

Potentialities and challenges of using artificial intelligence in chronic pain management: a scoping review

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Abstract *This study aims to map the scientific literature on using artificial intelligence (AI) in managing chronic pain, the leading cause of disability worldwide. A scoping review was conducted following PRISMA-ScR guidelines. We searched for articles in MEDLINE, LILACS, SPORTDiscus, SCOPUS, CENTRAL, Science Direct, IEEE Xplore, Association for Computing Machinery Digital Library, and arXiv databases. Descriptors “Chronic Pain” and its synonyms were combined with “Artificial Intelligence” or “Machine Learning” or their synonyms. Initially, 2,767 articles were identified, and 109 studies were selected and analyzed. The volume of scientific production has been increasing over the years. Most adopted AI algorithms focused on classifying individuals by type of chronic pain and predicting risk groups. Support Vector Machine, Random Forest, Neural Networks, Logistic Regression, and K-means were the most adopted algorithms. Few studies focused on AI use in primary health care. We underscore AI’s potential to prevent and improve chronic pain management.*

Key words *Chronic pain, Artificial intelligence, Machine learning, Primary health care, Family health*

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Introduction

Chronic pain is a common and complex health problem with a significant impact on society¹. It is one of the biggest global public health problems and the leading cause of disability worldwide, according to the Global Burden of Disease Study². Despite being one of the most researched health topics, evidence to date has been unable to change its status as the principal cause of disability on the planet³.

According to the International Association for the Study of Pain (IASP), pain is an unpleasant sensory and emotional experience associated with actual or potential tissue damage⁴. Chronic pain is when this pain is continuous or intermittent for more than 12 weeks. Primary chronic pain (PCP) is defined as pain with no apparent cause that persists for more than three months in one or more anatomical regions, causing significant emotional distress (anxiety, anger/frustration, or depressed mood) or functional disability (interference with daily activities and reduced participation in social roles)⁵. The process that can lead to PCD is multifactorial. Biological, psychological, and social factors contribute to the pain syndrome⁶. This classification describes that secondary chronic pain includes chronic pain related to cancer⁷, chronic post-surgical or posttraumatic pain⁸, chronic neuropathic pain⁹, orofacial pain or secondary chronic headache¹⁰, secondary chronic visceral pain¹¹, and chronic secondary musculoskeletal pain^{6,12} (Supplementary Material 1, available at: <https://doi.org/10.48331/scielodata.QFM-MDX>).

The most significant difficulty in treating chronic pain is the multiplicity of factors complexly interconnected in the genesis of the problem¹³. As the causes are diffuse, the management of the problem ends up being non-specific. This situation ends up reducing the effectiveness of therapeutic proposals¹⁴. Encouraging studies on interventions in which the treatment or prevention of pain in individuals is based on an individual's absolute risk and not a general risk could hypothetically generate evidence to better support the choice of therapeutic strategies¹⁵. The observation of the low effectiveness of interventions, the syndrome's recurrence, and its managing challenges seem to point to a necessary investment in new diagnostic and therapeutic tools.

Recently, the literature has suggested several uses of artificial intelligence (AI) in health. Among the possibilities for using AI, we under-

score screening and diagnosing health problems, supporting treatment decisions, indicating specialists, estimating prognosis, analyzing medical records, building knowledge bases, extracting information, and providing descriptive information. AI tools target healthcare professionals, healthcare managers, and patients or guardians¹⁶. As a tool that, based on previous data, can understand patterns and rules and thus estimate the risk of a given outcome¹⁷, AI has been increasingly used to support decision-making at different healthcare stages in recent years. However, we still do not have sufficient knowledge to indicate the potential and challenges of its use in health. Thus, research on the subject should be encouraged.

Exploring the potential of artificial intelligence algorithms used in the management of individuals with chronic pain can provide evidence to promote health and prevent new cases, increase the effectiveness of therapeutic proposals in the treatment of cases, and reduce the adverse consequences of such situations to the well-being and quality of life of individuals who suffer from the problem¹⁸.

