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AI-Assisted Physiotherapy for Patients with Non-Specific Low Back Pain: A Systematic Review and Meta-Analysis

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Abstract: Background: Non-specific low back pain (LBP) is a widespread condition with significant impacts on physical activity, muscle strength, psychological well-being, and economic status. Traditional physiotherapy shows variable efficacy, prompting growing interest in AI-assisted physiotherapy for its potential to offer personalized feedback and multidisciplinary care integration. Objective: This systematic review and meta-analysis aimed to evaluate AI-assisted physiotherapy's effectiveness in reducing pain intensity and functional impairment and improving mental health compared to usual physiotherapy. Method: A comprehensive search strategy was employed across Embase, MEDLINE, Cochrane Library, and Web of Science databases from inception to 30 May 2024. Comparative studies were identified and screened using PICOS criteria. Data extraction involved detailed study characteristics and outcomes, with methodological quality assessed via the Cochrane Risk of Bias tool. Meta-analyses using random-effects models calculated standardized mean differences (SMDs). Results: Eight studies met the inclusion criteria. Compared to usual physiotherapy, AI-assisted physiotherapy did not demonstrate any statistically significant differences in outcomes across the aspects studied, including pain intensity (SMD = −0.2711, 95% CI: −0.5109 to −0.0313, $p = 0.267$), functional impairment (SMD = −0.2508, 95% CI: −0.5574 to 0.0559, $p = 0.1089$), and mental health (SMD = −0.0328, 95% CI: −0.1972 to 0.1316, $p = 0.6956$). These findings indicate that AI-assisted physiotherapy had no demonstrable additional effect compared to usual physiotherapy for patients with LBP. Sensitivity analyses were conducted to address inter-study heterogeneity, confirming the robustness of these results. Conclusions: While AI-assisted physiotherapy shows potential in managing LBP by providing personalized treatment and feedback, the current evidence does not demonstrate significant advantages over usual physiotherapy. Further large-scale, long-term, and methodologically rigorous randomized controlled trials are necessary to validate these findings, assess their clinical relevance, and explore broader public health applications.

Keywords: low back pain; AI-assisted physiotherapy; meta-analysis; pain management; functional impairment

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1. Introduction

Low back pain (LBP) is a significant global public health challenge, affecting individuals across all age groups and socioeconomic strata. It is a leading cause of disability worldwide, with an estimated lifetime prevalence of 84%, with non-specific low back pain (NSLBP) constituting approximately 90% of all cases [1–3]. In 2020, the number of individuals living with LBP reached 619 million globally, with forecasts suggesting that this figure will rise to 843 million by 2050 [4]. This substantial prevalence is further reflected in a survey of 54 countries, where the mean point prevalence of LBP was 18.3%, and the 1-year prevalence reached 38.0% [5]. LBP not only impacts individuals' physical functioning but also imposes heavy economic burdens. For example, in the United Kingdom, the National Health Service (NHS) spends nearly £5 billion annually on LBP management and associated costs [6]. Among the spectrum of LBP conditions, NSLBP has garnered increasing attention due to its high prevalence and the complexity of its management.

NSLBP, unlike specific LBP, cannot be attributed to an identifiable pathological cause discernible through imaging or diagnostic testing [7]. Specific LBP, often resulting from conditions such as herniated discs or spinal fractures, can typically be addressed through targeted treatments, including surgery or pharmacological interventions. Conversely, NSLBP lacks definitive treatment pathways, necessitating a multidisciplinary approach involving physiotherapy, exercise programs, and behavioral interventions. Its prevalence is substantial across various demographics, including adolescents and older adults [7]. In Canada, a 1-year prevalence study among adolescents aged 13.8 years revealed a prevalence rate of 17.2% [8]. Similarly, in Portugal, the prevalence among adolescents was 15.7% [9]. The burden of NSLBP extends beyond physical symptoms, as it is often accompanied by psychological issues, such as anxiety and depression, which exacerbate its impact on daily life and work productivity [10,11].

Traditional approaches to managing NSLBP, including supervised physiotherapy and self-management strategies, have shown varying degrees of success. According to the National Institute for Health and Care Excellence (NICE) guidelines, exercise therapy, education, and behavioral interventions are central to NSLBP management [12]. While exercise physiotherapy has demonstrated benefits in improving pain and physical function [13], issues such as patient adherence and accessibility have hindered its effectiveness. For example, patients often lack adequate supervision during home-based rehabilitation, which can compromise the quality and consistency of exercise routines [12,14]. Studies have also shown that patients in self-management programs frequently report low motivation and limited adherence to prescribed physiotherapy regimens, further limiting the efficacy of these interventions [15].

Given these challenges, integrating artificial intelligence (AI) into physiotherapy presents a promising solution. AI-assisted physiotherapy employs machine learning (ML) algorithms and data-driven analytics to provide personalized rehabilitation plans, real-time feedback, and enhanced patient monitoring [16,17]. Mobile health (mHealth) platforms, including smartphone applications and wearable devices, are at the forefront of AI-assisted physiotherapy. These platforms enable patients to engage in home-based rehabilitation while receiving immediate feedback on their performance [18]. For example, AI systems can dynamically adapt exercise regimens based on real-time monitoring data, ensuring precision and continuity in treatment [19]. Moreover, studies indicate that AI-assisted physiotherapy can significantly enhance patient adherence. Features such as automated reminders and interactive feedback mechanisms increase compliance, leading to improved outcomes compared to traditional physiotherapy methods [20,21].

Emerging evidence highlights the potential of AI-assisted physiotherapy in addressing key outcomes of NSLBP management, such as pain reduction, functional improvement, and mental health enhancement. For instance, recent studies comparing AI-guided home training to clinic-based training have demonstrated comparable results in improving physical function and reducing pain perception [22,23]. Additionally, AI-guided interventions may offer unique advantages in addressing psychological challenges associated with chronic pain. Despite growing interest in its potential, there is a paucity of systematic evaluations synthesizing evidence on its efficacy. This systematic review and meta-analysis aim to address this gap by evaluating the impact of AI-assisted physiotherapy on pain intensity, functional impairment, and mental health outcomes in NSLBP compared to usual physiotherapy. By aggregating and analyzing data from relevant studies, this review seeks to provide robust, evidence-based insights into the effectiveness of AI-assisted physiotherapy and its potential to transform NSLBP management.

2. Methodology

This systematic review and meta-analysis adhered to the PRISMA guidelines, ensuring comprehensive and rigorous identification, screening, eligibility, and inclusion processes [24].

