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Intelligent Resource Allocation Model in Healthcare: A Solution for Distributed Systems in Pediatric Patients' Referral. A Structured Review

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Abstract

Background/Introduction: The social behaviour of some animals have been simulated to design intelligent systems capable of solving complex problems such as those experienced in healthcare. Researchers and medical practitioners are interested in swarm intelligence (SI) in the healthcare domain. However, there have been limited published research on this subject from the perspective of resource allocation especially in line with providing a solution to pediatric patients' referral.

Methods: The researchers were able to find 16,870 distinct data using a comprehensive literature review. 979 research were left for detailed review following titles and abstracts were screened. In the end, 90 research were found to meet the requirements. The paper filtered study characteristics of researchers (country of the corresponding author); social variables of authors (number of participants and type of disease or treatment studied); intervention parameters (SI methods models); and outcome characteristics, including patient, practitioner, and health-care system impacts.

Results: According to the assessment, there is a developing foundation of expertise. Clinical decision-making, quality healthcare organization and management, predictive medicine, clinical documentation and testing analysis , and patient data and diagnostics are among the topics covered. The highest number of studies came from the United States, China, and the United Kingdom. SI can also enable practitioners in developing diagnoses, forecasting disease spread, connecting patient needs to therapy continuums, and customizing treatment courses, according to the findings.

Conclusions:, Several AI applications for healthcare coverage are revealed in the literature, as well as a channel of study results that have not yet been thoroughly explored. with referral services forming minimal areas covered. Pediatric patients' referral completely

misses out. SI projects, as per the report, include knowledge and data integrity awareness for content analysis and knowledge-based management. These insights can be used by scientists and health practitioners to better understand and address future SI research in the care industry business.

Keywords: Nature inspired computing, swarm intelligence, Healthcare Distributed systems, Pediatric patients; Patient Referral;

1.1 Introduction

. Swarm intelligence (SI) is the study of decentralized and self-organized systems' mutual behavior and performance, whether organic or manufactured. [1-2]. SI systems, in particular, are concerned with the integrated behaviors that emerge from individuals' local interactions with one another and with their ecosystems.[1-2]. [The swarm metaphor indicates diversification, probabilistic thinking, variations, and inconsistency, yet intelligence denotes that the real-world process is effective in some way.2]. [Simple agents have been built based on natural systems, particularly the aforementioned biological systems. Without centralized control, these agents observe simple rules.4 -6]. SI ideas have likewise been included into some computer programs that are aimed to handle optimization and data handling problems.[12]. Given the significantly increased computing capacity of current computers and large volume of computerized information recorded for collection and use, interest and advancements in medical SI applications have increased significantly in the last few years[7]. SI is influencing medical practice in a positive way. Staffing and scheduling, resource utilization, procurement, treatment options, medical diagnostics, and preventative care are all areas where SI has been used to improve healthcare.[9]. Another important domain of medical science in which SI is having an influence is the resource (people, diagnostic equipment, and infrastructure) allocation challenges for emergency healthcare institutions, which takes into account many restrictions and objectives (including cost, number of admitted patients, cycle time, service capacity, etc.)[14]. SI technologies can receive, analyze, and present huge scale of information throughout multiple ways to recognize disease and guide clinical decisions [3, 8]. SI applications can concentrate on huge volumes of data created in the medical area, revealing raw data which might otherwise be lost. Swarm intelligence (SI) is a major topic for operational scholars in numerous industries, including healthcare.

[9 Plenty of the issues that operational research team encounter in healthcare are conceptually similar to issues in several other sectors. Healthcare delivery systems, on the other hand, have certain distinct features. The possibility of death or a low life expectancy in the remaining years, the difficulty of calculating value and quality of outcomes, the sharing of decisions among several decision makers (physicians, nurses, and administrators), third-party billing mechanisms for procedures and treatments, and the concept of healthcare access as a right of citizens in society are just a few of them.- 11]. Optimization using SI has been lauded in aiding decision making where amount of data to be considered is large and heterogeneous [12-13]. Some of the swarm intelligence algorithms that have widely used for optimization in healthcare include particle swarm optimization (PSO), ant colony optimization (ACO), artificial bee colony (ABC), and the firefly algorithm (FA) [9, 15].

Particle Swarm Optimization (PSO)

Given on its minimal effort of implementation in unstructured and complex situations, the PSO is a well-known meta-heuristic optimization algorithm. It's a tried-and-true method for dealing with a variety of optimization issues. It is, in fact, grounded on a practical framework where the transitional rules are created by simulating social cohesive tendencies observed in flocks of birds and/or schools of fish[15]. The PSO creates a swarm of particles that successfully navigate the search interior in pursuit of the optimum global solution.