The Unified Health System (SUS), established by the 1988 Constitution and based on the principles of universality, comprehensiveness, and equity, ensures free access to healthcare for all Brazilians¹⁹. Primary Health Care (PHC) holds a central position in the structure of the SUS and is the main gateway to the Healthcare Network (RAS)²⁰. In Brazil, PHC is predominantly organized by the Family Health Strategy (ESF), aiming at health promotion, disease prevention, and continuous and comprehensive care^{19,21}. Given the SUS complexity and scope, adopting emerging technologies, such as Artificial Intelligence (AI) tools, is a promising opportunity to streamline management and service delivery. In PHC, AI can improve screening, monitoring of chronic diseases, and care personalization, enhancing health promotion and disease prevention actions.

In order to expand knowledge about the use of AI in health services, this study aimed to conduct a comprehensive scoping review on the use of AI in the management of chronic pain in health services, especially PHC/ESF, identifying the AI application scenarios studied, the types of algorithms used for managing chronic pain and the most promising ones, the main predictors used in these algorithms, the population that benefits from the results of the AI application (managers, health professionals, and users), which chronic pain conditions have been most

studied and those with growth potential, besides pointing out knowledge gaps on the subject.

Methods

Drafting and registration

This review was planned, conducted, and written under the recommendations of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR)^{22,23}. The project was registered in the Open Science Framework (OSF) under Identification N° DOI 10.17605/OSF.IO/2GE63, available at <https://osf.io/2ge63/>.

Study design

This Scoping Review complies with the guidelines of the JBI Manual for Evidence Synthesis²⁴, available at <https://synthesismanual.jbi.global>.

Review question

What scientific literature on using artificial intelligence tools in managing chronic pain is currently available?

Eligibility criteria

Inclusion criteria

The inclusion criteria are a) sample/population – people with chronic musculoskeletal pain and healthy individuals; b) use of artificial intelligence technique at any time during rehabilitation; c) analysis of any type of outcome, preferably clinical outcomes; and d) no restrictions based on ethnicity, gender, age, or religion.

Exclusion criteria

As exclusion criteria, we considered a) studies published in journals without peer review, b) research protocols or other publications that do not bring original research results, and c) studies that have used any data analysis method other than Artificial Intelligence.

Bibliographic search strategy

On 28/03/2023, a bibliographic search was conducted without time or language filter in the following databases: MEDLINE (US National Library of Medicine); LILACS (Latin American and Caribbean Literature in Health Sciences);

SPORTDiscus; SCOPUS; CENTRAL; Science Direct; IEEE Xplore; Association for Computing Machinery Digital Library; and arXiv.

Two independent authors developed the search key, and disagreements were discussed and resolved with the entire group of authors. Boolean operators “OR” between synonyms and “AND” between descriptors were used to create the search key. The descriptors found in the Health Sciences Descriptors (DeCS) and Medical Subject Headings (MeSH) databases, “*Chronic Pain*” and its synonyms, were used in combination with “*Artificial Intelligence*” or “*Machine Learning*” or their synonyms. The descriptors were adapted for use in all databases, with only the search key being specific for better clarity of results and easy reproducibility. The complete search strategy used in the databases is available in Supplementary Material 2 (available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

After searching all databases, studies were analyzed, and duplicate studies were excluded. After excluding duplicate studies, two independent authors analyzed the studies by reading titles and abstracts, excluding those not meeting the previously defined selection criteria. Any disagreement between authors was discussed and resolved with the entire group of authors.

Two independent evaluators read the selected articles in full. The information of interest was extracted using a data extraction form focused on the following characteristics: author, year, country, journal publication area, chronic pain type, pain measurement, age of participants, care type, study type, sample size, study objective, tool target, AI type, AI objective, data sources, and data types.

Results

The search for articles in the nine databases resulted in a collection of 2,767 retrieved articles. Five hundred seventeen were duplicated in different databases and excluded. Of the remaining 2,250 articles, 2,087 were excluded after reading the abstracts because they did not address the topic. One hundred sixty-four articles were selected for full reading and eligibility analysis per the previously stipulated exclusion and inclusion criteria.