2.1. Search Strategy

The study conducted a digital search across Embase, MEDLINE, Cochrane Library, and Web of Science databases, covering literature published up to 30 May 2024, on the effects of AI-assisted physiotherapy for patients with low back pain (LBP). The search strategy employed a combination of terms related to "low back pain", "physiotherapy", and "artificial intelligence". Specific terms included back pain, lumbar pain, sciatic neuropathy, physiotherapy, manual therapy, AI, deep learning, machine learning, and digital health. Search strategies were tailored to each database, and detailed search protocols were provided. Only English-language publications were considered, and grey pieces of literature, such as unpublished research, working papers, and academic presentations, were excluded. Reference lists of prior systematic reviews and meta-analyses were also screened to enhance the comprehensiveness of the search [25–27]. To identify potential unpublished studies, conference proceedings and PhD theses by lead authors relevant to the topic were reviewed. References were cataloged in Covidence, which automatically identified and removed duplicates, facilitating screening.

2.2. Inclusion Criteria

The study utilized the PICOS framework to define eligibility as follows:

1. Type of Study: Only randomized controlled trials (RCTs) were included to ensure methodological robustness. Case studies, cohort studies, and uncontrolled studies were excluded due to inherent design limitations.
2. Participants: Adult patients (≥18 years) with NSLBP were included, without restrictions on pain duration. Studies involving LBP due to specific pathological causes (e.g., discogenic pain, spinal abnormalities) or pregnancy were excluded.
3. Experimental Group: Patients receiving AI-assisted physiotherapy, defined as personalized treatments using smart algorithms, wearables, or digital health platforms were included. These interventions adapt based on patient demographics, clinical data, and progress.
4. Control Group: Patients receiving usual physiotherapy, including exercise therapy, manual therapy, and patient education delivered by a physiotherapist were included.
5. Outcomes: Pain intensity (e.g., Visual Analog Scale, Numerical Rating Scale), functional impairment (e.g., Roland Morris Disability Questionnaire, Oswestry Disability

Index), and psychological conditions (e.g., Veteran's Rand 12-Item Health Survey, Fear Avoidance Beliefs Questionnaire) were included.

Exclusion criteria included studies lacking specific AI-assisted physiotherapy interventions, studies combining neck and low back pain without separate statistical analyses, unrelated studies, and full-text articles that were inaccessible despite efforts to obtain them through institutional or interlibrary access. This does not imply that only open-access journals were included, as non-open-access articles were accessed when available through institutional subscriptions or other means.

2.3. Data Extraction

After duplicate removal, study screening was conducted in two phases:

1. Title and Abstract Screening: Initial screening identified studies potentially relevant to the research topic.
2. Full-Text Review: Eligible studies underwent a detailed assessment against inclusion criteria. Reasons for exclusion were documented.

Standardized data extraction forms recorded study characteristics, including authorship, journal impact factor, sample size, intervention details, outcomes, and limitations. Extracted data were stored in Excel for analysis.

2.4. Assessment of Study Quality

The Cochrane Risk of Bias Tool [28] was employed to evaluate the methodological quality of included RCTs. Seven domains were assessed: random sequence generation, allocation concealment, blinding, outcome assessment, incomplete data, selective reporting, and other biases. Risk levels (high, low, unclear) were assigned, and studies were categorized as low, high, or unclear risk of bias based on aggregated scores.

2.5. Statistical Analysis

Meta-analyses were performed using R software, version 4.3.0. Standardized mean differences (SMDs) were computed to compare outcomes measured using different instruments, with random-effects models used to account for heterogeneity. Forest plots visualized pooled effect sizes. Heterogeneity was quantified using I^2 statistics, with thresholds interpreted as follows: <30% (insignificant), 30–60% (moderate), 60–75% (high), and >75% (very high). Egger regression tests assessed publication bias, and sensitivity analyses evaluated the robustness of results by sequentially excluding individual studies.

3. Results

3.1. Literature Search

The comprehensive database search yielded a total of 11,133 studies. After removing duplicates and studies automatically marked as ineligible by automation tools, 7154 unique studies remained. During the title and abstract screening phase, 7047 studies were excluded based on relevance to the study criteria, leaving 107 studies for full-text assessment.

Of the 107 full-text studies:

- A total of 11 studies were excluded for employing non-RCT designs, such as observational, cohort, or prospective studies, which did not meet the RCT inclusion criteria.
- A total of 36 studies were excluded for using non-AI-assisted interventions, such as video-based or teletherapy-based mHealth therapies.
- A total of seven studies were excluded for not reporting outcomes related to pain, functional impairment, or mental health status.

- A total of seven studies were excluded for not reporting outcomes related to pain, functional impairment, or mental health status.
- A total of 19 studies were excluded for combining LBP treatments with neck pain analysis, preventing independent assessment of LBP-specific outcomes.
- A total of 23 studies were excluded for not explicitly stating the use of AI-assisted physiotherapy, as verification of AI application was not possible.

This process resulted in eight studies being included in the qualitative synthesis. For the meta-analysis, six studies were included, as two studies lacked sufficient data to compute standardized mean differences (SMDs) or other statistical measures. The study selection process is illustrated in Figure 1.