A hybrid GA-PSO technique was presented by for efficient and accurate work distribution [16]. The suggested GA-PSO sought to reduce the following variables in cloud computing dependent tasks: makespan, cost, and load balance. However, similar investigation by [17] used a scalability technique to increase PSO outcomes by using a static task scheduling methodology. Further study [18] employed simultaneously the "longest job to fastest processor (LJFP)" and the "minimal completion time (MCT)" strategies to try to optimize PSO's startup. Furthermore, [19] presented M-PSO, a cloud technology tool centred on energy utilization that can handle the slow harmonization challenge and localized optimum.20] By merging PSO with imperialist competitive algorithm (ICA) techniques, a self-adaptive conventional approach known as ICA-PSO was created to tackle the multi-tasking scheduling issue. [21] presented an improved PSO to promote population heterogeneity by using inverted learning and genetic mutations approaches. [22] suggested a hybrid scheduling solution called GA-PSO, which uses PSO plus a genetic algorithm to reduce total execution time (GA). Furthermore, [23] proposed two hybrid algorithms, Best-Fit-PSO (BFPSO) and PSO-Tabu Search, for effectively delegating jobs to computer resources (PSOTS).

Ant Colony Optimization (ACO)

In handling multidimensional optimization challenges, the ant colony optimization strategy provides a significant benefit. Numerous studies in the virtualization computing environment looked into task assignment utilizing the ant colony method. They're usually divided into categories based on the goals they're trying to achieve, such as scheduling efficiency, performance of system and cost. The ACO algorithm is a smart trajectory planning method.[24 -26]. It features a powerful computational technique. [27]. In general, it is used for optimization by updating pheromone trails and orienting the ants in the entire browse space, where each ant provides a new strength training function that is then used to establish an average global fitness. The roulette wheel approach, which will be continued until the goal point is reached, determines the next state in the ACO strategy. The ants update the pheromone trails over the length of the path planning process when each iteration is completed. The ACO has largely been used to find societies with a single aim in the literature [28], but it has also been used to optimize cross ACOs using degradation process.[29]. In fact, researchers were motivated by ant colonies to study how ants determine the optimal approach to a food source. [30] proposes utilizing a modified ACO that recognizes alternative costs to update the pheromone trails.

To overcome the TSP challenge, [31] proposed Ant System Using Individual Memories (ASIM), a modified ACO method that uses individual memories (IM) to maximize ant heterogeneity in the search space. [32] proposed a modified ACO method that takes into account numerous aspects including as fuel economy, sailing duration, and navigation security in order to find the best alternative for the ship-weather routing multi-objective optimization problem. [33] Suggested a collective adaptive ACO technique for detecting SNP epistasis in GWAS datasets using multi-objective parameters.**Artificial Bee Colony Optimization (ABC)**

The ABC represents a meta-heuristic method to understanding bee behavior. Cloud computing and storage, image synthesis, large data analytics, and neural networks are all examples of typical ABC's uses. [34] The ABC algorithm is one of the most effective SI optimization strategies. They used numerous signal decomposition techniques to create a novel ABC strategy for large data optimization. Many research [35–37] combined ABS and PSO algorithms in order to find some form of optimization in terms of updating personal and worldwide optimal objective purposes. [38] presented a hybrid PSO-Bees method to address multi-objective optimization challenges in search of improved random distribution alternatives to the scout bees in the ABC optimization. [39] suggested a hybrid ABC-Heuristic approach to enhance virtual machine scheduling solutions in binary and ternary cloud computing settings. [40] incorporated the new control mechanisms to the initial ABC algorithm to represent the employed-bees' transitions into the dancing area. [41] proposed a novel discrete ABC method called DABC to tackle the "Job-Shop-Scheduling-Problem (JSSP)" by shortening make-span. Many SI strategies are being used in crowd evacuation studies as computer computation performance improves [42]. [43] proposed a multi-strategy ABC algorithm to improve the overall performance of the original ABC algorithm, which used a neighborhood search approach. In the subject of data-flow testing, a research by [44] employed the ABC approach to emphasize the definition-use pathways. Furthermore, [45] developed a redesigned ABC method to handle the job-shop planning problems (JSSP).

Firefly Algorithm (FA)

The firefly algorithm (FA) is a meta-heuristic technique which is inspired by firefly flickering characteristic [46]. It is an example of an evolutionary improvement strategy. It's been used in a variety of difficult situations [47]. [48] investigated the many forms, relevance, and uses of FA in biomedical engineering (BME) disciplines in detail. Conversely, [49] has offered a comparative of overall performance of the PSO and firefly algorithms, concentrating on variable estimation of a category competition algorithm. Their analysis was based upon earnings data from Indonesian rural and commercial banks. Furthermore, [50] presented a modified salp swarm algorithm (SSA) based on FA to improve the quality of the solution of the "Unrelated parallel machine scheduling problem (UPMSP)" by employing the operators of FA to improve SSA's exploitation potential for operating as a local search. [51] devised a hybridized technique based on FA and PSO to produce an enhanced solution for search space exploration in pursuit of an optimal machining parameter such as feed rate, spindle speed, and depth of cut. [52] suggested a modified FA method that ranks the firefly using a fast sort algorithm rather than the bubble sort approach to reduce the temporal complexity of the original FA algorithm.

