

REVIEW

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Optimizing Care Trajectories with Artificial Intelligence: A Systematic Review and Meta-Analysis

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Abstract

Objective: This study aims to provide a critical and comprehensive summary of existing research on the effectiveness of AI-assisted care pathways by analyzing their impact on hospital stays and readmissions. **Method:** This review was conducted in accordance with the PRISMA 2020 guidelines, which specify the selection and analysis steps from the outset. The search strategy targeted three international databases: Scopus, Web of Science (WoS), and PubMed (Medline). The inclusion criteria focused on randomized controlled trials (RCTs), before-and-after studies, quasi-experimental studies, longitudinal studies, and literature reviews involving hospitalized patients without age or pathology restrictions, provided that their care was based on the “clinical pathway” method. Studies that did not meet these criteria were excluded. A PRISMA diagram illustrates the systematic selection process, which resulted in the selection of 31 studies. Data extraction was performed using a structured methodology to ensure the validity and comparability of the results. The description of random sequence generation processes was adequate in 24 studies, partially addressed in five studies, and insufficient in two studies. This limits the ability to assess the risk of bias. **Results:** With regard to economic outcomes, such as length of stay and readmission, most studies [reported] positive effects associated with AI-assisted pathways. The Covidence tool (version 101) was used for the selection and extraction of data on the 18 studies analyzing pathways, AI, length of stay, and readmission. Group analyses indicated that the implementation of clinical protocols incorporating AI optimized care without increasing readmission rates or length of stay. **Conclusion:** However, the limited number and heterogeneity of studies on the application of artificial intelligence currently prevent the establishment of a universal framework for the implementation of AI-assisted clinical protocols.

Keywords: Critical Path- Artificial Intelligence- Systematic Reviews- Meta-Analysis- Length of Stay

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Introduction

Research into care trajectories now plays a central role in the organization of hospital systems. Insufficient or faulty coordination throughout the care pathway can lead to delays or even medical errors [1]. In the United Kingdom, for example, the phenomenon known as “corridor care” illustrates the structural limitations of the National Health Service (NHS): some patients are left on stretchers in corridors for more than 24 hours, without access to private space or rigorous clinical follow-up [2]. These situations profoundly degrade the care experience, and underline the urgency of continued investment in research to analyze, prevent and correct these dysfunctions, with the aim of sustainably improving the quality of the patient experience.

Furthermore, the patient experience in hospitals is based on a set of scenarios, referred to as “trajectories”. Optimizing these trajectories requires careful planning, commonly referred to as “itineraries”. Of course, by

the end of the 1980s, this patient-centered, evidence-based care compared with usual care [3]. This was the first review of its kind to use the Cochrane method, following a previous study in 2004 which focused on stroke patients [7]. Their aim was to see whether these clinical itineraries were effective in different types of medical situations.

The results showed that these itineraries reduced hospital complications and improved the way care was organized, without lengthening length of stay or increasing hospital costs [3]. However, some experts expressed reservations. They felt that these reviews might not be precise enough to capture the full complexity of clinical itinerary interventions [4-7]. To improve on this, it was suggested that a better definition of what is meant by a “clinical itinerary” would help to better target the studies to be analyzed [8].

On the other hand, in a constantly changing hospital environment, marked by increasingly complex patient profiles, structural constraints and external hazards, traditional management tools have significant limitations

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[9]. Indeed, conventional solutions often lack sufficient flexibility and predictive capabilities. In this respect, the innovative U.S.-based company Ellipsis Health has developed an intelligent conversational agent called “Sage”. This agent is capable of making automated calls to patients between consultations, analyzing their emotions using a voice artificial intelligence engine trained on over two million calls, and alerting healthcare professionals to critical cases detected. In this way, the system helps to overcome the shortcomings of post-hospital follow-up [10]. In addition, the use of generative artificial intelligence in the hospital context facilitates the automatic drafting of responses to patient messages, thus reducing the mental workload of healthcare professionals and increasing the responsiveness of services [11]. These advances testify to the potential of artificial intelligence to overcome the rigidity of current tools, streamline care paths and offer more continuous, personalized and efficient care in an increasingly constrained environment.

In healthcare, artificial intelligence (AI) refers to technologies that can simulate human cognitive processes to aid medical decision-making, predict clinical outcomes and personalise treatments. For an optimised care pathway to be considered a true clinical pathway in this context, it must incorporate four essential elements: a multidisciplinary approach aimed at translating recommendations into concrete actions; scientific evidence adapted to the local context; precise timelines or AI-driven progression algorithms; and targeting of specific patient populations [11]. In order to assess, on the one hand, the impact of these optimized trajectories on length of stay, readmission and costs, and on the other hand, the effect of these itineraries and artificial intelligence on the care trajectory (itinerary and artificial intelligence -----) optimized care trajectory-----) length of stay, readmission and costs). Although literature on clinical pathways has grown considerably over the past decade, rigorous studies comparing their effectiveness with traditional care remain limited and are often fragmented. Several literature reviews have been conducted, typically focusing on particular clinical contexts, such as chronic diseases, cancer, and perioperative care. These studies suggest that clinical pathways can improve care coordination, reduce hospital stays and boost patient satisfaction. However, they have several limitations, including methodological heterogeneity, a lack of standardisation of evaluation indicators and a lack of comparative data on long-term outcomes [11]. In this context, a systematic review appears necessary to fill this collection, critical evaluation, and synthesis of all available evidence, with the aim of better gap. It will enable the understanding the real effects of clinical pathways on the quality of care and clinical outcomes, compared with so-called “usual” care. Such a review will also help to identify optimal implementation conditions and provide up-to-date recommendations to decision-makers and practitioners.

That’s why it’s important to regularly update care pathways in line with new information and the medical context. Due to the rapid progress of digital technology and the lack of in-depth studies on the subject, our current understanding of how care pathways optimised by

artificial intelligence can enhance patient health is limited. This study therefore aims to provide a clear and critical summary of existing research on the effectiveness of these AI-assisted care trajectories, examining their impact on health outcomes for different patient groups.

To draw up a state-of-the-art report on how the use of such ‘intelligent’ trajectories can improve quality of care and patient health [12], A combined systematic and meta-analytical literature review was chosen for this study. The aim was to see how these new ways of managing patients reduce the time spent in hospital, avoid high costs, and improve the quality of care, compared with the usual way. Using this method, all existing evidence can be gathered and presented in a clear and reliable manner, to help hospitals and health centers decide whether these new methods are really effective or not.

