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A systematic review of artificial intelligence-based methods in healthcare

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ABSTRACT

Artificial intelligence (AI) in healthcare has enormous potential for transforming healthcare. AI is the ability of machines to learn and exhibit close to human levels of cognition in various specific ways. Leveraging AI software to support activities will improve patient satisfaction which is inextricably tied to the length of time patients spend in waiting queues. Literature searches were conducted in PubMed, Research Gate, BMC Health Services Research, JMIR Publications and Cochrane Central to find related documentation that was published between January 2011 and April 2021. The studies featured and reported on AI technologies that had been used in primary, secondary, or tertiary healthcare situations directed towards reducing waiting times. A total of 22 articles were primarily used, including 8 retrospective studies, 4 prospective studies and 3 case-control studies. AI technologies have enormous potential in the creation of a future with more reliable healthcare systems. It is however clear that more studies in the field are required to validate the existing evidence of its potential. AI in healthcare is crucial to reducing patients' time at healthcare facilities. The use of AI can also help improve patient outcomes and more research should be geared toward that.

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1. INTRODUCTION

The World Health Organization (WHO) mentioned patient wait times for healthcare services to be one of the most important indicators of a truly responsive healthcare system [1]. The time it takes for people seeking treatment at healthcare facilities to be seen for consultation and treatment is referred to as patient waiting time. Patient waiting times are lengthened when medical demand exceeds a hospital's capacity. There are two perspectives: real and perceived waiting times. Many studies have shown a substantial inverse link between patient satisfaction and waiting time. The idea of reducing perceived waiting time is a less discussed aspect although it may hold potential for general improvements in patient satisfaction. The presence of televisions and other information media in the out-patient department (OPDs) are examples of how perceived waiting time is reduced. The requirement to provide total patient satisfaction is growing increasingly crucial as healthcare solutions become more tailored and consumer-focused [1].

In general, hospital client waiting times differ depending on the setting, geographical location, and type of facility. According to a 2013 Nigerian survey, 61% of the respondents who participated waited between one and half hours to three hours in the clinic, while 36.1% of these patients spent lower than five minutes consulting with the doctor. The most prevalent cause of high waiting times was a significant number of patients and a shortage of healthcare staff [2]. Also, other studies showed similar results and on occasions where patients were given talks or shown infomercials during their wait, they reported higher levels of satisfaction with the healthcare services [3], [4]. The advent of AI technologies also offers an opportunity to make improvements to this age-old and worsening problem of lengthy OPD waiting times.

Artificial intelligence (AI) in healthcare is already here with enormous potential for change in the delivery of care. AI and automation are two expanding concepts in healthcare, and these are set to modernise the current workplace at healthcare institutions [5], [6]. AI in simple terms is the ability of machines to learn and exhibit close to human levels of cognition in various specific ways [7]. AI can shape the healthcare industry's future in many ways as the exponential growth of AI modules and systems will result in the development of tools that can be put into daily use in hospitals and health centres [8]. AI systems could organize patient routes for consultation, medical investigations as well as drug administration better, and provide physicians with literally all the information they need to make excellent decisions in almost every situation [9]. AI can range from electronic health record (EHR) systems to neural network-based guidance [10].

AI is a potential tool for streamlining both healthcare workflows and clinical treatment. Over the last few decades, the healthcare industry has experienced phenomenal expansion all over the world. At the same time, patients are becoming more health-conscious, and demand for high-quality services is increasing. The rapid rise in population densities especially in third-world countries also place a direct burden on healthcare facilities which indirectly affects patient satisfaction and quality of care. Patients' wait times are lengthened when a facility's capacity is exceeded by the demand for care. Outpatient clinic waiting times are universally recognized as one of the most important issues in healthcare all over the world [11]. There are two levels to it: real and perceived waiting times. According to several research, patient satisfaction is considerably inversely connected to real waiting time [12]. While some studies suggest that how people perceive waiting time affects overall happiness, actual waiting time does not [1]. Using AI software to assist operational processes will save costs, enhance patient satisfaction, and meet staffing and personnel requirements [13]. OPD wait times have always been an itch for clients of the healthcare system and according to several research, patient satisfaction is considerably inversely connected to waiting time. The time a patient has to wait to be seen is another factor influencing healthcare usage [14]. A patient, seeking healthcare at the OPD in Ghana spends an average of 2 hours 50 minutes just to receive services which is more than the recommended period of fewer than 2 hours according to the standards for Ghana Health Services [15].

