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Artificial Intelligence Interventions in Chronic Pain Management: A Scoping Review

Adesola Abiodun, Shravrantika Das, Alan Taylor

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Adesola Abiodun[1] BSc, MSc; Shravrantika Das[1] BSc, MSc; Alan Taylor[1] BSc, MSc, PhD

[1]University of Nottingham Nottingham GB

Corresponding Author:
Adesola Abiodun BSc, MSc
University of Nottingham
University of Nottingham
University Park
Nottingham
GB

Abstract

Background: Background
There are indicators that artificial intelligence may have the potential to improve chronic pain care globally. However, research in this field is still evolving. Hence, it is necessary to synthesize the available evidence and evaluate its current scope.

Objective: Objective
This scoping review presents a comprehensive synthesis of the available evidence, highlighting the types and delivery of biopsychosocial AI-based interventions, the chronic pain conditions managed, the population characteristics, and the context of care delivery.

Methods: Methods
The literature search was conducted using MEDLINE, Embase via Ovid, and AMED (until July 25, 2023) in line with the PRISMA guidelines. Eligible studies were appraised using the relevant JBI checklist for each study type. The results were synthesized and reported through a narrative review. The review included English-language studies of any research design that reported a form of AI-based intervention for chronic pain management.

Results: Results
32 RCTs and non-RCTs identifying 23 AI-based interventions were included. The results showed that many interventions targeted the management of one or more of the biopsychosocial components of chronic low back pain. These interventions were delivered through mobile apps, chatbots (text messages), computer-based or equipment-based algorithms, and robots. The interventions focused on exercises, CBT, and feedback.

Conclusions: Conclusions
The use of artificial intelligence in delivering chronic pain interventions is developing rapidly. However, most interventions were not delivered by an interdisciplinary care team as recommended by the IASP. Furthermore, the report of many systems, without sufficient evidence to support effectiveness, may limit translation to practice. Thus, a joint effort of a team of expert pain clinicians and researchers is required to facilitate the uptake of AI-based interventions for chronic pain management.

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Artificial Intelligence Interventions in Chronic Pain Management: A Scoping Review

Adesola Abiodun[1], Shravantika Das[1], Alan Taylor[1]

[1]Department of Physiotherapy, School of Health Sciences, University of Nottingham, Nottingham, United Kingdom

Corresponding Author:

Adesola Abiodun, MSc.

Department of Physiotherapy,

School of Health Sciences,

University of Nottingham,

Nottingham,

NG7 2UH.

Telephone number: +447851411904

Email: mxsaa134@nottingham.ac.uk

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Background

There are indicators that artificial intelligence may have the potential to improve chronic pain care globally. However, research in this field is still evolving. Hence, it is necessary to synthesize the available evidence and evaluate its current scope.

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Conclusions

The use of artificial intelligence in delivering chronic pain interventions is developing rapidly. However, most interventions were not delivered by an interdisciplinary care team as recommended by the IASP. Furthermore, the report of many systems, without sufficient evidence to support effectiveness, may limit translation to practice. Thus, a joint effort of a team of expert pain clinicians and researchers is required to facilitate the uptake of AI-based interventions for chronic pain management.

Keywords: AI, artificial intelligence, chronic pain, pain management

Introduction

Chronic pain is a public health issue with a global prevalence of about 11-40%, causing significant disability, distress, and impaired quality of life among the affected population.[1-3] Thus, there is a need for its effective management. Evidence (level 1) supports the effectiveness of interventions delivered by a multidisciplinary team in reducing pain and disability among people with chronic pain conditions such as low back pain.[4-6] However, there is generally poor evidence in support of its effectiveness above treatment as usual.[7-8] A meta-analysis conducted by Dragioti et al.[7] revealed that although there are probable associations between multidisciplinary rehabilitation programs and pain and disability outcomes, the available evidence is limited due to high risk of bias relating to small sample size and number of studies. Nonetheless, the biopsychosocial approach of chronic pain management delivered by a team of interdisciplinary healthcare professionals in a specialized pain center remains the gold standard recommendation by the International Association for the Study of Pain (IASP).[9-10]

Despite the IASP's recommendation, there have been reports of suboptimal access to quality care.[11-12] A systematic review of 14 studies evaluating multidisciplinary chronic pain treatment facilities across the United Kingdom, Canada, the United States, Australia, and Italy revealed a gross inadequacy of pain centers in these countries, with an average of one pain clinic serving 200,000 people.[13] This accessibility challenge was recently complicated by the COVID-19 pandemic that may have increased the chronic pain burden. Evidence suggests that the surge in social isolation while curtailing the spread of infection, and reduced accessibility to pain clinics may have increased vulnerability to psychosocial mediators of chronic pain perception during this period.[14-16] Hence, there has been a continuous rise in the incidence of chronic pain, reports of low quality of life and care dissatisfaction among individuals with chronic pain,[17-20] necessitating the development of innovative approaches to improving care delivery.

One such innovation is the introduction of 'automation-oriented' methods such as artificial intelligence (AI).[21] AI involves a problem-solving spectrum (such as machine learning, deep learning, natural language processing, and data mining) through which machines simulate human minds and processes.[22-23] These AI systems use data-driven algorithms to evaluate, detect, predict, and manage a variety of illnesses, including chronic pain.[24-26] Recent improvements in health information gathering through advanced technological systems and wearable devices have enabled researchers to obtain large datasets required to build reliable AI systems for chronic pain diagnosis, prediction, and management.[25,27-28] This innovation is expected to guide and reduce the duration of clinical reasoning (and consequently the waiting period) and improve the overall accessibility and effectiveness of chronic pain interventions.[25]

However, despite the promising nature of this innovation, it is a growing field, and it is necessary to evaluate and synthesize the available evidence on its current use in the biopsychosocial management of chronic pain. Previous reviews have focused on the use of AI interventions in pain assessment, diagnosis, and prediction,[29-36] while some have explored the management of specific conditions such as low back pain.[35] Zhang et al[21] also presented a scoping review of 30 studies to synthesize the available evidence on the potential clinical uses of AI-based interventions, with a focus on the machine learning frameworks of these interventions. However, it is still uncertain what the applications of AI are in the biopsychosocial management of chronic pain by an interdisciplinary team. Moreover, the developing nature of this field implies that research is rapidly ongoing, and newer evidence may now exist. Thus, this scoping review presents a more comprehensive synthesis of the available evidence, highlighting the types and delivery of these biopsychosocial AI-based interventions, the chronic pain conditions managed, the population characteristics, and the context of care delivery.