In order to address our research inquiry concerning the influence of artificial intelligence on the optimization of care pathways specifically regarding cost, length of stay, and rates of readmission we have structured our problem statement utilizing the PICO framework [12]:

- P (Population): all patients treated in healthcare facilities.

- I (Intervention): implementation of standardized protocols or AI-based tools for managing care pathways.

- C (Comparison): usual care or conventional protocols and AI-assisted protocols.

- O (Outcomes): cost, length of hospital stays, readmission rate

Materials and Methods

This study is a systematic review accompanied by a meta-analysis. The methodologies of the Cochrane Collaboration were adopted, with some adaptations, particularly with regard to the presentation of the meta-analysis results [13]. The steps in this review were carried out in accordance with the recommendations of the PRISMA 2020 (Preferred Reporting for Systematic Reviews and Meta-Analysis) guideline. A systematic review protocol was registered with PROSPERO, ID: CRD4202021066822. In this study, the targeted research question was “What is the effect of optimizing care pathways using AI on the patient experience?”

Study selection criteria

First, three databases were considered (Medline, Scopus, and WOS) because they reflect their scientific impact and relevance in the field studied. RCTs and before-and-after studies were included in the analysis [14], as well as quasi-experimental studies, longitudinal studies, and literature reviews, provided that they focused on groups of hospitalized patients, regardless of their age or health condition. In addition, their care was based on the management method known as the “clinical pathway.”

After the initial selection, a second selection phase was conducted. We defined minimum “inclusion criteria” to answer our research question. Based on the definition of the patient pathway (see Context), we developed four operational elements

1. Multidisciplinary approach integrating at least two pathway scenarios: (“care pathway” OR “care pathway optimization”).

2. Development of a standardized treatment protocol or clinical algorithm: (“care protocol” OR “professional protocol” OR “practice guide” OR “practice protocol” OR “clinical practice guideline”).

3. Analysis of medical-economic data or recommendations based on good professional practices: (“patient admission” OR “patient readmission” OR ‘stays’ OR “hospitalization costs”).

Each criterion in the pathway could be satisfied: (1) “yes”; (2) ‘uncertain’ due to poor communication and lack of contact with the lead author; or (3) “criterion not satisfied.”

The third selection phase was limited to those in the PICOTS framework, evaluating the effectiveness of AI in optimizing care pathways:

Population (P)

The target study includes a representative sample of hospitalized patients, ranging from children to adults, of all ages and with various medical conditions, for whom care followed a strategy based on optimizing clinical pathways.

Intervention (I)

Introduction of new care protocols or care pathways incorporating artificial intelligence technologies.

Comparator (C)

Standard care practices, in accordance with usual protocols, without the use of artificial intelligence systems.

Outcomes (O)

Evaluation of effectiveness, focusing in particular on patient readmission rates and the length of hospital stays associated with hospitalization. Please note that further information regarding included studies meeting these criteria or differing from each other is provided in the ‘Results’ section of this review.

Data sources and research strategy

On January 18, 2025, an in-depth bibliographic search was conducted using the Medline, Web of Science, and Scopus databases (see Table 1). For the Scopus database, the search was limited to the period from 2015 to 2025 due to the high volume of results, this period also being marked by a high number of citations. However, no limits were applied in Web of Science and Medline, given the

limited number of studies available in these databases. In addition, we analyzed the bibliographic references of all articles retrieved in full in order to identify any publications not initially detected, also conducting a search directly on Google Scholar. The search was conducted independently by two authors, following the four phases of the process described in the PRISMA diagram: identification, selection, eligibility, and inclusion.

Identification is based on the development of queries for electronic searches in various databases. These were developed by combining input terms related to the problem/population, intervention, comparison, and outcome (PICO) with Boolean operators, “AND” and “OR” to refine the results. After identifying all potential articles, selection was based on reading each title/abstract to exclude articles that did not meet the inclusion criteria (see Study Selection Criteria) for the systematic review. We considered low quality of assessment as an exclusion criterion to be applied during the eligibility phase of the PRISMA flow diagram. The remaining articles were considered eligible, to be retrieved in full text and evaluated in accordance with the pre-identification strategy for quality assessment (see paragraph on quality assessment). Finally, articles of medium/good quality were included in the systematic review (see results: study selection process).

Quality assessment and data analysis

To ensure the quality of our studies, we have adopted the Effective Care Organization (EPOC) module [14], defined three risk classes: Class I (low risk of bias), Class II (moderate risk of bias), and Class III (high risk of bias). Two assessors independently assessed and extracted data on intervention criteria, study characteristics, methodological quality, and risk of bias of the included articles (random sequence generation (selection bias), allocation concealment, blinding of participants/personnel (performance bias), incomplete outcome data (attrition bias), selective reporting (reporting bias), and other biases) [14]. Any disagreements were discussed with a third reviewer. We used Review Manager (RevMan) from the Cochrane Collaboration to calculate a pooled effect estimate, known as the Odds Ratio [14]. We used a random effects model because this model estimates the effect by taking into account the variance between studies, rather than ignoring heterogeneity by using a fixed effects model.

Heterogeneity and meta-analysis

Despite the expected clinical heterogeneity (clinical variability of the included interventions) within the review,

Table 1. Synthesis of the Keyword Box

Database	Search terms used
PubMed (Medline)	((“Artificial Intelligence”[MeSH] OR “artificial intelligence”[tiab] OR AI[tiab]) AND (“Patient Care”[MeSH] OR “care trajectory”[tiab] OR “care pathway”[tiab] OR “clinical pathway”[tiab]))
Scopus	(TITLE-ABS-KEY ((“care pathway” OR “care trajectory”)) AND TITLE-ABS-KEY ((“economic factors” OR “time” OR “cots”)) AND TITLE-ABS-KEY ((“optimization” OR “improvement”)) AND TITLE-ABS-KEY ((“systematic ” OR “review”))) AND PUBYEAR > 2014 AND PUBYEAR < 2026
Web of Science	((“care trajectory” OR “care pathway” OR “clinical pathway” OR “patient journey”) AND (“artificial intelligence” OR AI OR “machine learning”) AND (optimiz* OR improv*))

it is important to assess the comparability of the results of individual studies. A useful statistic for quantifying inconsistencies is $I^2 = [(Q \text{ df})/Q] \times 100\%$, where Q is the chi-square statistic and df is its degrees of freedom [14]. This quantifies the total variance explained by heterogeneity as a percentage. We considered an overall test value greater than 75% to be evidence of substantial heterogeneity of such magnitude that statistical pooling was not appropriate.

