (17). The health care workforce for primary health care services has increased with nurses outnumbering physicians and allied health workers between 2010 and 2014 (Figure 3) (13–17).

Many health care professionals, particularly nurses, move to management or other non-nursing departments within their organizations (37). This trend is also seen among physicians. A ministerial committee review found that the number of primary health care physicians was 40% less than the required (21). In 2013 the total number of physicians (excluding dentists) per 10 000 population in Saudi Arabia was 2.3 (16). The scarcity of physicians in Saudi Arabia is high compared with other countries (Figure 4) (16,38).

Despite the shortage of physicians, they continue to dominate because they hold key positions within the health care system (39,40). Physicians occupy a number of management and leadership positions at central and regional levels of the health authorities, which makes shortages of primary health care physicians worse.

Human resources' development:

The Ministry of Health has invested in training its employees and developing their skills (41). However, the large number of workers, differences in their educational and cultural background and the limited resources allocated for training have affected the number, type, and quality of available training programmes. The Ministry of Health has given local and international study scholarships to many employees. In addition, many training courses in different specialities have been launched in collaboration with the Saudi Commission for Health Specialties.

Despite these efforts, the Ministry of Health lags behind other countries in training funds for its workforce. For example, the ministries of health in both the United Kingdom and Malaysia allocate 5% of the total budget to training; in contrast, Saudi Arabia allocates only 0.4% (6).

The Ministry of Civil Service and the Ministry of Finance strictly control recruitment activities for health care jobs, which adversely affects the available health care workforce. These ministries must approve and oversee the creation of new jobs and the recruitment of new employees or professionals to the Ministry of Health. Such policies limit the flexibility and autonomy of the Ministry of Health if it needs to update its workforce.

Acceptability of and accessibility to primary health care:

Acceptability of and accessibility to the primary health care services are central to the performance and evaluation of health care systems. Acceptability is the willingness of people to seek services (42). Acceptability decreases when people perceive health services to be ineffective or when cultural and social factors (e.g. language, age, sex, ethnicity or religion) of the health care provider discourage the consumer from using services (42). Patient satisfaction studies have been used to determine the acceptability of health services among populations as well as the effectiveness of the services provided (43–46). Findings from patient satisfaction surveys have been found to play a key role in reforming health care systems (45,46).

A number of older studies of local health services concluded that patients in Saudi Arabia were not satisfied with primary health care services (47–51). The main reasons for dissatisfaction included the physical environment, waiting times, confidentiality measures, the location of centres, working hours, absence of speciality clinics, language and communication barriers, and the structure of the waiting area. Despite these findings, the past decade has seen a growing acceptance of primary health care services by the Saudi Arabian population. This acceptance is reflected in the total number of visits to primary health care centres during 2014, which was about 51.26 million. The average number of visits per primary health care centre was 22 473, while the average number of daily visits per centre was 90 (17). Non-availability of alternative services may lead the Saudi Arabian to accept primary care services despite their dissatisfaction. However, recent studies indicate an increased level of satisfaction with primary care services compared with previous studies (52–55).

Access to health services was been defined as "the opportunity to identify health care needs, to seek health care services, to reach, to obtain or use health care services and to actually have the need for services fulfilled" (56). The Ministry of Health identified the barriers to accessing health care services as environmental, social and economic conditions (e.g. geographical location, education level, income level and nutrition) (6). A 2014 study in Hail city, Saudi Arabia, found that the lowest level of satisfaction among primary health care users was accessing medical care and the availability of doctors (53). Another structural barrier to access to health care services is the weakness in the current referral system between the various levels of health care (57). While general, central and specialized public hospitals accept only referred cases, private hospitals are free to accept patients without referral. Furthermore, there is no system for sending patients back to primary health care services from general, central or specialized hospitals. More efforts are needed to reform this gap and to ensure a better continuity of primary care.

A study in Riyadh, Saudi Arabia, examined the factors influencing access to and use of primary health care centres in urban and rural areas (55). The findings highlighted important differences between urban and rural populations. For rural patients these factors included the distance to the primary health care centre, cleanliness of the centre, understanding the treatment and receiving health prevention and promotion services. Urban respondents were shown to want increased opening hours particularly in the evenings (55).

According to the World Health Organization (WHO), "The role of government with regard to sustainable health systems is to guarantee equity of access and to ensure that essential health system functions are maintained." (58). As a first level of contact between people and the health care system, primary health care services of good quality should be accessible and available to the whole population.

Primary care health information system

The Ministry of Health in Saudi Arabia developed a four-year (2008–2011) project to improve eHealth in health care organizations and facilities (59,60). However, the eHealth strategy was first implemented during 2011 in the hospitals in major cities (60). A study in 2013 aimed to identify the information needs and information-seeking behaviour of primary care physicians in Saudi Arabia (61). The findings indicated that the absence of an electronic system was a main contributor to the weaknesses of primary health care services. Primary health care physicians did not have up-to-date patient information. High-quality computing services, including electronic health records and clinical decision-making support tools, are essential to a good-quality health care service (62). Such initiatives can help deliver effective patient-centred care (63). Therefore, providing eHealth facilities within the current primary health care services is crucial to serve patients' needs and to enhance the knowledge base of physicians and other health care professionals.

New primary health care reform

To improve the quality of primary health care services, it is important to identify gaps in existing systems through review of the literature and existing health care policies and observations, and then develop and implement appropriate reforms in order to fill the gaps. This means the focus should be on primary health care structure, infrastructure, financing, management and leadership. The Ministry of Health has tried to reform the health system including primary health care services through its new reform strategy for 2010–2020 (6). The new strategy calls for the establishment of more primary health care centres to meet the growing need for health services. In addition, it calls for the establishment of planned institutional work and the strengthening of monitoring of quality and performance.

Another objective of the strategy is to develop an accurate database to integrate primary health care centres . The strategy also includes the decentralization of management and empowerment of the administrative, technical and finance sectors within each level of health care. The implementation of an effective referral system from primary health care to the next level and back to primary health care is also an important objective in the proposed strategy. The development of the primary health care workforce through further education and training and new recruitment and retention strategies to address workforce shortages is also part of the reform strategy.

Although it is almost six years since the strategy was publicly announced, few changes have been introduced (personal observation). To ensure the success of this strategy, the Ministry of Health in collaboration with regional directorates must set operational plans for its implementation.

