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RESEARCH PAPER

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Lean and Artificial Intelligence for Healthcare Operational Efficiency: A Systematic Literature Review of Implementation Strategies and Research Gaps

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Abstract **Healthcare organizations are under sustained pressure to improve operational efficiency without compromising quality, yet evidence on how artificial intelligence (AI) is combined with Lean methods, and whether such combinations produce measurable operational gains, remains fragmented. This systematic review aimed to synthesize implementation strategies, quantify reported operational outcomes, and identify research gaps in Lean–AI applications in healthcare. Scopus, PubMed, and IEEE Xplore were searched for English-language studies published in 2020–2025 following PRISMA 2020. Two reviewers screened records, appraised quality with design-specific tools, and extracted data; outcomes were harmonized as absolute differences, relative changes, and predictive metrics, and were synthesized through narrative and inductive thematic analysis. Of 729 records, 17 studies were included. Four themes emerged: predictive decision support (6/17; 35.3%), data-driven process analysis and redesign (5/17; 29.4%), intelligent workflow automation (4/17; 23.5%), and smart operational resource optimization (2/17; 11.8%). Only five studies (29.4%) explicitly integrated a Lean methodology with AI; the remaining 12 (70.6%) applied AI to operational improvement without a formal Lean method. Nine studies (52.9%) reported observed operational changes, whereas eight reported predictive performance, simulation estimates, or descriptive process analyses. Observed improvements included a 42.70% reduction in physics chart-check time (52.83 to 30.27 h), a 22.83% reduction in laboratory turnaround time (34.43 to 26.57 min), and a decrease in red blood cell wastage from 26% to 6% (−20 percentage points). Effects were not uniformly positive: one emergency department intervention reduced time to physician assessment by 13 min but increased length of stay by 29 min. AI can support operational improvements consistent with Lean principles, but evidence for explicitly integrated Lean–AI approaches is limited, mostly single-centre, and heterogeneous. Prospective multicentre evaluations with standardized operational metrics and long-term sustainability assessment are needed.**

Keywords **Artificial Intelligence; Healthcare Operations; Lean in Healthcare; Lean and AI Integration; Operational Efficiency**

I. Introduction

Health systems face rising demand driven by population ageing, chronic disease, workforce shortages, and growing expectations for safe, patient-centred care [1], [2]. Global health spending reached approximately US$9.8 trillion, or 10.3% of world gross domestic product, in 2021, yet higher spending has not guaranteed equitable access, efficient resource use, or resilient services [2], [3]. Improving operational efficiency, that is, achieving the same or better outcomes while consuming fewer resources and generating less waste, has therefore become central to sustainable, value-based healthcare [4]–[6]. Lean management is one of the most widely adopted approaches for this purpose. It targets non-value-adding activities, standardizes work, improves flow, and institutionalizes continuous improvement [7],[8]. It targets non-value-adding activities, standardizes work, improves flow, and institutionalizes continuous improvement [9]. Lean interventions have reduced waiting time and length of stay (LOS), and a four-year Lean redesign of a surgical process generated annual operational savings exceeding EUR 8.5 million [10]. Evidence from Indonesian healthcare settings further illustrates the application of Lean Management in improving operational efficiency. Meidawati and Arini [11] demonstrated how Lean Management can be applied to reduce waste in emergency department services. Similarly, Prima and Arini [12] reported improvements in Code Blue response time through Lean-based process redesign and Value Stream Mapping. In outpatient pharmacy services, Tohaga et al. [13] also demonstrated the potential of Lean interventions to reduce medication waiting time and improve process efficiency. These studies highlight the applicability of Lean principles across different healthcare services and operational processes. However, conventional Lean approaches rely largely on

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manual observation, value-stream mapping, and retrospective evaluation, which limits their responsiveness in data-intensive and rapidly changing hospital environments [8], [9].

Artificial intelligence (AI), including machine learning, predictive analytics, process mining, digital twins, and clinical decision support, offers capabilities that address these limitations: forecasting demand, prioritizing patients, automating repetitive tasks, and revealing actual process behaviour from event logs [14]–[16]. Nevertheless, AI deployment remains concentrated in individual units, and better model performance does not automatically yield operational benefit. In a review of 48 real-world imaging studies, 67% of the 33 studies that measured task time reported reductions, yet three meta-analyses of 12 studies showed no significant efficiency effect [17]. Adoption is further shaped by infrastructure, workload, trust, and ethical–legal factors [18]. These complementary strengths underpin the concept of Lean 4.0, in which Lean supplies the improvement logic (problem definition, waste identification, standardization, and Plan–Do–Study–Act [PDSA] cycles) and digital technologies supply sensing, prediction, and automation [19]–[21]. Primary studies have begun to operationalize this combination, for example by pairing Lean Six Sigma with machine learning to assess patient management [22], embedding deep-learning image inspection and simulation in Lean laboratory redesign [23], using Toyota Production System methods with time-series analytics to reduce blood wastage [24], developing an electronic case-finding tool through Lean and PDSA cycles [25], and combining Lean Six Sigma with predictive scheduling in patient logistics [26]. Other studies applied AI to emergency department (ED) capacity management [27], [28], appointment scheduling [29], and process mining of care pathways [30]–[32] without a formal Lean method.

Operational efficiency in healthcare is usually assessed through time-based indicators (waiting time, turnaround time, LOS), flow indicators (throughput, census, patients leaving without being seen), utilization indicators (bed, operating-room, or staff utilization), and waste indicators (unused blood products, cancelled procedures, rework) [4], [33]. These indicators are interdependent: queueing theory shows that utilization, arrival rate, and waiting time are linked, so improving one indicator can worsen another. Evaluating Lean or AI interventions therefore requires a coherent set of metrics rather than a single favourable indicator, a requirement that previous reviews have not operationalized. Previous reviews address this evidence only partly. Tlapa et al. reviewed 28 Lean interventions supported by digital technologies and identified simulation and automation as the main supporting technologies, with EDs and laboratories as the main settings [33]. Dionisio et al. mapped digital transformation in healthcare through bibliometric and content analyses without examining Lean [34], Talero-Sarmiento et al. synthesized 44 Lean healthcare reviews without considering AI [9], and application-specific reviews examined AI for scheduling [35] or process mining [36] in isolation. None distinguished studies that explicitly integrate Lean with AI from those that apply AI to operational problems without Lean, and none separated observed operational change from predictive accuracy or simulated benefit, although these distinctions determine how far the evidence can support managerial decisions.

This review therefore aimed to examine how Lean and AI are applied, separately or together, to improve healthcare operational efficiency, to synthesize recurring implementation patterns, and to identify research gaps. Three questions guided the review: (RQ1) How are Lean and AI applied or integrated to improve healthcare operational efficiency? (RQ2) Which implementation patterns recur across healthcare settings? (RQ3) Which research gaps and future directions emerge from the evidence? Using PRISMA 2020, design-specific quality appraisal, quantitative harmonization of outcomes, and inductive thematic synthesis, the review makes three contributions. First, it proposes an empirically grounded four-theme framework (predictive decision support, intelligent workflow automation, data-driven process analysis and redesign, and smart operational resource optimization) that links AI capabilities to Lean improvement objectives. Second, it explicitly separates the five Lean–AI integrated studies from the 12 AI-supported studies and classifies every outcome as observed, predictive, simulated, or descriptive, using 23 formally defined metrics. Third, it derives an implementation pathway and a research agenda for healthcare decision-makers.

II. Materials and Method

This systematic literature review followed established guidance for structured reviews [37] and was reported according to PRISMA 2020 [38]. The complete workflow is summarized in Fig. 1 (selection flow) and Fig. 2 (methodological block diagram) and comprised eight sequential steps: identification, pre-screening and duplicate removal, screening, eligibility assessment, quality appraisal, data extraction, metric harmonization, and thematic synthesis.

A. Review Framework and Search Strategy

The research questions and search strategy were structured with the Population–Concept–Context (PCC) framework, which suits reviews that map implementation mechanisms rather than test effectiveness against a predefined comparator. The population comprised healthcare organizations (hospitals, clinics, EDs, laboratories, and other providers); the concept was Lean management, AI, and their integration; and the context was healthcare operational processes, including workflow, patient flow, waiting time, LOS, resource utilization, waste, and productivity. Scopus (multidisciplinary), PubMed (biomedical and health services), and IEEE Xplore (engineering and computing) were searched on 16 July 2026 with database-specific Boolean strings adapted to each interface (Table 1).