Another literature by [53] suggested an enhanced FA technique called improved firefly algorithm (IFA) to lower the cost of electricity production fuel in order to address the optimal functioning of thermal generating units' issue. Another work [54] used a backward learning foundation and Levy perturbation techniques based on the FA algorithm to tackle the problem of FA falling into delayed convergence. To encourage the flies to explore more desirable sub-regions, [55] presented a hybrid optimizer based on PSO and FA called "FAPSO." [56] introduced a compact firefly technique that employs a reduced computational burden to lower the computational cost and memory storage of the standard FA algorithm. [57] Introduced pattern search (PS) to finish the FA to address the flaw in the normal FA's ending phase, which is that it fails to get the ideal value since the quality of the results does not increase. To solve unit commitment concerns, [58] proposed a modified FA method. They stated that in terms of generator selection and error between load and generation, the updated FA algorithm is more efficient than the standard FA.

2.0 Intelligent Model for Patient Referral

Recent studies [59 – 62] have demonstrated how SI models can be deployed to improve health outcome including referrals especially in resource poor countries. Patients' procedure times, the amount of on-time or no-show patients, healthcare personnel's physical condition and medical skills, and discrepancies in hospital devices all seem to be contributing attributes to the inconsistencies and sphericity of the healthcare industry environment in resource-poor countries. [61, 63]. According to Chen and Lin [63] the problem of heterogeneity in healthcare can be categorized through hospital collaboration, patient referral mechanisms, resource allocation using SI or AI. These categories help in solving the nightmare of matching patient characteristic with hospital resources [64].

2.1. Hospital collaboration

The pooling of hospital facilities amongst cooperating institutions is known as hospital cooperation. In the literature, there are two types of hospital partnership. For starters, hospitals have a variety of medical resources or professionals with whom they might collaborate [65 - 67]. This type of hospital partnership can help to eliminate the duplication of medical resources and personnel. Patients can be transferred to the appropriate hospital by the surveillance station of the partnering hospitals, depending on their condition. Hospitals within the second kind of collaboration share medical resources but have varying capabilities and patient counts depending to their image and location [68–69]. Patients tend to flock to well-known hospitals, resulting in greater wait times. A patient will be referred from a hospital with more patients to one with less if the hospital works with other hospitals.

In regards to healthcare administration, investigations on hospital partnership have yielded excellent results. Glinos and Baeten [70] investigated cross-border collaboration (CBC) amongst seven European hospitals in a case study. The researchers noted that everyone who benefitted from CBC would support CBC programs after questioning hospital workers and patients. The existence of a localized demand, engagement of motivated workers, synchronization of stakeholders' priorities, and fit with domestic health systems are all factors determining the strength or weakness of CBC programs, according to Glinos and Baeten [70]. Pollard et al. [68] investigated a southeast Michigan cooperative effort including twelve hospitals. Pollard et al. [68] looked examined the impact of hospital cooperation on the 7-day post-discharge follow-up (7dFU) rate and the 30-day heart failure readmission rate after a year of partnership. Relying on the dedication of employees and clinicians, the results demonstrated that hospital collaboration might minimize the 30-day cardiovascular disease relapse rates.

2.2 Patient referral

Patients are sent to emergency medical services (EMS) and non-emergency medical services (NMS) in available research [63]. The majority of patient referral researchers have concentrated on emergency medical services (EMS), which include the command center, ambulances, and collaborative medical hospitals [71]. When the overall operations center gets an emergency request/call, an ambulance must always be dispatched to the emergency location within a given amount of time. A patient is subsequently sent to closest hospital for treatment. Hospitals sign a memorandum of understanding for hospital partnership for the NMS. Following the establishment of hospital collaboration, clinicians can recommend patients from a packed hospital to an affiliated but less congested treatment center depending on the patients' waiting time, status, or other factors such as their capacity to pay for care. [72]. Patients can be treated in a fast and appropriate context as a result of this. This is supported by a number of research. According to [65], the coordinated patient-referring strategy might cut CT client wait times in the three partnering institutions in half. Chen et al. [67] used an extension of Chen and Juan's [65] approach to calculate the number of daily recommended MRI patients for two collaborating institutions. The binary decision parameters were integer variables with values ranging from 0 to the monthly highest number of daily incoming patients. To tackle the suggested patient referral problem, Chen et al. [67] used the same strategy as Chen and Juan [65]. The results revealed that the unfixed daily referred patient mechanism outperformed the fixed daily referred patient mechanism in terms of reducing average waiting time for patients. Chen et al. [73] also looked at a two-hospital MRI patient referral problem and utilized the bat method to figure out how many unfixed daily referred MRI patients there were.