Methods

Study Design

The data for this scoping review was sourced, collated, organized, and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for

Scoping Reviews (PRISMA-SR) guidelines.[38]

Eligibility criteria

Randomized controlled trials (RCTs) and non-RCTs (such as cohort studies and cross-sectional studies) that had been written in English and published in peer-reviewed journals were included in this systematic review. Preprints and other forms of grey literature were not considered. Publications examining any aspect of chronic pain management using artificial intelligence methods (including mhealth via mobile applications, robotics, and wearable devices) were included. The articles were not delimited to age, gender, geographical location, race, or socioeconomic status. Studies that did not primarily focus on artificial intelligence interventions for chronic pain management were excluded from this study.

Search Procedure

A systematic search was conducted on MEDLINE, Embase via Ovid, and AMED (Allied and Complementary Medicine Database) between May 1, 2023, and July 25, 2023. The research questions were used to develop a search strategy to identify the primary studies that provide relevant evidence. The keywords for the search were developed following a query search (titles and abstracts) on PubMed, in line with the PICO (population, intervention, comparator, outcome). The search strategy (Supplementary file 1) comprised all possible combinations of keywords under 3 broad themes: *(1) artificial intelligence or machine learning or robotics or internet of things (2) chronic pain (3) pain management or rehabilitation.* These keywords were refined during the search process[40] to suit the requirements of each database. For a more comprehensive evaluation, the reference lists of all the articles included were searched to identify other relevant studies.

Article Selection and Data Extraction

The references of all records found in the initial search of all databases were exported to ENDNOTE X7 and duplicate articles were removed. The remaining articles were screened in two stages by two independent reviewers (AO and SD). The first stage involved screening the titles and abstracts of all articles to identify and exclude irrelevant literature. The records were then further subjected to the screening of their main content (second stage). A third reviewer (AT) resolved conflicts that arose in this stage. A more comprehensive review of the reference list of the included studies was then undertaken to identify more relevant studies.

Subsequently, AO and SD individually extracted data from the included studies using a standardized Microsoft Excel template for data extraction (developed using the JBI data extraction form) to tabulate information from the included studies such as the authors, study location, setting, and context, study methods, type of intervention delivered, participant characteristics, among others.

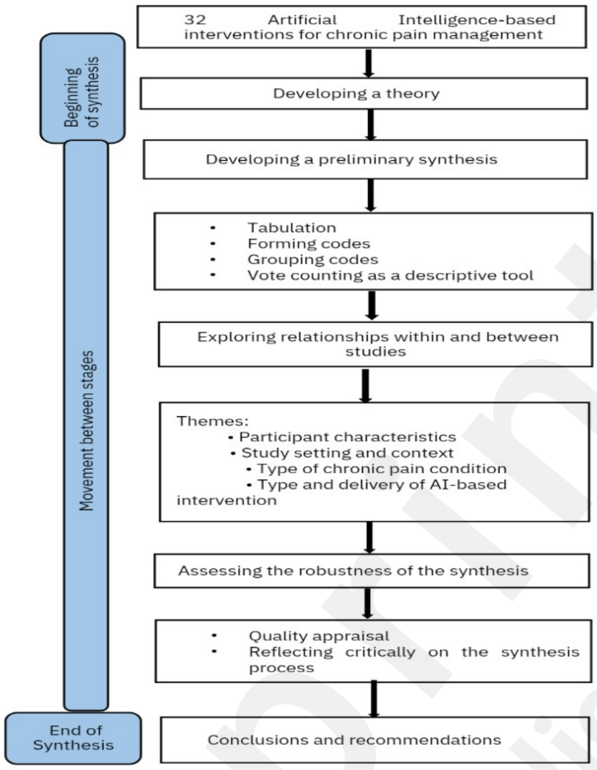
Methodological quality

Due to the diverse study types of the relevant studies, the Joanna Briggs Institute (JBI) checklist forms for case series, randomized controlled trials, cohort studies, quasi-experimental studies, and analytical cross-sectional studies[40-42] were used by the two independent reviewers (AO and SD) to evaluate their methodological quality. A third reviewer (AT) resolved conflicts relating to the quality of some studies. The JBI checklist was selected because of its wide range of applications.[43] The risk of bias (RoB) was graded as ‘high’ (yes scores below 50%), ‘moderate’ (50-69% yes scores), or ‘low’ (yes scores ≥ 70%).[44]

Data Analysis and Synthesis

The collated data was synthesized using descriptive statistics of frequencies and proportions and presented using charts and tables. The data was also categorized into themes and reported through a narrative summary due to its heterogeneity.[45] The synthesis was performed using the generic framework developed by Rodgers et al.[46] (Figure 5). To improve the validity and reliability of this report, the synthesis was performed using the synthesis without meta-analysis (SWiM) reporting checklist (Supplementary file 3).[47]

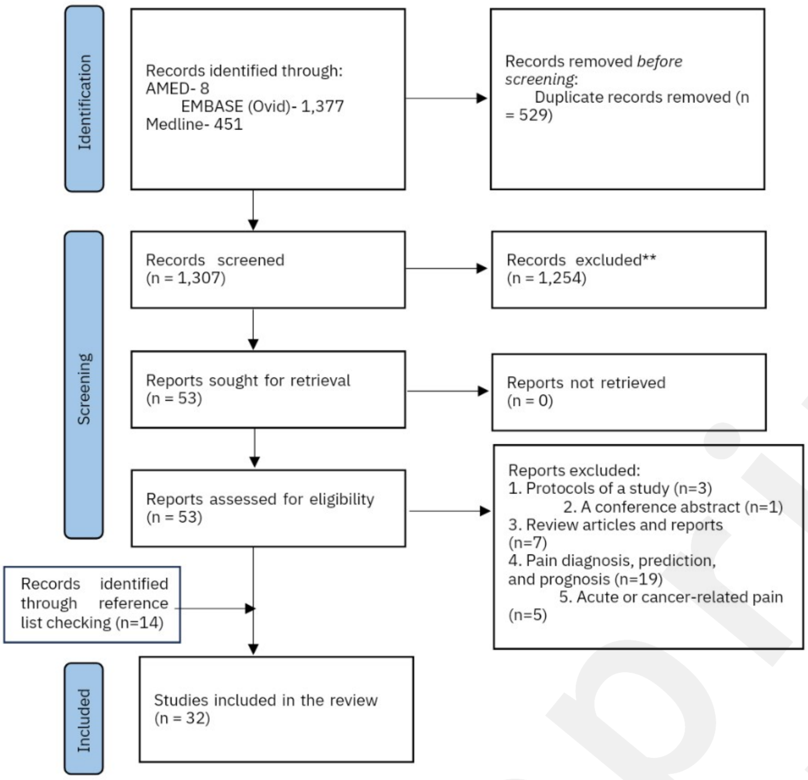
Figure 5: Synthesis Process[46]