A variety of methods and initiatives are being used and developed constantly for patient flow improvement in hospitals, and the introduction of AI in healthcare expands the possibilities. AI-powered systems could offer solutions through the automation of administrative tasks and coordinate the workflow between patients, nurses, consultants, laboratory technicians, radiologists, and surgeons. The integration of deep learning to diagnose diseases and machine learning to boost the speed and accuracy of radiological analysis can significantly reduce the time spent in a consultation session. Strategic implementation could cut costs, allowing providers at all levels to increase their budgets. More resources for hospitals, more time for patients, and much better outcomes for many will occur because of this. Reducing outpatient waiting times is beneficial not just to patients, but also to the hospital's burden. Considering this, an AI-assisted strategy to improve the efficiency of the outpatient procedure is on the horizon.

Several studies have demonstrated that AI algorithms can manage patient flow, enhancing clinical treatment by minimizing administrative burdens on physicians [12], [16]–[18]. Analysis of hospital processes is necessary for the creation of new procedures, policies, and decision tools to improve the healthcare system's overall performance [14]. Also, one of the major patient grievances is the time they spend waiting in OPD.

There currently are limited studies that systematically examine the applications of AI in the direction of reducing patient waiting times [19]. It was however noted that there exists some research conducted on the use of such technologies in particular clinical conditions, such as the identification of breast cancer, cerebrovascular accident prediction as well as diabetes management [20]. Some reviews also focused on the comparison of AI performance with clinician performance to buttress the need or needlessness of AI in various healthcare domains [21]. In contrast, here is an attempt to specifically outline the available evidence found through various studies to elucidate a correlation or lack thereof between the implementation of AI technologies and patient waiting times [22], [23].

Patients spend a significant amount of time waiting in OPD queues, while the time spent evaluating and treating them in the consultation room is very brief [2]. According to Muelly *et al.* [24] machine learning can be used to reduce the mean patient wait times by estimating examination lengths on the basis of the demographic characteristics of patients [24]. This study analysed the factors that contributed to prolonged waiting times. The study also identified AI technologies that can reduce waiting times to aid decision-makers in identifying potential areas for improvement in patient waiting times with the implementation of AI technologies to achieve higher levels of client satisfaction and to allow the OPD to see more patients and even prevent needless hospital visits.

Modern technology and devices are widely used for innovation and value generation across many sectors in today's Fourth Industrial Revolution. There is no exception in the healthcare business. Digital technologies include AI which encompasses machine learning, deep learning, natural language processing (NLP), smart sensors and robots, big data analytics, and the Internet of Things (IoT) are being aggressively deployed by hospitals and healthcare organizations all around the world, particularly in developed economies, in an attempt at improving the care quality and operational efficiency [21]. Algorithms for many types of tasks, such as regression, clustering, and others, are included in machine learning, and these algorithms are taught on data. An algorithm will improve as more data is submitted to it. Deep learning, based on artificial neural networks, is a relatively new branch of artificial intelligence. In order to learn to solve problems, deep learning algorithms also require data. Furthermore, powerful virtual human avatars are being utilized to conduct dialogues necessary for diagnosing and treating mentally ill patients. While healthcare practitioners may be enthusiastic about AI, its applications provide both new opportunities and new threats as well as challenges to overcome [21]. There are three types of statistical learning: supervised, unsupervised, and semi-supervised. An algorithm is coded to extract output from an input dataset in supervised learning. In the input dataset, the result has already been determined. Electrocardiogram interpretation using pre-set data on diagnosis is an example of supervised learning. When estimating the risk of certain pathologies, supervised learning is frequently applied [12], [25]

There is no way to anticipate the outcome of unsupervised learning since there is no predetermined outcome. The goal here is to go through the data and figure out what's going on. Unsupervised learning is used to classify disorders utilizing biomedical data based on random neural network clustering. Unsupervised learning is divided into two categories: clustering and dimensionality reduction [12], [26]. To obtain a meaningful output, semi-supervised learning necessitates the use of both supervised and unsupervised approaches. It investigates observations where the result is only known for a small set of data [12]. AI can clearly be used in a variety of settings, from hospital management to therapeutic decisions.