Statistical analysis

The criteria taken into account for the meta-analysis were: the effect of clinical protocols on optimizing care pathways; the effect of artificial intelligence on optimizing care pathways; and the effects of optimizing care pathways on length of stay and readmission, which were evaluated using the I^2 measure, considering low ($I^2 < 25\%$), moderate ($25\% < I^2 < 75\%$), and high ($I^2 > 75\%$) heterogeneity (20). Associations were represented by adopting odds ratios (OR) with 95% confidence intervals (95% CI) extracted for each study and grouped for each criterion. As not all meta-analyses included at least ten studies, the comparison-adjusted funnel plot was used to assess the effects of small studies on the results [14].

Assessment of publication bias

We used funnel analysis to assess publication bias, i.e., bias caused by a lower probability of publication for non-significant studies. The funnel plot is a scatter

plot with the x-axis representing the estimated effects from the primary studies and the y-axis representing the sample size of each study (standard error of the mean) [8]. In the absence of publication bias, the diagram shows a symmetrical inverted funnel.

Results

This section may be organized into subsections and will provide a concise and precise overview of the experimental results, their interpretation, and the conclusions that can be drawn from them.

Study selection process

As described in Figure 1, our electronic searches identified 234 entries from the developed queries (n = 13 in Medline; n = 118 in Scopus; n = 161 in Web of Science) and 15 additional entries from the manual search conducted to review the bibliographic references of all full-text articles retrieved during the eligibility phase. After removing duplicates, two authors reviewed 187 titles and abstracts. During this phase, 64 entries were excluded because the main subject of these articles was not mentioned as being clinical pathways. Of the remaining 123 articles, two authors checked the abstract to verify that the inclusion criteria were met, and 24 articles were excluded because they did not have an experimental component. The 99 eligible articles were then retrieved in full text and their content and quality were assessed

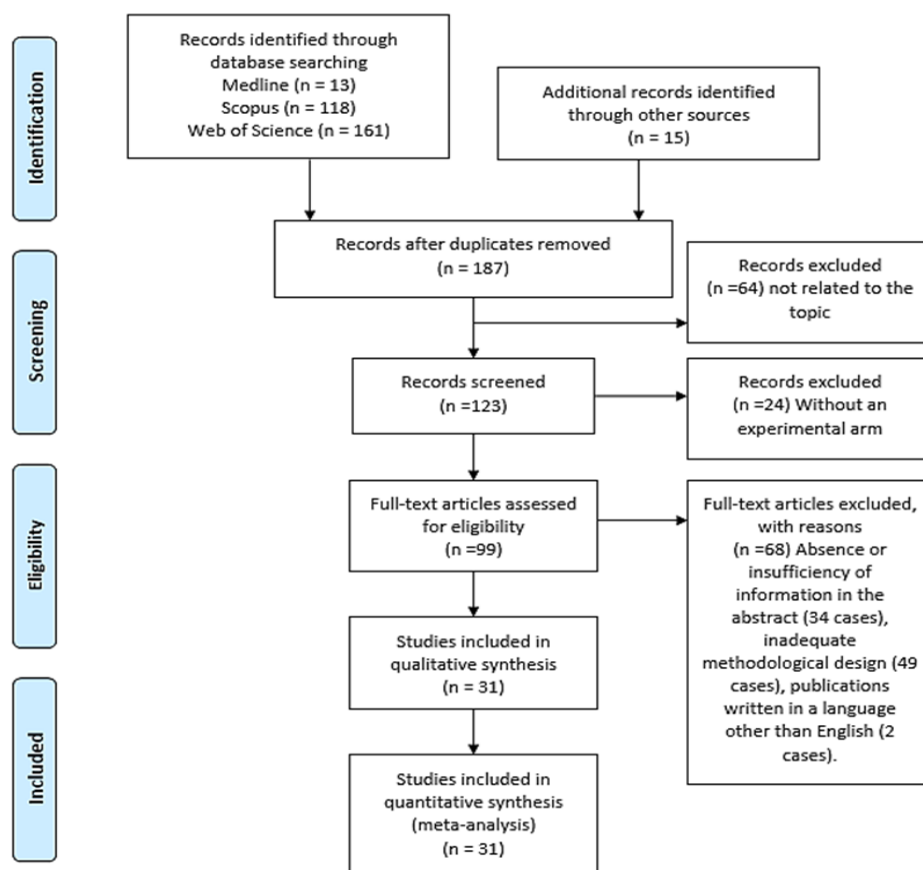


Figure 1. PRISMA Diagram

according to the criteria described in the “Quality assessment” section. Before assessing the quality and risk of bias of the eligible articles, 68 additional articles were excluded because they did not meet certain inclusion criteria, including lack of or insufficient information in the abstract (34 cases), inadequate methodological design (49 cases), and publications written in a language other than English (2 cases). As a result, 31 studies were included in this systematic review. After evaluating the content of the included studies, length of stay (LOS)/readmission was a patient-related outcome common to 6 studies, and the care protocol was common to 7 studies. Only 11 studies mentioned the impact of digital transformation with AI on optimizing the care pathway. A meta-analysis of fewer than four studies could not enrich the narrative synthesis (see the qualitative analysis section).

Assessing the risk of study bias

Figure 2 shows the overall assessment of risk of bias, and Appendix A provides a detailed analysis of each study. Random sequence generation was correctly described in 24 studies. However, five studies required a more precise description of this step, and two studies did not provide sufficient information to enable an adequate assessment of

the associated risk of bias. Assignment concealment could be assessed in all 26 included studies, but nine would have benefited from additional information to strengthen this assessment. Due to the nature of the interventions (the use of care trajectories versus standardized care pathways); it was not feasible to blind participants and staff in some studies. However, blinding the statistician was considered a relevant criterion for assessing performance bias, and this approach was deemed satisfactory for the majority of studies.

Additionally, detection bias was evaluated based on the procedures used to implement care trajectories. The management of missing outcome data (attrition bias) was clearly documented in half of the studies. Three reports presented a risk of selection bias due to selective reporting. Finally, other forms of bias were identified, including the use of a non-representative sample in five studies.

Descriptive analysis

Characteristics of included studies

A total of thirty-one manuscripts were included in this review. Some of the results selected in the meta-analysis on initial interventions, such as artificial intelligence, length of stay, and readmission, are presented in (Table 2).