In addition, a substantial portion of the Ministry of Health budget should be directed to primary health care services in order to promote population health in Saudi Arabia. The importance of such changes has increased because the Ministry of Health has recently decided to provide paid primary health care services to expatriates who work in the private sector (64), thus potentially placing an even greater burden on the primary health care system. To support this trend and promote population health, upcoming programmes and initiatives of the Saudi Vision 2030 for health should focus more on public health and primary health care services.

Conclusion:

The Saudi Arabian health care system is going through a period of evolution. This has been brought about by the new vision of the Ministry of Health and the development of a national health strategy to meet the challenges. There is an urgent need to take new initiatives to improve the health care services in Saudi Arabia with a focus on reforms of primary health care services. Such reforms require the challenges in many areas of health and health to be tackled including: scope, structure, infrastructure, financing, increased demand, increased costs, workforce, inequitable access to the services, quality and safety of services, growing burden of chronic diseases, information systems, management and leadership issues, and the referral system.

Results:

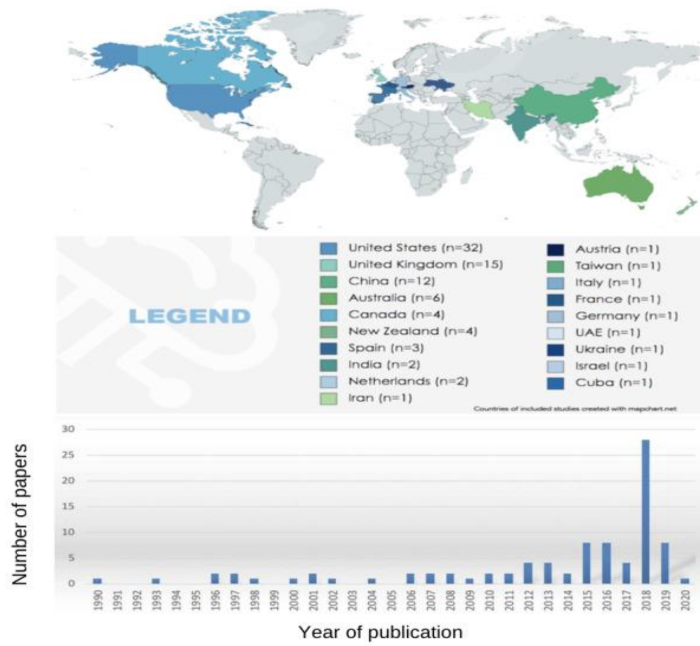
We identified 16,870 unique records. After screening their titles and abstracts, 979 studies remained for full-text review. Ultimately, 90 studies met our inclusion criteria (Figure 1).

Study Characteristics:

Countries and Publication Dates:

The number of studies published annually has increased gradually since 1990, especially since 2015. Figure 2 shows the timeline of the AI-based studies. Moreover, the four countries publishing a high number of studies are the United States (32/90, 36%), the United Kingdom (15/90, 17%), China (12/90, 13%), and Australia (6/90, 7%). The remaining are New Zealand (4/90, 5%), Canada (4/90, 5%), Spain (3/90, 3%), India (2/90, 2%), and the Netherlands (2/90, 2%), followed by Iran, Austria, Taiwan, Italy, France, Germany, the United Arab Emirates, Ukraine, Israel, and Cuba publishing 1 study each (1%). North America accounts for the highest number of studies (37/90, 41%) followed by Europe (25/90, 28%), Asia (18/90, 20%), and Oceania (10/90, 11%).

Figure 2.



Distribution and timeline showing the publication of studies based on artificial intelligence.

Aims of the Included Studies:

The included studies sought to describe and test or implement either a novel AI model in CBPHC (16/90, 18%) or an off-the-shelf AI model, which is a modified or improved version of existing AI models in CBPHC (74/90, 82%).

Conceptual Frameworks:

Among the 90 studies, 2 (2%) reported using a sociocognitive theoretical framework [35,36]. One of these used the I-change model [35], a model that evolved from several cognitive models, explores the process of behavioral change and the determinants that relate to the change, and focuses on individuals’ intentions for adopting innovations [35,37]. In the first study [35] using the I-change model, the authors investigated the cognitive determinants associated with Dutch general practitioners’ intention to adopt a smoking cessation expert AI system in their respective practices and found that workload and time constraints are important barriers.

The second study used a continuing medical education framework [38] and compared traditional expert-led training (control group) with an online multimedia-based training activity supplemented with an AI-driven simulation feedback system (treatment group) [36]. Diagnosis accuracy significantly improved in the treatment group when compared to the control group, providing evidence supporting the efficacy of AI medical training methods.

Time Frame of the Collected Data Sets:

Among the included studies, 25% (23/90) used data collected over a period of 1 year or less, 20% (17/90) used data collected over a period between 1 and 5 years, 12% (11/20) used data collected over a period between 5 and 10 years, and 9% (8/90) used data collected during more than a 10-year period. One study (1%) used three data sets, collected data from three different sites with over three different time periods (<1 year, 1-5 years, >10 years) [39]. The remaining studies (30/90, 33%) did not specify the time frames of their data set collections.

Population Characteristics:

Patients:

Sample Size:

Overall, 88% (79/90) of the included studies reported their sample size. A total of 21,325,250 patients participated in the testing, training, or validation of the AI systems.

Sex, Gender, and Age:

Among the 79 studies reporting their sample size, 46 (58%) reported the sex distribution and none of the studies reported on gender-relevant indicators. Further, 32 (41%) reported the participants’ mean age and standard deviation. Overall, the mean age of the participants in these studies was 60.68 (±12.15) years. Age was reported as a range in 21% (17/79) of the studies reporting the sample size, and the remaining 38% (30/79) did not report the age of their participants.

Ethnicity:

Among all the included studies, 22% (19/79) reported the participants’ ethnic origins, which included Caucasian, Asian-Middle eastern, South Asian, African, American Indian, Alaskan Native, Hispanic, Pacific Islander, Māori, and mixed (Table 1).

Table 1.

Characteristics of the participants in the included studies (N=90).