Results

1,836 records were produced by the initial search across all databases. Three phases of screening—deduplication, title, abstract, and full-text—were applied to the articles. 18 articles met the requirements for inclusion. 15 studies were found after further screening of the selected articles' reference lists. 32 papers in total (Supplementary File 2) were thus determined to be pertinent to this review. The PRISMA flow chart for the publication selection process is displayed in Figure 6.

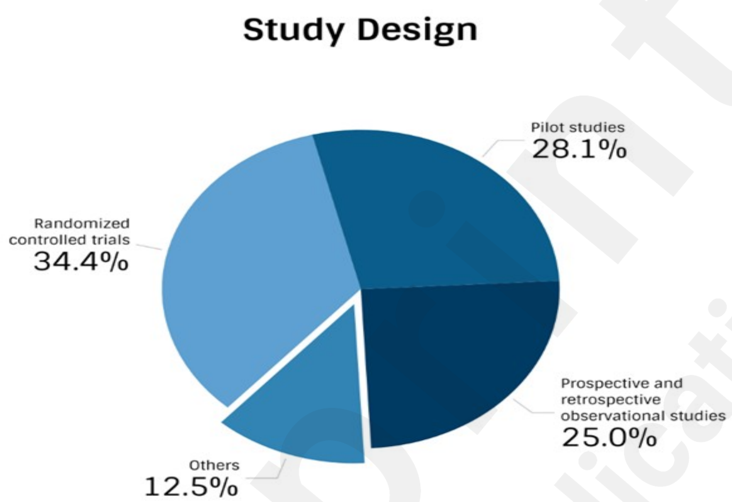
Figure 6: Flowchart of the study selection[48]



Characteristics of Included Articles

All the studies were written and published between 2001-2023, with more than two-thirds (n= 22) published between 2020 and the present. This systematic review comprised 32 publications that were printed in 16 journals. Of these studies, the Journal of Medical Internet Research (JMIR) and its sibling publications published 43.4% (n=14) of them. Others (56.6%) were written about in various journals devoted to pain management. Randomized controlled trials made up 34.4% (n= 11) of the research,[49-59] while others were pilot studies, observational studies, quasi-experimental studies, among others (Figure 7). The authors of the articles included were affiliated with different organizations in thirteen (12) countries across four (4) continents (Asia, Australia, Europe, and North America). Half of the authors (50.0%, n=16) were from the United States (Table 1). The geographic focus of the studies was similar to the distribution of the authors. The countries were further categorized according to the World Bank's income status. [60] Most (n= 29, 90.6%) of the studies were conducted in high-income countries (Figure 8).

Figure 7: A pie chart illustrating the distribution of study design



Key: Others include quasi-experimental studies, analytical cross-sectional studies, and case series

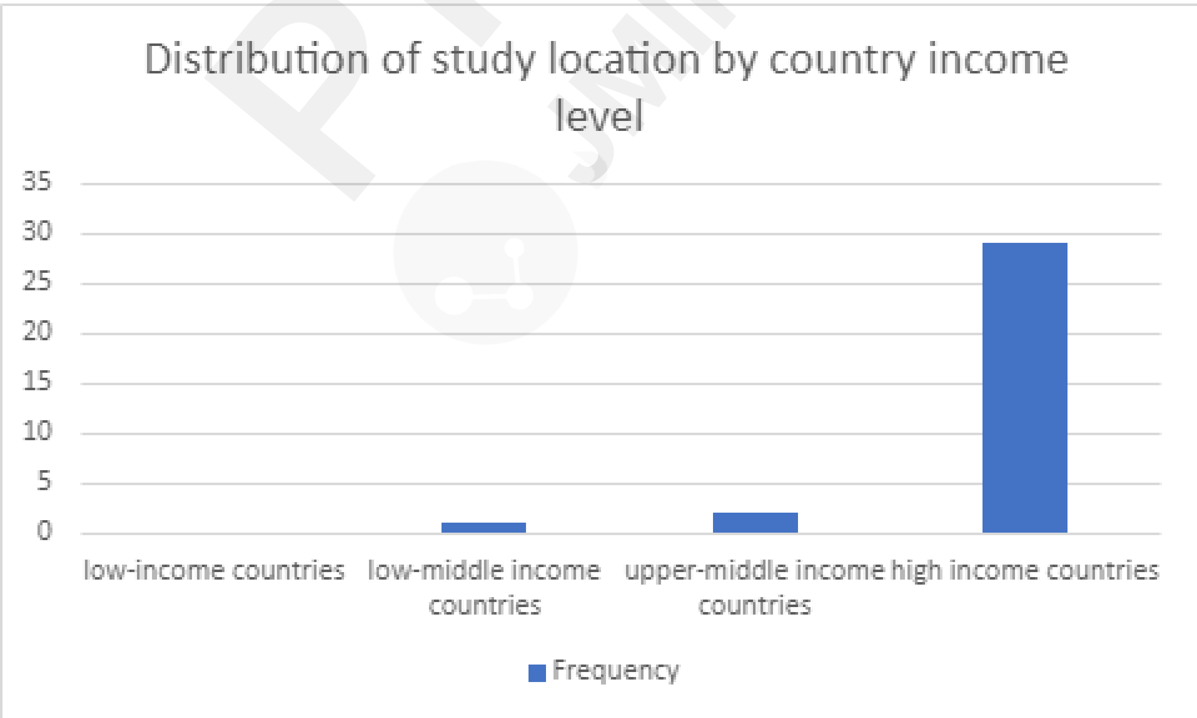
Table 1: Country of affiliation of the authors (N= 32)

Country of Affiliation[a]	Number of articles, n (%)
United States	16 (50.0)
Germany	3 (9.4)
Denmark	3 (9.4)
Norway	3 (9.4)