At this screening stage, 75 articles were excluded for the following reasons: inadequate population (n = 31), inadequate outcome (n = 23), inadequate intervention (n = 15), and inadequate study type (n = 6). Thus, 89 articles were

selected after passing the eligibility screening in the full reading. Then, 26 additional articles were retrieved by manual citation search, six of which were excluded in eligibility due to inadequate outcome analysis, leaving 20 additional articles. Therefore, 109 articles met the stipulated eligibility criteria and were included in this scoping review (Figure 1).

The studies selected in this scoping review were quite comprehensive per the pre-established criteria (sample, use of artificial intelligence technique at any time during rehabilitation, analysis of any outcome without restrictions based on ethnicity, gender, age, and religion). The selected studies were published from 2002 to March 2023 (search date). The countries with the most significant number of publications in the field were the United States, with 44 studies; England, with 16 studies; and Canada, with 10. Only two studies were conducted by Brazilian researchers. The gradual growth in the number of publications in the field is visible, especially since 2018 (Figure 2).

The use of AI-based tools had different objectives, with significant variation regarding the level of healthcare intended. Most studies did not specify whether the tool would be helpful in primary, secondary, or tertiary care ($n = 60$). Most studies reporting where the AI-based tool would be intended focused on tertiary care ($n = 31$), followed by secondary care ($n = 12$). Only five studies indicated PHC as the destination for AI-based tools. Furthermore, one study was developed for multiple destinations ($n = 1$) (Supplementary Material 3, available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

Four of the five studies aimed at PHC were longitudinal (3 observational and 1 Randomized Controlled Study), and one was cross-sectional. Fodeh *et al.*²⁹ (2017) focused on analyzing patterns in unstructured assessment data from the medical records of patients with chronic pain, seeking to understand trends in information such as medical record notes and patient reports and offer a broader and more integrated view of the patient's health status.

Nijeweme-d'Hollosy *et al.*²⁸ (2018) aimed to explore the possibilities of using Machine Learning to support clinical decision-making in individuals with chronic low back pain, involving creating tools that would guide professionals in their therapeutic choice. Tsai *et al.*²⁶ (2021) analyzed the performance of predictors related to movement and sleep hours to identify factors that could prevent chronic pain or shape the response to treatment.

The study by Nephew *et al.*²⁵ (2022) investigated associations of individual variables with depression and chronic pain to identify relationships between specific factors and health outcomes, facilitating an understanding of how some characteristics of patients and treatments are connected to specific results. Liew *et al.*²⁷ (2023) focused on using AI to classify subgroups of individuals with low back pain to find specific treatment strategies, increasing therapeutic efficacy.

Using the current classification of chronic pain suggested by IASP⁶, which classifies chronic pain into seven subtypes, we observed that most studies were directed at chronic musculoskeletal pain ($n = 39$). Primary chronic pain was also the target of most studies ($n = 25$). Fewer studies were found focusing on chronic visceral pain ($n = 9$), chronic cancer pain ($n = 7$), chronic headache or orofacial pain ($n = 4$), chronic post-surgical and posttraumatic pain ($n = 4$), and chronic neuropathic pain ($n = 2$). Notably, some publications did not report the chronic pain type for which the study was conducted ($n = 19$) (Figure 3).

When analyzing the studies by body topography of the pain they target, it is clear that the body regions differ between the studies. Although most selected studies did not specify the chronic pain location ($n = 57$), a large part of the studies targeted chronic low back pain ($n = 32$), followed by chronic back pain (where the location of the pain in the spine was not specified) ($n = 7$), chronic pelvic pain ($n = 5$), chronic neck pain, and chronic knee pain with the same number of studies ($n = 3$); lastly, chronic headache or orofacial pain ($n = 2$) (Supplementary Material 4, available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

When analyzing the tool's target population, we highlight the large number of studies focused on the patient; that is, the individual with a chronic condition ($n = 97$) would be the primary user of the tool. A few studies were developed to support health professionals ($n = 9$) and health managers ($n = 2$) in chronic pain management.