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Table 1. Database-specific search strategies used to identify studies on Lean management, artificial intelligence, and healthcare operational efficiency. Searches were conducted in Scopus, PubMed, and IEEE Xplore on 16 July 2026 using Boolean operators and database-specific search fields. The searches targeted journal articles published between 2020 and 2025.

Scopus	16 July 2026	TITLE-ABS-KEY(("Lean Management in Healthcare" OR "Lean Six Sigma" OR "Lean Management" OR "Lean Thinking" OR Kaizen OR "Process Improvement") AND ("Artificial Intelligence" OR AI OR "Machine Learning" OR "Deep Learning" OR "Large Language Model" OR LLM OR "Natural Language Processing" OR NLP OR "Predictive Analytics" OR "Process Mining" OR "Digital Twin" OR "Decision Support System") AND (Hospital OR Healthcare OR Clinic) AND ("Operational Efficiency" OR "Patient Flow" OR Workflow OR "Resource Utilization")) AND LIMIT-TO(OA, "all") AND LIMIT-TO(SRCTYPE, "j") AND PUBYEAR > 2019 AND PUBYEAR < 2026
PubMed	16 July 2026	("Total Quality Management"[MeSH Terms] OR "Lean Management in Healthcare"[Title/Abstract] OR "Lean Six Sigma"[Title/Abstract] OR "Lean Management"[Title/Abstract] OR "Kaizen"[Title/Abstract]) AND ("Artificial Intelligence"[MeSH Terms] OR "Machine Learning"[MeSH Terms] OR "Large Language Models"[MeSH Terms] OR "artificial intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "large language model"[Title/Abstract] OR "natural language model"[Title/Abstract] OR "process mining"[Title/Abstract] OR "predictive analytics"[Title/Abstract]) AND ("Delivery of Health Care"[MeSH Terms] OR healthcare[Title/Abstract] OR clinic[Title/Abstract]) AND ("Workflow"[MeSH Terms] OR "operational efficiency"[Title/Abstract] OR "patient flow"[Title/Abstract] OR workflow[Title/Abstract] OR "resource utilization"[Title/Abstract] OR "waiting time"[Title/Abstract])
IEEE Xplore	16 July 2026	("Mesh_Terms":lean OR "Mesh_Terms":lean healthcare OR "Mesh_Terms":lean six sigma OR "Mesh_Terms":kaizen) AND ("Mesh_Terms":artificial intelligence OR "Mesh_Terms":machine learning OR "Mesh_Terms":deep learning OR "Mesh_Terms":process learning) AND ("Mesh_Terms":hospital OR "All Metadata":healthcare OR "Mesh_Terms":clinic)

B. Eligibility Criteria

Eligible records were peer-reviewed original research articles published in English between 2020 and 2025, available in full text, conducted in a healthcare service setting, applying Lean (e.g., Lean, Lean Six Sigma, Kaizen, or the Toyota Production System), AI (e.g., machine learning, deep learning, natural language processing, clinical decision support, predictive analytics, process mining, digital twins, or intelligent scheduling), or both, and reporting at least one operational efficiency outcome. Reviews of any type, editorials, letters, conference abstracts, book chapters, theses, commentaries, conceptual papers, and non-peer-reviewed publications were excluded, as were studies outside healthcare services, studies of conventional information systems without AI, and studies limited to diagnosis, disease prediction, imaging, genomics, drug discovery, or therapeutic effectiveness without an operational link.

C. Study Selection

Records were imported into Rayyan for duplicate detection and blinded screening; Mendeley was used only for reference management. Two reviewers independently screened titles, abstracts, and full texts against the criteria and resolved disagreements through discussion. The searches yielded 729 records (Scopus 218, PubMed 322, IEEE Xplore 189). Fifty-two records were removed before screening (51 by database filters and one duplicate), leaving 677 records. Title screening excluded 452 records, and title–abstract assessment excluded a further 191, leaving 34 full texts. Of these, 17 were excluded (13

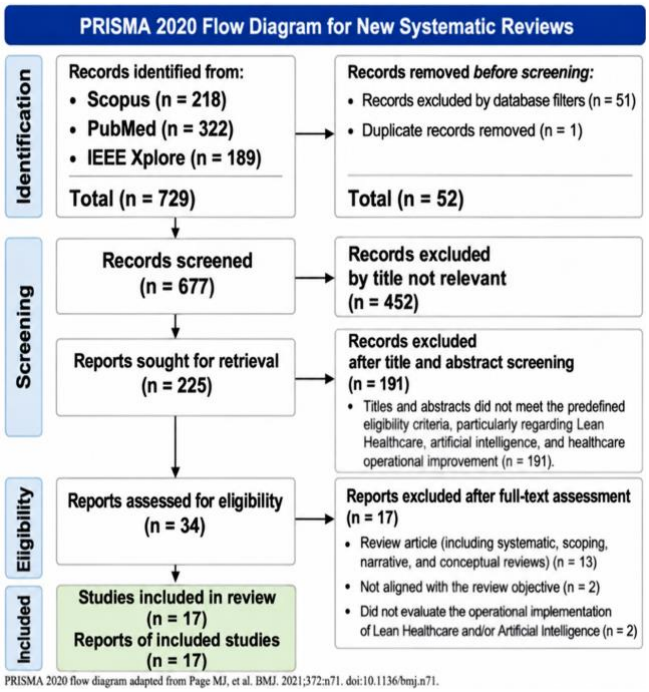

Fig 1. PRISMA 2020 flow diagram of the identification, screening, eligibility assessment, and final inclusion of studies in the systematic literature review. A total of 729 records were retrieved from Scopus (n = 218), PubMed (n = 322), and IEEE Xplore (n = 189), yielding 17 eligible studies.

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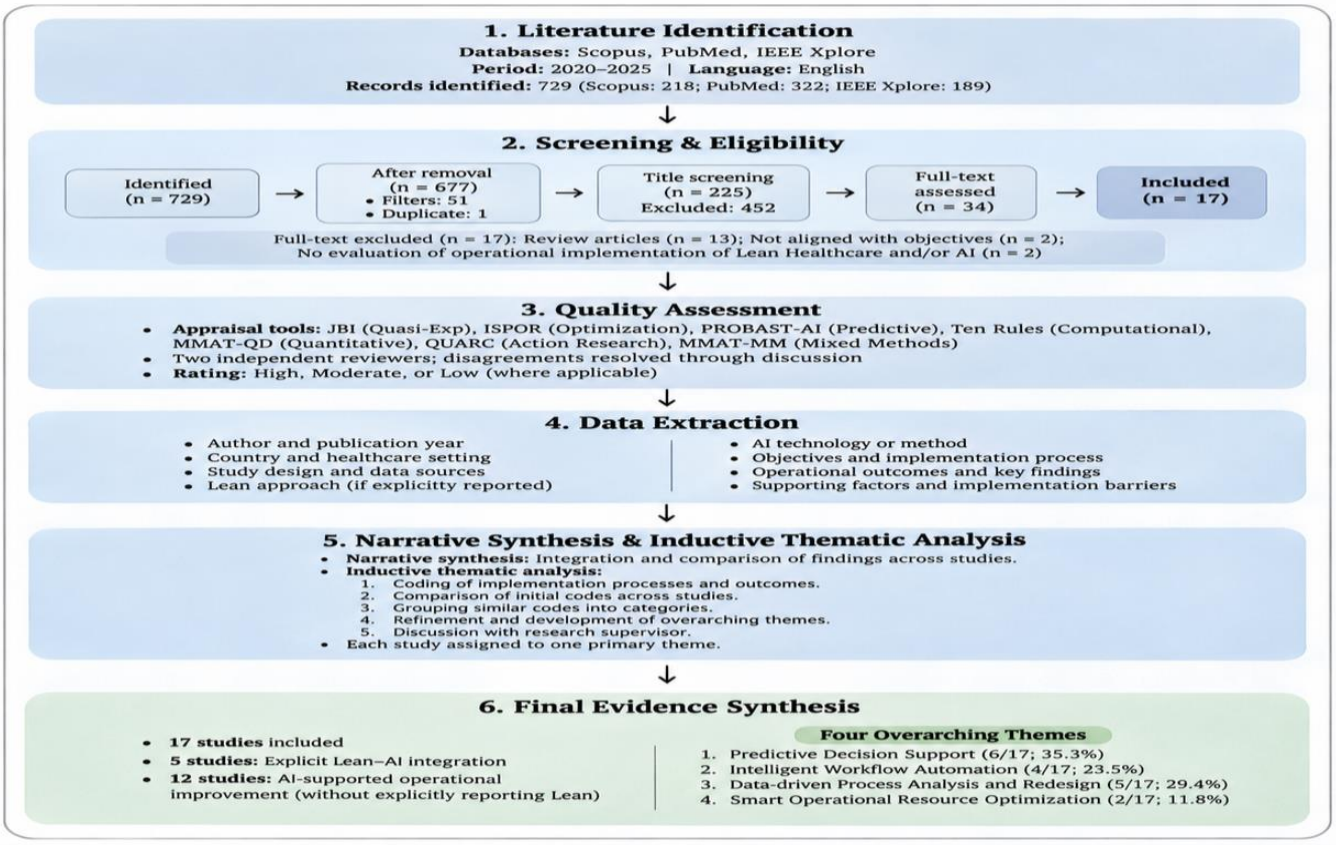

Fig 2. Methodological framework of the systematic literature review, depicting the sequential process of literature identification, screening and eligibility assessment, methodological quality appraisal, data extraction, harmonization of quantitative results, and narrative and inductive thematic synthesis. The framework distinguishes studies that explicitly integrate Lean and artificial intelligence (AI) from AI-supported operational improvement studies.

review articles, two not aligned with the review objective, and two without an operational evaluation of Lean and/or AI), and 17 studies were included (Fig. 1).