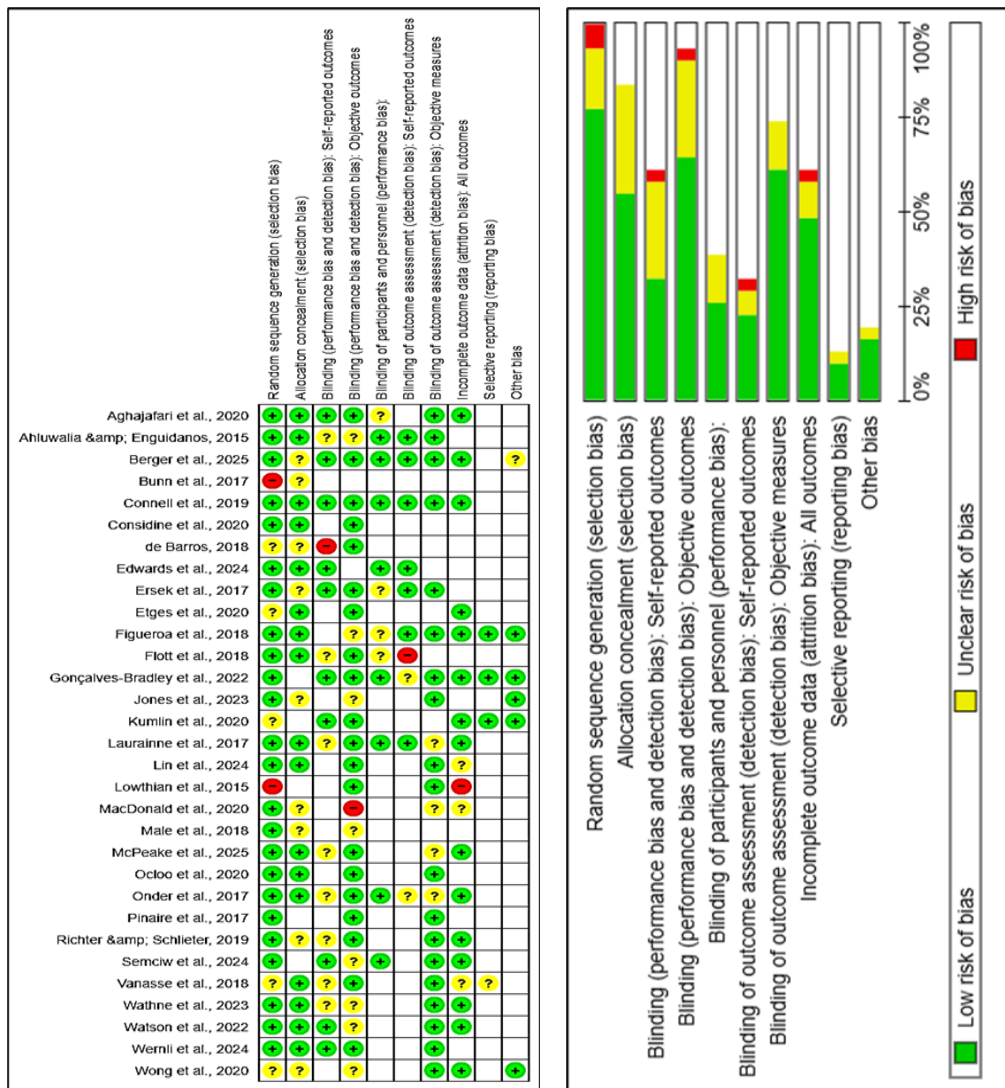


Figure 2. Risk of Bias Generated by Use of the Cochrane Risk-of-Bias Assessment Tool. Source: Authors et al; 2025

Table 2. Summary Table

Study	Multidisciplinary approach	Treatment protocol	Medicoeconomic data	Geographical areas studied	Types of studies	Research designs	Collection methods	P: Population	I: Intervention C: Comparison:	O: outcomes
Rotter et al. [3]	1	1	1	United States, Australia, Japan, United Kingdom, Canada, Taiwan	13 randomized controlled trials (RCTs) and 4 controlled clinical trials (CCTs)	Individual RCTs, 1 cluster trial (19 hospitals)	Standardised extraction of indicators	Hospitalized children and adults	Multidisciplinary, protocolised/algorithmic clinical pathways	Length of stay (LOS): 12/16 studies show a significant decrease; estimated average reduction -25% (95% CI -36% to -14%) Readmission: overall OR 1.10 (95% CI 0.57-2.08)
Flott K et al. [29]	1	1	2	Angleterre	Mixed: Quantitative and Qualitative	Analyse transversale	Exploitation de données publiques et bases nationales	patients hospitalisés	Comparison des différentes organisations NHS en fonction de la présence ou du niveau de ces facteurs organisationnels (par ex. Hôpitaux Numérique)	Mettre l'expérience liée à plus de soutien aux équipes cliniques et la numérisation
Watson et al. [35]	1	1	1	Europe, the United States, Asia	Mixed: Quantitative and Qualitative	RCT	hospital information systems, surveys	Hospitalized patients monitored in various clinical settings (oncology, intensive care, surgery, stroke, cardiology).	Integration of artificial intelligence (AI) tools into clinical care pathways/standard care pathways	Average length of stay (LOS): reduced by 0.67 to 3.0 days depending on the context (e.g., sepsis, stroke, surgery). - Readmission rate: decrease ranging from 5% to 12%.
Ersek JL et al. [27]	1	1	2	France	Observational study, cross-sectional survey	Cross-sectional analysis	Mail questionnaires to patients	Patients at high risk of cutaneous melanoma, identified by their primary care physicians	Targeted screening with AI	satisfaction, costs, flow efficiency
Bunn et al. [26]	1	1	1	North America, Europe, and Australia.	Systematic review of interventional studies	Randomized controlled trials (RCTs), quasi-experimental studies	Documentary search in MEDLINE, Embase, CINAHL, Cochrane Library	Patients admitted to public and private hospitals	Electronic discharge plans/ patient education programs, involvement in error detection, shared checklists, active participation in the care pathway	Hospital adverse events: relative decrease of 15 to 25%.
Wenli et al. [36]	1	1	1	China	Observational studies	Quasi-experimental studies	electronic health records	Patients hospitalized in various departments (oncology, intensive care, internal medicine)	decision algorithms, automated monitoring tools, expert systems integrated into EMRs	- Average length of stay (LOS): reduction of 1.5 to 3.2 days on average, depending on the department - Hospital costs: decrease of 12% to 17%
Wong et al. [37]	1	1	1	United Kingdom, Australia, United States, Canada, Netherlands, Scandinavia.	Systematic review of the literature.	Randomized controlled trials (RCTs), quasi-experimental studies	Recherche documentaire dans bases (MEDLINE, CINAHL, PsycINFO, Cochrane Library)	Patients admitted to public hospitals	eHealth combined with a structured care pathway: Usual care without systematic integration of patient feedback, or comparison before/after implementation of patient feedback.	5-15% increase in patient experience scores
Berger et al. [25]	1	1	2	USA, Europe, Aise, Africa	Quantitative	RCT	dossiers médicaux électroniques	Oncology, emergency care.	ECR of a browser-based virtual platform for a transition and recovery program provides highly personalized assistance	readmission, cost, stays,
Richter & Schlieter. [34]	1	1	1	Germany	Mixed: Quantitative	Quasi-experimental before/after studies	Analysis of hospital databases	Patients hospitalized in surgery, oncology, and intensive care	integrating digital tools and standardized protocols	Length of stay (LOS): average reduction of 1.2 to 2.8 days