For better understanding, the study's results were systematically organized into two large tables: general and methodological characteristics of the studies (Chart 1, available at: <https://doi.org/10.48331/scielodata.QFMMDX>) and Characteristics of the tools and data used in the research (Chart 2, available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

This scoping review identified and systematized several important aspects of the scientific

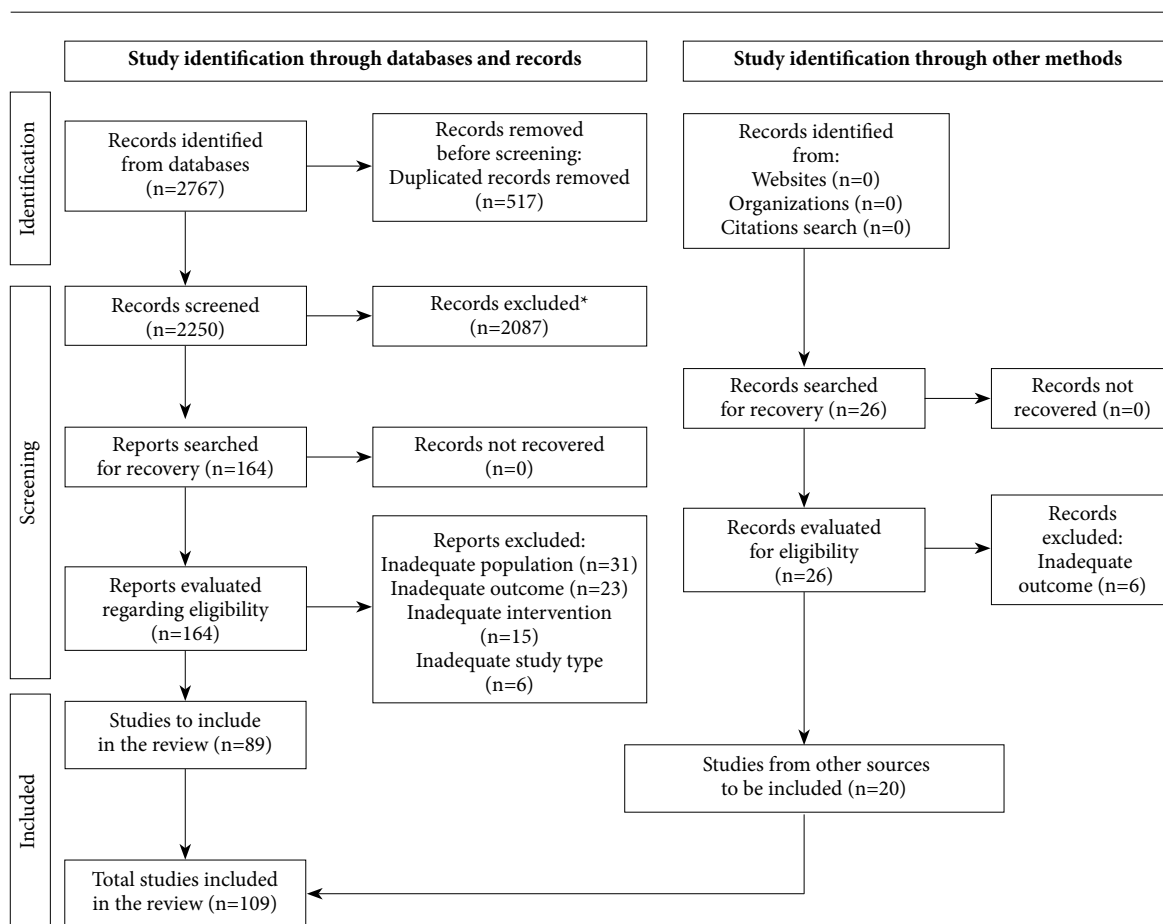


Figure 1. Study selection flowchart.

* Studies excluded after reading the abstract because they did not address the topic.

Source: Adapted from The Prisma 2020 Statement: An Updated Guideline for Reporting Systematic Reviews¹⁵.