D. Quality Appraisal and Data Extraction

Because the included studies used diverse designs, methodological quality was appraised with design-specific instruments: the Joanna Briggs Institute (JBI) checklist for quasi-experimental studies for before–after and interrupted time-series designs; International Society for Pharmacoeconomics and Outcomes Research (ISPOR) guidance for optimization modelling; the Prediction model Risk Of Bias ASsessment Tool for AI (PROBAST+AI) for predictive modelling; the Ten Simple Rules for computational modelling; the Mixed Methods Appraisal Tool (MMAT 2018) for quantitative descriptive (MMAT-QD) and mixed-methods (MMAT-MM) studies; and the Quality Appraisal and Review Checklist (QuARC) for action research. Two reviewers appraised each study independently and reached consensus, and the overall judgement was categorized as high, moderate, or low. Because the instruments use different criteria, no common numerical score was calculated. Moreover, the categories are not directly equivalent across instruments; therefore, item-level judgements are provided in the Supplementary Material.

Data were extracted independently by the two reviewers into a standardized form covering author, year, country, setting, design, data source, Lean approach, AI technique, objectives, operational outcomes with their numerical values, enabling factors, and barriers. The extracted data were cross-checked against the original articles, and any discrepancies were resolved by consensus. Microsoft Excel was used to compile the extraction and appraisal matrices.

E. Thematic Synthesis and Lean–AI Classification

Narrative synthesis was combined with inductive thematic analysis. The primary reviewer coded the implementation mechanisms and operational outcomes of each study; codes describing similar mechanisms were grouped into categories and iteratively refined into overarching themes until no substantially new category emerged, and the coding structure was reviewed with the supervising author for conceptual consistency. Each study was assigned to one primary theme according to its predominant operational mechanism. Explicit Lean–AI integration was defined as the reported application of both a Lean methodology and an AI technique within the same study, whereas AI-supported operational improvement denoted the use of AI to improve operational processes without a reported Lean methodology; improvements merely consistent with Lean principles were not counted as Lean implementation. Finally, each study's principal outcome

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was classified as an observed operational change, predictive performance, a simulation-based estimate, or a descriptive process analysis. The complete procedure is formalized in Algorithm 1, and the resulting codebook is reported with the thematic results.

Table 2. Characteristics and methodological quality appraisal of the 17 studies included in the systematic review. The table summarizes publication year, country, healthcare setting, study design, Lean methodology, AI technique, thematic classification, and quality appraisal. T1–T4 denote the four thematic categories; ED, emergency department; QI, quality improvement; JBI, Joanna Briggs Institute; ISPOR, International Society for Pharmacoeconomics and Outcomes Research; MMAT, Mixed Methods Appraisal Tool; PROBAST+AI, Prediction Model Risk of Bias Assessment Tool for Artificial Intelligence; and QuARC, Quality Appraisal and Review Checklist. H, M, and L denote high, moderate, and low methodological quality, respectively.

No	Study	Country; setting	Design	Lean approach	AI technique	Theme	Q (tool)
1	Yeoh et al., 2025 [27]	Australia; ED	QI before–after	Not explicit	Real-time and predictive analytics (Azure ML)	T1	M (JBI)
2	Valenzuela-Núñez et al., 2024 [29]	Chile; outpatient specialties	Optimization modelling	Not explicit	No-show prediction (SVM, DT, NN, LR, NB) with overbooking optimization	T1	H (ISPOR)
3	Feral-Pierssens et al., 2024 [40]	Canada; ED	Interrupted time series	Not explicit	Electronic clinical decision support for redirection	T2	M (JBI)
4	Agius et al., 2025 [28]	Malta; ED	Retrospective predictive	Not explicit	XGBoost triage, admission, and ward models	T1	M (PROBAST+ AI)
5	Yuan et al., 2025 [41]	China; paediatric surgery ward	QI before–after (prospective)	Not explicit	AI-assisted closed-loop mobile nursing system	T2	M (JBI)
6	Ricciardi et al., 2024 [42]	Italy; ED	Retrospective predictive	Not explicit	ML classifiers for ED-LOS (random forest best)	T2	H (PROBAST+ AI)
7	Moretti et al., 2025 [43]	UK; histopathology laboratory	Computational modelling	Not explicit	Space-aware digital twin, BIM–DES, IoT	T3	M (Ten Rules)
8	Salehinejad et al., 2024 [44]	USA; inpatient wards	Retrospective predictive	Not explicit	Contrastive transfer learning vs. XGBoost, RF, SVM	T1	H (PROBAST+ AI)
9	Bakhtiari, 2025 [30]	USA; radiation oncology	QI before–after	Not explicit (process-mining quality management)	Process mining (Alpha, Inductive, Heuristic Miner)	T3	M (JBI)

ED = emergency department; QI = quality improvement; H/M/L = high/moderate/low; ML = machine learning; DES = discrete-event simulation; AGV = automated guided vehicle; EHR/EMR = electronic health/medical record.

III. Results

A. Characteristics of the Included Studies

The 17 included studies were conducted in 11 countries (Table 2). Applying Eq. (1), the United States contributed four studies (23.5%), Italy three (17.6%), Germany two (11.8%), and Australia, Canada, Chile, China, Malta, Mexico, Singapore, and the United Kingdom one each (5.9% each). EDs were the most frequent setting (5/17; 29.4%), followed by inpatient wards (4/17; 23.5%), hospital logistics and patient transport (3/17; 17.6%), clinical laboratories (2/17; 11.8%), radiation oncology

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Table 2. (Continued) Characteristics and methodological quality appraisal of the 17 studies included in the systematic review. The table summarizes publication year, country, healthcare setting, study design, Lean methodology, AI technique, thematic classification, and quality appraisal. T1–T4 denote the four thematic categories; ED, emergency department; QI, quality improvement; JBI, Joanna Briggs Institute; ISPOR, International Society for Pharmacoeconomics and Outcomes Research; MMAT, Mixed Methods Appraisal Tool; PROBAST+AI, Prediction Model Risk of Bias Assessment Tool for Artificial Intelligence; and QuARC, Quality Appraisal and Review Checklist. H, M, and L denote high, moderate, and low methodological quality, respectively

No	Study	Country; setting	Design	Lean approach	AI technique	Theme	Q (tool)
10	Improta et al., 2022 [22]	Italy; neurology and stroke unit	Retrospective observational	Lean Six Sigma (DMAIC)	ML (DT, RF, GBT, SVM, LR)	T1	H (MMAT-QD)
11	Franco-Alucano et al., 2025 [23]	Mexico; public clinical laboratory	Action research	Lean Healthcare 4.0	Deep learning (YOLOv11/v12) with simulation	T2	L (QuARC)
12	Liu et al., 2020 [39]	Singapore; greenfield hospital	Computational modelling	Not explicit	Digital twin, robotic process automation (AGVs, robotic porters), SIMIO	T3	L (Ten Rules)
13	Stoffel et al., 2023 [24]	USA; paediatric inpatient	Interrupted time series	Toyota Production System	EHR ordering decision support; changepoint and causal-impact analytics	T4	M (JBI)
14	Kropp et al., 2023 [31]	Germany; patient transport	Retrospective observational	Not explicit	Process mining (Fuzzy and Heuristic Miner, Celonis)	T3	H (MMAT-QD)
15	Zeiler & Strazovska, 2025 [26]	Germany; three urban hospitals	Mixed methods	Lean Management and Six Sigma	Predictive analytics, dynamic scheduling, real-time dashboards	T4	M (MMAT-MM)
16	Gallagher et al., 2024 [25]	USA; ED case management	QI before–after	Lean and PDSA	EMR-based automated case-finding priority score	T1	M (JBI)
17	Placidi et al., 2021 [32]	Italy; radiotherapy	Retrospective observational	Not explicit	Process mining (Markov models, pMineR)	T3	M (MMAT-QD)

ED = emergency department; QI = quality improvement; H/M/L = high/moderate/low; ML = machine learning; DES = discrete-event simulation; AGV = automated guided vehicle; EHR/EMR = electronic health/medical record.