Participant characteristics	Value
Patients	
Total number	21,325,250
Female	2,087,374
Male	1,814,912
Did not report the sex	17,422,964
Age (years), mean (SD)	60.68 (12.15)
Number of studies reporting the sample size of patients (n)	79
Health care providers	
Total number	2,581
Female	467
Male	224
Did not report the sex	1,890
Age (years), mean (SD)	48.50 (7.59)
Number of studies reporting the sample size of health care providers (n)	17
Ethnicities reported for patients (number)	
Caucasian	814,467
Asian	8550
African	42,057
American Indian/Alaskan native	13
Hispanic	5066
Mixed ethnicity	11
Unknown	2,241,937
Number of studies reporting patients’ ethnicities (n)	19
Number of studies reporting health care providers ethnicities (n)	0

Other Sociodemographic Information:

Only 27% (25/90) of the included studies reported other sociodemographic characteristics of their participants. Socioeconomic status (ie, income level) was the most commonly reported (12/90, 13%). Other characteristics reported were educational status, marital status, area of residence, employment status, smoking status, and insurance status.

Health Care Providers:

Among the 90 included studies, 55 (61%) reported the involvement of primary health care providers. Further, 41 of these 55 studies (75%), involved general practitioners, 5 (9%) included nurses, 1 (2%) involved psychiatrists, 1 (2%) involved occupational therapists, and 1 (2%) involved an integrated care specialist. Six studies (7%) involved general practitioners together with other types of health care providers, specifically nurses (3/55, 5%), physician assistants, (1/55 2%), nurses, surgeons, and non-surgeon specialists, (1/55, 2%) and respirologists (1/55; 2%).

Sample Size:

Among these 55 studies, 17 (31%) reported the sample size. The data pertaining to 2581 primary health care providers were collected in these studies.

Five of these studies (29%) reported the sex distribution and none reported on gender-relevant indicators. Moreover, 2 (12%) studies reported the age of the primary health care provider participants. The mean age and SD obtained in all the studies for which we collected information is 48.50 (±7.59) years (Table 1).

Sociodemographic Information:

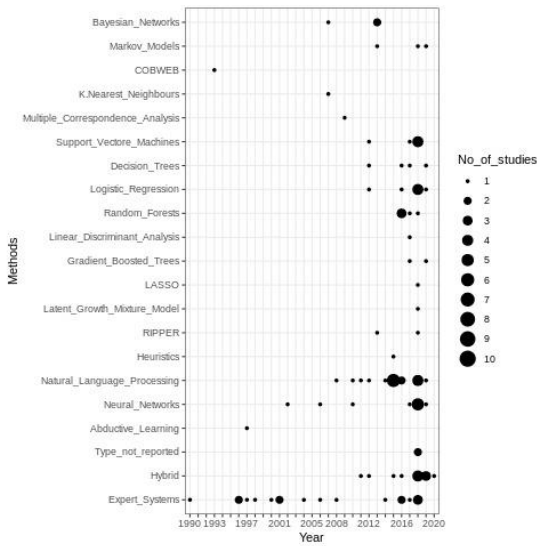
Out of 17 studies, only 1 (5%) reported the primary health care providers' locations of practice. Among the 120 providers in this study, 57 providers practiced in rural areas and 63 practiced in urban areas.

Intervention:

AI Methods:

Most of the included studies (78/90, 86%), used a single AI method (non-hybrid) and the remaining 14% (n=12) used hybrid AI models—meaning that they integrated multiple AI methods. The most commonly used methods were machine learning (ML) (41/90, 45%) and natural language processing (NLP), including applied ML for NLP (24/90, 27%), and expert systems (17/90, 19%). Figure 3 illustrates the number of studies published according to the type of AI method and year of publication (see Multimedia Appendices 3 and 4 for details regarding the AI methods).

Figure 3.



Number of studies published according to the artificial intelligence method used and years of publication.

Performance Measures of AI Interventions:

In terms of evaluating the performance of AI models, we considered the following performance metrices: True positive (TP), True negative (TN), False positive (FP), False negative (FN), sensitivity, specificity, precision, F1 score (ie, the weighted average of precision and recall, and area under the curve [AUC]). Among the 90 included studies, 31 (34%) did not report the performance of their models. Among the 59 studies that reported model performance, 13 (22%) used 2 or more performance measures and the remaining 46 (78%) used one measure (see Multimedia Appendix 4 for detailed information on studies' AI methods used in the included studies and their performance measures).

Generated Knowledge:

Most of the included studies (81/90, 91%) were either diagnosis- or prognosis-related or focused on surveillance, and the remaining involved operational aspects (eg, resource allocation, system- level decisions) (see Multimedia Appendix 4 for detailed information).

Health Conditions:

The majority of the 90 included studies (68/90, 76%) investigated the use of AI in relation to a specific medical condition. Conditions studied were vascular diseases including hypertension, hypercholesteremia, peripheral arterial disease, and congestive heart failure (10/90, 11%) [40-49]; infectious diseases including influenza, herpes zoster, tuberculosis, urinary tract infections, and subcutaneous infections (8/90, 9%) [50-57]; type 2 diabetes (5/90, 6%) [58-62]; respiratory disorders including chronic obstructive pulmonary disease and asthma (6/90, 8%)

[63-69]; orthopedic disorders including rheumatoid arthritis, gout, and lower back pain (5/90, 5%) [36,39,70-72]; neurological disorders including stroke, Parkinson disease, Alzheimer disease [73-75], and cognitive impairments (6/90, 5%) [76,77]; cancer including colorectal cancer, and head and neck cancer (4/90, 4%) [78-81]; psychological disorders including depression and schizophrenia (3/90, 3%) [82-84]; diabetic retinopathy (3/90, 3%) [85-87]; suicidal ideations (2/90, 2%) [88,89]; tropical diseases including malaria (2/90, 2%) [90,91]; renal disorders (2/90, 2%) [92,93]; autism spectrum disorder (2/90, 2%) [94,95]; venous disorders including deep vein thrombosis and venous ulcers (2/90, 2%) [96,97]; and other health conditions (8/90, 8%) [98-105].