3. Distributed Systems

Distributed systems comprise of self-sufficient PCs connected by a conveyance middleware [74 -75]. Decentralized technologies allow several clients to share special resources, data, or information for decision-making [76]. Distributed systems have several key characteristics, including: (1) the ability to share facilities and software from other several systems network - connected, in other words, system components are synchronous [77]; (2) the absence of a global clock in a distributed system; and (3) fault sensitivity in a decentralized network is much higher than in other network models, resulting in a much better performance/price ratio [78]. Transparency, openness, dependability, performance, and scalability are all important goals in distributed systems [76]. Transparency refers to presenting the image of a single framework to clients without obscuring specifics about issues such as significant exposure, localization, relocation, malfunction, parallelism, commodities, resettlement, and retention [76]. Openness [79] refers to making it easier to alter and configure the network. A distributed system's reliability is defined as its capacity to hide errors, maintain security and consistency [80]. Performance is determined by capacity to provide much-anticipated and desired boost. In terms of topography, organization, and scale, distributed systems should be flexible [81-83]. The distributed database system may confront problems and challenges such as security, which is a significant difficulty in the distributed system environment [84-85]. This is especially true while using a public network [86]. When the distributed model is built on unreliable assets, fault tolerance becomes a challenge [84]. Teamwork and resource sharing in a remote setting are difficult to achieve without adequate protocols or regulations [85]. The following are some examples of distributed systems:

3.1 Cloud computing Systems

Cloud computing offers inexpensive and fast access to computer resources including: servers, networks, storage, and services. Cloud providers need to control, distribute and assign these resources effectively to offer services to cloud users based on service level agreements (SLAs) whereby both parties agree to use the services prior to the user. An appropriate and scalable resource allocation system is required to properly distribute these resources and satisfy the demands of users [80, 87].

3.2 Cellular network Systems

The fifth generation communication is a system that has features beyond the present generation technology. In the fifth generation of mobile networks, one of the most important developments is device-to-device connectivity. Increased spectral performance, power and energy, capacity, and service networks, decreased congestion and latency, enhanced reliability, improved coverage and cost effectiveness are the advantages of using device-to-device communications. In cellular networks, device-to-device communication creates interference, which interferes with device-to-device communication users and cellular users. The way to avoid or decrease interference is to properly distribute resources. Power management or spectrum allocation is the object of resource allocation. Optimal spectrum allocation implies how to optimally distribute user-available frequency sources that maximize qualitative or quantitative criteria [88-89].

3.3. Software-Defined Networking (SDN)

The Software Defined Network (SDN) is a system that provides scalability and network efficiency by detaching the control plane and the data plane. Depending on task styles and user requirements, it is often hard to assign resources. The central SDN controller offers a global view of the network that makes the allocation of resources more reliable [90-91].

This paper reviewed studies related to intelligent resource allocation models which are used in healthcare distributed systems and explored their potential in solving the problem of pediatric patient referrals

4 Methods

4.1 Study Design

The researcher devised a methodology based on Levac et al's [92] scoping review methodological framework and the Joanna Briggs Institute's (JBI) scoping review methodological advice [93]. (1) defining the article's intent, (2) recognizing related research and stabilizing viability with broadness and thorough comprehensiveness, (3) teamwork to recursively designate investigations and retrieve their data, (4) charting the extracted data and introducing an arithmetical overview, (5) collating, outlining, and communicating the findings, and (6) consulting the performance with interested parties on an ongoing basis about developing and ultimate results. On the JBI and Open Science Framework (OSF) websites, this protocol has been registered and is available. According to the specified criteria, the researcher executed this review.

Figure 1 depicts the screening procedure. For describing the study, the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analysis-Scoping Reviews)

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reporting standard was used [94]. Publications which did not indicate actual research design are grouped by technique using the National Institute for Health and Care Excellence's categorization [95].