(2/17; 11.8%), and outpatient scheduling (1/17; 5.9%). Quality improvement before–after studies were the most common design (4/17; 23.5%), followed by retrospective predictive modelling (3/17; 17.6%), retrospective observational studies (3/17; 17.6%), interrupted time series (2/17; 11.8%), computational modelling (2/17; 11.8%), and optimization modelling, action research, and mixed methods (1/17 each; 5.9%). Methodological quality was high in five studies (29.4%), moderate in ten (58.8%), and low in two (11.8%); the low ratings concerned an action-research study with limited reporting of data collection [23] and a computational model without empirical validation [39].

B. Lean Approaches and AI Technologies

Five studies (5/17; 29.4%) explicitly reported a Lean methodology alongside AI: Lean Six Sigma using DMAIC [22], Lean Healthcare 4.0 [23], the Toyota Production System [24], Lean with PDSA cycles [25], and Lean Management with Six Sigma [26]. The remaining 12 studies (70.6%) pursued Lean-consistent goals, such as better flow, shorter waiting, and higher utilization, without a formal Lean method. By primary technique, supervised machine learning and predictive analytics were most common (8/17; 47.1%), followed by process mining (3/17; 17.6%), decision support and AI-assisted automation (3/17; 17.6%), digital twins and simulation (2/17; 11.8%), and deep-learning computer vision (1/17; 5.9%). Explicit Lean–AI integration focused on resource optimization (2/2 studies) and predictive decision support (2/6), but was absent from data-driven process analysis and redesign

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Table 3. Harmonized operational and predictive outcomes reported across the 17 included healthcare studies. The table presents observed operational changes, predictive model performance, simulation-based estimates, and descriptive process findings. Quantitative measures include absolute difference (Δ; Eq. 2), relative change (RC; Eq. 3), relative reduction (RR; Eq. 4), percentage points (pp; Eq. 5), area under the receiver operating characteristic curve (AUC), length of stay (LOS), and turnaround time (TAT). Positive and negative changes are distinguished to identify operational improvements and unintended consequences.

No	Study	Outcome type	Key quantitative results
1	Yeoh et al. [27]	Observed	Ambulance transfer ≤30 min 61.4%→64.9% (+3.5 pp; RC +5.70%); category 2 seen ≤10 min 76.3%→78.8% (+2.5 pp; +3.28%); did not wait 6.28%→6.19% (−0.09 pp; RR 1.43%).
2	Valenzuela-Núñez et al. [29]	Observed	Occupancy 52.26%→56.29% (+4.03 pp; +7.71%; p < 0.05); SVM no-show model AUC 0.85.
3	Feral-Pierssens et al. [40]	Observed	Time to physician −13 min (95% CI −16 to −11; SE 1.28, Eq. 15); left without being seen −2 pp; LOS +29 min (95% CI 13–44; SE 7.91; z = 3.67); category 2 LOS +58 min.
4	Agius et al. [28]	Predictive	Accuracy: prioritization 0.75→0.76 (+1.33%), admission 0.80→0.82 (+2.50%), ward 0.80→0.86 (+7.50%), sub-ward 0.69→0.75 (+8.70%); AUC 0.81, 0.90, 0.87, 0.78.
5	Yuan et al. [41]	Observed	Workflow completion 73.17%→94.89% (+21.72 pp; +29.68%); bedside settlement 66.16%→83.30% (+17.14 pp; +25.91%); critical-value reception +41.83 pp; satisfaction +14.35 pp; efficiency 3.03→25 tasks/h (as reported).
6	Ricciardi et al. [42]	Predictive	Random forest for ED-LOS > 3 h: accuracy 74.88%, precision 72.85%, recall 74.88%, F-measure 72.85% (Eqs. 16–19).
7	Moretti et al. [43]	Simulation	BIM-to-DES model showed longer specimen transfer and lower workflow efficiency during lift failures; reconfiguration evaluated as potential gain.
8	Salehinejad et al. [44]	Predictive	Accuracy 74.9%→81.9% (+7.0 pp; +9.35%); AUC 0.82→0.91 (+0.09).

(0/5).

C. Operational Outcomes and Effect Magnitudes

Table 3 summarizes the outcomes recomputed with Eqs. (2)–(5). Nine studies (52.9%) reported observed operational changes, four (23.5%) reported predictive or screening performance, two (11.8%) reported simulation-based estimates, and two (11.8%) reported descriptive process analyses. Observed operational evidence was more frequent among explicit Lean–AI studies (4/5; 80.0%) than among AI-supported studies (5/12; 41.7%), although the small numbers preclude statistical comparison. Among observed changes, the largest time reductions came from process redesign. In radiation oncology, physics chart-check time decreased from 52.83 to 30.27 h, an absolute difference of −22.56 h and a relative reduction (Eq. 4) of 42.70%, while overall throughput time fell from 15.48 to 10.29 days (−5.19 days; 33.53%) [30]. In a public laboratory, turnaround time decreased from 34.43 to 26.57 min (−7.86 min; 22.83%), turnover time from 1.93 to 0.17 min (−1.76 min; 91.19%), and pre-analytical lead time from 48.90 to 40.14 min (−8.76 min; 17.91%) [23]. In German patient logistics, triage waiting time fell from 45.2 to 30.3 min (−14.9 min; 32.96%), admission processing from 3.5 to 2.5 h (−1.0 h; 28.57%), and discharge processing from 2.00 to 1.02 h (−0.98 h; 49.00%) [26]. Across these nine time-based indicators from four studies, relative reductions ranged from 8.22% to 91.19% (median 32.96%); this descriptive summary is not a pooled estimate. Proportion-based outcomes were smaller but consistent. RBC wastage decreased from 26% to 6%, a change of −20 percentage points (Eq. 5) and a relative reduction of 76.92%; the crossmatch-to-transfusion ratio fell from 1.54 to 1.38 (−10.39%), and causal-impact analysis estimated that approximately 3,470 RBC units (61% of expected wastage) were not wasted [24]. Nursing workflow completion increased from 73.17% to 94.89% (+21.72 percentage points; +29.68%) and bedside settlement from 66.16% to 83.30% (+17.14 percentage points; +25.91%) [41]. Clinic occupancy increased from 52.26% to 56.29% (+4.03 percentage points; +7.71%; p <0.05) [29], and ambulance transfers within 30 min increased from 61.4% to 64.9% (+3.5 percentage points; +5.70%) [27]. Average LOS in a neurology and stroke unit decreased from 11.19 to 10.27 days (−0.92 days; 8.22%)[22]. One study showed opposite effects within the same pathway. After electronic redirection of low-acuity ED patients, time to initial physician assessment decreased by 13 min (95% CI −16 to −11), whereas overall LOS

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Table 3. (Continued) Harmonized operational and predictive outcomes reported across the 17 included healthcare studies. The table presents observed operational changes, predictive model performance, simulation-based estimates, and descriptive process findings. Quantitative measures include absolute difference (Δ; Eq. 2), relative change (RC; Eq. 3), relative reduction (RR; Eq. 4), percentage points (pp; Eq. 5), area under the receiver operating characteristic curve (AUC), length of stay (LOS), and turnaround time (TAT). Positive and negative changes are distinguished to identify operational improvements and unintended consequences.