Data Sets (Training, Testing, and Validation):

In this section, we briefly explain the training, testing, and validation of the data sets, and then present our results. The training data set is the subset of the data that are used to fit in the initial AI model and to train it. The testing data set is the subset of the data used to evaluate the model that fits the initial training data set. The validation data set is a subset of the data used to conduct an unbiased evaluation of the model that fits the training data set, while simultaneously optimizing the model's hyperparameters, namely the parameters whose values are used to control the learning process [106]. The evaluation of these parameters is important because it provides information about the accuracy of predictions made by the AI model, and the prospective effects of hyperparameter tuning [107].

Among the 90 included studies, 9 (10%) reported on all three data sets, 33 (36%) reported on the training and testing data sets, and 36 (40%) reported on the training and validation data sets. No descriptions of these data sets were provided in 49 (54%) of the included studies.

Legal Information and Data Privacy:

Legal information concerning privacy was mentioned in 4% (4/90) of the studies in our review. Although health care records were anonymized to protect participants' information in all four of these studies, only one explicitly reported ensuring data collection, storage, and sharing security. The remining studies did not report on data privacy and other legal information.

Artificial intelligence (AI) embodies the quest to instil machines with capabilities that mimic human intelligence. Historically rooted in the ground-breaking Dartmouth summer research project of 1955, where luminaries like McCarthy, Minsky, Rochester, and Shannon postulated foundational ideas of AI, the field has aimed to create machines capable of human-like thought processes.(1) Core facets of AI include learning—where systems accumulate information and the guiding rules for its utilization; reasoning—the act of leveraging these rules to derive either general or precise conclusions; or the ability for self-refinement. Over the decades, the propulsion of AI can be attributed to technologies such as machine learning (which allows computers to glean insights from data and enhance their performance), neural networks, and natural language processing (NLP).(2)

Artificial intelligence (AI) has a broad range of applications, transforming various sectors with its advanced capabilities. Voice and speech recognition technologies, as exemplified by Siri from Apple and Alexa from Amazon, allow users to interact with devices using natural language commands, assisting in everyday tasks like communication, entertainment, and home automation. In the realm of image recognition, tools such as Google Lens, Amazon Rekognition, and Microsoft Azure Cognitive Services harness AI to identify and interpret elements within images and videos, offering functionalities crucial for security, content moderation, and user interaction. The field of autonomous vehicles, particularly Tesla's self-driving cars, showcases AI's role in navigation and road safety, employing a combination of sensors and algorithms to analyse and respond to real-time road conditions.(3,4)

Predictive analytics, another significant AI application, utilizes machine learning and statistical methods to forecast future events from historical data, proving invaluable in sectors like finance, marketing, and healthcare for risk assessment, consumer behaviour prediction, and disease management. Furthermore, AI-driven chatbots and virtual assistants are revolutionizing customer service and information dissemination, using natural language processing to deliver efficient and responsive assistance.

Lastly, AI in platforms like Netflix and Amazon personalizes user experiences by curating content recommendations based on individual preferences, thereby enhancing user engagement and satisfaction. This diverse array of applications highlights AI's transformative impact across various domains, continually evolving to meet an expanding range of human needs and challenges.(5)

Revolutionizing Primary Care with AI:

In an era where technology intersects with healthcare, Artificial intelligence (AI) emerges as a linchpin in redefining the landscape of primary care. Through its myriad applications, AI offers avenues to bolster patient care, streamline administrative processes, and create a more proactive healthcare model.

Central to this transformation is the role of AI in Clinical Decision Support. General practitioners, often the first point of contact for patients, grapple with a deluge of diverse cases daily. AI-driven support systems can be invaluable allies in this scenario. By meticulously analysing patient data, these systems can proffer potential diagnoses or suggest treatment avenues.(6) The implications of this are profound, especially when one considers the pervasive issue of diagnostic errors in primary care.

Furthermore, the promise of predictive analytics reshapes the traditional reactive model of primary care. By gleaning insights from patient records, AI stands poised to flag patients at heightened risk of chronic ailments or potential complications. Such early identification paves the way for timely interventions, potentially staving off hospital admissions, and ensuring better patient outcomes.(7)

On the administrative front, AI promises reprieve from the often-tedious tasks that dominate a significant chunk of a physician's workday. From patient scheduling to intricate billing processes and meticulous records management, AI-driven automation can ensure efficiency and accuracy, freeing physicians to channel their focus where it truly matters: their patients.[8]

In a world forever changed by the COVID-19 pandemic, the pertinence of telemedicine and virtual health assistants has skyrocketed. AI-powered virtual health platforms have emerged as frontline responders, providing initial medical consultations based on robust medical datasets. While they adeptly manage minor medical queries, their true prowess lies in discerning when to escalate more intricate cases to human doctors.[9]

Beyond virtual consultations, the scope of AI in primary care stretches into the realm of remote patient monitoring. The ubiquity of wearable tech, armed with AI capabilities, has opened avenues for continuous health monitoring. These devices vigilantly track vital statistics, flagging any aberrations and ensuring that primary care providers can intervene promptly.[10]

Lastly, AI serves not just as a clinical tool but also as a medium for patient engagement and education. Through chatbots and specialized applications, AI can demystify medical jargon, offer timely medication reminders, and even extend motivational support, particularly crucial for patients navigating the challenges of chronic conditions.[11]

In essence, AI, with its multifaceted applications, stands poised to redefine primary care, blending technological prowess with the core tenets of patient-centric care.

Artificial Intelligence in Primary Care: Paving the Way for Enhanced Patient Care:

The infusion of Artificial intelligence into primary care heralds a paradigm shift, redefining healthcare delivery through its numerous advantages.[12]

a) Enhanced diagnostics:

The prowess of AI algorithms lies in their ability to sift through voluminous datasets at a pace unparalleled by human capacity. By discerning intricate disease markers or patterns, these algorithms offer a level of diagnostic precision that could prove elusive to even the most seasoned clinicians.[13]

By suggesting potential diagnoses or treatments rooted in data-centric analyses, AI emerges as a valuable adjunct, complementing a doctor's clinical acumen.[14, 15]

b) Proactive patient management & predictive analysis:

Beyond diagnostics, AI stands out in its capability for foresight. Predictive analytics, a cornerstone of AI, arms primary care providers with the insights needed to pinpoint patients at an augmented risk of complications or readmissions.[16] Such pre-emptive identification facilitates timely interventions, tailor-made care plans, and, crucially, improved patient outcomes. Moreover, AI's capability to forecast those on the brink of specific ailments offers a more proactive stance in patient care.[17]

Artificial intelligence systems used in the first step for provider and patient acceptance can assist in various ways. These systems can support processes such as appointment scheduling, triage, and patient routing.[18]

Appointment scheduling:

Artificial intelligence can analyse providers' current appointment calendars and communicate with patients to determine suitable appointment times. This can enable more efficient appointment scheduling and reduce waiting times.