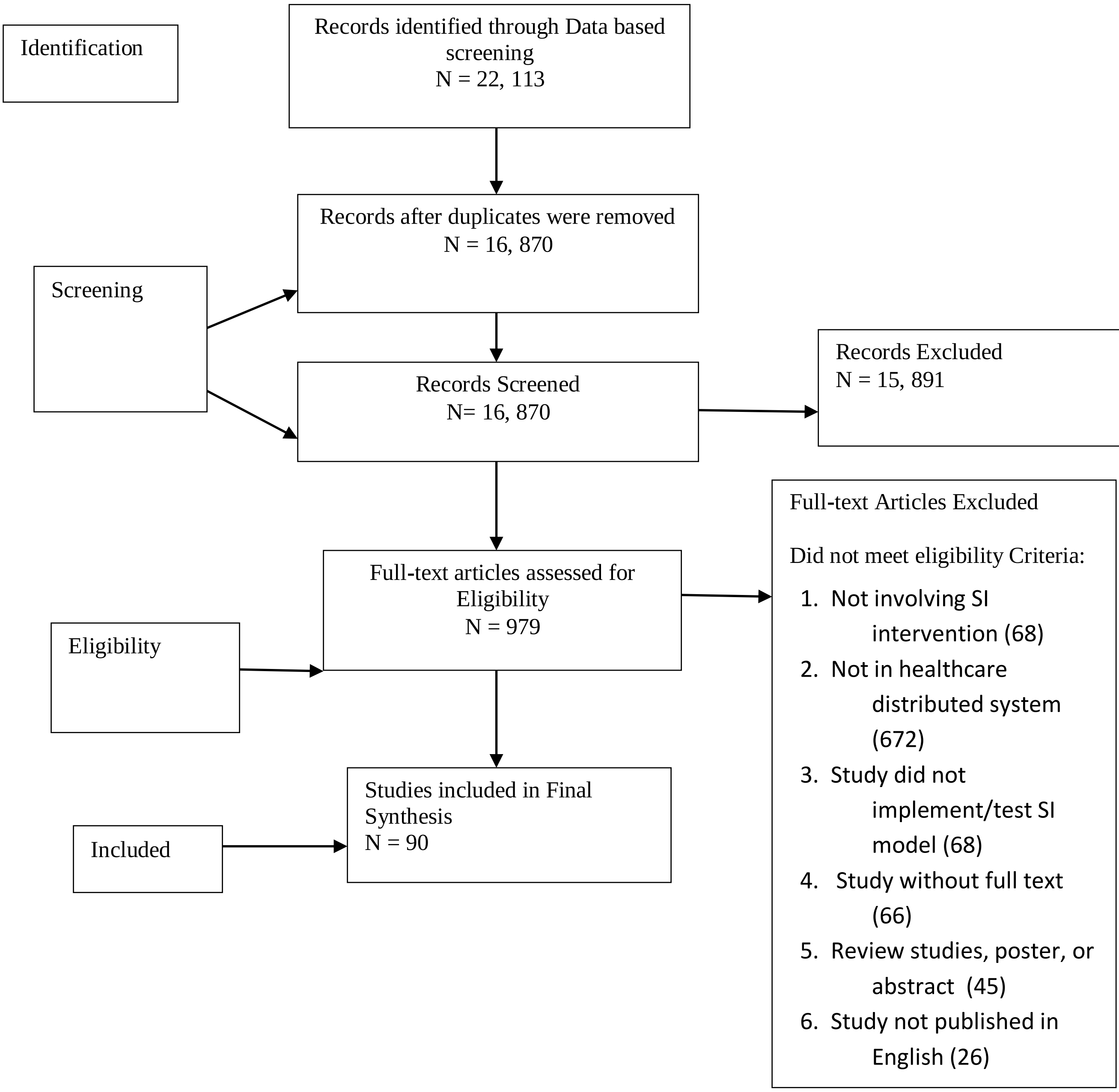

Figure 1: PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)

flowchart of the selection procedure. SI: Swarm intelligence.

This paper used the PROBAST (Prediction Model Risk of Bias Assessment Tool) tool to assess 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: (1) participants (covers potential sources of bias related to participant selection methods and data sources); (2) predictor variables (encompasses possible elements of bias linked to the definition and characterization of predictor variables); (3) model parameters (covers potential sources of bias related to the definition and measurement of predict (covers potential sources of bias in the statistical analysis methods) [96]. Bias risk was rated as low, high, or unknown. The cumulative decision was "high risk" [97] if one or maybe more categories were assessed to have a high risk of bias.

4.2 Eligibility Criteria

Using the Population, Intervention, Comparison, Outcomes, Setting, and Study (PICOS) design parameters, this article specified its bibliographic database search approach for peer-reviewed papers in English [98].

4.3 Population

Nurses, social workers, pharmacists, dietitians, public health practitioners, doctors, and community-based workers (an unregulated category of professional) were also eligible, as were studies regarding any groups that get CBPHC services. Patient referral was defined in terms of emergency medical services (EMS) and non-emergency medical services (NMS) in the study [63]. Investigations that occurred in any type of healthcare facility, such as community health centers, integrated care systems, clinics, and hospital outpatient departments, were included. Studies done in acute case management rooms were not considered.

4.4 Intervention

Only studies that “tested” or “implemented” or “tested and implemented” SI models, such as Ant colony optimization (ACO), **Particle Swarm Optimization** (PSO), Artificial Bee Colony (ABC), and the firefly algorithm (FA) were included [15]. Studies related to robot-assisted care were excluded.

4.5 Outcomes

Individuals receiving care (e.g., cognitive outcomes, health outcomes, behavioral outcomes), providers of care (e.g., information processing outcomes, health outcomes, social cognition), and health care systems (e.g., cognitive outcomes, health outcomes, behavioral outcomes) were the primary outcomes of interest (eg, process outcomes). We also looked at the SI systems' results to see how accurate they were and how they affected care performance.