As is well known, healthcare workers are frequently overburdened with paperwork. Due to the increased workload, the sector has begun to migrate to electronic systems that integrate and digitize medical records, with the help of AI technologies. Understanding the technology of AI can help improve healthcare processes to also improve patient outcomes [27]. Clinical decision support systems (CDSS) have the potential to improve the quality of service provided to patients [28].

Chatbots have been highlighted as a potentially effective method for interacting with hospital patients and family members [29]. Chatbots represent a group of computer software applications that conduct automated activities or scripts to replicate human dialogue. Chatbots are AI systems that can create and retrieve information for human users via text or computer speech. Medical chatbots may be able to offer patients with instant access to medical information, recommend diagnoses at the first indication of disease, or link patients with appropriate healthcare professionals in their area. Although there is a reduction in the number of annual hospital visits by patients who utilize medical chatbots, it is still unclear if this technology is superior overall at improving all of a patient's clinical health outcomes [29]. It however improves patient privacy and removes the bias associated with interacting with a human agent.

AI has the ability to not only improve medical care but also to transform the architecture of systems to optimize patient flow [19]. A retrospective cohort study conducted by Beson *et al.* [15] using the information from paediatric patients in a Children's Medical Centre between August 1, 2019, and January 31, 2020, utilized a NLP model with integrated deep learning to create an inquisition platform which provided automated diagnoses. This is then followed by suggested basic laboratory or imaging investigations which the patient could start before going into the consulting room. This creates more meaningful engagement for the patients while waiting which improves apparent waiting time and reduces the total amount of minutes or hours, they spend at the OPD.

Inpatient flow management AI is used to predict patient flow or efficiently manage patients' activities in OPDs. Ellahham and Ellahham studied triage-based prediction models which were used in grouping patients into five categories according to the level of risk. This was done using integrated deep neural networks (DNN -I) for early detection of patients in need of admission to reduce time spent in waiting and for hospital resource optimization.

Johns Hopkins Hospital partnered with General Electric Healthcare to create a seamless connection between physical healthcare facilities and sophisticated AI technologies that maximize resources, expedite operational procedures and workflow, and, most importantly, enhance patient outcomes. The IoT is used in their facilities as part of this technology. The centre's AI analyses the data to control patient flow and volume, as well as trigger interventions to prioritize high-risk situations [30].

Uncancelled missed appointments have been demonstrated in several studies to significantly influence efficiency, cost savings, and patient outcomes [16]. Weka (http://www.cs.waikato.ac.nz/ml/weka/), an open-source machine-learning program was used to assess a classifier's performance against a particular dataset employing a variety of performance indicators. Appointments with a high chance of no-show can be forecasted in real-time using data stream classification methods like the Hoeffding tree algorithm [16]. This provides one more avenue for improving OPD workflow to facilitate efficiency.

A study was done by Islam *et al.* [31] who used a Deep Learning-based model to prescribe tests based on outpatient medical history. Because the model demonstrated a high level of discrimination, its deployment would assure accurate laboratory testing, enhance patient safety, and eliminate wasteful expenses associated with incorrect prescriptions. The system just needed a few pieces of information to get started, such as sex, age, disease, and medication prescription information, hence it can simply be integrated into medical systems. The study was however limited to a cardiology department [31].

Sandhu *et al.* [32] conducted a qualitative study with the goal of learning more about the factors that influence the adoption of a machine learning early warning system in care processes. A process was created by a multidisciplinary team of physicians, administrators, and data scientists to transform the model's results into therapeutic action. Three main issues emerged: apparent utility and trust, strange process implementation, and several personnel concerns. Machine learning models were reported as being foreign to the participants. This study showed that more research studies are required to fully comprehend the real-world challenges to the development and proper implementation of machine learning solutions [32]. Understanding how these components interact in different circumstances can help determine implementation techniques for different situations.