Triage process:

Artificial intelligence can evaluate patients' symptoms and health conditions and prioritize them based on urgency. This ensures the rapid detection of urgent cases and intervention when needed.

Patient routing:

Artificial intelligence can answer questions related to patients' health issues and direct them to the appropriate healthcare provider or specialist. This can ensure that patients receive the right treatment and care.[19]

Artificial intelligence systems can save time for healthcare providers, optimize appointment scheduling, and help patients be directed more quickly and effectively. However, the use of these systems should be carefully managed, taking into account ethical and privacy considerations.[20,21]

c) Optimized operations & administrative efficiency:

The operational landscape of primary care clinics, often mired in complexities, stands to gain immensely from AI. By analyzing patient inflow trends, AI can finetune appointment schedules, ensuring minimized wait times and maximized clinic throughput. Additionally, the automation of administrative chores, such as the intricate management of patient records, translates to valuable time savings for physicians, allowing them to redirect their focus on patient care.[8]

d) Telemedicine and enhanced patient engagement:

The digital age has ushered in the era of telemedicine, further catalyzed by AI innovations. AI-powered chatbots, virtual health assistants, and advanced telemedical platforms can adeptly manage rudimentary patient concerns, orchestrate appointments, and even provide rudimentary care guidelines.[22]

More than just a conduit for remote consultations, these platforms foster a heightened level of patient engagement, delivering timely reminders, demystifying medical complexities through educational content, and offering sustained support.[23]

e) Continuous monitoring:

The ubiquity of wearables, especially those imbued with AI capabilities, brings forth the prospect of uninterrupted patient monitoring. These devices vigilantly track vital metrics, providing both patients and their caregivers real-time notifications about any health deviations, ensuring that timely interventions aren't just possible but a norm.[9] In its totality, AI in primary care represents more than just technological innovation; it encapsulates the essence of enhanced, data-driven, patient-centric care.

Artificial Intelligence in Primary Care: Unravelling the Complexities:

The proliferation of Artificial Intelligence (AI) in primary care has undeniably unlocked new horizons of patient care. However, this nascent integration is not without its challenges and disadvantages, warranting an in-depth scrutiny.[24]

a) Reliability, trust, and data privacy:

The foundational bedrock of AI is its data. The accuracy of AI recommendations hinges critically on the calibre of this training data. Flawed, biased, or piecemeal data can skew AI outputs, leading to potentially detrimental recommendations.[1] Concomitantly, the magnified data collection and analysis open the Pandora's box of heightened cybersecurity threats, accentuating the risk of breaches or misuse.[25]

b) Loss of human touch and over-reliance on technology:

The sanctity of the doctor-patient relationship, underscored by human touch and empathy, might be compromised with an overriding dependency on AI.[26] The seductive allure of technology runs the risk of clinicians leaning excessively on AI, potentially sidelining patient-specific subtleties that may not be evident in cold, hard data.[27]

c) Interoperability and integration issues:

The marriage between AI systems and incumbent Electronic Health Record (EHR) systems is fraught with challenges. These teething issues arise from compatibility concerns and the quagmire of data standardization. Moreover, the maiden voyage into AI's integration within primary care infrastructures can bleed finances, given the steep initial costs.[28]

d) Potential misdiagnosis and over-reliance

The infallibility myth surrounding AI can lead to unwarranted complacency. Excessive trust, devoid of critical human oversight, can culminate in misdiagnoses. This is especially pertinent if the AI lacks training on specific, especially rare, pathologies.[29]

e) Provider and patient acceptance

The challenges of provider and patient acceptance of Artificial intelligence in primary care are notable, with several experts highlighting key aspects:

Provider Acceptance: Healthcare providers often have reservations about AI, including concerns about the reliability of AI systems and potential loss of professional autonomy.[30] Providers may worry about an over-reliance on technology, potentially overshadowing clinical judgment and experience. Adapting to AI-integrated workflows also poses a challenge, requiring not only technical training but a shift in approach to patient care.

Patient Acceptance: Patients also express concerns regarding the use of AI in primary care. These include worries about privacy, the impersonal nature of AI interactions, and a potential reduction in the quality of human aspects of care. The security of personal health data managed by AI systems and the lack of personal interaction are significant points of apprehension for patients.[31]

Trust in AI Systems: Building trust in AI systems is a central issue for both provider and patient acceptance.[32] Ensuring that AI systems are accurate, reliable, and safe is crucial. Providers and patients need confidence that AI can enhance healthcare outcomes without compromising care quality.

Cultural and Societal Perceptions: Societal and cultural attitudes towards technology and AI significantly influence acceptance levels.[33] These perceptions can either facilitate or hinder AI adoption in primary care, depending on how technology and its role in healthcare are viewed culturally.

f) Training and education

Healthcare providers need adequate training to use AI tools effectively. Understanding how to interpret AI recommendations and when to rely on human judgment is critical. This requires ongoing education and adaptation. The metamorphosis into an AI-infused primary care ecosystem necessitates rigorous training for physicians and auxiliary staff, demanding significant investments in both time and resources.[34]

Additionally, there's a need for practical training in AI applications within primary healthcare settings.[34] This includes learning how AI can assist in diagnosis, treatment guidance, disease screening, hospital management, and patient monitoring, requiring hands-on experience with these tools.

Addressing ethical and privacy concerns in AI usage is also a key challenge.[35] It's essential for healthcare professionals to be educated on maintaining patient confidentiality, addressing biases in AI algorithms, and ensuring fair and unbiased AI usage.

Another significant challenge lies in equipping healthcare staff with the skills to interpret and critically evaluate the large volumes of data processed by AI systems.[36] This skill set is vital for making accurate diagnostics and treatment decisions.