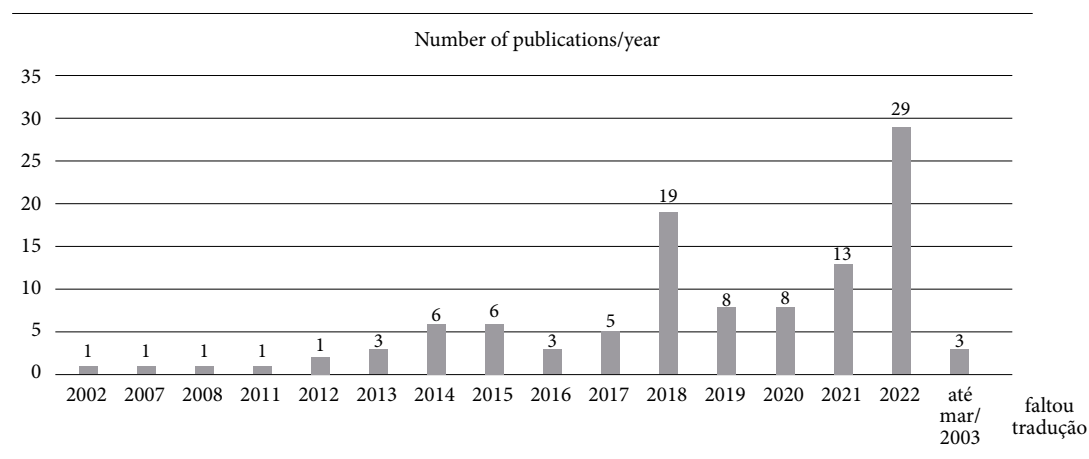


Figure 2. Distribution of articles that participated in the scoping review by year of publication.

Source: Authors.

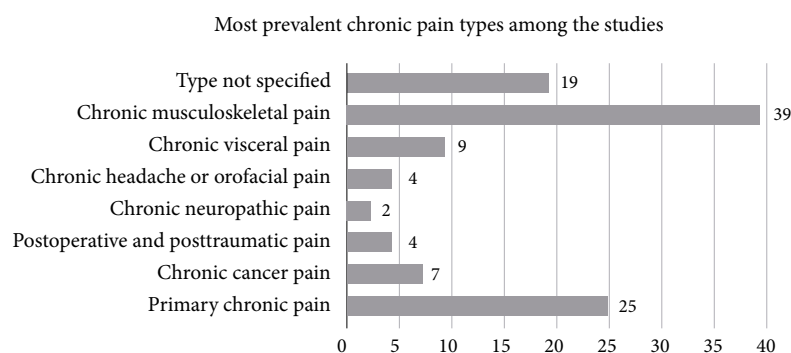


Figure 3. Distribution of articles by subtype of chronic pain under the IASP criteria⁶.

Source: Authors.

literature related to AI tools applied to chronic pain. As can be seen in Chart 1 (available at: <https://doi.org/10.48331/scielodata.QFMMDX>), most studies were conducted in North American and European countries, followed by Asian countries. South America had only two studies, both conducted by Brazilian researchers. Most journal publications fields focused on medical sciences, technology, and diagnostic imaging.

The most prevalent chronic pains were, respectively, chronic musculoskeletal pain ($n = 39$), chronic primary pain ($n = 25$), chronic visceral pain ($n = 9$), chronic cancer pain ($n = 7$), chronic headache or orofacial pain ($n = 4$), chronic post-surgical or posttraumatic pain ($n = 4$), and, lastly, chronic neuropathic pain ($n = 2$). The most used tools to measure pain were the Visual Analog Scale ($n = 24$), the Numerical Estimation Scale ($n = 19$), and specific questionnaires.

The mean age of the total sample reported was 50 years. Most studies did not report the healthcare level ($n = 60$). Studies emphasizing tertiary care had the most significant publications ($n = 31$), and PHC had the smallest number ($n = 5$). Observational study designs were predominant in the review ($n = 102$), with a small number of experimental studies ($n = 7$). The total sample of data used for analysis was 733,106,571. The most prevalent study objectives were classifying individuals by type of chronic pain and predicting risk groups (Chart 1, available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

Besides the general and methodological characteristics, we found that the main targets

of these tools are patients, but some studies targeted health professionals, and very few targeted managers. The AI types adopted include supervised, semi-supervised, and unsupervised learning. Supervised learning was the most common in the studies of this review ($n = 92$), notably Support Vector Machine ($n = 32$), Random Forest ($n = 31$), Logistic Regression ($n = 26$), Neural Networks ($n = 13$) and K-means ($n = 10$). AI algorithms are aimed at classifying, predicting, and grouping variables.