Nadarzynski *et al*. [33] ran a study to see how willing people were to interact with AI-powered medical chatbots. Three primary themes emerged: "Understanding of chatbots," "AI hesitation," and "Motivations for health chatbots," highlighting worries about accuracy, cyber-security, and AI-led services' incapacity to empathize. The study found moderate acceptance, which was adversely connected with inferior IT skills and hate for communicating with computers, but favourably correlated with perceived benefit, a positive attitude, and perceived trustworthiness. The qualitative investigation revealed that a significant number of people were wary of AI and health chatbots, owing to worries about their accuracy and security. There was also a belief that chatbots may allow certain people to talk about personal and potentially humiliating health conditions, hence increasing access to standardized treatments. Although they were viewed as a handy and anonymous solution for minor health conditions that may be stigmatized, other users found chatbots to be less acceptable due to a lack of emotion and a humane attitude [33]. These findings are supported by previous research and theoretical perspectives on the acceptance of novel healthcare interventions.

A significant number of physicians express a range of opinions about the importance of machine learning in healthcare in general [34]. Lack of expertise, fear of over-stepping, and opposition to changes in medicine are seen as serious potential roadblocks by several practitioners. Some also recognized an opportunity to use machine learning to solve operations and logistics issues before its implementation in clinical decision support [32]. Globally, healthcare expenditures are under growing pressure to reduce costs while preserving quality and guaranteeing safety and quality of care [31]. This becomes a big hindrance to research, trials, and implementation of AI-based technologies due to the high cost of setting up although they have the potential for reducing operational costs in the long term. The application of AI-based technologies in healthcare is also still in the very early stages and lacks the overwhelming evidence required to garner widespread utilization.

2. METHOD

Preferred reporting items for systematic reviews and meta-analyses (PRISMA) criteria were followed for conducting the systematic review. A preliminary search was conducted with the goal of discovering current systematic reviews as well as determining the number of possibly relevant studies. After that, trial searches were done using varying combinations of search phrases obtained from the study topic. The research outcomes were then reviewed. Study designs considered systematic review, randomized controlled trial, cohort study (prospective observational study), retrospective cohort studies, cross-sectional studies, case-control studies, exploratory surveys, case reports and series, ideas, editorials and opinions put forth by experts in the field.

A Google search of "artificial intelligence used in outpatient settings" Boolean search (AND/OR): The following keywords were used to identify terms in the titles, abstracts, and keywords of the publications. The first group of keywords targeted AI-related terms, while the second group of keywords were related to clinical implementation. The following terms were used in the search: "artificial intelligence" OR "machine learning" OR "deep learning" AND "outpatient" AND "waiting times" OR "delays". Databases searched include ResearchGate, PubMed, BMC Health Services Research, JMIR Publications and Cochrane Central. All the databases were searched using the keywords outlined and the selected were articles downloaded and imported all of the identified articles using the Mendeley application Figure 1.

The total results from the databases were 73,166. It was filtered from 2011 to 2021 and a total of 72,347 including duplicates were removed. This resulted in 819 articles.

Inclusion criteria

- *Study must not be older than 11 years.*
- *Study must be conducted in a primary, secondary, or tertiary healthcare setting.*
- *Participants may be either first-time visitors to the OPD or patients with scheduled appointments.*
- *Study must implement an AI application with patients or healthcare providers.*

Exclusion criteria

- *The AI application targeted nonclinical tasks, such as biomedical research and operational tasks.*
- *Conference abstracts.*
- *Unpublished material like dissertations, commentaries, simulation papers and ongoing studies.*

The document types chosen for this review study lowered the total number of results to 419. One hundred and eighty-six (186) articles were excluded based on full texts, while another 208 were excluded based on titles and abstracts. A total of 22 extractions were integrated into a table to identify author and year, country, characteristics of participants, characteristics of the intervention (e.g., duration, type), data collection instruments, model of AI application used, design and results Figure 1.

2.1. Quality assessment

The review paper considered an instrument comprising eleven (11) items developed by Jadad *et al.* [35]. The studies were evaluated to see if they were randomized or double-blind. Any dropouts or withdrawals were documented. The investigations' aims and result measures are required to be clearly outlined as well. For all systematic reviews included, a detailed description of the inclusion and exclusion criteria was necessary. The justification of sample size and a clear explanation of treatments were evaluated, as were the statistical analysis methodologies utilized in the various research.