Finally, the rapid evolution of AI technology presents a challenge in ensuring continuous education and adaptation for healthcare professionals.(35) Staying updated with the latest AI developments and undergoing regular training is imperative for effective and up-to-date patient care. Addressing these challenges is key to the successful integration of AI in primary healthcare, ensuring that healthcare professionals are equipped with the necessary AI skills and are prepared to navigate its ethical and security aspects.

h) Cost and resource allocation

Implementing AI solutions in primary care can be expensive. The cost includes not just the technology itself but also the infrastructure to support it, training for staff, and ongoing maintenance.

The cost and resource allocation of AI in primary healthcare depend on the complexity of the technology and applications used, the scale of the organization, and the available resources. Each healthcare organization should assess the costs and resource requirements of AI usage based on their specific circumstances.(37) The cost and resource allocation of artificial intelligence in primary healthcare can vary depending on several factors.

Investment Costs:

The implementation and application of AI systems typically incur initial costs. These costs may include the procurement of hardware and software infrastructure, the creation of databases, the collection of training data, and the employment of experts for model development. These investment costs can vary depending on the scale of the healthcare organization, the complexity of AI technologies, and the scope of the applications to be used.

Data Sources and Data Management:

AI systems require a substantial amount of data to function effectively. Therefore, it is important to establish sufficient and reliable data sources for the use of AI in primary healthcare. The processes of data collection, storage, and updates may require additional resources and costs.

Expert Employment and Training:

Having personnel with the necessary skills is crucial for the effective use of AI. This may require the employment of AI experts and the training of existing personnel in AI. Expert employment and training may incur additional costs and resource allocation.

Maintenance and Updates:

AI systems require ongoing maintenance and updates. This includes software updates, data refreshes, model enhancements, and monitoring system performance. Allocating time, resources, and costs is necessary to sustain these processes.(38)

i) Limited scope and generalizability :

AI models developed in one setting may not perform well in another due to differences in patient populations, healthcare practices, and data collection methods. Generalizing AI solutions across diverse healthcare settings remains a challenge.

j) Accountability and legal liability

Determining who is responsible when an AI system fails or causes harm is complex. The legal framework for AI accountability in healthcare is still evolving.

k) Regulatory, ethical concerns

The blurry lines of accountability in the wake of AI-induced misdiagnoses create a regulatory conundrum. Simultaneously, the ethical maelstrom surrounding the sanctity of patient data and AI-driven medical decisions cannot be sidestepped.(39)

In essence, while AI's promise in redefining primary care is undeniable, a balanced perspective, cognizant of its challenges, is imperative for its holistic and ethical integration.

Noteworthy AI Utilization in Primary Care:

In the realm of primary care, Artificial Intelligence (AI) has made significant strides, reshaping healthcare dynamics. Here are some pioneering examples:

Disease Identification and Diagnosis:

IBM's Watson Health stands out as a flagship example. By juxtaposing patient medical data against a comprehensive database of research, clinical trial outcomes, and academic articles, it aids doctors in pinpointing diseases.(40)

Forecasting and Predictive Analytics:

In the realm of medical imaging, Zebra Medical Vision has carved a niche for itself. Its state-of-the-art algorithms meticulously analyze imaging data to spot a spectrum of diseases, acting as a catalyst for timely interventions.(41)

Personal Health Surveillance:

The Apple Watch, with its embedded ECG functionality and fall detection mechanism, is a testament to the power of AI in real-time health monitoring. By discerning anomalies like irregular heartbeats or detecting abrupt falls, it ensures that users and their designated emergency contacts receive prompt alerts, potentially mitigating health complications.(42)

Interactive Chatbots and Digital Health Assistants:

Babylon Health's AI-driven chatbot is revolutionizing patient interaction. Capable of offering medical insights based on user-provided health data, it demystifies symptoms and guides patients towards informed decisions. (43)

Guidance on Treatment Modalities:

Google's DeepMind has broken new ground with its AI model that scrutinizes 3D eye scans. With a staggering 94% accuracy rate, it provides therapeutic recommendations for a wide array of ocular conditions. (44)

Streamlining Administrative Responsibilities:

Nuance Communications has spearheaded the transition towards a seamless healthcare workflow. Its AI-infused platform adeptly transcribes patient-doctor dialogues, freeing physicians from the shackles of time-consuming paperwork.(45)

Pharmaceutical Research and Drug Discovery:

Venturing beyond primary care but with implications for it, Benevolent AI harnesses the prowess of AI to trailblaze drug discovery pathways. Such avant-garde approaches promise to usher in innovative treatment modalities and drugs into primary care landscapes. (46)

Conclusion:

Artificial Intelligence, a term once relegated to the realm of science fiction and academic speculation, has permeated our modern reality, holding promise and potential in various sectors, primary healthcare being a notable beneficiary. AI, now a critical component of modern healthcare, brings with it a suite of advanced capabilities, thanks to breakthroughs in machine learning, neural networks, and natural language processing. Its integration into primary care is reshaping the healthcare landscape, offering improved diagnostic accuracy, operational efficiency, and patient-centric care.

Yet, as we embrace this technological marvel, it is imperative to navigate its adoption with a keen awareness of the challenges and ethical considerations it presents. The integration of AI in healthcare necessitates a delicate balance, ensuring that technological advancements augment human expertise and empathy rather than supplant them. This approach will safeguard the essential human element in healthcare, preserving the irreplaceable personal touch in patient care.

Looking forward, the potential of AI to transform healthcare is boundless. It promises not only to enhance existing medical practices but also to unlock new realms of personalized treatment and proactive health management. As we chart this course, it is vital to foster a synergy between AI and human medical professionals, ensuring that the path ahead is guided by both technological innovation and ethical responsibility.

This harmonious blend of AI and human insight is poised to redefine healthcare, making it more accessible, effective, and attuned to the unique needs of each patient. In this AI-augmented future, we envision a healthcare system that is not only more capable but also more compassionate and patient-focused.

Involvement of Users:

Development:

Two of the 90 included studies (2%) reported about the AI developers, all of whom were engineers [60,86]. None of the studies reported the involvement of the end users, including health care providers and patients, in the development stage.

Testing and Validation:

Seven out of the 90 (8%) included studies reported information about those who participated in testing or validating the AI. This included general practitioners and nurses [86], engineers [60], general practitioners [51,81], occupational therapists [74], respirologists [64], and nurses [108].

Outcomes:

Extraction of the data related to the benefits for patients, primary health care providers, and the health system explained in this section was conducted according to what the authors of the included studies clearly reported as specific benefits to each of these categories.