Source, Authors et al; 2025

Table 2. Continued

Study	Multidisciplinary approach	Treatment protocol	Medicoeconomic data	Geographical areas studied	Types of studies	Research designs	Collection methods	Population	I : Intervention C: Comparison	O : outcomes
Gongqvist-Bradley DC et al. [30]	1	1	1	Australia, Canada, China, Japan, Netherlands, United Kingdom, United States, Italy	Cochrane systematic review including randomized controlled trials (RCTs) and controlled clinical trials (CCTs)	Quantitative comparative analyses	Comprehensive documentary research	patients hospitalized in various settings	Implementation of clinical pathways	Average length of stay (LOS): reduction of -2.5 days (95% CI -4.1 to -0.9). Readmissions: no difference (OR = 0.96; 95% CI 0.72-1.29).
(Aghajari et al. [24])	1	1	1	USA, Europe, Asia, Africa	Systematic review	Randomized controlled trials (RCTs), quasi-experimental studies	Documentary research	Hospitalized patients	Electronic care plan alerts -Computer-generated communication systems - Electronic discharge plans.	day readmission rate corresponds to a relative Odds Ratio reduction of 0.94
Figuerola et al. [19]	1	1	2	USA	Quantitative	Quasi-experimental before/after studies	Analysis of hospital databases	Patients hospitalized in various departments	Several proven programs to reduce rehospitalization Ø STAIR (State Action on Avoidable Rehospitalizations) Ø BOOST (Better Outcomes for Older adults through Safer Transitions) Project RED (Re-Engineered Discharge)	The higher the HCAPHS scores, the lower the readmission rate.
(Lin et al. [32])	1	1	1	North America, Europe, and Australia	Mixed: Quantitative and Qualitative	Cross-sectional analysis	Mail-in questionnaires for patients	Hospitalized children and adults	An algorithm to predict patients' readiness-for-discharge (machine learning)	Observed ICU readmission rates: 2% to 5.6%.
Jones et al. [31]	1	2	2	Europe	Mixed: Quantitative and Qualitative	Observational study.	Mail-in questionnaires for patients	Hospitalized patients	Patients cared for by native staff are 3 times more likely to finish their stay without self-discharge	Hospital discomfort or cultural rejection can lead to disruptions in follow-up, resulting in more readmissions.
Male et al. [18]	1	1	1	America	Comparative observational study	Prospective, comparative study	Data extracted from a hospital database	patients with large vessel occlusion (LVO) transferred from a PSC to a CSC	Using Viz.ai LVO software (AI for automatic LVO detection and alerting of care teams).	PSC→CSC (CTA→arrival) delay: reduced from 132.5 min to 110 min (-22.5 min; p = 0.047).
Ochoa et al. [33]	1	1	1	single-center study	Randomized controlled trial (RCT).	Prospective, randomized, controlled study with 12 weeks of follow-up.	Data collected through hospital monitoring	patients with heart failure (HF)	12-week telehealth program	Significant decrease in readmission (p < 0.001).
(Lauraine et al. [16])	1	1	1	USA	Quantitative	Quasi-experimental before/after studies	Analysis of hospital databases	Patients hospitalized in various departments	- Digital workflow or preconfigured sorting. - Scheduling tool Effect of anticipated protocols anticipated validation/preparation = ↓ waiting, ↑ flow	We expect a 25% reduction in length of stay, which corresponds to a reduction of more than 60% in waiting time
(Vanasse et al. [20])	1	1	1	USA	Randomized controlled trial (RCT), open-label, controlled	Prospective, randomized, open-label study (factorial, open-label RCT).	clinical data collected continuously in the EMR	Adults ≥18 years old admitted to intensive care	Machine Learning Algorithm (MLA) for predicting severe sepsis – alert system triggering clinical assessment and a sepsis bundle.	Average length of stay (LOS): 13.0 days (control) → 10.3 days (AD); reduction of 2.7 days (p = 0.042).

Source, Authors et al.; 2025

to facilitate their interpretation (see quantitative analyses).

The majority of the studies included were interventions, with the exception of four literature reviews. A total of 600,922 patients were analyzed, ranging in age from 6 to 70 years. In terms of the geographical location of the studies, the majority were conducted in the United States (50.2%), followed by Australia (20.1%), Europe (10.4%), Asia (11.6%), and Africa (7%). In terms of methodological quality, 12 articles (30.87%) were classified as high quality (score of 7), nine articles (29.03%) as medium quality (score of 6 to 5), five articles (16.11%) as adequate quality, and five articles (16.11%) as low quality (score below 4).

Quantitative analysis

The effect of clinical protocols on optimizing care trajectories

The results of several studies evaluating the effect of care protocols on optimizing care pathways. In fact, thirty-one studies evaluated the effect of clinical pathways, but twenty-four of them did not provide sufficient data to be included in the meta-analysis (Figure 3).

According to the meta-analysis presented, all studies comparing clinical pathways with standard practices show an overall favorable effect on optimizing the care pathway. Indeed, the combined effect according to a random effects model shows an odds ratio of 0.73 [0.60–0.88], with a p-value of 0.001, indicating a relative

reduction of approximately 27% in the risk of events in the experimental group. The majority of the included studies (Aghajafari 2020, Bunn 2017, Cédric Rat 2017, Diane 2022, Flott 2018, Watson 2022) report a benefit in favor of care pathways, while only one study (Figuroa 2018) shows the opposite result, in favor of standard care. However, statistical analysis highlights significant heterogeneity between studies ($I^2 = 96%$, $\text{Chi}^2 = 330.80$, $p < 0.00001$), suggesting considerable variability in contexts, populations, and definitions of clinical outcomes.

The effect of artificial intelligence on optimizing care trajectories

The meta-analysis of 11 studies evaluated the impact of AI transformation on optimizing care pathways. Each line represents an included study comparing a group conducting experiments using AI-based solutions to a group receiving standard pathway data (Figure 4).