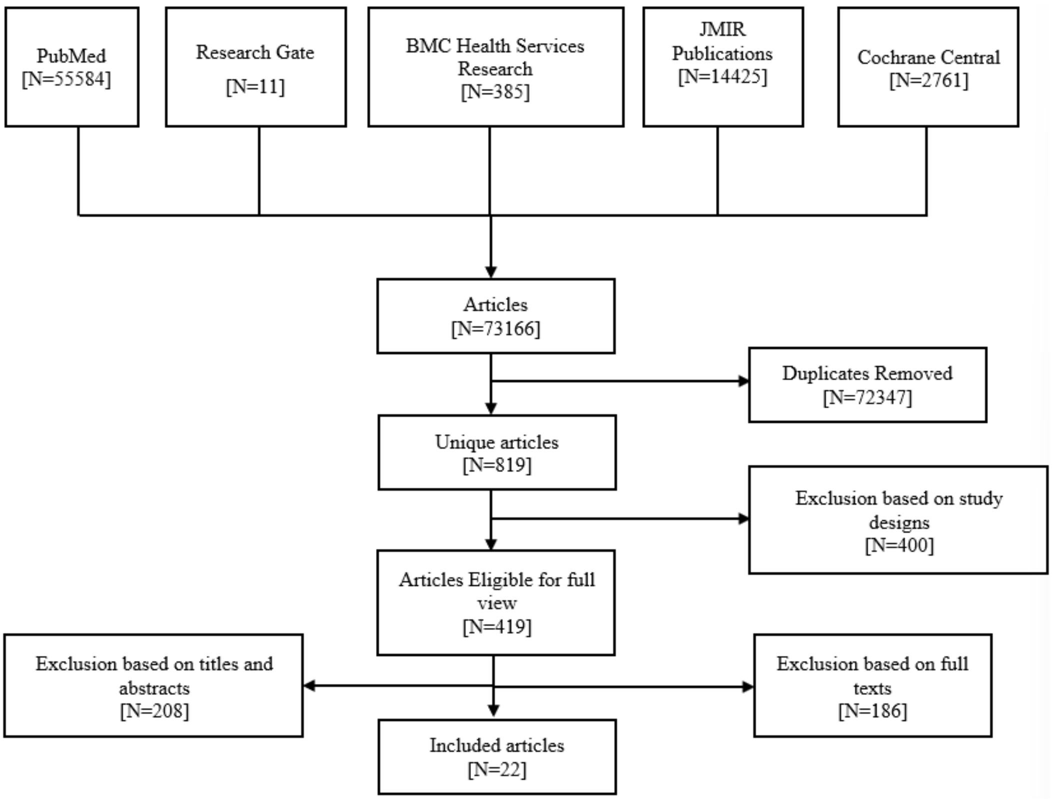

Figure 1. Flow diagram of PRISMA

The overview of the included studies can be found in Table 1 (see in Appendix). Table 1 lists the study designs and sample sizes used for the research. Table 1 also includes AI intervention, subject, and citations [2], [11], [16], [18], [19], [21], [24], [31]-[33], [36]-[47].

3. RESULTS AND DISCUSSION

3.1. Geographical distribution of the studies analysed

The global distribution of the articles discussing the usage of Artificial Intelligence based methods is displayed in Figure 2. Results from the 22 articles collected gave a representation of various countries. The USA recorded the highest with 36.4%, followed by China with 22.7% and the UK constituted 9.1%. The remaining countries, Australia, Norway, Pakistan, the Republic of Korea, Saudi Arabia, Singapore, and South-Western Nigeria represented 4.5% each.

This represents the general distribution of advanced technologies comparing developed countries to developing countries. The presence of a developed science and technology-based industry in these countries provides the foundation for innovations like AI and its implementation in fields like healthcare. The American Food and Drugs Authority for example has authorized the use of an AI-based diagnostic system. While simulation is widely utilized in the healthcare business in wealthy nations, the notion of employing simulation in developing countries is new [18]. Although a step in the right direction it may not be as utilitarian to developing countries which face a lack of basic infrastructure and systems for disease diagnosis and treatment. Some still face major challenges in effectively running traditional healthcare systems. In spite of this, AI technologies focused on streamlining workflow, and facilitating administrative and clerical tasks may be more beneficial with only the cost of integration being the chief barrier.