No	Study	Outcome type	Key quantitative results
9	Bakhtiari [30]	Observed	Physics chart-check 52.83→30.27 h (Δ −22.56 h; RR 42.70%); throughput 15.48→10.29 days (−5.19 days; RR 33.53%).
10	Improta et al. [22]	Observed	Mean LOS 11.19→10.27 days (−0.92 days; RR 8.22%); DRG weight 1.15→1.35 (+17.39%); year effect OR 0.976 (LOS), 1.437 (DRG).
11	Franco-Alucano et al. [23]	Observed	TAT 34.43→26.57 min (−7.86; RR 22.83%); TOT 1.93→0.17 min (RR 91.19%); pre-analytical lead time 48.90→40.14 min (RR 17.91%); registration wait −25%, pre-sampling wait −20%; YOLOv11 precision 94.0%, recall 92.7%.
12	Liu et al. [39]	Simulation	AGVs 26→21 (−5; RR 19.23%); mean lift utilization 20.33% (< 75%, Eq. 22); 15 robotic porters for ~175 trips/day.
13	Stoffel et al. [24]	Observed	RBC wastage 26%→6% (−20 pp; RR 76.92%, Eq. 23); C:T ratio 1.54→1.38 (RR 10.39%); ~3,470 units saved (61% of expected wastage).
14	Kropp et al. [31]	Descriptive	36% of transports (~22,308) delayed ≥10 min; > 9,000 h annual delay; endoscopy route 774 delayed cases (~50%), ~330 h.
15	Zeiler & Strazovska [26]	Observed	Triage wait 45.2→30.3 min (RR 32.96%); admission 3.5→2.5 h (RR 28.57%); discharge 2.00→1.02 h (RR 49.00%); OR utilization +10 pp; surgery delays −17 pp; rescheduling −10 pp.
16	Gallagher et al., 2024 [25]	Predictive	EDCMPS vs. manual case-finding (retrospective EMR + CM survey): 30-day return OR 4.21 (95% CI 3.59–4.95) vs. 1.69 (95% CI 1.42–2.02); 7-day return OR 3.20 (95% CI 2.63–3.90) vs. 1.64 (95% CI 1.31–2.06); high-risk identification 5.1% vs. 10.3%; improved case-finding efficiency.
17	Placidi et al., 2021 [32]	Descriptive	Process mining of 500 radiotherapy plans (Eclipse TPS event logs + SpeedRo data): prescription-to-treatment mean days for 8 Gy (6.57 d vs. ref ≤3 d), 20 Gy (8.65 d vs. ≤10 d), 30 Gy (9.54 d vs. ≤15 d); conformance checking mapped care pathway variations and

increased by 29 min (95% CI 13 to 44), including a 58-min increase for triage category 2 patients [40]. Applying Eq. (15), the standard errors were 1.28 min and 7.91 min, giving z = 10.2 and z = 3.67 (p < 0.001), so both the improvement and the deterioration are statistically robust. Predictive studies reported discrimination rather than operational change. Adding clinical data increased accuracy from 0.75 to 0.76 for prioritization, 0.80 to 0.82 for admission, and 0.80 to 0.86 for admitting ward, with AUCs of 0.78–0.90 [28]; contrastive transfer learning increased accuracy from 74.9% to 81.9% (+7.0 percentage points; +9.35%) and AUC from 0.82 to 0.91 [44]; and random forest predicted prolonged ED-LOS with 74.88% accuracy and 72.85% precision [42]. The EMR- based case-finding score approximately halved the proportion of patients flagged as high-risk (10.3% to 5.1%) while showing stronger associations with 30-day ED return or hospitalization (odds ratio [OR] 4.21 vs. 1.69 for manual case-finding) [25]. Simulation estimated that automated guided vehicles for breakfast delivery could be reduced from 26 to 21 (−19.23%), with mean lift utilization of 20.33%, well below the 75% threshold (Eq. 22) [39], and space-aware digital twins showed how lift failures prolonged specimen transfer [43]. Descriptive process mining found that 36% of approximately 61,970 patient transports (about 22,308 cases) were delayed by at least 10 min, generating more than 9,000 h of annual delay [31], and that median time from prescription to palliative radiotherapy ranged from 3.31 to 7.90 days, with guideline deviations of 8.8%–54.9% [32].

A sensitivity analysis excluding the two low-quality studies [23], [39] left 15 studies and did not change the main conclusions. Observed operational change was reported by 8 of 15 studies (53.3%), by 3 of 4 remaining Lean-explicit studies (75.0%), and by 5 of 11 remaining AI-supported studies (45.5%). Across the six remaining time-based indicators, relative reductions ranged from

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8.22% to 49.00%, with a median of 33.25%, compared with 32.96% when all studies were included. Recomputation with Eqs. (2)–(5) reproduced the values reported in the original studies within rounding error. Two minor differences were resolved in favour of the recomputed values: the reduction in physics chart-check time, reported as 43% in the source, equals 42.70% when calculated from the reported means [30], and the relative increase in nursing workflow completion equals 29.68% rather than 29.69% [41]. These checks ensure that the numerical values in the abstract, results, tables, and conclusion are mutually consistent.

Table 4. Thematic classification of Lean and AI applications in healthcare operational improvement based on inductive synthesis of the 17 studies. The table summarizes initial codes, corresponding Lean principles, references to the included studies, frequency and percentage distribution, explicit Lean–AI integration, and main operational outcomes across the four identified themes.

Theme	Example initial codes	Lean principle served	Studies	n (%)	Lean-explicit; main outcomes
T1 Predictive decision support	demand forecasting; admission or ward prediction; no-show prediction; risk scoring; case-finding	Pull and levelled flow; right patient, right place	[22], [25], [27]–[29], [44]	6 (35.3)	2/6; prioritization, admission, scheduling, LOS
T2 Intelligent workflow automation	automated documentation and alerts; triage redirection; real-time flagging; image-based inspection	Standard work; built-in quality (jidoka)	[23], [40]–[42]	4 (23.5)	1/4; workflow completion, waiting, TAT
T3 Data-driven process analysis and redesign	event-log discovery; conformance checking; bottleneck detection; what-if simulation; layout testing	Value-stream mapping; gemba; waste identification	[30]–[32], [39], [43]	5 (29.4)	0/5; bottlenecks, throughput, logistics
T4 Smart operational resource optimization	waste monitoring; ordering redesign; dynamic scheduling; capacity dashboards	Waste elimination; flow efficiency	[24], [26]	2 (11.8)	2/2; waste, utilization, processing time
Total	**–**	**–**	**17 studies**	**17 (100)**	**5/17 (29.4%)**

D. Thematic Synthesis of Lean and AI Applications

Inductive analysis produced four themes (Table 4). Predictive decision support (6/17; 35.3%) used forecasting and risk models to inform prioritization, admission, scheduling, and case management [22], [25], [27]–[29], [44]. Data-driven process analysis and redesign (5/17; 29.4%) used process mining, digital twins, and simulation to expose bottlenecks and test alternative configurations [30]–[32], [39], [43]. Intelligent workflow automation (4/17; 23.5%) embedded AI in the execution and monitoring of routine work [23], [40]–[42]. Smart operational resource optimization (2/17; 11.8%) addressed blood utilization and patient logistics [24], [26]. The themes describe predominant mechanisms rather than mutually exclusive technology classes or comparative effectiveness. Fig. 3 shows how outcome types and explicit Lean integration were distributed across themes. Predictive decision support translated data into anticipatory decisions. A real-time ED escalation system combined capacity metrics with forecasting to trigger escalation before crowding [27], machine-learning no-show prediction informed overbooking rules that raised clinic occupancy [29], and triage-level models estimated priority, admission, and ward from routinely collected data [28]. Two studies in this theme embedded prediction within Lean cycles: Lean Six Sigma DMAIC structured the analysis of how COVID-19 altered stroke-unit LOS [22], and Lean and PDSA cycles with frontline case managers shaped an automated priority score in the medical record [25]. Half of the theme's studies (3/6) reported only model performance, which is why this theme contributed proportionally less observed operational evidence.

Intelligent workflow automation embedded AI in the execution of routine tasks. The closed-loop mobile nursing system automated documentation and alerts and produced the largest proportional workflow gains in the review [41]; electronic decision support redirected low-acuity patients at triage [40]; an ED-LOS classifier was proposed for real-time flagging of likely prolonged stays [42]; and computer-vision inspection of samples was combined with Lean redesign and simulation in a laboratory [23]. Automation typically served the Lean principles of standard work and built-in quality, detecting errors at their source rather than downstream.

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Data-driven process analysis and redesign replaced manual process mapping with evidence from event logs and models. Process mining reconstructed radiation-oncology [30], palliative radiotherapy [32], and patient-transport [31] pathways and located where time accumulated, whereas digital twins combined building information models, simulation, and Internet of Things (IoT) data to test layouts and failure scenarios [43] or to size robotic logistics before a hospital opened [39]. Although none of these studies named a Lean method, their logic mirrors value-stream mapping, and only one progressed from diagnosis to a measured redesign [30].