United Kingdom	2 (6.3)
Switzerland	1 (3.1)
India	1 (3.1)
Australia	1 (3.1)
China	1 (3.1)
Turkey	1 (3.1)
Korea	1 (3.1)
Japan	1 (3.1)

[a]*Some articles focused on more than one country.*

Figure 8: Number of articles based on the World Bank's classification of countries by income level (N=32)



The 32 studies that were incorporated into this systematic review enrolled a total of 16,912 participants. Only 826 (42.9%) of the 1,927 participants in the RCTs were randomly assigned to the intervention study, which involved receiving an AI-based intervention. A ≤10% attrition rate was also present in the majority of trials (n=24, 75.0%). A quarter of them (n=8, 25.0%), however, reported considerable attrition rates ranging from 14.9% to 82.2%. Attrition occurred for a variety of reasons, including failure to begin the study or onboarding on the app,[61-62] quitting midway through the study due to follow-up or noncompliance with study requirements,[48-49, 63-65] and exclusion due to insufficient data being provided.[63] Additionally, according to Toelle et al.,[49] several control group participants withdrew owing to workplace restrictions, while those in the intervention group discontinued due to lack of internet access. Other studies did not report reasons for participant loss. [59, 66-67]

Risk of Bias Assessment

Generally, most (n= 18, 56.25%) of the studies included in this systematic review had a moderate risk of bias, whereas an equal proportion (21.9%, n=7) had high and low RoBs. Due to the lack of participant, intervention coordinator, and outcome assessor blinding, all RCTs and pilot RCTs reported bias in the administration of the intervention and exposure, assessment, detection, and outcome measure (Table 2). Similarly, selection bias appeared to be the most common bias among other study types (quasi-experimental, cohort, case series, and cross-sectional) (Table 3-6).

Table 2: JBI checklist for RCTs

Author/ year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
Rafferty et al./2021	Y	Y	Y	Y	Y	Y	N/A	Y	Y	UC	Y	Y	Y
Marcuzzi et al./2023	Y	Y	Y	N	N	Y	UC	Y	Y	Y	Y	Y	Y
Anan et al./2021	Y	UC	Y	N	N	Y	UC	Y	Y	Y	Y	Y	Y
Piette et al./2022	Y	Y	Y	UC	UC	Y	UC	Y	Y	N	Y	Y	Y
Sandal et al./2021	Y	Y	Y	N	N	UC	Y	Y	Y	Y	Y	Y	Y
Rughani et al./2023	Y	Y	Y	N	N	UC	Y	Y	Y	Y	Y	Y	Y
Hauser-Ulrich et al./2020	Y	N	Y	N	N	Y	N	Y	Y	Y	Y	Y	Y
Pu et al./2020	UC	UC	UC	N	N	Y	N	Y	Y	Y	N	Y	UC
Chahabara et al./2018	Y	Y	Y	UC	UC	Y	UC	Y	Y	UC	Y	Y	Y
Jamison et al./2017	UC	UC	UC	N	N	Y	N	UC	Y	Y	N	Y	N
Skrepnik et al./2017	Y	Y	Y	UC	UC	Y	UC	Y	Y	Y	Y	Y	Y
Toelle et al./2019	Y	N	Y	UC	N	Y	N	Y	Y	Y	Y	Y	Y
Chiauzzi	Y	U	Y	U	U	Y	UC	Y	Y	Y	Y	Y	Y

et al./2010		C		C	C								
Bates et al./2023	Y	UC	N	N	N	Y	UC	Y	Y	UC	Y	Y	Y

Key: Y= Yes; N= No; N/A= Not applicable; UC= Unclear

1=participant randomization; 2=allocation concealment; 3=similar treatment groups at baseline; 4=participant blinding; 5=intervention coordinator blinding; 6=similar treatment of control and intervention groups; 7=assessor blinding; 8=uniformity of outcome assessment; 9=reliability of outcome assessment; 10=follow-up analysis; 11=group analysis; 12=statistical analysis appropriateness; 13=appropriate trial design

Table 3: JBI checklist for Quasi-experimental Studies

Authors/ year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Barreveld et al./2023	Y	N/A	N/A	N/A	Y	UC	Y	Y	Y
Karakan et al./2021	Y	N	UC	Y	Y	Y	Y	Y	Y
Polston et al./2022	Y	UC	UC	UC	UC	UC	UC	UC	UC
Rabbi et al./ 2018	Y	Y	Y	N	UC	Y	Y	Y	Y
Huber et al./2017	Y	N	N	N	Y	N	Y	Y	Y
Singh et al./ 2015	Y	N	N	N	Y	UC	Y	Y	Y
Blanchard et al./2022	Y	N	N	Y	Y	Y	Y	Y	Y
Sinha et al./ 2022	Y	N	N	N	Y	Y	Y	Y	Y

Key: Y= Yes; N= No; N/A= Not applicable; UC= Unclear

1=clear 'cause' and 'effect'; 2=inclusion of participants in similar comparisons; 3=inclusion of participants in other interventions; 4=control group; 5=multiple measurements of outcome; 6=follow-up analysis; 7=inclusion of outcomes in similar comparison; 8=reliability of outcome measurement; 9=statistical analysis

Table 4: JBI checklist for cohort studies

Authors/ year	1	2	3	4	5	6	7	8	9	10	11
Sandal et al./2020	N	N	Y	N	N	Y	Y	Y	Y	UC	Y
Knab et al./ 2001	N	N	Y	N	N	UC	Y	Y	Y	N	Y
Han et al./2022	Y	Y	Y	N	N	UC	Y	Y	Y	UC	Y
Leo et al./2022	Y	Y	Y	N	N	Y	Y	Y	UC	N	Y
Bailey et al./2020	N/A	N/A	Y	N	N	N	Y	Y	Y	N	Y
Clement et al./2018	UC	UC	Y	N	N	UC	Y	Y	Y	N	Y

Key: Y= Yes; N= No; N/A= Not applicable; UC= Unclear

1=similarity of groups; 2=similar measurement of exposure; 3=valid and reliable measurement of exposure; 4=identification of confounding factors; 5=dealing with confounding factors; 6=free of outcome at onset of study; 7=valid and reliable measurement of outcomes; 8=follow-up time sufficiency; 9=follow-up analysis; 10=strategies for incomplete follow-up; 11-statistical analysis

Table 5: JBI checklist for case series

Authors/ year	1	2	3	4	5	6	7	8	9	10
Jang et al./ 2022	Y	Y	Y	N	N	Y	N	Y	Y	Y

Key: Y= Yes; N= No; N/A= Not applicable; UC= Unclear

1=clear criteria for inclusion; 2=standard and reliable measurement of condition; 3=valid method of identifying condition; 4=consecutive inclusion of participants; 5=complete inclusion of participants; 6=clear demographic report; 7=clear clinical information report; 8=clear outcome reports; 9=clear reporting of the presenting site/clinic/demographic information; 10=statistical analysis .