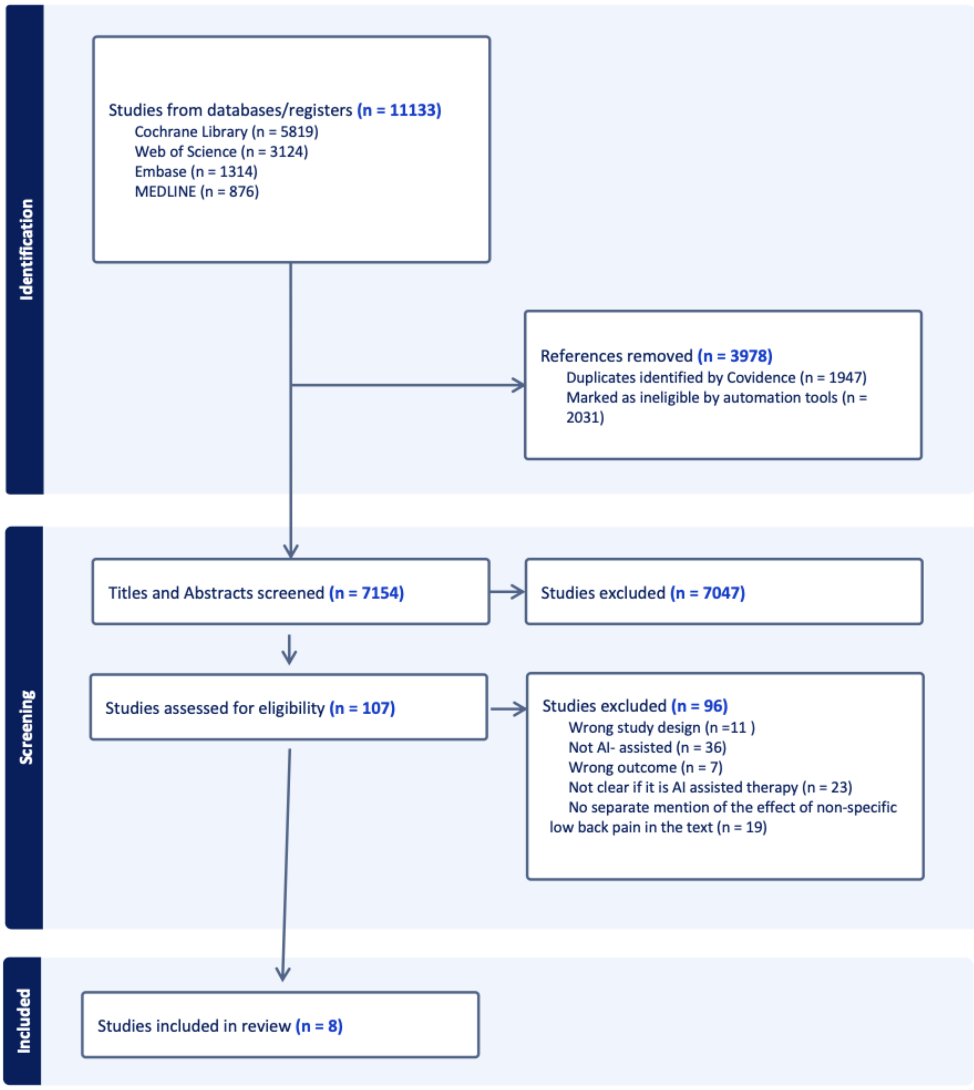


Figure 1. PRISMA flowchart of the study selection process.

3.2. Study Characteristics

The characteristics of the eight studies included in the systematic review and meta-analysis are summarized in Tables 1 and 2. These studies [21,29–35] involved a total of 2147 participants, with 1379 in the experimental (AI-assisted physiotherapy) group and 768 in the control group. Sample sizes ranged from 8 to 1245 participants, with a median of 100.5 (interquartile range 83.5–191).

The studies were geographically diverse, including one study from the United States [35], two from Germany [32,33], and one each from Denmark and Norway [31], Japan [21],

Table 1. The characteristics and data of participants included in the systematic review and the meta-analysis.

Authors and Year	Country	Sample Size	Intervention Size	Control Size	Gender	Age
Bates et al., 2023 [35]	United States	40	13	27	Intervention group: Female = 77% Control group: Female = 66%	Intervention Group: mean 37.8 (SD 11.5) Control group: mean 40.3 (SD 12.4)
Sandal et al., 2021 [31]	Denmark and Norway	461	232	229	Intervention Group: Female = 52% Control Group Female participants: 59%	Intervention Group: mean 48.3 Control group mean 46.7
Priebe et al., 2020 [32]	Germany	1245	933	312	Intervention group: Female = 65% Control: Female = 64%	Intervention: mean 42.0 years (SD 12.4) Control: mean 37.0 years (SD 12.6)
Park et al., 2023 [29]	South Korea	100	50	50	Intervention group: Female = 40% Control group: Female = 40%	Intervention Group: mean 37.8 (SD 11.5) Control group: mean 40.3 (SD 12.4)
Itoh et al., 2022 [21]	Japan	99	48	51	Intervention group: Female = 40% Control group: Female = 66%	Intervention Group: mean 47.11 (SD 8.33) Control group: mean 33.21 (SD 6.11)
Toelle et al., 2019 [33]	Germany	101	53	48	Intervention group: Female = 56.3% Control group: Female = 54.9%	Intervention Group: mean 47.9 (SD 10.2) Control group: mean 46.9 (SD 12.3)
Yang et al., 2019 [30]	Hong Kong	8	5	3	Intervention group: Female = 20% Control group: Female = 100%	Intervention Group: mean 35 (SD 10.93) Control group: mean 50.33 (SD 9.29)
Chhabra et al., 2018 [34]	India	93	45	48	/	Intervention Group: mean 41.4 (SD 14.2) Control group: mean 41 (SD 14.2)

The studies were geographically diverse, including one study from the United States [35], two from Germany [32,33], and one each from Denmark and Norway [31], Japan [21], South Korea [29], Hong Kong [30], and India [34]. Intervention durations varied from 4 weeks [29,30] to 6 months [31].

The study population primarily consisted of middle-aged individuals. The mean age of participants in the intervention group was 43.23 years (SD = 12.39), and the mean age in the control group was 41.52 years (SD = 13.34), indicating comparable demographics. The proportion of women in the intervention group ranged from 20% to 77%, while in the control group, it ranged from 40% to 100%.

Two studies were conducted in primary care settings [31,32], recruiting participants through general practitioners (GPs) or social media platforms such as Facebook. The other six studies were conducted in secondary or specialist care facilities [29–31,33,34], including community centers and outpatient spine departments in private hospitals.

Table 2. The characteristics and data of studies included in the systematic review and meta-analysis.

Authors and Year	Study Design	Duration	Comparison Groups	Intervention Groups	Outcome	Results
Bates et al., 2023 [35]	Randomized Clinical Trial	8 weeks	Clinical care	A supervised moderate-intensity AI-resistance training intervention	NPRS, PROMIS physical function, PROMIS Pain Interference, TSK	Subjects supported with an AI-guided moderate resistance exercise intervention achieved improved clinical examination scores and PROs, while controls were largely absent.
Sandal et al., 2021 [31]	Randomized Clinical Trial	12 weeks	Usual care (e.g., advice or treatment from a clinician)	AI-based self-BACK app on a smartphone and wear a pedometer wristband connected to the app.	NRS, PSEQ, RMDQ, FABQ, BIPQ, EQ-5D, EQ-VAS, SG-PALS, OPES	At 3 months, the intervention group improved their RMDQ score by four points or more than the control group. Among adults seeking care for LBP, the use of the SELFBACK system as an adjunct to usual care resulted in a reduction in back pain-related disability over 3 months.
Priebe et al., 2020 [32]	Cluster-randomized Controlled trial	3 months	Standard care by the GP	Educational content, physiotherapy, and positive thinking exercises through the AI app (Kaia App)	NRS pain index, DASS, HFAQ, VR-12, GCPS	The Rise-up approach has an overall advantage over standard care procedures in the control group, and teleconsultation has a powerful impact on symptom development in high-risk patients.
Park et al., 2023 [29]	RCT	4 weeks	Conventional physiotherapy by physiotherapists	Digital Application Physical Therapy	NPRS, ODI, QBPDS, RMDQ, FMS, SF-12, MSE, Dr AI-ROM, PCEA, PISQ, PTQR-COVID-19	DPT was as effective as CPT in improving structural and functional impairments, activity limitations, and participation restrictions.
Itoh et al., 2022 [21]	RCT	12 weeks	Usual care	AI-assisted chatbot program	NRS, RMDQ, CWP, WPAI-GH, EQ-5D-5L, TSK, K-6	No significant difference in work productivity (QQ method), pain intensity, and RDQ-24 was observed in the exercise group.
Toelle et al., 2019 [33]	RCT	12 weeks	Physical exercise	Educational content, physiotherapy	NRS, HFAQ, GCPS, VR-12, MQS	After 12 weeks, the treatment regimen offered by Kaia App was superior in terms of the primary outcome:
Yang et al., 2019 [30]	RCT	4 weeks	Manual therapy, electrophysical therapy, and traction.	Self-management through the AI app Pain Care	VAS, PSEQ, RMDQ, SF-36	APP with self-management was commendable to physiotherapy alone for improvement in LBP.
Chhabra et al., 2018 [34]	Single-blinded randomized controlled trial	12 weeks	Written prescription	Accomplish daily activity goals with the AI app Snapcare	NPRS, MODI, CSS	Efficacy of Smartphone Apps in Increasing Physical Activity and Functioning, and Thus Reducing Disability Indices, in People with LBP.