Smart operational resource optimization targeted waste directly. Electronic blood-ordering redesign guided by the Toyota Production System and evaluated with changepoint and causal-impact analysis reduced RBC wastage and unnecessary crossmatching [24], while Lean Management and Six Sigma combined with predictive analytics and dynamic scheduling shortened triage, admission, and discharge processing and increased operating-room utilization in three hospitals [26]. Both studies were Lean-explicit and reported observed change, making this the theme with the most consistent integration, albeit with only two studies.

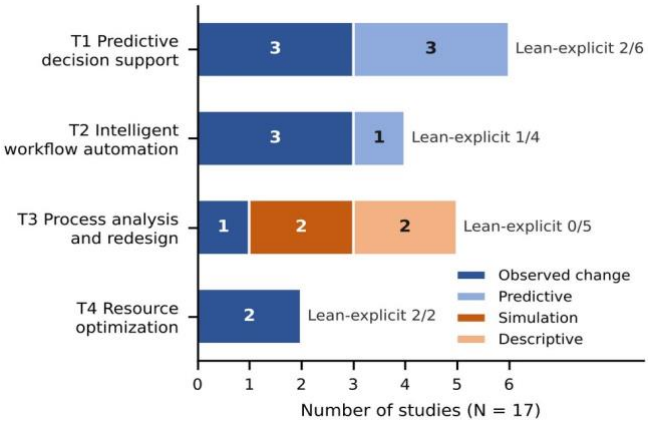

Fig 3. Distribution of the 17 included studies across four thematic categories by outcome type and explicit Lean–AI integration. Outcomes were classified as observed operational change, predictive performance, simulation-based estimates, or descriptive process analysis. T1–T4 represent predictive decision support, intelligent workflow automation, data-driven process analysis and redesign, and smart operational resource optimization, respectively.

E. Research Gaps

Cross-study synthesis identified four gaps. First, Lean and AI were mostly examined separately: only 5 of 17 studies (29.4%) combined them explicitly, and none compared integrated with AI-only implementations. Second, the mechanisms linking Lean stages to AI functions were rarely described, limiting transferability. Third, outcomes focused on efficiency indicators; patient-centred outcomes, staff experience, costs, and sustainability were seldom measured, and only 9 studies (52.9%) reported observed operational change. Fourth, all studies except one three-hospital study were single-centre or single-department evaluations, constraining generalizability.

Table 5. Summary of research gaps identified in the systematic literature review and recommended directions for future research. The table presents four principal gaps: limited explicit Lean–AI integration, inadequate reporting of integration mechanisms, narrow measurement of operational outcomes, and limited generalizability because most studies were conducted in a single centre. Each gap is supported by evidence from the included studies and linked to specific methodological recommendations.

No.	Research Gap	Evidence in This Review	Required Research
1	Limited explicit integration	5/17 (29.4%) studies explicitly examined Lean–AI integration; no head-to-head comparison was identified.	Comparative research involving Lean–AI, AI-only, and Lean-only designs.
2	Mechanisms rarely described	The relationship between Lean stages and AI functions was rarely reported.	Explicit reporting of integration mechanisms (Fig. 4).
3	Narrow outcome set	9/17 (52.9%) studies reported observed changes, but no cost-related or long-term outcomes were identified.	Standardized whole-system outcome measures (Eqs. 2–15).
4	Limited generalizability	16/17 studies were conducted in single-centre or single-department settings.	Multicentre and longitudinal validation.

IV. Discussion

This review shows that AI supports healthcare operations through four recurring mechanisms that map onto Lean improvement logic: prediction informs pull and prioritization, automation stabilizes standard work,

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process analytics replace manual value-stream mapping, and optimization reduces resource waste. The evidence, however, is uneven. Explicit Lean–AI integration was reported in fewer than one-third of studies, and nearly half reported no observed operational change. The findings should therefore be read as evidence that AI can support Lean-consistent improvement, not as evidence that fully integrated Lean–AI systems outperform other approaches.

Each theme operationalizes a distinct Lean principle. Predictive decision support enables pull and levelled flow by anticipating demand rather than reacting to queues, so its benefit depends on whether capacity can actually be adjusted within the prediction horizon. Intelligent workflow automation supports standard work and built-in quality by reducing variation and rework; the nursing and laboratory studies suggest that the largest gains arise where manual, error-prone steps are numerous [23], [41]. Data-driven process analysis replaces gemba walks and manual value-stream maps with complete, objective event data, but diagnosis alone does not remove waste unless it is followed by redesign, which explains why this theme produced the fewest observed changes (1/5). Resource optimization addresses inventory and overproduction waste most directly, and both studies in this theme combined explicit Lean governance with analytics, suggesting that resource decisions benefit from structured improvement cycles that assign ownership and monitor results [24], [26]. Taken together, the themes form a sequence of seeing, measuring, predicting, acting, and sustaining that is formalized in the implementation pathway below.

The evidence can be organized as an outcome chain: model performance, decision change, process change, operational outcome, and patient or system outcome. Four studies reported only the first link, with accuracies of 0.75–0.86 and AUCs of 0.78–0.91 [25], [28], [42], [44]; two simulation studies estimated process change without implementation [39], [43]; and nine studies reported operational outcomes, of which only one measured a patient-relevant consequence (satisfaction) and one documented an adverse system effect [40], [41]. Each link can fail. A well-calibrated admission model adds value only if bed managers act on its output early enough to change placement, and an AGV fleet sized by simulation saves resources only if demand, lift reliability, and staff routines match the model assumptions. Accordingly, AUC and accuracy should be reported as intermediate outcomes, and claims of operational efficiency should rest on measured changes in time, throughput, utilization, or waste, ideally expressed with Eqs. (2)–(5) and accompanied by uncertainty estimates (Eqs. 12–15). Table 6 contrasts the five explicitly integrated studies with the 12 AI-supported studies. The integrated studies were more often real-world implementations (4/5 vs. 4/12) and more often reported observed operational change (80.0% vs. 41.7%), whereas AI-supported studies more often stopped at prediction, simulation, or description. In integrated studies, the improvement method defined the problem, set measurable targets, involved frontline staff, and monitored results, while AI supplied the analytical capability; for example, the Toyota Production System

Table 6. Comparative characteristics of studies that explicitly integrated Lean methodology with artificial intelligence (n = 5) and studies that applied AI without a formal Lean methodology (n = 12). The comparison covers thematic distribution, real-world implementation, observed operational improvements, predictive and simulation-based outcomes, methodological quality, time-based relative reductions, and unintended system effects. The results are descriptive and should not be interpreted as evidence of comparative effectiveness.

Characteristic	Lean–AI explicit (n = 5)	AI-supported (n = 12)
Themes	T1 2, T2 1, T3 0, T4 2	T1 4, T2 3, T3 5, T4 0
Real-world intervention designs*	4/5 (80.0%)	4/12 (33.3%)
Observed operational change	4/5 (80.0%)	5/12 (41.7%)
Predictive / simulation / descriptive	1 / 0 / 0	3 / 2 / 2
Quality high / moderate / low	1 / 3 / 1	4 / 7 / 1
Time-based RR, median (range)	28.57% (8.22–91.19%); 7 indicators	38.12% (33.53–42.70%); 2 indicators
Adverse or mixed system effect	None reported	1 study (LOS +29 min)
Before–after, interrupted time series, action research, or mixed-methods implementation studies. RR = relative reduction (Eq. 4). Descriptive comparison only; no statistical test was performed.		

structured successive ordering-redesign cycles whose effects were evaluated with changepoint analysis [24], and Lean and PDSA cycles governed the co-design of an automated case-finding score [25]. Effect magnitudes, however, did not favour either group consistently: the median relative reduction across time-based indicators was 28.57% in integrated studies (seven indicators) and 38.12% in AI-supported studies (two indicators from one study). Given the small sample sizes, differences in settings and study designs, and the absence of head-to-head comparisons, these data show that explicit integration is associated with more complete implementation and evaluation, rather than necessarily producing larger effects.