Table 6: JBI checklist for analytical cross-sectional studies

Authors/ year	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Lo et al./2018	Y	Y	Y	N	N	N	Y	Y
Meheli et al./2022	Y	Y	Y	UC	N	N	Y	Y

Key: Y= Yes; N= No; N/A= Not applicable; UC= Unclear

1=criteria for inclusion; 2=description of study subjects and setting; 3=valid and reliable measurement of exposure; 4=objectivity of condition measurement; 5=identification of confounding factors; 6=strategies for confounding factors; 7=valid and reliable measurement of outcomes; 8=statistical analysis

Study setting

Many of the studies recruited participants online (n=11, 34.3%) or from urban areas (n=18, 56.3%). Only Blanchard et al.[68] delivered an AI-based intervention to rural dwellers. In addition to recruiting participants online, some studies were conducted in tertiary, teaching, or university-based hospitals (n=11; 45.8%), wellness centers/university communities/organizations (n=4; 16.7%), or both. Others were sourced from community hospitals, veteran clinics, or for-profit pain management centers.

Participant characteristics

Overall, most studies (65.6%) had more female participants than males. Only 4 studies had a higher proportion of males than females [50, 59, 69-70] while two (2) recruited an equal number of males and females.[71-72] Others (n=5, 15.6%) did not report the gender distribution of their participants. About 80.1%-97.7% of the participants were white Caucasians.[50-54, 73-74] All participants were aged 18 years and above, with a cumulative mean age of 50.0 years. 5 studies had no report on the age distribution of their participants. Only a few studies (n= 6, 18.8%) reported the level of education or employment status of their participants (Table 7). The reports revealed that most of (65.5-98%) the participants who used the AI-based interventions had at least year 12 education. Although some studies reported that more than half of the subjects had a full-time job,[55-57, 75] the accounts by Piette et al.[50] and Chiauzzi et al.[52] reported that just about one third of their participants were fully employed.

Most participants were selected based on characteristics that are categorized into *(1) condition-of-interest-related (2) intervention-related (3) confounding factors-related*. Many studies expected participants to have certain characteristics related to the chronic pain condition of interest, such as minimum self-reported pain intensity (which ranged from 1-9/10 for all studies), baseline pain-related disability (Roland Morris Disability Questionnaire), and IBS-SSS score ≥ 175,[52] and most importantly, triaging was carried out to ensure no participant had red flags such as evidence of current malignancy, or any other serious pathology such as severe psychopathology, epilepsy, renal or liver failure, acute exacerbation of chronic obstructive Pulmonary Disease (COPD), among others. [53, 62, 67, 70-71, 73, 76-77] However, certain eligibility requirements focused on confounding and intervention-related aspects. 13 studies required access to the internet, possession of a smartphone, tablet, or computer, and skill in their use. Furthermore, 37.5% (n=12) only recruited participants were proficient speakers of the languages (English, Norwegian, Danish, and German) used in the AI-based intervention. Finally, other confounding variables were considered, and participants with these characteristics were excluded from the study. These variables included other severe chronic pain conditions (n=13), significant or acute psychiatric illnesses or substance use (n=13), prior or planned surgeries (n=9), involvement in other interventions (n=9), inability to engage in physical activity (n=8), and pregnancy (n=8).

Table 7: Included studies and population characteristics[a-m]

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-time employment (%
Barreveld et al./2023	Chronic low back and neck pain	Pain drainer	[a]≥ 18	-	≥4	-	-	-	-
Jang et al./ 2022	Knee Osteoarthritis	IB LAB analyzer + AI algorithm	62.7 ± 8.9	25.6 ± 3.2	[c]59.5 ± 9.7	[f]49.7	-	-	-
Karakan et al./2021	Irritable bowel syndrome	Embiosis personalized nutrition model	46.06 ± 13.11	-	-	-	-	-	-
Rafferty et al./2021	Irritable bowel syndrome	Heali mobile app	27.2 ± 9.5	27.7 ± 5.8	-	-	-	-	-
Marcuzzi et al./2023	Chronic low back and neck	selfBACK	50.6 ± 14.9	26.9 ± 4.0	6.8 ± 2.0	10.1 ± 5.3	[m]89.9	72.7	57.6

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/ m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-ti emplo ent (%
Lo et al./2018	Chronic low back and neck pain	Well Health app	[a]31-40	-	6.0	-	-	-	-
Polston et al./2022	Neck, shoulder and/ or low back pain	Pain drainer	-	-	-	-	-	-	-
Anan et al./2021	Neck, shoulder, and/ or low back pain	Unnamed AI-assisted chatbot	41.8 ± 8.7	-	[d]4.06	-	-	-	-
Piette et al./2022	Chronic low back pain	Artificial Intelligence-Cognitve Behavioral Therapy for Chronic Pain (AI-	63.9 ± 12.2	-	6.16 ± 0.12	13.48 ± 0.33 [g]4.72 ± 0.17	82.6	64.7	30..5

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/ m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-ti emplo ent (%
Meheli et al./2022	All forms of chronic pain such as migraine, musculoskeletal, neuropathic, or visceral pain	Wysa app	-	-	-	-	-	-	-
Rabbi et al./2018	Chronic back pain	My Behavior CBP	[a]31-60	-	-	-	-	-	-
Sandal et al./2021	Chronic non-specific low back pain	selfBACK	47.5 ± 14.7	27.3 ± 4.7	4.8 ± 2.0	10.3 ± 4.4	66	75	59
Sandal et al./2020	Chronic low back pain	selfBACK		27.2 ± 5.5	-	8.6 ± 5.1	98	-	59
Knab et al./2001	All forms of chronic pain	CDBS (Pain Management		-	-	-	-	-	-