Potential Benefits for Patients:

Included studies reported the following potential benefits of implementing AI in CBPHC: improvements in treatment adherence, person-centered care, quality of life, timeliness of high-risk patient identification, screening speed and cost-effectiveness, enhanced predictability of morbidities and risk factors, benefits related to early diagnosis, as well as early prevention of diseases for the elderly, and facilitated referrals.

Potential Benefits for Primary Health Care Providers:

The included studies reported the following information regarding primary health care provider-related benefits of implementing AI in CBPHC: enhanced interprofessional communication and quality of primary care delivery, reduced workload of these providers, and facilitation of referrals and patient-centered care.

Other benefits included benefits with respect to use of AI as a reminder system, application of AI tools to inform commissioning health care priorities, the benefit of an AI system as a quality improvement intervention by generating warnings in electronic medical records and analyzing clinical reports, facilitating monitoring of the diseases, and using AI to reduce health risks.

Potential Benefits for the Health Care System

Studies in our review found that AI can play a role in improving individual patient care and population-based surveillance, can be beneficial by providing predictions to inform and facilitate policy makers decisions regarding the effective management of hospitals, benefits to community-level care, cost-effectiveness, and reducing burden at the system level.

Economic Aspects:

Only one study (1%) among the included 90 papers assessed the cost-effectiveness of the AI system studied. The Predicting Out-of-Office Blood Pressure in the Clinic [PROOF-BP] system that the study authors developed for the diagnosis of hypertension in primary care was found to be cost-effective compared to conventional blood pressure diagnostic options in primary care [49].

Challenges of Implementing AI in CBPHC:

Our results suggest that challenges of using AI in CBPHC include complications related to the variability of patient data as well as barriers to use AI systems or to participate in AI research owing to the age or cognitive abilities of patients.

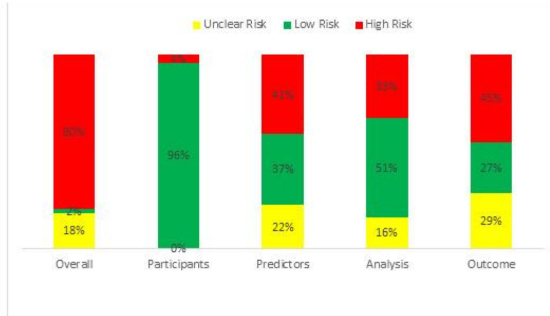
With respect to the health care system, our review found challenges related to how information is recorded (eg, the use of abbreviations in medical records), poor interprofessional communication between nurses and physicians, inconsistent medical tests, and a lack of event recording in cases of communication failures. The included studies also mentioned problems with respect to the restricted resources and administrative aspects such as legislations and administrative approvals, as well as challenges with respect to the lack of digital or computer literacy among the primary health care providers.

In the included studies, other challenges were reported at the level of the health care system such as the data available for use with AI as well as challenges at the level of AI itself (eg, complexity of the system and difficulty in interpretation). The following were identified as the main barriers regarding the data: (1) insufficient data to train, test, and validate AI systems, leading to negative impacts on the robustness of AI models and the accuracy of their predictions; (2) poor quality data, inaccuracies in the data, misclassifications, and lack of representative data; (3) deidentification of protected medical data; and (4) variability in the data sets and combining different data sets. Regarding AI, computational complexity and difficulties in interpreting or explaining some AI model compositions were among the barriers at the AI level.

Risk of Bias:

We identified the studies that were eligible to be evaluated using PROBAST. Among our included studies, 54% (49/90) were eligible to be evaluaeted using the PROBAST tool and most (39/49, 80%) were at high risk of bias according to our assessment with PROBAST (Figure 4). With respect to risk of bias for each of the four domains assessed, few studies presented risks regarding participants, (2/49, 4%), whereas 45% (22/49) studies exhibited risks of bias regarding outcomes. See Multimedia Appendices 5 and 6 for details on common causes of risks in each study).

Figure 4.



Risk of bias graph: assessing risk of bias in five categories namely overall, participants, predictors, analysis, and outcome (presented as percentages).

Discussion:

Principal Findings:

We conducted a comprehensive systematic scoping review that included 90 studies on the use of AI systems in CBPHC and provided a critical appraisal of the current studies in this area. Our results highlighted an explosion in the number of studies since 2015. We observed variabilities in reporting the participants, type of AI methods, analysis, and outcomes, and highlighted the large gap in the effective development and implementation of AI in CBPHC. Our review led us to make the following main observations.

AI Models, Their Performance, and Risk of Bias:

ML, NLP, and expert systems were the most commonly used in CBPHC. Convolutional neural networks and abductive networks were the methods with the highest performance accuracy within the given data sets for the given task. We observed that a small number of studies reported on the development and testing or implementation of a new AI model in their study, and most of the included studies (74/90, 82%) reported on the usage and testing or implementation of an off-the-shelf AI model. Previous work has demonstrated how off-the-shelf models cannot be directly used in all clinical applications [109]. We observed a high risk of overall bias in the diagnosis- and prognosis-related studies. The highest risk of bias was in the outcome, predictor, and analysis categories of the included studies; validation of studies (external and internal) was poorly reported, and calibration was rarely assessed. A high risk of bias implies that the performance of these AI models in a new data set might not be as optimal as it was reported in these studies. Given the high risk of bias observed in the included studies, AI models used in other settings (ie, with other data) may not exhibit the same level of prediction accuracy as observed.

Where to Use AI?:

Primary health care providers are more likely to use AI systems for system-level support in administrative or health care tasks and for operational aspects, rather than for clinical making decisions [1]. However, our results show that few AI systems have been used for these purposes in CBPHC. Rather, the existing AI systems are mostly diagnosis- or prognosis-related, and used for disease detection, risk identification, or surveillance. Further studies in this regard are needed to evaluate the reason behind this tendency in addition to studies for proving the efficiency and accuracy of AI models for assisting in clinical decision making within CBPHC settings. In our review, we found that only 2 of the 90 studies used a (sociocognitive) theoretical framework. Future research needs to use knowledge, attitudes, and behavior theories to expand AI usage for clinical decision making, and more efforts are required to develop and validate frameworks guiding effective development and implementation of AI in CBPHC.