NRS (NPRS): Numerical Rating Scale; PSEQ: Pain Self-Efficacy Questionnaire; RMDQ: Roland-Morris Disability Questionnaire; FABQ: Fear Avoidance Beliefs Questionnaire; EQ-5D (EQ-5D-5L): EuroQol-5 Dimensions Questionnaire; EQ-VAS: EuroQol Visual Analog Scale; SG-PALS: Saltin-Grimby Physical Activity Level Scale; OPES: Overall Perceived Effectiveness Scale; DASS: Depression-Anxiety-Stress Scale; HFAQ: Hannover Functional Ability Questionnaire; VR-12 (Veterans SF-12): Veteran's Rand 12; GCPS: Graded Chronic Pain Status; ODI: Oswestry Disability Index; QBPDS: Quebec Back Pain Disability Scale; FMS: Functional Movement Screen; SF-12: Short Form-12; MSE: Muscle Strength Examination; Dr AI-ROM: Dr Al-based Motion Capture Range of Motion; PCEA: Preliminary Cost-Effectiveness Analysis; PTQR-COVID-19: Post-Questionnaire for Perceived Transmission Risk of COVID-19; PISQ: Postintervention Satisfaction Questionnaire; CWP: Change in Work Productivity; WPAI-GH: General Health—Work Productivity and Activity Impairment; TSK: Tampa Scale for Kinesiophobia; K-6: Kessler Screening Scale for Psychological Distress.

Control group treatments varied across studies. Five studies described control interventions as standardized care provided by clinicians, in accordance with national guidelines [21,31,32,35]. The remaining three studies specified that control participants received treatments from experienced physiotherapists, including heat therapy, ultrasound, transcutaneous electrical nerve stimulation (TENS), and exercise physiotherapy such as stretching, sling exercises, and core stability training [29,30,33].

All eight studies assessed pain outcomes, with data extracted at a 4-week follow-up for meta-analysis. Seven studies also evaluated functional impairment, while three studies examined mental health outcomes, including fear avoidance behaviors, psychological distress, and mood disorders. Most interventions relied on mobile device apps for AI-assisted physiotherapy, while one study utilized AI calibration on a tonal exercise trainer.

3.3. Quality Assessment

The risk of bias assessment for the included studies is summarized in Figure 2, using the Cochrane Risk of Bias tool. This assessment incorporated multiple domains, including random sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessors, incomplete outcome data, selective reporting, and other biases. Funding sources and conflict of interest disclosures were also evaluated to determine the potential for other biases.

Among the eight included studies:

- Funding Sources:
    - One study did not explicitly report its funding source.
    - Three studies were funded by public or governmental organizations, including the European Union's Horizon program, the German Innovation Fund (G-BA), and the U.S. National Institutes of Health (NIH).
    - Commercial entities funded three studies, including Tonal Systems Inc. (San Francisco, CA, USA), Kaia Health Software GmbH (80331 München, Germany), and Snapcare Technologies Pvt. Ltd. (Delhi, India).
- Overall Risk of Bias:
    - Most studies were categorized as low risk of bias overall.
    - The studies by Priebe et al. and Toelle et al. were rated as high risk of bias.
- Specific Domains of Bias:
    - Blinding of Participants and Personnel: All studies were rated at high risk of bias due to the nature of the interventions, as participants were necessarily aware of their treatment modality.
    - Blinding of Investigators: Six studies [29–34] were at high risk of bias in this domain.
    - Allocation Concealment: Three studies [30,33,34] were rated as high risk of bias.
    - Random Sequence Generation: The study by Toelle et al. [33] was at high risk of bias, as participants were assigned using an alternating method rather than true randomization.

This quality assessment highlights key strengths and limitations of the included studies, ensuring transparency in evaluating the robustness of their findings. While most studies demonstrated methodological rigor, certain biases—particularly related to blinding and allocation concealment—require careful consideration when interpreting results.