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/ m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-ti emplo ent (%
Rughani et al./2023	Chronic non-specific low back pain	selfBACK	47.5 ± 14.7	27.3 ± 4.7	-	10.3 ± 4.4	65.5	75	59.5
Hauser-Ulrich et al./2020	All forms of chronic pain such as headaches, musculoskeletal and idiopathic pain	SELMA chatbot	43.77 ± 12.72	-	[e]5.52 ± 1.64	[g]4.06 ± 1.91	95	-	-
Han et al./ 2022	All forms of chronic pain	The pain watch + pillow + activity apps + wearable health	50.1 ± 12.8	33.4 ± 7.7	5.48 ± 1.50	-	-	-	-

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-time employment (%)
Pu et al./ 2020	Chronic pain due to dementia	PARO social robot	84.36	-	-	-	-	-	-
Leo et al./ 2022	Musculoskeletal pain	Wysa app	[a]18-83	29.0 ± 7.0	-	-	-	-	-
Bailey et al./2020	Back pain and knee pain	Hinge health app	43.57 ± 11.4	30.25 ± 7.42	[c]45.13 ± 22.42	-	-	-	-
Huber et al./2017	Low back pain	Kaia app	33.9 ± 10.9	-	-	-	-	-	-
Chahabra et al./2018	Low back pain	Snapcare app	41.4 ± 14.2	23.15 ± 4.2	7.3 ± 1.9	[h]52.13 ± 14.4	-	-	-

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/ m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-ti emplo ent (%
Jamison et al./2017	Musculoskeletal, visceral or cancer-related pain	Fitbit tracker + mobile app	47.1 ± 13.5	31.1 ± 7.3	6.2 ± 2.3	[i]41.5 ± 12.4	-	-	-
Skrepnik et al./2017	Knee osteoarthritis	Jawbone UP 24 +OA GO (mobile app)	61.6 ± 9.5	29.4 ± 3.9	4.6 ± 2.3	-	-	-	-
Toelle et al./2019	Non-specific low back pain	Kaia app	41 ± 10.6	24.4 ± 3.31	5.10 ± 1.07	[j]0.79 ± 0.14	-	-	-
Nordstoga et al./2020	Non-specific low back pain	selfBACK	[b]51.1 ± 13.9 [b]43.0 ± 7.5	26.2 ± 4.2	-	[k]5.0	-	-	-
Chiauzzi et	Chronic low	PainACTi	46.14	-	-	[l]46.36 ±	71.57	56.85	38.95

Authors/ Year	Pain-related condition	AI-based intervention	Age ± S.D (years)	BMI ± S.D (Kg/ m^2)	Pain intensity, NRS	Pain-related Disability, RMDQ	Educational level ≥ year 12 (%)	Married or living with a partner (%)	Full-ti emplo ent (%
Singh et al./ 2015	Chronic low back pain	Go-With-the-Flow	[a]36-68	-	-	-	-	-	-
Blanchard et al./2022	Chronic low back pain	Poppy humanoid robot	42.9 ± 12.8	27.6 ± 5.5	-	11.8 ± 3.7	-	-	-
Sinha et al./2022	Chronic musculoskeletal pain	Wysa app	-	-	-	-	-	-	-
Bates et al./2023	Low back pain	Tonal-AI exercise trainer	41.2 ± 12.1	-	3.6 ± 2.5	-	-	-	-

a= age range

b= study performed in two stages

c= VAS

d= 5-point self-reported pain scale

e= Deutscher Schmerzfragebogen (German Pain Survey)

f= Korean-Western Ontario and McMaster Universities (K-WOMAC) Osteoarthritis Index

g= Brief Pain Inventory

h= Modified Oswestry Disability Index (MODI)

i= pain disability inventory (PDI)

j= Hanover Functional Ability Questionnaire (HFAQ)

k= median RMDQ score

l= Oswestry Disability Index (ODI)

m= ≥ year 1s

Type of chronic pain condition

More than two-thirds (n= 22; 68.8%) of the AI interventions used in the reviewed studies targeted the management of one or all the biopsychosocial components of chronic low back pain (specific or non-specific). Irritable bowel syndrome was the only chronic visceral pain that was reportedly managed by any of these interventions.[64,78] The AI-based therapies delivered in other studies were for the management of chronic neck pain, knee osteoarthritis, chronic shoulder pain, chronic musculoskeletal pain, chronic pain among people with dementia, headaches, and fibromyalgia among others. Although few (n= 13, 40.6%) of these interventions were used to manage multiple conditions, many of them were focused on a type of chronic pain condition. Overall, chronic musculoskeletal pain was the most managed painful condition using AI-based interventions.

Type and delivery of AI-based Intervention

From 32 studies, 23 artificial intelligence-based systems were found (Table 8). These systems ranged from chatbots, sensing devices, computer and equipment-based algorithms, robotics, and mobile and web-based apps. The results showed that half (n= 16, 50.0%) of the interventions were given through mobile applications, and the SELFBACK app was the most popular (n= 5). Wearable health technologies were an adjunct in 4 of the mobile app interventions. More than four-fifths of the interventions (n=26, 81.2%) were given via a mobile device, tablet, or computer with internet connection.

Exercise and physical activity-related interventions were the most delivered (n=19, 59.4%) using the AI-systems. However, only 15.8% (n= 3) of these delivered these interventions only.[54,58,79] Others (n=16, 84.2%) incorporated other elements such as feedback and motivation[63,68,71,73]; education[69]; education, goal setting, mindfulness, and sleep reminder[49,51,55-57,66,70,75-76]; and activity-related pain intensity prediction.[62,81] In addition, a quarter of the studies (n=8) focused solely on psychology-related interventions such as cognitive behavioral therapy, dialectical behavioral therapy, self-efficacy, coping and the provision of feedback and/or motivational messages only.[50,52-53,61,67,72,74,64-80] Other interventions delivered through the AI-systems include decision support,[49] nutritional support,[64,78] bone structure analysis,[65] and social interactions.[77]

Table 8: Types of AI-based Interventions and modes of delivery

Mode of delivery	**AI-based Intervention**	**Number of studies, n (%)**
Web-based application	Pain Drainer PainACTION	3 (9.3%)
Equipment-based algorithms	IB Lab Analyzer Tonal AI exercise trainer	2 (6.3%)
Mobile application only	Heali app SELFBACK app Well Health app MyBehaviourCBP Kaia app Snapcare app	13 (40.6%)