Consideration of Age, Sex, and Gender:

Our results show that AI-CBPHC research rarely considers sex, gender, age, and ethnicity. In general, the effect of age is rarely investigated in the AI field and ageism is often ignored in the analysis of discrimination. In health research, AI studies that have evaluated facial and expression recognition methods identified bias toward older adults [109]. This bias could negatively affect the accuracy of the predictions made by AI systems that are commonly used by health care providers.

Furthermore, sex and gender are sources of variations in clinical conditions, affecting different aspects including prognosis, symptomatology manifestation, and treatment effectiveness, among others [110,111]. Despite this importance, big data analytics research focusing on health through the sex and gender lens has shown that current data sets are biased given they are incomplete with respect to gender-relevant indicators with sex-disaggregated data. Indeed, less than 35% of the indicators in international databases have full disaggregation with respect to sex [112]. Our results are consistent with this observation, as we found just half of the AI-CBPHC research with patient participants and nearly one-third with health care provider participants described the sex distribution. Moreover, no AI-CBPHC research has reported on gender-relevant indicators. These are important aspects that need to be considered in the future AI-based CBPHC studies to avoid potential biases in the AI systems.

Consideration of Ethnicity and Geographical Location:

Less than one quarter of included studies have reported patient participants' ethnicities, with no discussion on the ethnicities of participating health care providers. Moreover, for those studies that reported patient ethnicity, we observed that the collected data were related to causation populations, thus raising questions regarding the representativeness of the data set, leading to biases. Such biases could result in the AI system making predictions that discriminate against marginalized and vulnerable patient populations, ultimately leading to undesirable patient outcomes.

According to our results, most of the AI research in CBPHC has taken place in North American and Europe-centric settings. Several factors contribute to ethnoracial biases when using AI, including not accounting for ethnoracial information, thereby ignoring the different effects illnesses can have on different populations [113]. Consequently, studies can yield results with historical biases as well as biases related to over- or under-representation of population characteristics in data sets and in the knowledge, bases used to build AI systems. In turn, stereotypes and undesirable outcomes may be amplified. Ensuring ethnic diversity in study populations and accounting for this diversity in analyses is an imperative for developing AI systems that result in equitable CBPHC.

Involvement of Users:

Despite the many potential benefits of AI to humans, the development of AI systems is often based on "technology-centered" design approaches instead of "human-centered" approaches [114]. Our results indicate that no AI-CBPHC study has involved any end users in the system development stage and involving primary health care professional users during the validation or testing stages has been rare. This results in AI systems that do not meet the needs of health care providers and patients; they suffer from poor usage scenarios and eventually fail during implementation in clinical practice. A recent assessment of the current user-centered design methods showed that most of the existing user-centered design methods were primarily created for non-AI systems and do not effectively address the unique issues in AI systems [115]. Further efforts are needed to include health care providers and patients as users of the developed AI systems in the design, development, validation, and implementation stages in CBPHC. Nevertheless, effectively involving these users in the development, testing, and validation of AI systems remains a challenge; further studies are required to overcome them.

Ethical and Legal Aspects:

Ethical and legal challenges related to the use of AI in health care include, but are not limited to, informed consent to use AI, safety and transparency of personal data, algorithmic fairness, influenced by the aforementioned biases, liability, data protection, and data privacy. Our results indicate that ethical and legal aspects have rarely been addressed in AI-CBPHC research, except with respect to privacy and data security issues. There is a need to address all legal and ethical aspects and considerations within AI-CBPHC studies to facilitate implementation of AI in CBPHC settings. For instance, to increase the use of AI systems by CBPHC providers, clarifying scenarios in which informed consent is required could be useful, as would clarifying providers' responsibilities regarding the use of AI systems. To improve patient outcomes related to AI use in CBPHC, defining the responsibilities of providers and researchers regarding the development and implementation of AI-health literacy programs for patients may be necessary, together with gaining an understanding of how and when patients need to be informed about the results that AI systems yield.

Economic Aspects:

AI systems can provide solutions to rising health care costs; however, only one (1%) AI-CBPHC study has addressed this issue by conducting a cost-effectiveness analysis of AI use. This is consistent with other study results showing that the cost-effectiveness of using AI in health care is rarely and inadequately reported [116,117]. Thus, further research analyzing cost-effectiveness is needed for identifying the economic benefits of AI in CBPHC in terms of treatment, time and resource management, and mitigation of human error; this would be valuable as it could influence decisions for or against implementing AI in CBPHC.

AI in Clinical Practice:

Our results show different barriers and facilitators for implementing AI in clinical practice. Aspects related to the data were among mostly mentioned ones. For instance, the lack of high amounts of quality data, specifically when using modern AI methods (eg, deep learning), is a challenge commonly faced when developing AI systems for use in CBPHC. The promotion of AI-driven innovation in any setting, including CBPHC, is closely linked to data governance, open data directives, and other data initiatives, as they help to establish trustworthy mechanisms and services for sharing, reusing, and pooling data [118] that are required for the development of high-quality data-driven AI systems.

In addition, some data security and privacy laws can create a bottleneck, limiting the use of AI systems in CBPHC and the sharing of health care information that is required for developing high- performance AI systems. To facilitate the implementation and adoption of high-quality AI systems in CBPHC and ensuring benefits to patients, providers and the health care system, research providing insights for addressing these implementation challenges is needed.

Limitations of the Study:

Our review has some limitations. Firstly, given that we used the Canadian Institute of Health Research's definition of CBPHC to determine our inclusion criteria and given that the definition of CBPHC differs from one country to another, our search strategy may not have captured all relevant records. Secondly, we excluded studies conducted in emergency care settings. In many countries, emergency departments are the points of access to community-based care. The European Commission recently released a legal framework (risk-based approach) for broad AI governance among EU member states [118] and categorized emergency care and first aid services as "high risk." Requirements of high-quality data, documentation and traceability, transparency, human oversight, and model accuracy and robustness are cited as being strictly necessary to mitigate the risks in these settings [118].

Conclusion:

In this systematic scoping review, we have demonstrated the extent and variety of AI systems being tested and implemented in CBPHC, critically evaluated these AI systems, showed that this field is growing exponentially, and exposed knowledge gaps that remain and that should be prioritized in future studies.

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