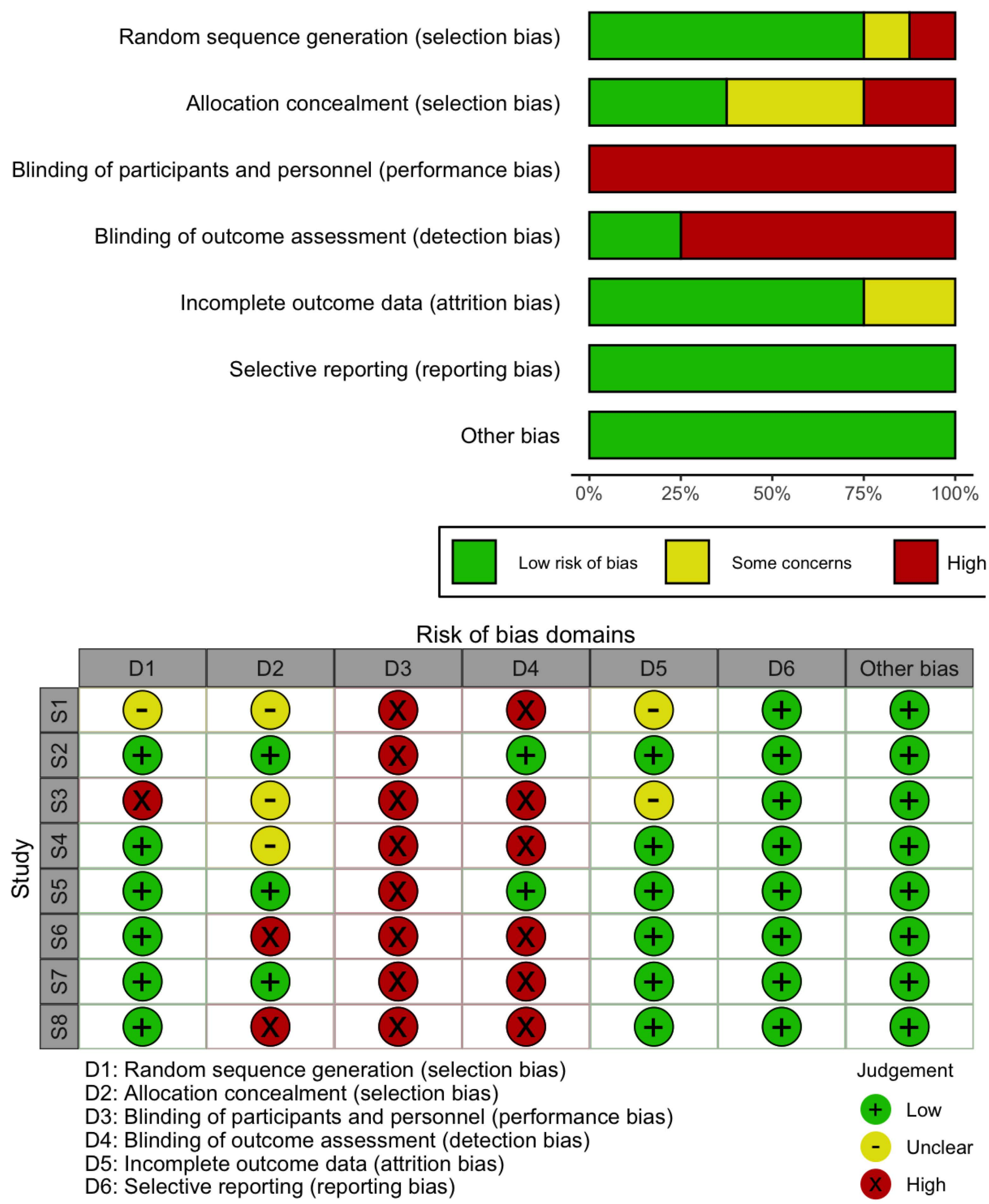


Figure 2. Risk of bias assessment and summary for each study. Note: Study 1 = [35], Study 2 = [31], Study 3 = [32], Study 4 = [29], Study 5 = [21], Study 6 = [33], Study 7 = [30], Study 8 = [34].

3.4. Synthesis of Results

3.4.1. Effect of AI-Assisted Physiotherapy on Pain Intensity

Pain intensity outcomes were reported in all eight included studies. Among these, three studies [29,31,32] demonstrated significant efficacy of AI-assisted physiotherapy for pain reduction, while five studies [21,30,33–35] reported no significant differences compared to usual physiotherapy. Pain intensity was consistently measured before and after intervention in all six studies included in the meta-analysis [29–31,33–35]. Five studies employed the Numerical Pain Rating Scale (NPRS) or Numerical Rating Scale (NRS) [21,31,33–35], and one study used the Visual Analog Scale (VAS) [30].

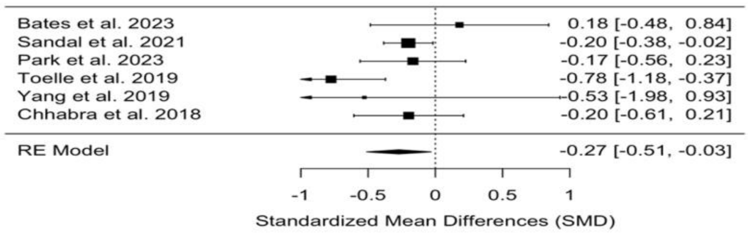
A pooled effect size was calculated using a random-effects model. The results indicated that AI-assisted physiotherapy did not demonstrate a statistically significant effect in pain management compared to usual physiotherapy, suggesting no conclusive advantage of AI-assisted physiotherapy in this aspect (SMD = −0.2711, 95% CI: −0.5109 to −0.0313,

showed a negative SMD, suggesting that AI-assisted physiotherapy has a potential advantage over usual physiotherapy in pain reduction, despite the lack of statistical significance (See Figure 3b).

These findings suggest that while AI-assisted physiotherapy may offer slight benefits in reducing pain intensity, further high-quality studies are needed to confirm its clinical significance and better understand its role in pain management.

$p = 0.267$) (Figure 3a). Heterogeneity analysis revealed a moderate level of heterogeneity among the included studies ($I^2 = 48.10\%$, $\tau^2 = 0.0284$, $p = 0.1200$).

(a)



(b)

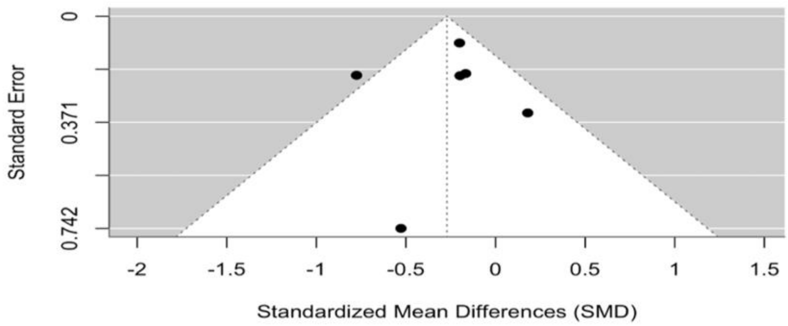


Figure 3. (**a**,**b**) Pain Intensity Outcomes: Forest Plot, Funnel Plot, and Sensitivity Analysis Comparing AI-Assisted Physiotherapy to Usual Therapeutic Interventions [29–31,33–35].

Publication bias was assessed using the Egger regression test, which found no significant evidence of bias (intercept = −0.2083, 95% CI: −0.7837 to 0.3671, $t = -1.005$, $p = 0.3717$). This finding was further corroborated by visual inspection of the funnel plot (Figure 3b), where data points were distributed symmetrically around the center axis ($x = 0$).

To explore the source of heterogeneity, a sensitivity analysis was conducted using a random-effects model (See Figure 3a). Each study was excluded individually to assess its impact on the overall meta-analysis results. The sensitivity analysis revealed that excluding any individual study did not significantly alter the overall effect size, demonstrating the robustness of the meta-analysis findings. Additionally, the analysis consistently showed a negative SMD, suggesting that AI-assisted physiotherapy has a potential advantage over usual physiotherapy in pain reduction, despite the lack of statistical significance (See Figure 3b).

These findings suggest that while AI-assisted physiotherapy may offer slight benefits in reducing pain intensity, further high-quality studies are needed to confirm its clinical significance and better understand its role in pain management.

3.4.2. Effect of AI-Assisted Physiotherapy on Functional Impairment

Functional impairment was assessed in seven of the eight included studies. Among these, five studies reported significant improvements in functional impairment following AI-assisted physiotherapy [29–32,34], while two studies found no significant differences compared to usual physiotherapy [21,33]. Of the six studies included in the meta-analysis, five measured functional impairment and activity limitations both before and after the intervention [29–31,33,34]. Three studies used the Roland Morris Disability Questionnaire (RMDQ) [29–31], one used the Oswestry Disability Index (ODI) [29], and the remaining

ies (I² = 65.86%, τ² = 0.0707, p = 0.0433).