The data sources used by AI tools are diverse, including electronic medical records, patient reports, biometric sensors, and monitoring devices. Data from clinical trials and longitudinal studies are also integrated to provide a comprehensive and robust knowledge base. The types of data processed by AI tools range from structured to unstructured. These data can be in text, audio, or image format. Textual data include patients' verbal descriptions of pain, clinical notes, and questionnaires. Images, such as medical imaging scans or photographs of affected areas, provide complementary visual information. Audio, such as recordings of pain reports, are analyzed to capture nuances in patients' verbal communication about their pain experience (Chart 2, available at: <https://doi.org/10.48331/scielodata.QFMMDX>).

Discussion

This comprehensive scoping review reveals that the volume of scientific production on AI in chronic pain has been growing, especially after

2018. The first selected study was published in 2002, and the last was published in 2023 (search date). This massive increase in recent studies on the subject is possibly due to the popularization of AI tools, greater technical capacity, and computational capacity to process an ever-increasing amount of data^(30,31). Also, the high prevalence of chronic pain worldwide and health professionals' difficulties in improving the management of individuals with these conditions encourage the production of new studies and the incorporation of new technologies, including AI³². Using AI in different ways, as shown in this review, can be a path to address such a complex and challenging issue.

Contrary to expectations, only five studies focused on activities developed in PHC, a setting that is usually the gateway for patients with these conditions. As indicated in the Results section, the five studies differ regarding their objectives and show methodological differences that hinder quantitative synthesis, suggesting that this is still an incipient area of research. The scarcity of studies focusing on PHC also reveals that although AI tools have great potential to assist in screening populations at risk for chronic pain at the first moment of contact with the health system, we still have a long way to go. Encouraging researchers with AI and experience in PHC seems to be a viable path to increasing publications in the field and, consequently, advancing practical applications of new technologies in PHC.

Chronic musculoskeletal pain was the most prevalent in the studies ($n = 39$), followed by primary chronic pain ($n = 25$). According to the specialized literature, this finding was unexpected because primary chronic pain is the most prevalent worldwide⁵. Many studies selected in this review focused on chronic low back pain ($n = 32$) since it is the world's most prevalent chronic musculoskeletal condition. Thus, we should avoid generalizing the results of these studies to all chronic pains. AI algorithms in the selected studies were almost entirely focused on patient use. This characteristic of the target to be reached by the tools may translate into a perception that managing chronic pain conditions by patients is genuinely an important focus in the care of this field of research.

The 109 studies had different objectives and designs and employed different algorithms. This thematic and methodological diversity indicates that AI in chronic pain is a broad field of study with its thematic underlying areas increasingly explored in the coming years. Another important

result is that most AI algorithms focused on classifying individuals and predicting risk groups ($n = 93$). Few studies effectively focused on treating chronic pain ($n = 5$), converging with the findings of reviews already published on the subject^{33,34}. This appears to be a significant gap despite the algorithms potentially being of great use in assisting clinical support decisions in treatment and prognosis.

One of the most researched topics is using biomarkers and neuroimaging to understand which variables can predict responses to treatment in patients with chronic pain³⁵⁻³⁸. In this field, the analysis of functional brain images, such as Functional Magnetic Resonance Imaging, has been used to identify brain patterns that correlate with the response to pain and treatment with drugs, such as opioid analgesics³⁹⁻⁴¹.

Another important theme was assessing the performance of the integration of movement sensors and electromyography (EMG) with Machine Learning algorithms in identifying anomalous patterns in patients with chronic pain. Analysis of data captured by sensors can distinguish subtle motor characteristics that may contribute to pain^{42,43}. The issue of prolonged use of opioids and the prediction of abuse of these substances is also an area of focus. Studies suggest that predictive algorithms have been effective in identifying patients at risk of prolonged opioid use after surgical procedures or chronic pain^{44,45}. This aspect is directly related to the growing effort to mitigate the opioid epidemic, as evidenced by Jones *et al.*⁴⁶ (2018), who argue that predicting inappropriate use behaviors may be key to reducing the impact of this global health crisis.