4.6 Analysis Methods

All research designs, whether qualitative, quantitative, or hybrid approaches, were considered. Experimental and quasi-experimental studies (randomized controlled trials, quasi-randomized controlled trials, nonrandomized clinical trials, interrupted time series, and controlled before-and-after studies) as well as observational (cohort, case control, cross-sectional, and case series), qualitative (ethnography, narrative, phenomenological, grounded theory, and case studies) and mixed methods studies were included by the researcher (sequential, convergent).

4.7 Information Sources and Search Criteria

The systematic search was conducted from inception until February 2022 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 for the search strategies used on each database).

4.8 Data Collection

The study employed a data extraction form that we devised based on the Cochrane Effective Practice and Organisation of Care Review Group (EPOC) data collection checklist [95], which was authorized by our advisory committee. The journal retrieved study characteristics (e.g., design and corresponding author's country), population characteristics (e.g., number of participants and type of disease or treatment), intervention attributes (e.g., SI methods used), and consequential characteristics, which included patient-related outcomes (e.g., cognitive outcomes, health outcomes, behavioral outcomes), provider-related outcomes (e.g., cognitive outcomes, health outcomes, behavioral outcomes), and healthcare related outcomes (e.g., cognitive outcomes, health outcomes, behavioral outcomes) (eg, process outcomes).

4.9 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 [96]. A third reviewer verified their appraisals.

4.10 Synthesis

To summarize the findings in respect to their population (patients, primary care providers), treatments (SI systems, assessed parameters), and outcomes, the researcher used an illustrative synthesis [97]. The PICOS format was used to organize the results. Textual explanations of the research, classification and grouping, and tabulation were among the tools and approaches used to create an exploratory synthesis.

5. Results

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

5.1 Study Characteristics

5.1.1Countries and Publication Dates

The number of studies published annually has increased gradually since 2000, especially since 2015. 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%).

5.1.2 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). The remaining studies (30/90, 33%) did not specify the time frames of their data set collections.

5.1.3 **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%).

5.2 Interventions

5.2.1 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%).

5.2.2 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)

5.2.3 Health Conditions

The majority of the 90 included studies (68/90, 76%) investigated the use of SI in relation to a specific medical condition. Conditions studied were vascular diseases including hypertension, hyper-cholesteremia, peripheral arterial disease, and congestive heart failure (10/90, 11%) [68-69]; emergency and medical operations (8/90, 9%) [60, 71-72]; orthopedic disorders including rheumatoid arthritis, gout, and lower back pain (5/90, 5%) [10, 12]; neurological disorders including stroke, Parkinson disease, Alzheimer disease [48, 63], and other health conditions (8/90, 8%) [64 - 69].

5.3 Outcomes

The data on the advantages for patients, fundamental health care providers, and the health system discussed in this part was extracted based about what the researchers of the featured studies plainly specified as distinct rewards to all of these groups.

5.3.1 Potential Benefits for Patients

Modifications in medication compliance, person-centered treatment, living standards, promptness identification of patient at high risk , health check speed and cost-effectiveness, augmented predictive ability of adverse outcomes and comorbidities, advantages associated with early prediction and diagnostic prevention of diseases in the elderly, and fostered referrals were all reported as prospective advantages of integrating AI in CBPHC.

5.3.2 Potential Benefits for Primary Health Care Providers

The research found the following benefits of applying AI in CBPHC for primary health care clinicians: improved interdisciplinary team interaction and efficiency of fundamental care provision, reduced work burden for these practitioners, and streamlining of transfers, referrals and patient-centered care.

Other advantages also considered AI as an alert mechanism, using AI tools to notify design and construction healthcare needs, using an AI system as a quality outcome measure by producing warning messages in telemedicine and evaluating diagnostic findings, fostering disease management and control, as well as using AI to minimize health hazards.

5.3.3 Potential Benefits for the Health Care System

AI can help improve personal patient healthcare outcomes and population-based monitoring, according to research findings in our analysis. It can also allow administrators, policy makers and the government to make better decisions about hospital management, case management, purchase price, and lowering workload at the structural level by providing forecasts to notify and expedite policymakers' right choices.

5.3.4 Economic Aspects

Only one research (1%) of the 90 publications examined the expense of the AI technology under consideration. When contrasted to traditional blood - glucose testing alternatives in primary care, the research authors' Predicting Out-of-Office Blood Pressure in the Clinic [PROOF-BP] approach for such identification of hypertensive patients in fundamental treatment was determined to be more cost-effective. [49].

5.4 Challenges of Implementing SI in HDS

Our findings imply that issues linked to the unpredictability of patient data, as well as hurdles to adopting SI systems or participating in SI research, exist in HDS. These barriers might be connected to the patients' age or cognitive skills. In the health-care system, we discovered issues such as how information is recorded (for example, the use of abbreviations in medical records), poor inter professional information exchange between nurses and physicians, conflicting diagnostic tests, and an absence of occasion documentation in cases of communication failures. Problems with limited resources and administrative factors such as laws and administrative permissions were also addressed in the included research, as well as obstacles with primary health care practitioners' lack of technological or computer literacy.