This forest plot shows the events favorable to care trajectory optimization in each group, together with the odds ratio (OR) and its 95% confidence interval (CI). An OR less than 1 suggests a favorable effect of RN, while an OR greater than 1 would indicate an effect in favor of the control group. The majority of studies show an OR below 1, suggesting an overall trend towards a beneficial effect of AI on trajectory optimization. For example, studies by Aghajafari (2020), Connell (2019) and Wong (2020)

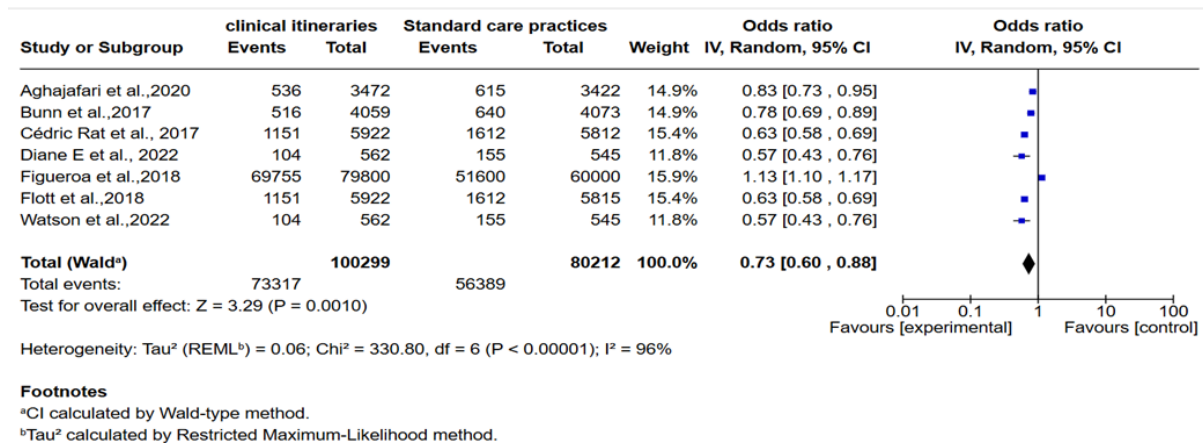


Figure 3. The Effect of Clinical Itineraries on Optimizing Care Trajectories. Source: Authors et al; 2025

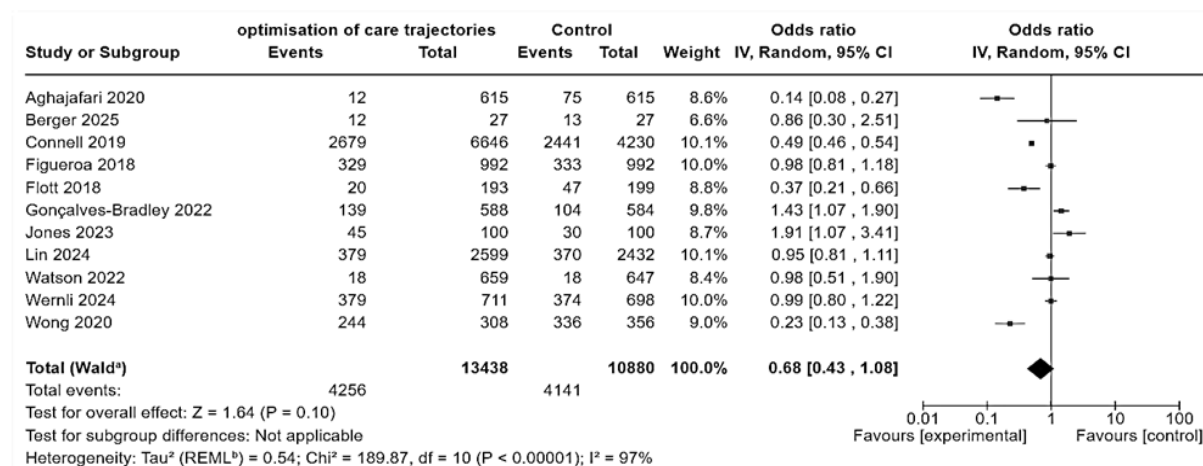


Figure 4. The Effect of Digital Transformation with AI on Care Trajectory Optimization. Source: Authors et al; 2025

show statistically significant effects in favor of AI, with confidence intervals not crossing the line of no effect. On the other hand, some studies, such as those by Berger (2025) or Lin (2024), show wide CIs crossing the line of no effect, indicating uncertainty or a non-significant effect. The overall estimate (represented by the black diamond at the bottom of the graph) gives a combined odds ratio of 0.68 [0.43, 1.08], suggesting a 32% reduction in the risk of IA on optimizing care trajectories. However, as the confidence interval crosses the value of 1, this effect is not statistically significant ($p = 0.10$). Furthermore, the analysis reveals high heterogeneity between studies ($I^2 = 97\%$), indicating that results vary significantly from one study to another, likely due to differences in clinical settings, AI types, or study populations, which suggests that these factors may influence the effect size in randomly selected trials.

Effects of trajectory optimization on length of stay

Improvements in care pathways, particularly through the use of artificial intelligence (AI), can have a significant impact. This highlights indicators such as length of hospital stay (Figure 5).

This meta-analysis compares the average length of hospital stay (LOS) between care pathways incorporating artificial intelligence (AI) and standard care. After pooling the data using a random effects model, the results show

a significant reduction in length of stay in favor of care pathways incorporating AI: the overall mean difference is -1.43 days [95% CI -2.49 to -0.37], with a significant overall test ($Z = 2.64$; $p = 0.008$). The majority of studies (Aghajafari 2020, Eskreis-Winkler 2023, Flott 2018, Hassan 2020, Thomas Rotter 2008) report a net benefit from the integration of AI, ranging from -1.8 to -3 days on average, while one study (Shimabukuro 2017) shows a non-significant trend. The heterogeneity between studies is moderate but significant ($I^2 = 63\%$, $\text{Chi}^2 = 13.37$; $p = 0.02$), reflecting some methodological and contextual variability, likely related to patient types, clinical contexts (emergency, intensive care, scheduled care), and AI integration modalities.

The effect of trajectory optimization on readmission

Six studies analyzed the impact of optimizing the care pathway using artificial intelligence (AI) on patient readmission rates. Overall, the results of these different studies reveal heterogeneity in the observed effectiveness (Figure 6).