Table 7 compares the findings of the present review with those of seven earlier reviews. Overall, the findings are consistent with and extend previous evidence. Tlapa et al. found that Lean interventions supported by digital technologies, across 28 studies, mainly reported positive patient-flow outcomes such as shorter turnaround time, LOS, and waiting times, but rarely reported patient health,

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staff wellbeing, or cost savings [33]; the present review observed a similar imbalance, with efficiency indicators dominating and no included study reporting costs. Wenderott et al. reported that 67% of 33 imaging studies measuring task time found reductions, yet meta-analyses of 12 studies showed no significant effect [17]; similarly, the mixed ED results here [40] show that local time savings do not guarantee system-level gains. Williams et al. identified 31 admission-prediction studies, of which only seven were methodologically rigorous (AUC 0.81–0.93), and 24 had unclear or high risk of bias; the AUCs reported by the included predictive studies (0.78–0.91) fall in the same range, yet none evaluated real-world patient-flow effects, which Williams et al. also identified as the main evidence gap. Knight et al. found only 11 real-world AI scheduling studies among 3,415 citations [35], mirroring the single scheduling study included here [29]. Kamel Rahimi et al. rated 21 of 26 hospital AI implementation studies (81%) as poor quality and identified 28 enablers and 18 barriers [45]; by contrast, only 2 of 17 studies (11.8%) here were rated low, possibly because operationally focused studies report outcome data more systematically. Ahmed et al. synthesized 59 articles and grouped barriers into ethical, technological, regulatory, workforce, social, and patient-safety domains [46], which correspond to the implementation conditions discussed below. Aiwerioghene and Osuchukwu likewise mapped 13 articles and concluded that cost, bias, and staff acceptance must be addressed before AI benefits can be realized [47]. Finally, whereas a Lean-only surgical programme documented annual savings exceeding EUR 8.5 million [10], none of the 17 included studies quantified financial return, so the economic case for Lean–AI integration remains unproven. Rathi et al. reported that Lean Six Sigma in healthcare improves process capability and efficiency but that sustaining gains remains difficult [48], which accords with the absence of follow-up beyond the initial evaluation period in most included studies. Likewise, Huang et al. showed that robotic process automation could serve as a vehicle for Lean transformation in a hospital case study [19], supporting the interpretation that automation delivers the most value when it is embedded in standardized work rather than added to unstable processes.

Two differences in approach distinguish the present review. Earlier reviews of Lean and digital technology examined Lean as the primary intervention and technology as a support [33], whereas AI reviews examined single applications such as admission prediction, scheduling, or process mining [35], [36]. This review instead compares mechanisms across applications and separates explicit Lean–AI integration

Table 7. Comparison of the present review findings with previous reviews and studies on Lean, AI, and healthcare operational efficiency.

Study	Main findings of earlier work	Comparison with the present review
Tlapa et al. [33]	28 studies of Lean supported by digital technologies; mainly positive flow outcomes (TAT, LOS, waiting time); patient health, staff wellbeing, and savings rarely reported.	Same imbalance: efficiency indicators dominated and no included study reported costs.
Wenderott et al. [17]	67% of 33 imaging studies measuring task time reported reductions; meta-analyses of 12 studies showed no significant effect.	The mixed ED result [40] shows that local time savings do not guarantee system-level gains.
Knight et al. [35]	11 real-world AI scheduling studies among 3,415 citations.	Mirrored by the single scheduling study included here [29].
Kamel Rahimi et al. [45]	21 of 26 hospital AI implementation studies (81%) rated poor quality; 28 enablers and 18 barriers identified.	Only 2 of 17 studies (11.8%) were rated low, possibly because operational studies report outcome data more systematically.
Ahmed et al. [46]	59 articles; barriers grouped into ethical, technological, regulatory, workforce, social, and patient-safety domains.	The domains correspond to the implementation conditions discussed in this review.
Aiwerioghene and Osuchukwu [47]	13 articles; cost, bias, and staff acceptance must be addressed before AI benefits can be realized.	Governance and costs were rarely reported in the included studies.
Rathi et al. [48]	Lean Six Sigma improves process capability and efficiency, but sustaining gains remains difficult.	Most included studies had no follow-up beyond the initial evaluation period.
Huang et al. [19]	Robotic process automation served as a vehicle for Lean transformation in a hospital case study.	Automation delivers most value when embedded in standardized work.
Sales Coll et al. [10]	Lean-only surgical programme with annual operational savings above EUR 8.5 million.	None of the 17 included studies quantified financial return.

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from AI-supported improvement and observed from predicted or simulated effects. In settings, it adds laboratory, radiotherapy, blood-management, and logistics evidence to the ED-dominated literature.

Local gains did not always translate into better overall performance, and the redirection study illustrates why individual indicators may improve while overall performance deteriorates [40]. By Little's law (Eq. 21), at a constant arrival rate, a longer mean LOS implies proportionally more patients in the department; for an illustrative arrival rate of 10 patients per hour, a 29-min increase in LOS would add about 4.8 patients to the average census, increasing crowding even as the first physician contact becomes faster. Plausible mechanisms include workflow displacement, in which faster front-end assessment shifts queues to diagnostics, consultation, or disposition, and a change in case mix after low-acuity patients are redirected, leaving a more complex population whose LOS naturally lengthens. These mechanisms were not tested in the original study and remain hypotheses, but they are consistent with constraint-based reasoning: improving a non-bottleneck step cannot raise system throughput. Evaluations should therefore report end-to-end indicators (time to assessment and treatment, LOS, left-without-being-seen rate, and safety) together with census or utilization, so that genuine improvement can be distinguished from redistributed delay.

Implementation conditions help explain why similar technologies produced different results. Data quality and interoperability were prerequisites in every theme: process mining and digital twins required complete, time-stamped event logs and building data [31], [43], and predictive models were developed on retrospective datasets whose transfer to live, changing data was not tested [28], [42], [44], a transition that Kamel Rahimi et al. identified as the most difficult step in hospital AI implementation [45]. Workforce engagement was equally important; the case-finding tool was co-designed with ED case managers in Lean improvement events, which supported its acceptance [25], whereas barriers reported in the wider literature include workload, trust, digital skills, and perceived usefulness [18], [46]. Downstream capacity also constrained benefit: the case-finding tool identified high-risk patients more accurately, yet follow-up was limited by access to primary care, housing, and insurance [25], and redirection improved front-end ED metrics without improving LOS [40]. Governance, including privacy, model validation, accountability, and monitoring for drift, and the costs of acquisition, integration, and maintenance were rarely reported, although they are decisive for adoption [46], [47]. Because organizational readiness, staff acceptance, process standardization, and implementation fidelity were not measured consistently, their independent contributions to effectiveness cannot be quantified.

The four research gaps identified in this review are interrelated. Because Lean and AI are rarely combined explicitly, few studies describe how an AI function maps to a specific improvement stage, and without such descriptions, implementations cannot be replicated or compared. The narrow outcome set compounds the problem: when only one efficiency indicator is reported, a local improvement can conceal deterioration elsewhere, as the ED redirection study shows [40], and the absence of cost, staff, and patient-centred outcomes prevents a value-based assessment of whether the investment is justified. Finally, the predominance of single-centre evaluations means that context, including leadership, Lean maturity, data infrastructure, and staffing, cannot be separated from the intervention itself. Addressing these gaps requires not only more studies but better reporting: describing the integration mechanism (Fig. 4), reporting the minimum metric set defined in Eqs. (2)–(15), and evaluating implementations in more than one organization. The review has several strengths. It followed PRISMA 2020 with dual independent screening, appraisal, and extraction; it used design-specific appraisal

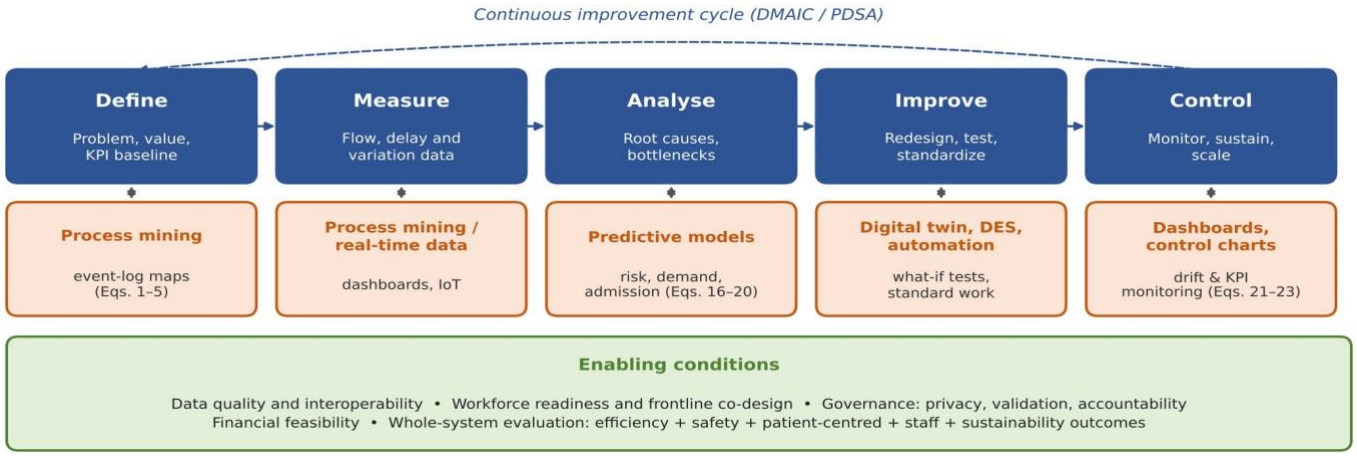

Fig 4. Proposed Lean–AI implementation framework linking the five continuous-improvement stages (Define, Measure, Analyze, Improve, and Control) with corresponding AI capabilities and operational objectives. The framework illustrates the application of process mining, predictive analytics, digital twins, discrete-event simulation, automation, and monitoring dashboards, supported by data interoperability, workforce readiness, governance, and financial viability.