Other obstacles were noted at the level of the health care system, such as the data accessible for use with SI, as well as challenges at the level of SI itself, in the research included (eg, complexity of the system and difficulty in interpretation). The preceding were recognized as the key information obstacles: (1) inadequate data for training, testing, and validating SI systems, resulting in unfavorable implications on the complexity of SI modeling techniques and the efficiency of their predictions; (2) poor quality data, inaccuracies in the data, misclassifications, and a lack of representative data; (3) de-identification of protected medical data; and (4) variability in the data sets and combining different data sets. At the SI level, computational burden and problems comprehending or interpreting certain SI model combinations are also among the AI hurdles.

5.4.1 Risk of Bias

The paper identified the studies that were eligible to be evaluated using PROBAST. Among our included studies, 54% (49/90) were eligible to be evaluated using the PROBAST tool and most (39/49, 80%) were at high risk of bias according to the assessment with PROBAST (Figure 2). 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.

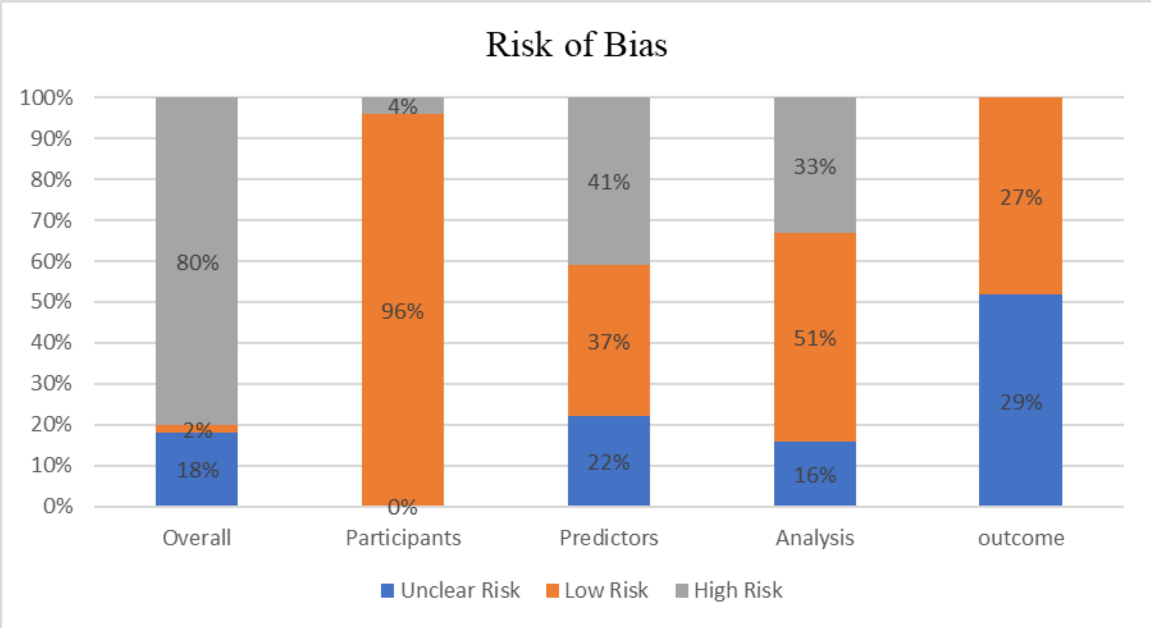

Figure 4. Risk of bias graph: assessing risk of bias in five categories namely overall, participants, predictors, analysis, and outcome (presented as percentages).

6. Discussions

6.1 Principle Finding

The researcher performed a systematic preliminary investigation that comprised 90 studies on the application of SI systems in HDS and gave a critical evaluation of the existing research in this field. Since 2015, the number of research has exploded, according to the findings. Variability in the reporting of participants, types of SI methods, analysis, and results were discovered, highlighting a significant gap in the successful development and application of SI in HDS. The below are the crucial conclusions drawn from this review.

6.2 SI Models, Their Performance, and Risk of Bias

In HDS, the most widely employed technologies were machine learning, natural language processing, and expert systems. The approaches with the greatest execution accuracy throughout the available data sets for the particular challenge were convolutional neural networks and hypothetical - deductive networks. The majority of the considered research (74/90, 82%) reported on the use, testing, or execution of an off-the-shelf SI model, according to the publication. Previous research has shown that off-the-shelf models cannot be employed in all therapeutic settings. [74]. The study found a substantial likelihood of overall bias in research including diagnosis and prediction. The consequence, predictive, and analytic classifications of the selected studies had the highest risk of random error; affirmation of research (both external and internal) was inadequately recorded, and calibration was seldom addressed. Because there is a substantial possibility of bias, the effectiveness of these SI models on a new data set may not be as good as stated in these researches. SI models employed in other circumstances (i.e. with different data) may not demonstrate the same degree of probabilistic accuracy as reported in the included research because to the significant risk of bias.