Most studies selected in this scoping review were observational ($n = 102$). This methodological characteristic reveals that data from individuals were used for some indirect analysis with AI, such as classifying individuals into subgroups, associating variables that may be related in search of risk and prognostic factors, identifying genes involved in chronification processes, creating new means of assessment for individuals with chronic pain, creating models to predict chronic post-surgical pain, predicting the amount of post-surgical opioid, among others.

Few intervention studies and analyses of therapeutic efficacy, such as randomized controlled clinical trials, were found ($n = 7$) and should be further encouraged⁴⁷. On the other hand, one of the strengths of the studies included in this review is that most works ($n = 56$) used pain scales commonly adopted in the

literature on the subject to assess pain intensity in individuals, following a pattern already identified in chronic pain studies⁴⁸.

Another notable finding was that many of the selected studies used public databases and/or patient self-reported data ($n = 25$), in which data quality may not be ideal. AI requires a large amount of data with known origin and reliable quality to make good predictions⁴⁹. In health, structured data is generated in more significant amounts than unstructured data⁵⁰, which was reflected in the findings of this review since the number of studies in which structured data was used as a basis for AI analysis ($n = 89$) was much higher than those that used unstructured data.

As indicated in the Results section, supervised algorithms were the most frequently found in the studies that participated in this review ($n = 92$), notably Support Vector Machine ($n = 32$), Random Forest ($n = 31$), Logistic Regression ($n = 26$), Neural Networks ($n = 13$) and K-means ($n = 10$). This characteristic aligns with (structured) data types most accessible in health systems and that much of the research aims to classify individuals. The high representation of supervised algorithms in studies on chronic pain was also highlighted in the first review on the subject published in 2021³³. The scoping review included 53 studies, prioritizing the description of which Machine Learning methods and data types had been used. Unlike this study, the review selected only studies where the origin of chronic pain was unknown, used only three databases, and was limited to the descriptors “*machine learning*”, “*pain*”, and “*fibromyalgia*”, which reduced its scope.

Recently, Zhang *et al.*³⁴ (2023) published a scoping review on AI in pain. Unlike our study, the authors selected all pain types. Although the search strategy was more comprehensive and not limited to chronic pain, the researchers selected only intervention studies. From the 30 articles selected for the review, the authors found that most studies focused on pain assessment, followed by AI-based approaches related to pain prediction and clinical decision support, and a minority of studies on AI-based approaches related to pain self-management.

Despite the great potential of using AI in PHC to better manage chronic pain, the automatic use of AI can lead to biased and misleading interpretations of a data set (algorithmic bias). In PHC, where diversity is the norm, algorithms should be developed, trained, and adjusted in a way that avoids discrimination that can lead to unequal management between different

economic and social groups in pain treatment. Given health inequalities and inequities, we can postulate that vulnerable population subgroups may have less access to these new technologies. Ensuring universal access to the potential benefits of AI is a huge challenge for governments in the coming years.

Notably, using AI depends on sensitive patient data, usually stored in the Unified Health System's information system. Thus, it is necessary to ensure that the data will be protected against misuse. The General Personal Data Protection Law (LGPD), Law N° 13.709/2018, was created in Brazil in 2018 to guarantee the ethical use of personal data. This Brazilian legislation regulates the processing of personal online and offline data to protect citizens' privacy and fundamental rights⁵¹. Inspired by the European Union's General Data Protection Regulation (GDPR), the LGPD establishes rules for collecting, storing, using, sharing and deleting personal data. This initiative aims to ensure transparency in the use of personal data, protecting the privacy rights of individuals and promoting responsible and ethical practices by companies in processing information⁵².

Another point to be discussed and that deserves attention is how much the introduction of this new technology may impact the relationship between health professionals and patients. If technology replaces rather than complements professionals, it may lead to a “dehumanized” health system. For AI to be an ally and not a problem, government decisions must regulate its use so that it benefits everyone without compromising fundamental healthcare values.