This meta-analysis examines the impact of integrating artificial intelligence (AI) into care pathways compared to standard practices, based on odds ratios of clinical events. The overall effect, estimated using a random effects model, gives a combined OR of 0.37 [95% CI 0.11–1.24], with a non-significant overall test ($Z = 1.60$; $p = 0.11$). This

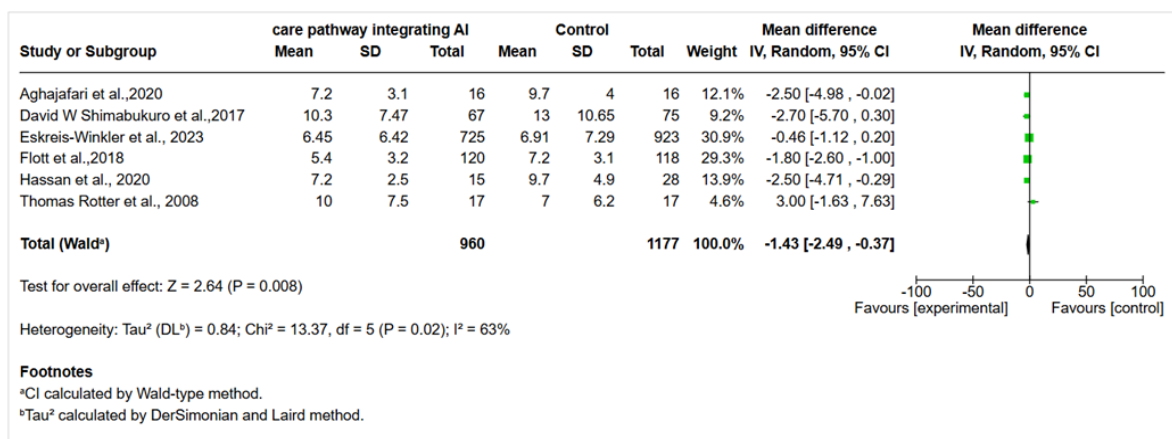


Figure 5. Effects of Care Path Optimization on Length of Stay. Source: Authors et al; 2025

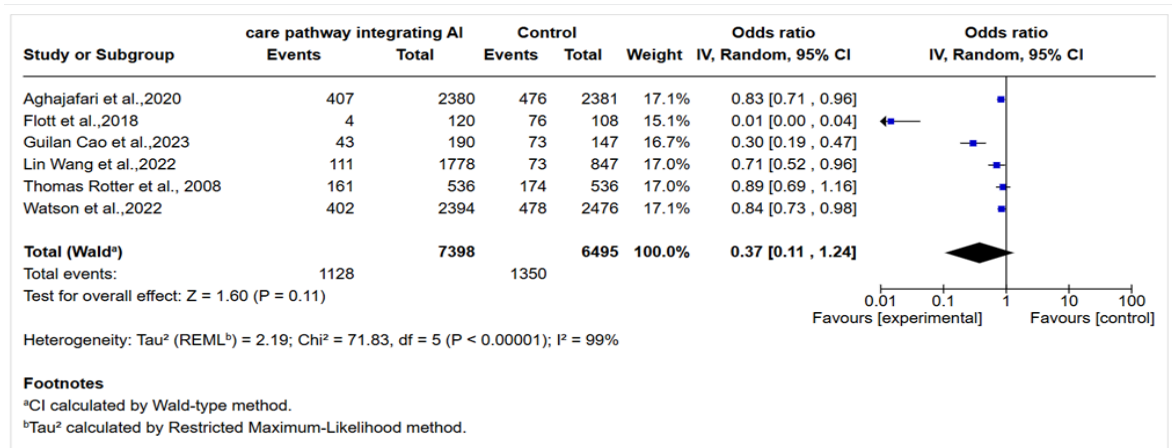


Figure 6. The Effect of Trajectory Optimization on Readmission. Source: Authors et al; 2025

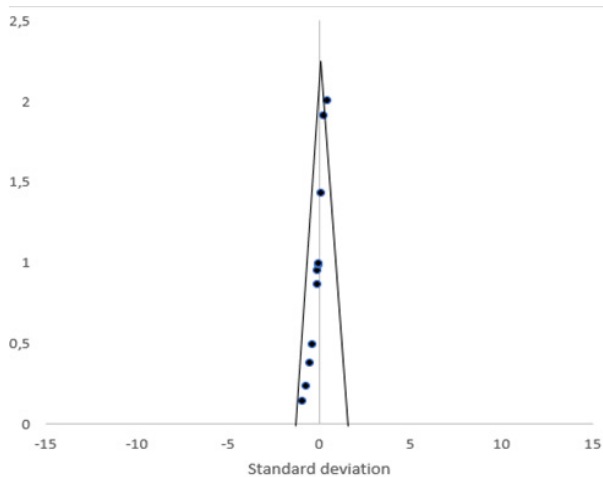


Figure7. Funnel Chart Analysis. Source: Authors et al; 2025

result suggests a trend in favor of AI-integrated pathways (reduced risk of events), but without reaching statistical significance.

Study report

The results section concludes with a review of studies reporting non-significant results. Which are less likely to be published, such as “The effect of digital transformation with AI on the optimization of care pathways,” which could introduce bias into the conclusions of the meta-analysis. In this sense, the funnel plot shows a relatively symmetrical distribution (Figure 7), as the points are generally concentrated around the central line, suggesting certain symmetry. This symmetry indicates that the published studies include both positive and negative results, thus reinforcing the reliability of the meta-analysis conclusions. Furthermore, the concentration of points in the upper part of the graph reflected relatively high statistical precision for several studies. However, given the limited number of studies included, this visual assessment remained indicative and would have benefited from being supplemented by specific statistical tests. This suggested a notable absence of publication bias.

Discussion

This study provided a systematic review complemented by a meta-analysis of interventions concerning the effectiveness of adopting AI-optimized pathways on patient-related outcomes. Of course, the graphical presentation of the effect of these pathways on optimizing care trajectories with the diamonds and confidence interval facilitated understanding of the effects, the 12 studies highlighting the variability of results across studies. The odds ratio of 2.02 is particularly significant, as it indicates a marked increase in the chances of success with these protocols, which include “e.g. fast-track, rapid diagnosis” [15]. The Structured Care Protocol (SCP) would enable patients to be discharged 1.83 times faster [16]. However, some studies present uncertainties, particularly when the confidence interval crosses the no-effect line, reflecting a rigorous and nuanced scientific approach [17]. Overall,

these results support the idea that standardising and optimising care processes can have a tangible effect, while calling for cautious interpretation of the data.