Publication bias was evaluated using the Egger regression test, which showed no significant evidence of bias (intercept = −0.0387, 95% CI: −0.83689 to 0.7594, t = −0.1545, p = 0.887). This finding was further supported by a visual inspection of the funnel plot (See Figure 4b). Although minor asymmetries were observed in the funnel plot, they were deemed insignificant, confirming the absence of substantial publication bias.

To explore the sources of heterogeneity, a sensitivity analysis was performed using a random-effects model (Figure 4c). The sensitivity analysis involved the sequential exclusion of individual studies to assess their impact on the overall effect size. The results suggested that AI-assisted therapies and usual physiotherapy were largely comparable in managing functional impairment, with no single study disproportionately influencing the overall findings.

two employed the Modified Oswestry Disability Index (MODI) [34] and the High Fear Avoidance Beliefs Questionnaire (HFAB) [35] as outcome measures.

Pooled effect sizes were calculated using a random-effects model. The results showed that AI-assisted physiotherapy demonstrated a potential for greater efficacy in reducing functional impairment compared to usual treatment; however, this difference did not reach statistical significance (SMD = −0.2508, 95% CI: −0.5574 to 0.0559, p = 0.1089) (See Figure 4a). A heterogeneity test revealed a fairly high degree of variability between studies (I^2 = 65.86%, τ^2 = 0.0707, p = 0.0433).

(a)

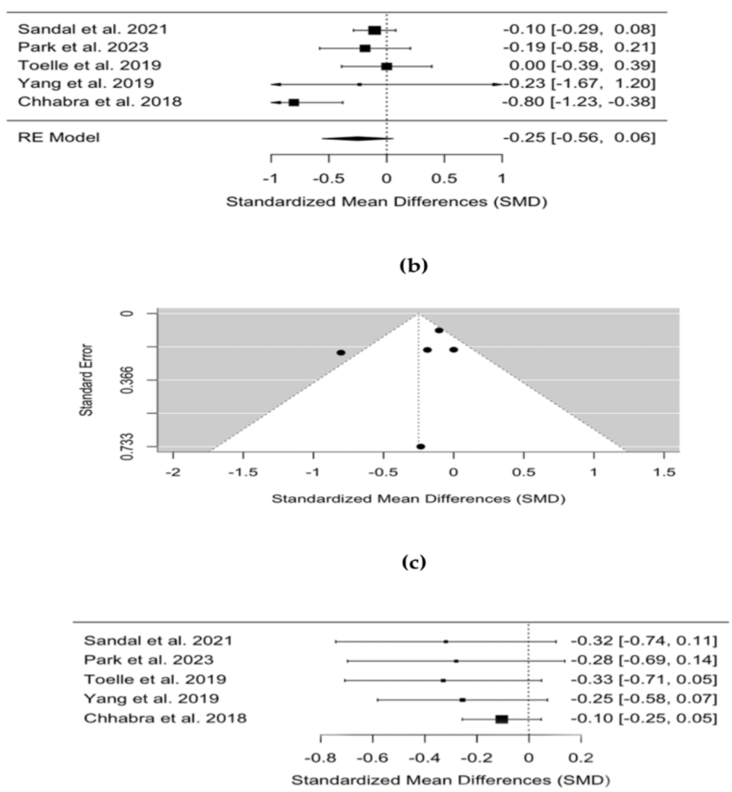


Figure 4. (**a**–**c**) Functional Impairment Outcomes: Forest Plot, Funnel Plot, and Sensitivity Analysis Comparing AI-Assisted Physiotherapy to Usual Therapeutic Interventions [29–31,33,34].

Figure 4. (a)–(c) Functional Impairment Outcomes: Forest Plot, Funnel Plot, and Sensitivity Analysis Comparing AI-Assisted Physiotherapy to Usual Therapeutic Interventions.

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3.4.3. Effect of AI-Assisted Physiotherapy on Mental Health

Mental health outcomes were assessed in five of the eight included studies. Among these, four studies reported significant improvements in mental health with AI-assisted physiotherapy [21,30,32,33], while one study found no significant differences compared to usual physiotherapy [31]. Of the six studies included in the meta-analysis, three specifically measured mental health status before and after the intervention [30,31,33]. Two studies employed the Veteran's Rand 12-Item Health Survey Mental Component Summary (VR-12-MCS) [21,30], while one used the Fear Avoidance Beliefs Questionnaire (FABQ) [31].

Pooled effect sizes were calculated using a random-effects model. The results indicated that while AI-assisted physiotherapy demonstrated a slight improvement in mental health status compared to usual physiotherapy, the statistical analysis did not show a significant difference between the two treatments (SMD = −0.0328, 95% CI: −0.1972 to 0.1316, p = 0.6956) (Figure 5a). Heterogeneity analysis revealed no significant heterogeneity between studies ($I^2 = 0$, $\tau^2 = 0$), indicating consistency in the reported outcomes.

mary (VR-12-MCS) [21,30], while one used the Fear Avoidance Beliefs Questionnaire (FABQ) [31].
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Publication bias was assessed using the Egger regression test, which found no significant evidence of bias (intercept = −0.1133, 95% CI: −1.0113 to 0.7847, t = −1.6034, p = 0.355). This was further confirmed by visual inspection of the funnel plot (Figure 5b), which showed a uniform distribution of scatter points with no clear tendency toward bias. Despite these findings, the limited sample size may preclude the complete exclusion of bias.
A sensitivity analysis was conducted using a random-effects model to evaluate the robustness of the results (See Figure 5a). The analysis involved sequential exclusion of individual studies to observe their impact on the pooled effect sizes. The results showed no significant changes in the overall findings regardless of which studies were excluded, indicating the robustness of the meta-analysis results (See Figure 5b).