The graph indicates (Figure 3) the number of studies included from the year 2011 to 2021. The relevant result from the data shows varied numbers for each year with no included study before 2014. The year 2020 recorded the highest on the list with 7 representing 31.8%, followed by 2021 with 5 constituting 22.7% and the years 2017 and 2019 recorded 2 depicting 13.6% respectively. This represents the increasing number of studies being done now compared to earlier years. AI application in health is very young and as more research is conducted and more innovations are made, the discussion will be more informed soon with growing evidence to either support its implementation, modify its application, or disregard it as a meaningful tool in the advancement of healthcare.

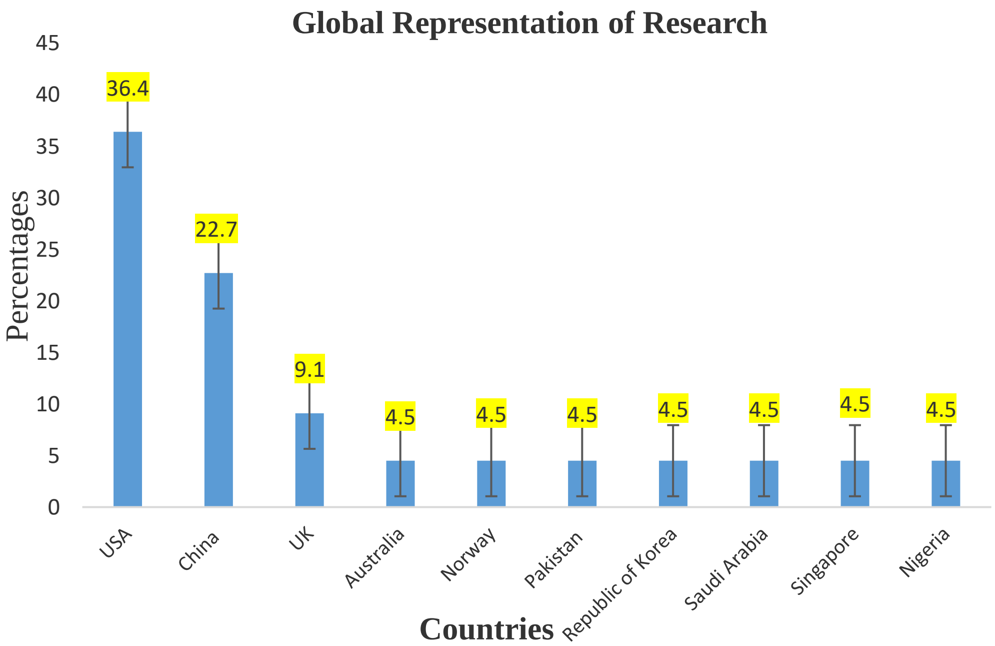

Figure 2. Country-based distribution according to the usage of AI-based methods

3.2. AI techniques employed

The most relevant application of AI to this study was in disease screening, triaging and risk analysis. Other popular areas of application in clinical decision-making were diagnosis and non-pharmacological management of certain conditions. The AI applications used in the studies included machine learning, deep learning algorithms, event simulations, the Internet of Things, and other undisclosed techniques. It was realized that most of the existing implementations were in specific subfields for disease conditions.