Text messages	Unnamed Chatbot SELMA Chatbot Wysa app	4 (12.5%)
Phone calls	AI-CBT-CP	1 (3.1%)
Computer-based	Pain Management Advisor CDBS	1 (3.1%)
Mobile application + WHT	Pain watch + pillow and activity apps + WHT Jawbone UP 24 + OA GO Unnamed app + Fitbit WHT Hinge health app + WHT	4 (12.5%)
Robot	PARO social robot Poppy humanoid robot	2 (6.3%)
Sensing device	Go-With-the-Flow	1 (3.1%)
Unclear	Personalized nutrition model	1 (3.1%)

Discussion of Principal Findings: Implications for Practice and Research

The studies included in this systematic review were published between 2001 and 2023. This reveals that although the use of AI in healthcare systems is still evolving, its history extends beyond two decades. In fact, evidence suggests that despite its functional limitations, AI systems were first used in medicine in the 1970s.[82-83] Kaul et al.[83] noted that the earlier AI systems used traditional methods such as forward reasoning (data to conclusions), backward reasoning (conclusions to data), or manually developed if-then rules. This was demonstrated in the study by Knab et al.[63] in which the Pain Management Advisor (PMA) computer-based decision support (CBDS) system was developed using a sequence of rule-based (if-then) algorithms. Besides this study that was published in the early 2000s, other AI systems (published between 2017 and 2023) used natural language processing and machine learning to analyze datasets supplied by the users to generate individualized and evidence-based responses.[83] Thus, the evolution of this field is evident, and as research continues, more efficient and effective AI-based interventions for chronic pain management may be developed.

Type and Quality of Studies

The developmental phase of AI may also be deduced from the type and quality of the studies included in this study. Only about a third (34.4%) of the articles were RCTs investigating the therapeutic effects or the effectiveness of novel AI-based interventions for chronic pain management. This reflects a dearth of studies (RCTs) that are perceived to be critical to the development of new therapeutic strategies since they provide the highest level of evidence based on a single experiment.[84-85] However, Deaton and Cartwright[86] argue that this hierarchy may be unjustifiable since no method is likely to sufficiently support conclusions when little prior knowledge is available on the subject matter. Although the area of artificial intelligence is being sufficiently explored, the variety of AI-based interventions noted in our results requires that each intervention is well-researched, a necessity that is currently unavailable in the field. In addition, Moffat et al.[87] noted the complexity of the recruitment process for RCTs. The authors posited that this process is commonly subjected to several factors such as difficulties arranging appointments and pre-existing doctor-patient relationships, among others. Hence, researchers may often be discouraged from exploring this study design despite its position in the hierarchy of evidence. It is also worth noting that most of the RCTs and pilot RCTs reported bias relating to group concealment and non-blinding of participants, intervention coordinators, and assessors. This is consistent with research that shows blinding cannot be achieved in all RCTs.[88] A methodological study of 622 RCTs by Penic et al.[89] found that only 25% of the studies presented an explicit report of the three major group's blinding process. Literature further opines that although blinding is considered a critical component of the internal validity of an RCT,[90] it may be difficult to achieve for some non-pharmacological interventions like physiotherapy due to their nature.[91] Therefore, some experts have proposed that in cases where blinding is unachievable, objective, rather than subjective outcomes, should be assessed to minimize bias.[92,93]

Study Setting and Context

16,912 participants were recruited from mostly (91.7%) upper-middle to high-income countries. It is also important to note that these participants were predominantly from various parts of Europe and North America (mainly the United States), revealing a dearth of AI research in low- and middle- income countries (LMICs). This corroborates the report that the United States and European countries produced a significant proportion of global publications relating to artificial intelligence and pain research.[94] This may be due to the availability and easy accessibility to advanced technologies and research support needed to develop the required artificial intelligence systems for chronic pain management. To further strengthen this argument, it was noted that two-fifths of the included studies required that their participants had access to and proficiency in using smartphones (iOS or Android), tablets, or computers, as well as good internet connection. Given this requirement, it is unsurprising that only 9.4% of the studies recruited participants from rural regions. This is because evidence suggests that digital connectivity in rural areas is typically low due to low population densities, need to cover a wider distance, and income and educational disparities, factors that discourage investment in information and communication technologies.[95-96] However, evidence suggests that the prevalence of chronic pain in rural and suburban areas (30.9% and 30.8% respectively) is significantly higher than in urban areas (19.6%).[64] Furthermore, Goode et al.[97] reported that this group may be more vulnerable to functional limitations due to chronic pain, and inaccessibility to specialty care. Hence, it is important to explore the use of AI-based interventions which may bridge the care gap among people in rural regions.

Study Population

Significantly more female participants than male participants were reported in 65.5% of the studies. This confirms the reports that chronic pain prevalence is higher in women.[98-99] The origin of this variation in prevalence is unknown,[97] although laboratory research by Fillingim et al.[99] revealed that women are more sensitive to experimental pain stimuli. Evidence further posits that women exhibit smaller conditioned pain modulation (descending inhibitory pathway) relative to men.[99-102]

The result further demonstrated that, despite this review's lack of age delimitation, all the participants were at least 18 years old. This resonates with the reports that the prevalence of chronic pain increases with age. A systematic review of 19 articles sampling 139,933 residents of the United Kingdom, revealed a higher prevalence (about 62%) of chronic pain among the older population (people over 75 years).[103] However, King et al.[104] opined that there is generally a dearth of research evaluating chronic pain in children and adolescents.

Type of Chronic Pain Condition

The various interventions included in this review were used to manage a variety of chronic pain conditions such as low back pain, neck pain, knee osteoarthritis, shoulder pain, various unnamed chronic musculoskeletal pain, chronic pain among people with dementia, headaches, and fibromyalgia among others. However, more than two-thirds were focused on managing one or more of the biopsychosocial components of chronic low back pain. This reflects the prevalence of the condition. Reports show that low back pain is the most common (53%) type of chronic pain, and one of the leading causes of disability globally, causing a huge medical and economic burden.[3,105-106] Hence, experts are focused on effectively managing low back pain to reduce its impact, and consequently reduce the overall burden of chronic pain management.