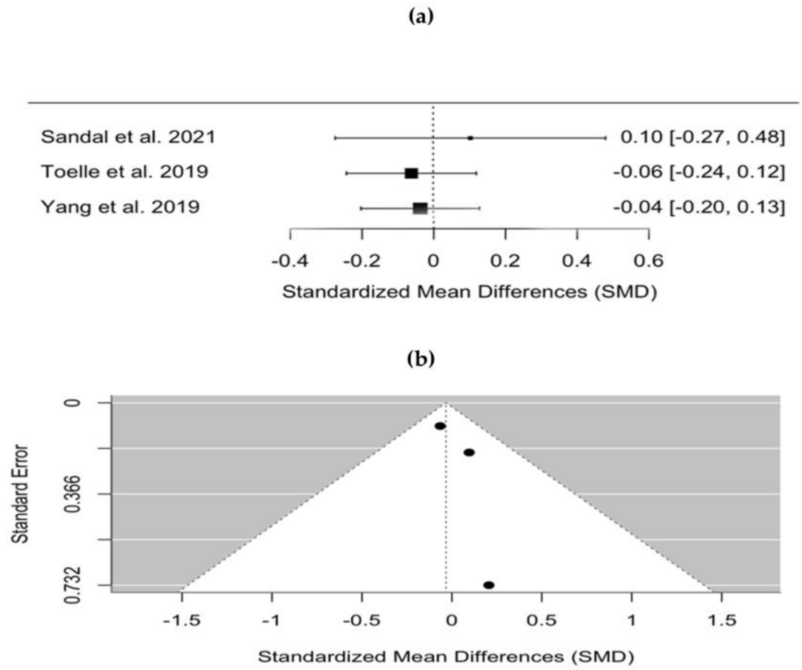

Figure 5. (**a**,**b**) Mental Health Outcomes: Forest Plot, Funnel Plot, and Sensitivity Analysis Comparing AI-Assisted Physiotherapy to Usual Therapeutic Interventions [30,31,33–35].

Figure 5. (**a**)-(**b**) Mental Health Outcomes: Forest Plot, Funnel Plot, and Sensitivity Analysis Comparing AI-Assisted Physiotherapy to Usual Therapeutic Interventions.

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4. Discussion

This systematic review and meta-analysis evaluated the efficacy of AI-assisted physiotherapy for managing non-specific low back pain (NSLBP). The findings suggest that AI-assisted physiotherapy showed some advantages over usual physiotherapy in reducing post-intervention pain intensity and functional impairment and improving psychological well-being. However, these differences were not statistically significant. These results highlight the potential benefits of integrating AI technologies in physiotherapy while emphasizing the need for further research to establish robust and consistent evidence.

AI-assisted physiotherapy has garnered increasing attention in recent years, expanding its application beyond NSLBP to conditions such as shoulder, knee, and ankle rehabilitation. However, systematic reviews specifically addressing AI-assisted physiotherapy for NSLBP remain scarce. This study fills a critical gap by providing a comprehensive meta-analysis focused on this intervention. Previous systematic reviews, such as Aki et al. (2022) [26], examined the effectiveness of mHealth self-management apps for LBP. Their findings, consistent with this study, showed encouraging results in pain reduction. However, the scope and methodology of Aki et al. differ significantly from this study. While their review included mobile apps with various functionalities beyond AI assistance, this study focused solely on AI-assisted interventions. Additionally, Aki et al. included controls such as web-based email support and placebo applications, whereas this review strictly compared AI-assisted physiotherapy to usual physiotherapy. Differences in study populations, pain types (acute, subacute, or chronic), and intervention designs also contribute to the discrepancies between findings.

Other reviews, such as Lewkowicz et al. (2021) [25], examined digital therapeutic care broadly, including internet-based platforms, text-based chatbots, and interactive apps. Their findings indicated significant benefits for LBP, but methodological limitations, including the inclusion of non-randomized studies and non-clinical guideline-based controls, reduce their generalizability compared to this study. Similarly, Du et al. [36] evaluated telemedicine for chronic pain but included a wider scope, incorporating web-based and mHealth interventions. While they reported clinically significant effects, this study offers a more focused assessment of AI-specific physiotherapy. By integrating recently published studies and narrowing its scope to AI-assisted physiotherapy, this meta-analysis provides an updated perspective on its effectiveness compared to usual physiotherapy. This is the first meta-analysis to specifically assess AI-assisted physiotherapy for NSLBP, highlighting its unique contributions to existing literature.

The meta-analysis revealed no significant therapeutic effects of AI-assisted physiotherapy on pain intensity, functional impairment, or mental health compared to usual physiotherapy. This contrasts with some prior reviews, potentially due to differences in study populations, intervention designs, and outcome measures. For example, the study by Toelle et al. [33] noted that high baseline functional capacity in participants may have limited improvements observed over the study period, a phenomenon known as the ceiling effect. Heterogeneity in the results was notable, with variations in study designs, sample sizes, and intervention protocols. Small sample sizes in several studies likely amplified individual differences, contributing to higher variability. Moreover, as AI physiotherapy is an emerging technology, inconsistent implementation and learning curves among researchers and clinicians may have further influenced outcomes. Differences in control group interventions also played a role; while some studies employed standard physiotherapy protocols, others relied on clinician-guided treatments, which varied widely.

Blinding was a common methodological challenge across studies. Given the nature of AI-assisted physiotherapy, it is difficult to blind participants or clinicians, which may introduce bias and disadvantage these studies in risk assessments compared to easily blinded pharmacological trials. Adverse events associated with AI-assisted physiotherapy were sparsely reported, limiting a comprehensive evaluation of its safety. Future studies should systematically document and report adverse events to inform clinical guidelines and regulatory policies [24]. Lastly, publication bias remains a potential concern. Statistical analyses and funnel plot inspections suggested minor biases, potentially due to small sample sizes or selective reporting favoring positive findings [28]. This bias could lead to an overestimation of the effectiveness of AI-assisted physiotherapy [35].

5. Strengths and Limitations

This systematic review and meta-analysis exhibit several notable strengths. First, the study employed a comprehensive and systematic search strategy across four major scientific databases, ensuring the inclusion of diverse comparative studies on AI-assisted physiotherapy for non-specific low back pain (NSLBP). This approach resulted in the inclusion of eight studies for systematic review and six for meta-analysis, providing a robust dataset for analysis. Furthermore, this review uniquely focuses exclusively on the effects of AI-assisted physiotherapy for NSLBP, addressing a critical gap in the literature. Unlike prior reviews that broadly grouped various digital interventions, such as AI-based, video-based, and web-based treatments, this review isolated AI-assisted physiotherapy to provide a targeted and nuanced evaluation of its potential benefits. By focusing on AI-specific approaches, this review highlights the distinct capabilities of AI models, such as real-time adaptive feedback, personalized treatment plans, and remote monitoring, which are less feasible with traditional digital methods. These contributions not only enhance our understanding of the unique role of AI in physiotherapy but also offer a valuable foundation for future research and clinical applications aimed at integrating AI-driven solutions into standard care practices.

The study also adopted rigorous methodologies to ensure accuracy and reliability. A double-checking strategy was implemented during full-text screening and data extraction, with two independent reviews conducted at each stage. This approach minimized errors and enhanced data completeness. Additionally, the use of Google search verification ensured that only studies explicitly involving AI-assisted physiotherapy were included, excluding other forms of interventions and reinforcing the specificity and accuracy of the review.