On the other hand, the impact of artificial intelligence on the optimization of care pathways is presented by the meta-analysis of 11 studies, which brings together a diverse population of 4,256 patients and offers a very interesting overview. It is encouraging to see that the majority of studies show a trend in favor of AI, particularly with statistically significant results in some cases. This highlights the hope that this technology can bring concrete improvements in clinical practice, notably through shadowing, deep/machine learning, Random Forest, latent class analysis (LCA), optimal matching [16], continuous-time hidden Markov models [16], streaming [16], Business Process Model [16]. and Notation, the Seizure Care Pathway [18], (PPDL, NHSEDA, BOOST, STAAR, and Digital Workflow) [16]. The overall estimate, with an odds ratio of 0.68 indicating a potential reduction in risk, is both encouraging and prudent. The mention of the confidence interval crossing the no-effect line shows that it is important to continue investigating, but this does not detract from the potential that this technology has already shown. The significant heterogeneity between studies also reflects the complexity of the subject and the need to better understand the contexts in which AI can be most effective. A total of 31 interventions involving 60,922 patients were identified. The application of AI in care pathways did not reduce the number of hospital readmissions after discharge from the emergency department, but it did significantly improve length of stay and hospitalization costs. In fact, three of 16 of these studies [16, 17, 19] found a significant improvement in these indicators with an odds ratio (OR=1.33), suggesting that AI-optimized pathways may be adequate for improving these indicators, namely length of stay and hospitalization costs. Among the advantages listed in “Appendix A”, “a 25% reduction in length of stay, corresponding to a reduction of more than 60% in waiting time.” Also, “a reduction in stays in nursing homes from 34% to 11%. In addition, the available studies are highly heterogeneous in terms of patients, interventions and outcomes, which complicates the identification of the most relevant configurations according to context. Furthermore, the lack of a unified and reliable database limits the transferability of conclusions, forcing decision-makers to assess the benefits, costs and constraints specific to each local situation before implementing these pathways [20].

Furthermore, the majority of studies show stability in the results, with confidence intervals that include the value of 1. Based on current research, this suggests that the implementation of AI in these contexts has not yet had a statistically significant effect on readmission rates. However, this lack of overall effect should not discourage further research, but rather encourage it, in order to better understand the conditions under which AI could ultimately bring about concrete improvements. The overall impression, with an odds ratio (OR) of around 0.83, shows a promising trend, even if it is not yet strong enough to draw definitive conclusions. Optimising patient care pathways requires a comprehensive approach that considers individual characteristics, environmental

influences and the seamless coordination of services across various healthcare settings. By deepening our understanding of these pathways and implementing evidence-based practices, patient outcomes can be improved, the quality of care enhanced, and positive transformations in healthcare practices promoted.

Further exploration is needed to investigate innovative strategies for effectively implementing optimal care pathways with AI across diverse healthcare settings. Overall, our results are similar to those of other studies. The research conducted by Vanasse et al. [20] highlights the importance of identifying optimal care pathways tailored to each patient's reality.

By defining patient care pathways based on various individual and environmental factors, it becomes possible to assess differences in these pathways and their effects on patient health outcomes [20]. Of course, according to Fernandes et al., optimizing patient pathways faces significant obstacles, particularly when it comes to coordinating care for people with multimorbidity [21]. Furthermore, according to Allam et al., technological advances such as robot-assisted total knee arthroplasty (TKA) introduce new considerations for optimizing care pathways. Although these innovations offer advantages such as increased precision and reduced radiation exposure, challenges regarding implant specificity and cost-effectiveness must be addressed to facilitate wider adoption [22]. Overall, socioeconomic factors also play an important role in determining hospital care pathways and costs. Recognizing how socioeconomic status affects care pathways can help create more effective and inclusive healthcare strategies [23]. From a strategic standpoint, these findings highlight the importance of establishing clear governance structures for digital innovation. This requires the development of comprehensive ethical, legal and operational frameworks to facilitate the deployment of artificial intelligence in healthcare settings while securing the support and involvement of healthcare professionals and patients. Furthermore, longitudinal studies are particularly pertinent in order to elucidate the long-term effects of these technologies on clinical outcomes such as mortality, morbidity and quality of life, as well as organisational performance including efficiency, continuity and coordination of care. Without such evaluations, it would be imprudent to implement these tools more widely when their long-term implications remain uncertain.

In conclusion, the limitations of the systematic review are acknowledged. Firstly, there was considerable variability in control conditions, outcome definitions, measurement methods and assessment timing. Additionally, significant heterogeneity was observed due to the diversity of clinical contexts, which added to the complexity of the meta-analysis. Furthermore, the meta-analysis includes data from several countries with significant differences in healthcare systems, which contributes to the observed variability. Secondly, many studies appear to provide insufficient or imprecise descriptions of AI-based interventions aimed at improving care pathways. Finally, while this study includes interventional research,

the objectivity and reliability of the collected data may be questionable. The quality of the included studies is also a limitation, as the risk-of-bias assessment may indicate that other types of bias influenced the results. To assess the robustness of the evidence, the GRADE criteria were applied, taking into account the limitations inherent in the included studies.

In Conclusion, this systematic review aims to evaluate the impact of clinical pathways and AI on care pathways, as well as the effect of the latter on hospital length of stay, healthcare costs, and patient outcomes. The aim is to develop a framework to help healthcare organizations optimize clinical pathways and care protocols as a patient management strategy. A selection strategy was implemented to identify all relevant studies. Thirty-one studies that met the inclusion criteria were included. The quality of the included studies was moderate, and those reporting economic data generally had a limited scope. Overall, most studies on economic outcomes (length of stay and hospital costs) reported positive effects. Specifically, of the 16 studies on length of stay, three showed significant reductions. Group analyses revealed that clinical pathways optimized the care pathway. There was no evidence of an increase in hospital readmissions or complications associated with the use of clinical pathways.

The overall odds ratio (OR) for readmission was 0.68, indicating a moderate but significant decrease in the average length of hospital stay. However, substantial heterogeneity was observed among studies reporting the effect of AI on pathway optimization. Finally, due to the limited number of studies that met the inclusion criteria, there is insufficient evidence to establish a universally applicable framework for all clinical pathway strategies. The data suggest that clinical pathways are particularly effective in healthcare settings. When implementing AI-based clinical pathways, decision-makers must consider the potential benefits and costs within the context of specific healthcare settings and market dynamics.

Author Contribution Statement

Conceptualization, formal analysis, methodology, writing - original draft, software, and visualization, M.A.; data curation, writing- review and editing, and validation, N.B.K.; resources, project administration, supervision, and validation, L.A.; validation and writing- review and editing, A.B. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

OR: odds ratio;

PRISMA: Preferred Reporting Items for Systematic reviews and Meta- Analyses;

CI: Confidence Intervals;

RCTs: Randomized controlled trial

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