It is also important to note that although Jenssen et al.[28] reported in their scoping review of 39 studies relating to machine learning in chronic pain research, that fibromyalgia was the second most frequently researched pain condition after chronic low back pain, the result of this review varies significantly. Only 1 study which sampled participants with any form of chronic pain mentioned fibromyalgia.[80] This reveals that despite advances in the use of machine learning for fibromyalgia diagnosis and clinical decision support,[28] there is a paucity of AI-based therapies for its actual care. Research on AI-based interventions for chronic visceral pain also showed a similar pattern.[107-108] This may be due to the need to develop effective solutions to difficulties encountered in the correct diagnosis of the condition, and a quest for a better understanding of these complex pain conditions.[109] However, the reason for this is largely unknown. Nonetheless, an extensive exploration of the possibilities in this field may be necessary. The results of this review revealed that AI may be quite useful in delivering nutritional interventions to people with irritable bowel syndrome.[64,78] Further research into other domains of chronic visceral pain may contribute significantly to improving care.

Type and Delivery of AI-based Intervention

The delivery of chronic pain care using 23 different AI systems across the 32 included studies indicates that most of the studies utilized novel systems. The review reveals a wealth of evidence on AI-based interventions for the management or self-management of one or more of the biopsychosocial components of pain. Most of the interventions revolved around exercise, physical activity, cognitive behavioral therapy, and pain education. These interventions reflect some of the recommendations for the non-pharmacological management of chronic primary pain by the National Institute for Health and Care Excellence (NICE).[110] Acupuncture is the only recommendation that was not explored, and this may be because it is usually delivered by healthcare professionals and most of the interventions were geared towards improving self-management. Most importantly, it is worthy of note that less than half of the studies (37.5%, n= 12) delivered interventions catering to all the biopsychosocial components of pain. These interventions provided exercise/physical activity suggestions, education, goal setting, mindfulness, and sleep reminders. This suggests that most of the AI-based interventions being used do not comply with the recommendation of the IASP to deliver biopsychosocial care by an interdisciplinary team to individuals with chronic pain. Rather, the interventions are focused on various aspects of care delivered by specific healthcare providers. Hence, AI utility for chronic pain management may be severely limited by the need for multiple AI interventions to deliver holistic care.

Significantly, most of the self-management interventions were delivered via mobile applications, reflecting the global trend in the use of m-Health due to a marked increase in the access of individuals to smartphones and internet.[111] Notwithstanding, many AI-based interventions incorporated the use of self-monitoring and goal-setting trackers, sensing devices, and wearable health technology to provide real-time feedback that users may use to track their progress and provide reminders or motivation to carry out tasks. These devices were fundamentally used for activity recognition and pattern classification, to provide important movement information to users. In cases where the devices were synchronized with mobile applications, the data collected was used by the AI-system to generate treatment recommendations.[51,71,73-74,79] This is very useful in supporting the adoption of helpful behaviors and motivating users to increase their daily activities within reasonable pain limits.[112-113] Evidence further suggests that self-monitoring and goal setting positively influence adherence.[114] Hence, this component of AI-based interventions may be helpful in promoting adherence to chronic pain management strategies.

Strengths and Limitations

The purpose of this systematic review was to provide a comprehensive synthesis of literature with regards to AI-based intervention used for chronic pain treatment. The search was performed using three major databases (MEDLINE, Embase via Ovid, and AMED). The review was also limited to studies published in English, and excluded grey literature (editorials, conference abstracts, dissertations, and reviews). To reduce the risk of overlooking important studies, generic and specific queries were used, and additional studies were identified from the reference list of included papers. The aforementioned process, and all aspects of data extraction, and quality appraisal were independently performed by two researchers, with third party adjudication when there was conflict. However, although efforts were geared towards presenting a comprehensive review, publications that are not indexed in the major databases utilized in this study, or published in other languages may have been left out of this review.

Conclusion

This systematic review summarizes evidence from various studies on the use of AI-based interventions for chronic pain management. Specifically, the review details, the types of chronic pain conditions, types of AI-based interventions, delivery of the interventions, population characteristics and the context in which the interventions were delivered.

Overall, there is substantial (moderate-high quality) evidence demonstrating the use of AI-based interventions for delivering different components of care for people with chronic pain conditions. However, the interventions delivered by these AI systems mirror the current practice in pain medicine, and many users do not receive interdisciplinary interventions (as recommended by the IASP). Furthermore, the review revealed an abundance of individual systems, with a dearth of in-depth research into the utility and effectiveness of each. This means that translation to practice is difficult, since there may be a lack of evidence to inform decision making. Thus, it is recommended that pain clinicians, researchers, and patients collaborate to improve research in this field and develop feasible and standardized multidisciplinary AI systems that may effectively transform chronic pain care. LMICs may also benefit from conducting more research in this field. Furthermore, more extensive research is required to evaluate the clinical and cost-effectiveness of these AI-based interventions. These recommendations may influence the development and adoption of AI-based interventions while strengthening the quality of evidence in this field.

Authors Contributions

AA and AT contributed to the design and implementation of the research. AA and SD were the reviewers of relevant articles while AT served as the third reviewer who resolved any conflicts. AA contributed to the analysis of the results. Finally, AA and AT contributed to the preparation and formatting of the manuscript.

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Conflicts of Interest

There are no potential conflicts of interest or funding for this study.

Appendix of supplementary files

Supplementary file 1: Database search

Supplementary file 2: Results of included studies

Supplementary file 3: Synthesis Without Meta-Analysis (SWiM)

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Abbreviations

AI- Artificial intelligence

AMED- Allied and Complementary Medicine Database

BPI- Brief Pain Inventory

CDBS- Computer-based Decision Support

COVID-19- Corona Virus Disease 2019

Embase- Excerpta Medica Database

HFAQ- Hanover Functional Ability Questionnaire

IASP-International Association for the Study of Pain

IBS-SSS- Irritable Bowel Syndrome Symptom Severity Scale

iOS- iPhone Operating System

JBI- Joanna Briggs Institute

JMIR- Journal of Medical Internet Research

K-WOMAC- Korean-Western Ontario and McMaster Universities Osteoarthritis Index

MEDLINE- Medical Literature Analysis and Retrieval System Online

MODI- Modified Oswestry Disability Index

NICE- National Institute for Health and Care Excellence

NPRS- Numerical Pain Rating Scale

ODI- Oswestry Disability Index

PDI- Pain Disability Inventory

PICO- population, intervention, comparator, outcome

PMA- Pain Management Advisor

PRISMA- Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PubMed- Public/publisher MEDLINE

RCTs- Randomized Controlled Trials

RMDQ- Rolland Morris Disability Questionnaire

RoB- Risk of Bias

SWiM- Synthesis Without Meta-Analysis

VAS- Visual Analogue Scale

WHTs- Wearable Health Technology