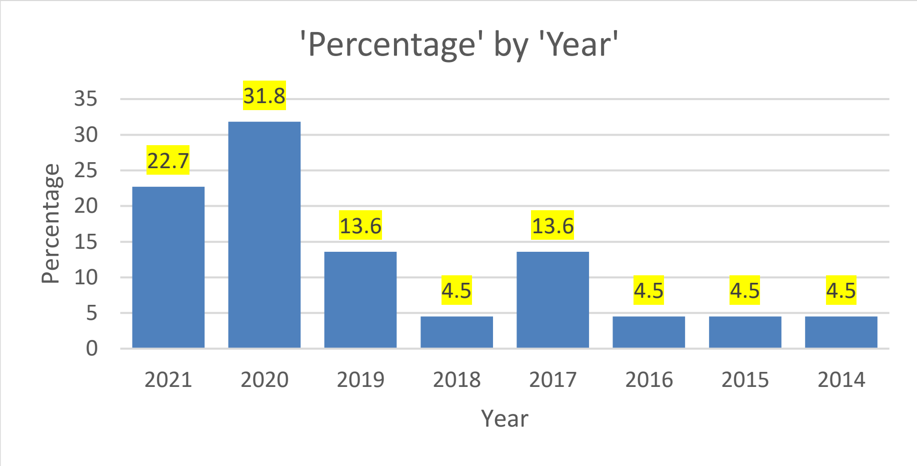

Figure 3. Distribution of studies on AI-based methods according to year

3.3. Outcome evaluation

Generally, it was seen that AI impacted patient waiting times through the application of simulation techniques and laboratory test suggestions prior to consultation. It also improved administration workflows and efficiency through applications of machine learning algorithms. This significantly improved patient triaging having an impact on real waiting time while being able to correctly estimate waiting times and scheduled appointment delays can improve perceived waiting times and patient satisfaction while allowing staff to monitor and respond to patient flow more precisely [41]. One study reported units with high numbers of client backlogs. These were the Lab, Ultrasound, and X-ray units. During the analysis of the system, every one of these units was overburdened, with much longer waiting times than other units [18]. When comparing the present and proposed systems, waiting times can be dropped by a significant factor [18].

In a simulation-based trial, mean patient wait times were drastically reduced and the scheduling rate was optimized, resulting in lower cost per test and improved patient satisfaction [24]. It was also found that machine learning may be used to estimate exam lengths based on patient demographics, reducing mean patient wait times [24]. With regards to automated screening, a deep-learning algorithm-driven screening option allowed for results reporting at the point of service, resolving many of the concerns associated with delayed results transmission [40]. Patients who used the system in an outpatient setting appeared to find our AI-based model viable and acceptable [40].

The computing power of machine learning, which already outperforms the human brain in many data-processing tasks, makes it a good candidate for detecting and forecasting complex and noisy phenomena like waiting times, as presented in Curtis *et al.* [39]. Predicting patient waiting times and facility delays is an important strategy in clinical practice management. Patient satisfaction depends on accurate delay and waiting for predictions. Elastic nets, a machine learning model that has been applied to RIS data, provide an accurate and efficient wait and delay time predictions according to [24].

One study used various machine learning algorithms to predict and analyse data sets generated by health units. When compared to lab technicians, the system handled the data set more effectively using various machine and deep learning algorithms, resulting in a low error rate and higher prediction accuracy [41]. In a fraction of the time, AI learning algorithms can process many datasets collected from various smart IoT devices and predict the outcome. Its predictive capability will improve over time and can eventually be implemented in more outpatient points of service to serve a larger number of clients who do not need to wait long periods of time for specialist attention. These systems can also generate electronic health reports for doctors to use for further analysis and recommendations to ensure quality and safe service provision [6].

One area of development which could indirectly impact the daily number of OPD visits with enormous potential is 5G. Patients' health may be monitored via 5G communication technologies and smart wearable gadgets. Real-time diagnosis, scheduling, and suggestions are now possible because of enhanced machine-learning algorithms [41]. However, for illness prediction accuracy and user confidence, data authenticity and integrity should be preserved during communication, which will open new options for researchers [41].

The results of one study's model gave useful information for clinic management. Furthermore, the process of building the model with clinic employees demonstrated the need of taking unpredictability into account when designing how the clinical systems work. A more general discovery was that a basic simulation model may be used to identify bottlenecks and effective strategies to restructure an outpatient clinic for speedier workflow and shorter real and perceived waiting times [44].

4. CONCLUSION

AI-based technology is on the point of shattering the bounds of healthcare, well-being, and life itself, beyond the limits of expert knowledge. In this regard, while AI-based medical systems now focus on patient-centred illness management, it is envisaged that the scope will broaden over time, from pre-disease through treatment and post-care to everyday living. As a result, AI-enabled technology is infiltrating not just all sectors of healthcare but also our everyday lives, and it should be implemented from a broad view that considers the whole spectrum of people's lives.

The use of AI-based health technology to streamline OPD workflow and cut wait times has significant potential, but it will require much more research, development, and examination to avoid some of the flaws and drawbacks associated with it. The goal is for AI to help improve patient outcomes. Thus, the introduction of AI into healthcare processes must be geared towards enhancing healthcare services.