6.3 Where to Use SI?

SI systems are more commonly used by primary health care professionals for system assistance in administrative or health-care duties, as well as for operational elements, than for clinical decision-making [66]. Our findings demonstrate, however, that few SI technologies have already been deployed in HDS for these goals. Rather, current SI systems are generally diagnostic or prognostic in nature, and are utilized for illness detection, risk assessment, or surveillance. More research is needed in this area to determine the cause of this trend, as well as studies to demonstrate the efficacy and efficiency of AI models in supporting clinical decision making in HDS situations. Only two of the 90 papers examined employed a (socio-cognitive) theoretical framework, according to the findings. Future research should focus on expanding SI's application in clinical decision-making by including knowledge, attitudes, and behavior theories, and more effort should be put into developing and validating frameworks to guide the design and implementation of SI in HDS.

6.4 Consideration of Geographical Location

The ethnicities of patient respondents were mentioned in less than a quarter of the investigated research, with no mention of the ethnic groups on participating health care professionals. Furthermore, we discovered that the gathered data for all studies that included patient ethnicity were associated to proximate cause groups, creating concerns about the data set's representativeness and resulting in biases. As a result of these biases, the SI system may make predictions that discriminate against disadvantaged and vulnerable patient groups, resulting in unfavorable patient results.

According to our findings, the majority of SI research in HDS has taken done in North America, the Republic of China, and Europe. When employing SI, a number of variables lead to ethno-racial biases, including not taking account on ethno-racial information and therefore neglecting the various impacts diseases might impact upon various populations [73]. As a result, research might provide results that contain historical biases as well as biases linked to over- or under-representation of demographic features in data sets and knowledge bases used to construct SI systems. As a result, preconceptions and negative effects may become more prevalent.

Involvement of Users

Despite the numerous prospective advantages of SI to humans, SI systems are frequently developed using "technology-centered" design techniques rather than "human-centered" procedures. [94]. According to our findings, no SI-HDS studies have included end users in the system development stage, and principal health care provider users in the verification or testing phases have been uncommon. As a result, SI systems fail to suit the demands of health-care practitioners and patients; they have poor utilization scenarios and finally fail throughout care delivery deployment. Most present user-centered layout approaches were largely established for non-SI systems and do not successfully handles the special difficulties in SI systems, according to a recent study of current user-centered design methodologies [91]. In the design, innovation, verification, and deployment stages of HDS, more initiatives are required to include healthcare professionals and clients are among users of the produced SI systems. Nonetheless, integrating these users successfully in the creation, testing, and reassurance of SI systems remains a barrier, and further research is needed to address it.

Economic Aspects

SI systems have the potential to reduce growing health-care costs, however only one (1%) SI-HDS research specifically looked into this by doing a cost benefit analysis of SI adoption. This is in line with other research findings that suggest the cost-effectiveness of employing SI in health care is underreported [65,71]. As a result, further cost-effectiveness study is sought to determine the economic advantages of SI in HDS in respect to treatment, capacity and assets management, and human error mitigation; this would be useful since it might impact choices on whether or not to deploy SI in HDS.

SI in Clinical Practice

The findings reveal a variety of obstacles and enablers to using SI in clinical practice. Aspects relating to data were among the most often highlighted. For example, when designing SI systems for use in HDS, a major difficulty is the absence of large volumes of high-quality data, especially when employing newer SI approaches (e.g., deep learning).

Data governance, public data guidelines, and other data initiatives are closely linked to the promotion of SI-driven transformation in any setting, including HDS, because they seek to build dependable frameworks and services for interaction, recycles, and consolidating data [68], which are needed for the innovation of high-quality data-driven SI systems.

Furthermore, various data protection and privacy rules may create obstacles, restricting the usage of SI systems in HDS as well as the exchange of healthcare information necessary for the development of high-performance SI systems. To make it easier to deploy and adopt high-quality SI systems in HDS, as well as to ensure patients, health practitioners, and the health system gain, research that provides valuable information into how to overcome such implementation problems is required.

Limitations of the Study

There are certain limits to the assessment. To begin with, our search algorithm may not have acquired all applicable data since we utilized the Canadian Institute of Health Research's definition of HDS to generate our selection criteria, and because the concept of HDS varies by nation. Second, researches done in emergency rooms were not included in the evaluation. In many nations, emergency rooms are the only places where people may get community-based care. The European Union

Conclusion

The researcher has shown the scope and diversity of SI systems currently being evaluated and adopted in HDS, critically assessed the SI systems, which indicated that this area of study is developing and identified information gap which should be emphasized in future research in this comprehensive meta - analysis.

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