The research results should be interpreted in light of its strengths and limitations. In terms of strengths, we should underscore that this review was comprehensive, without time or language filter, in nine databases (MEDLINE; LILACS; SPORTDiscus; SCOPUS; CENTRAL; Science Direct; IEEE Xplore; Association for Computing Machinery Digital Library, and arXiv) from different areas. Two independent authors conducted the search, and a third author was requested for disagreements. Additional studies that were not found in the initial search but included in references of studies found were also included. Another strength was that the structure of this scoping review followed the PRISMA-ScR recommendations, making its methodology more robust and facilitating comparison with international studies.

On the other hand, we must be cautious in interpreting the findings since this scoping re-

view was designed to be a comprehensive search of the scientific literature on the topic and not evaluate the quality of the studies found or to make a quantitative synthesis of the results obtained in the original studies. The lack of methodological detail and a formal assessment of the articles' quality are limitations of this study. Furthermore, while comprehensive, the literature search is challenging in a new field such as Artificial Intelligence since the nomenclatures are still being consolidated to become keywords and scientific descriptors, and the academic production covers several interconnected areas. Encouraging international standardization in publications in the field can facilitate future reviews.

Regarding this study's implications, research focusing on clinical interventions should be the focus of new AI studies in chronic pain. Currently, we have a range of observational studies focusing mainly on the prediction and classification of subgroups. The next step is to direct new research to use these predictors in randomized controlled clinical trials to study the effectiveness of the entire process. This will be the question that future chronic pain studies will answer: Does the group using the AI-based strategy have better outcomes than the control group using the current best strategy (without AI)?

The potential of using Artificial Intelligence (AI) in managing chronic pain is promising. AI algorithms have shown great capacity to classify individuals based on chronic pain type and predict risk groups. These technologies offer new possibilities for a more accurate and individualized diagnosis and the development of personalized treatment strategies, which can increase therapeutic efficacy and the quality of life of patients with chronic pain. However, AI implementation in this field also faces significant challenges, mainly the lack of studies focused on PHC. It is necessary to develop robust studies to validate these technologies in different populations and care settings, ensuring that AI solutions are accessible, effective, and safe for all patients.

Finally, the study found results that indicate progress in the field, especially in diagnosing and predicting pain, analyzing brain activity, personalized interventions, and mobility and sensor technology. However, only two studies were randomized controlled clinical trials^{18,47} aimed at estimating the effect of an intervention (Cognitive Behavioral Therapy), indicating that it is necessary to encourage research with this focus so that the question can be answered whether the incorporation of AI modifies the most important outcomes related to chronic pain.

Conclusion

Our study's results indicate that the potential of using AI in managing chronic pain is a reality. It is a fertile area for knowledge generation, especially in recent years. Considering the diverse AI applications in different scenarios and populations and the heterogeneity of its uses, we understand that there are several possibilities for improving the management of individuals with chronic pain, whose treatment is currently challenging.

Systematic reviews with specific questions and formal analyses of the quality of the included studies should be encouraged. There is still a significant lack of studies focused on PHC, paradoxically the place with the most significant potential for applying Artificial Intelligence algorithms and the main gateway to health systems, including the SUS, for patients with this condition.

Therefore, research focusing on the use of cutting-edge technology to aid in screening, clinical decision-making, and management of individuals with chronic pain, especially in PHC, should be encouraged. Finally, we emphasize that our study can be considered the most comprehensive ever conducted in the field of chronic pain on Artificial Intelligence, serving as a reference for new research with this focus.

Collaborations

Conception: FO Meirelles; CL Moraes; KMB Edmundo. Methodology: FO Meirelles; CL Moraes; KMB Edmundo. Data curation: FO Meirelles; MI Matos; CL Moraes; KMB Edmundo. Formal analysis: FO Meirelles; MI Matos; KMB Edmundo; CL Moraes. Investigation: FO Meirelles; MI Matos. Literature review: FO Meirelles; MI Matos. Data interpretation: FO Meirelles; MI Matos; KMB Edmundo; CL Moraes. Writing – original version of the manuscript: FO Meirelles; KMB Edmundo; CL Moraes. Writing – review and editing: FO Meirelles; KMB Edmundo; CL Moraes.

Data availability statement

The data sources adopted in the research are indicated in the article's body. Figures, tables and supplements available at: <https://doi.org/10.48331/scielodata.QFMMDX>.

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