Despite these strengths, the study had significant limitations. Sample size constraints were a significant limitation of this study, as the relatively small number of available studies on AI-assisted physiotherapy for NSLBP restricted the robustness of the analysis. Variability in participant numbers across studies further exacerbated this issue, leading to imprecise results reflected in wider 95% confidence intervals. This imprecision limits the strength of the conclusions that can be drawn and underscores the need for careful interpretation of the findings. Additionally, differences in intervention protocols, including variations in AI technologies used, treatment durations, and assessment methods, may have contributed to heterogeneity, further challenging the generalizability of the results. Future research should prioritize larger, well-designed randomized controlled trials with consistent intervention protocols to enhance precision and provide more definitive evidence. Furthermore, studies exploring the underlying mechanisms of AI integration in physiotherapy could inform tailored interventions, optimize outcomes, and address the gaps identified in this analysis.

Heterogeneity among studies was another limitation, arising from variations in study designs, intervention frequencies, treatment software, and the use of sensors. These inconsistencies prevented systematic analysis of these influencing factors and increased uncertainty in the interpretation of results. Additionally, most included studies relied on self-reported outcome data, which is subject to response bias, potentially affecting the reliability of findings. Moreover, none of the included studies monitored participants' use of additional healthcare services during the study period. This lack of monitoring made it unclear whether other treatments were received, introducing the possibility of confounding effects that could skew results. The inability to account for these variables limits the study's ability to fully isolate the effects of AI-assisted physiotherapy.

In summary, while this review offers a comprehensive and focused analysis of AI-assisted physiotherapy for NSLBP, its findings must be interpreted with caution due to sample size limitations, study heterogeneity, reliance on self-reported data, and potential confounding factors. Future studies with larger, globally diverse samples and standardized protocols are recommended to address these limitations and further establish the efficacy of AI-assisted physiotherapy.

6. Recommendations

This review represents a significant milestone in the evolving field of AI-assisted physiotherapy, addressing a critical area of inquiry at a time when such technologies are becoming increasingly relevant. While the findings of this review highlight promising trends, the absence of statistically significant results underscores the nascent stage of research in this domain. As more advanced AI tools become available and their adoption in clinical practice grows, the groundwork laid by this review will be instrumental in shaping future investigations. By providing a comprehensive, methodologically sound analysis of current evidence, this review offers a foundation for subsequent studies that will benefit from larger datasets and enhanced AI capabilities, ultimately advancing our understanding of how effective these tools may become in revolutionizing physiotherapy practices.

To address the limitations observed in this meta-analysis, future research should prioritize larger sample sizes to improve the robustness and generalizability of findings. This review relied on 4-week follow-up data due to the short follow-up periods of included studies. This limits our understanding of the long-term efficacy and potential enduring benefits or side effects of AI-assisted physiotherapy. Future studies should incorporate longer follow-up periods to determine the durability of treatment effects and assess potential long-term outcomes.

Stratified analyses in future research could provide more nuanced insights into how specific variables, such as age and baseline functional status, influence treatment effectiveness. Age-related differences, such as recovery speed and adaptability to treatment, may significantly impact outcomes. Similarly, baseline functional status, reflecting a patient's initial health and limitations, could affect the degree of improvement observed. Additional confounders, including comorbidities and adherence to treatment regimens, should also be considered to produce a more comprehensive analysis.

Furthermore, personalized treatment regimens should be explored to optimize outcomes for specific patient subgroups. For example, tailored approaches such as adjusting treatment intensity or incorporating psychological support may benefit older patients or those with poorer baseline functional status. Such personalized interventions could enhance treatment efficacy, improve patient satisfaction, and ultimately enhance quality of life. To facilitate large-scale randomized controlled trials (RCTs) examining the impact of AI-assisted physiotherapy on NSLBP, governments and relevant authorities should increase investments in resources and infrastructure. This would enable researchers to conduct more comprehensive studies that could validate the efficacy of AI-assisted physiotherapy and guide its clinical application.

On the other hand, the findings of this review suggest that public health organizations should explore the integration of AI-assisted physiotherapy into broader healthcare practices, particularly for managing chronic pain and rehabilitation. This integration has the potential to enhance treatment accessibility, improve patient outcomes, and optimize resource utilization. By implementing AI-assisted physiotherapy in healthcare facilities, public health systems can address the growing demand for effective and personalized care, especially in underserved areas or resource-constrained populations. The remote monitoring capabilities of AI-assisted physiotherapy are particularly valuable for extending healthcare services to remote regions, minimizing geographical barriers, and supporting continuity of care.

Furthermore, these findings can inform healthcare policies by highlighting the cost-effectiveness and scalability of AI-based solutions, encouraging investment in digital health infrastructure and workforce training to support implementation. Policymakers and healthcare providers should collaborate to establish clear guidelines and ethical frameworks to ensure equitable access, data privacy, and safety in the adoption of AI technologies. Future research and pilot programs should aim to demonstrate the clinical efficacy and economic benefits of AI-assisted physiotherapy, providing the robust evidence needed to drive policy changes and integration into standard care pathways.

Training healthcare professionals to effectively operate AI-assisted physiotherapy technologies is essential for ensuring successful integration. These training programs could focus on familiarizing clinicians with AI systems, interpreting real-time feedback, and personalizing treatment plans based on patient data. Promoting AI-assisted physiotherapy has the potential to revolutionize the delivery of care by combining advanced technology with humanized treatment approaches. By doing so, public health organizations can offer more efficient, scalable, and accessible care, ultimately improving patient outcomes and addressing disparities in chronic pain management and rehabilitation services.

7. Conclusions

To the best of our knowledge, this systematic review and meta-analysis represents the most comprehensive evaluation of AI-assisted physiotherapy for non-specific low back pain (NSLBP) to date. By leveraging an extensive search strategy across multiple databases and journals, we ensured that the available evidence was captured comprehensively. This review identified AI-assisted physiotherapy modalities and their frequency to assess the intervention's effectiveness in reducing pain intensity and functional impairment and improving psychological well-being. Current evidence suggests that AI-assisted physiotherapy may be more effective than general physiotherapy in alleviating pain, enhancing daily functional abilities, and improving psychological status in NSLBP patients. Specifically, AI-assisted interventions not only reduce pain and functional limitations but also improve mental health outcomes, including symptoms of anxiety and depression associated with chronic pain. By offering personalized treatment plans and real-time feedback adjustments, AI-assisted physiotherapy aligns more closely with individual patient needs, potentially improving overall treatment outcomes and patient satisfaction.

However, these promising findings are tempered by significant limitations. The small number of included studies and their heterogeneity reduces the statistical robustness of the results. Consequently, it is not possible to draw definitive conclusions about the efficacy and safety of AI-assisted physiotherapy for NSLBP. To address these limitations, future research must prioritize large-scale, long-term, and methodologically rigorous randomized controlled trials. These trials should include diverse patient populations to enhance the generalizability of findings and provide detailed data collection, particularly regarding long-term efficacy and safety outcomes. Such advancements are essential to validate and expand the clinical applications of AI-assisted physiotherapy, ensuring its optimal use in managing NSLBP.

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