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Appendix

Table 1. Overview of included studies (*continue*)

Author(s)	Description	Study design	Sample size	AI intervention	Subject	Cited in	Results (+/)
[11]	Using a smartphone enabled AI system to reduce outpatient waiting times	Case control study	4	Case-based reasoning (CBR) algorithm	Medicine	506	+
[36]	Computational modelling in an outpatient clinic to improve health care delivery	Retrospective study	96	Discrete event simulation (DES) modelling	Medicine	1,355	+
[37]	Reducing patient waiting times for phlebotomy	Prospective study	4	Queuing theory	Clinical Pathology	2,933	+
[38]	Reducing waiting times in OPD pharmacy	Case control study	8	Qmatic queuing system (Qmatic United States, Fletcher, NC).	Pharmacy	960	+
[39]	Predicting patient wait times and appointment delays using machine learning	Retrospective study		Machine learning models (elastic net model)	Radiology	1,546	+
[24]	Using machine learning and dynamic exam block lengths to reduce patient wait times and increase the fill rate of MRI schedules	Retrospective study	34,611	Historical scanner data and stochastic simulation	Medicine	42	+
[40]	A pilot study of the feasibility and patient acceptability of a novel AI-based diabetic retinopathy screening model at endocrinology outpatient services	Prospective study	96	Deep learning algorithm (DLA)	Endocrinology	1,121	+
[16]	Artificial intelligence systems for predicting hospital no-show appointments	Predictive modelling.	1,087,979	JRip and Hoeffding tree algorithms	Medicine	373	+
[33]	A mixed-methods research into the acceptability of chatbot services powered by AI in healthcare.	Exploratory survey	240	Chatbots	Medicine	31,719	+
[41]	Artificial intelligence, IoT, and 5G connectivity being used to create a paradigm change in the digital healthcare sector.	System development	2,110	IoT and 5G communication	Medicine	271	+
[18]	A computational model study to better manage	System development	1,300	SIMIO simulation software	Medicine	2,211	+

Table 1. Overview of included studies (*continue*)

Author(s)	Description	Study design	Sample size	AI intervention	Subject	Cited in	Results (+/)
	hospital resources and reduce patient waiting times.						
[42]	Predictive analytics using AI in the management of outpatient MRI appointment no-shows	Predictive model	32,957	Machine learning predictive analytics	Medical Physics and Informatics	724	+
[31]	Retrospective investigation of the national health insurance database for the development of an AI–based automated recommendation system for clinical laboratory tests.	Retrospective study	3,321	Artificial Intelligence – based automated	Medicine	321	+
[43]	Clinical validation study of automatic grading of stroke symptoms for quick assessment utilizing improved machine learning and 4-limb kinematics	Clinical validation study	60	Machine learning and wearable sensors	Medicine	214	+
[2]	Gaps and determinants of patient waiting time for quality services in community hospitals	Descriptive cross-sectional study	223		Medicine	177	+
[32]	A qualitative study of integrating a machine learning technology into clinical processes	Inductive and exploratory	15	Sepsis watch	Medicine	22,421	+
[44]	A computer simulation modelling study of capacity and patient flow planning in post-term pregnant outpatient clinics.	Factorial experimental	1,072	Event simulation model		1,213	+
[21]	Opportunities and difficulties in the application of artificial intelligence-based technology in the healthcare industry.	Prospective study	60,000	AI-based technology/system	Medicine	4,127	+
[19]	A retrospective cohort study of artificial intelligence-assisted reductions in patients' waiting times for outpatient procedures.	A matched case – control study	12,342	AI-assisted module, XIAO YI	Medicine	37,105	+
[45]	An algorithm developed based on electronic health records, that detects individuals with atrial fibrillation and prescribes anticoagulant therapy.	Randomized control trial	75	Machine learning	Medicine	19	+
[46]	A systematic examination of the use of artificial intelligence applications in real-world clinical practice	Prospective and retrospective studies	51	Various AI applications	Medicine	117,417	+
[47]	Model creation and validation for using external medical knowledge to improve intelligent diagnosis in obstetrics	Retrospective studies	24,192	Intelligent diagnosis model based on deep learning	Medicine	25,304	+