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instruments rather than a single checklist unsuited to modelling and action-research designs; and it recomputed every extractable numerical result with explicitly defined metrics, which exposed rounding discrepancies and allowed absolute and relative changes to be reported consistently. It also separated explicit Lean–AI integration from AI-supported improvement. It observed predicted or simulated effects, and it tested the robustness of its main findings by excluding low-quality studies. Together, these features make the conclusions traceable to the underlying data and the synthesis reproducible.

Several limitations should be acknowledged. At the study level, most evidence came from single-centre before–after or retrospective designs without concurrent controls, so secular trends (for example, pandemic-related practice change in the stroke unit [22]) cannot be separated from intervention effects. Multicomponent interventions combined AI with workflow redesign, training, and monitoring, preventing attribution to AI alone. Predictive studies were rarely externally or temporally validated, simulation studies were not followed by implementation, and few studies reported dispersion measures, so Eqs. (6)–(14) could seldom be applied and no meta-analysis was possible. In addition, outcome definitions varied across studies (for example, LOS measured from arrival to departure or from triage to disposition), and baseline and follow-up periods differed in length and season, which further limits comparability of effect magnitudes. At the review level, only three databases were searched; the Scopus search was restricted to open-access journal articles, and grey literature and non-English publications were excluded, introducing possible selection and publication bias. Classification of Lean–AI integration depended on authors' reporting and may have misclassified studies that used Lean tools without naming them. Theme development was led by one reviewer and checked by a second author rather than double-coded; the appraisal instruments are not equivalent across designs, and the four-theme framework is a conceptual synthesis that still requires empirical validation.

For healthcare decision-makers, the evidence supports a staged pathway (Fig. 4) that aligns AI capabilities with the Lean cycle rather than deploying AI as a stand-alone tool. In the define and measure stages, process mining can replace manual mapping by quantifying actual flow, delays, and variation from event logs [30], [31]. In the analyse stage, predictive models can forecast demand, admissions, or risk [28], [44], provided that each prediction is linked to a specific decision and owner. In the improve stage, digital twins and simulation allow alternative configurations to be tested before implementation [39], [43], and automation is best reserved for standardized, well-understood tasks [41]. In the control stage, real-time dashboards and statistical monitoring sustain gains [24], [27]. Applicability depends on data quality and interoperability, workforce readiness and engagement, governance covering privacy, validation, and accountability, and a realistic assessment of implementation and maintenance costs [45]–[47]. Organizations with mature Lean programs and integrated electronic records are best positioned to benefit, whereas those without them should first establish standard work and data infrastructure.

For managers considering Lean–AI projects, the review suggests six practical questions before investment: (1) Which operational problem and baseline indicator will the project change? (2) Which decision will the AI output trigger, who owns it, and is there capacity to act on it? (3) Is the underlying process stable and standardized enough for automation? (4) Are data complete, timely, and interoperable? (5) Which balancing indicators, such as LOS, safety, and staff workload, will be monitored to detect displaced delays? (6) How will benefits, costs, and model performance be monitored after go-live? Projects that cannot answer these questions are likely to produce accurate models without operational benefit.

The included evidence came largely from high-income settings; only two studies were conducted in upper-middle-income countries (China and Mexico) [23], [41], and none in South-East Asia or Africa. Several features of the findings are nevertheless relevant to resource-constrained health systems such as Indonesia's. First, the largest relative improvements came from process redesign supported by comparatively simple analytics rather than from complex models [23], [24], [30], suggesting that organizations can begin with process mining or rule-based decision support built on existing hospital information systems. Second, predictive and digital-twin applications require large, well-structured datasets, such as 653,546 ED visits in one model [28], which hospitals with fragmented or partly paper-based records cannot yet provide; investment in data standards and interoperability is therefore a precondition rather than an afterthought. Third, Lean methods require little capital and build the problem-solving routines into which AI can later be embedded. A sequenced strategy that first stabilizes processes with Lean, then digitizes measurement, and only then introduces prediction and automation may therefore offer the best return where budgets and digital skills are limited. Prospective evaluations in low- and middle-income settings are needed to test this proposition.

Future studies should (i) use prospective, multicentre, preferably controlled or stepped-wedge designs comparing explicit Lean–AI integration with AI-only and Lean-only implementations; (ii) adopt a standardized operational outcome set reporting baseline and follow-up values, absolute and relative changes, dispersion, and uncertainty as defined in Eqs. (2)–(15); (iii) evaluate whole-system, patient-centred, staff, and cost outcomes alongside efficiency; (iv) follow implementations for at least 12 months to assess sustainability and model drift; and (v) examine emerging technologies, including large language models and explainable AI, within explicit continuous-improvement cycles.

V. Conclusion

This review aimed to examine how Lean and AI are applied to improve healthcare operational efficiency, to synthesize implementation patterns, and to identify

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research gaps. Seventeen studies were included, and four themes were identified: predictive decision support (35.3%), data-driven process analysis and redesign (29.4%), intelligent workflow automation (23.5%), and smart operational resource optimization (11.8%). Only five of the 17 studies (29.4%) explicitly integrated Lean with AI, whereas 12 (70.6%) applied AI to operational improvement without a formal Lean method, and only nine (52.9%) reported observed operational change. Representative improvements included a 42.70% reduction in physics chart-check time, a 22.83% reduction in laboratory turnaround time, an increase in nursing workflow completion from 73.17% to 94.89%, and a decrease in RBC wastage from 26% to 6%; however, one ED intervention shortened time to physician assessment by 13 min while increasing LOS by 29 min. The review contributes a four-theme framework, a clear distinction between explicit Lean–AI integration and AI-supported improvement, and a harmonized set of 23 operational and predictive metrics. AI can support Lean-consistent operational improvement, but the effectiveness of explicitly integrated Lean–AI approaches remains uncertain. Future research should prioritize prospective multicentre validation, standardized operational metrics, whole-system and patient-centred outcomes, and long-term evaluation of implementation sustainability.

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Conflicts of Interest

The authors declare that they have no financial, professional, or personal conflicts of interest that could have influenced the design, conduct, analysis, interpretation, or reporting of this study.

Author Contributions

Noni Rinasmara Fadhilah: conceptualization, methodology, literature search, study selection, data extraction, methodological quality appraisal, formal analysis, data interpretation, and writing—original draft. Merita Arini: supervision, methodology, study design, validation, critical interpretation, and writing—review and editing. Both authors reviewed and approved the final manuscript and agree to be accountable for the accuracy and integrity of the work.

Ethical Approval

Ethical approval was not required because this study is a systematic literature review based exclusively on previously published studies and did not involve direct recruitment of human participants, interventions, or collection of identifiable personal data.

Informed Consent

Informed consent was not applicable because this study used previously published literature and did not involve direct participation of human subjects.

Consent for Publication

Not applicable. This manuscript does not contain identifiable participant information, photographs, or personal data requiring consent for publication.

Data Availability

The data supporting the findings of this systematic literature review were extracted from previously published scientific articles. The study extraction matrix and item-level methodological quality appraisal are provided in the Supplementary Material. No new primary data were generated.

Declaration of the Use of Artificial Intelligence (AI)

The authors declare that ChatGPT, developed by OpenAI, was used exclusively for English-language editing, grammar correction, and readability improvement of the manuscript. AI tools were not used for literature searching, study selection, methodological quality appraisal, data extraction, statistical analysis, evidence synthesis, interpretation of findings, or formulation of scientific conclusions. All AI-assisted editorial changes were reviewed and verified by the authors, who remain fully responsible for the accuracy, originality, scientific integrity, and final content of the manuscript.

Transparency and Research Reporting

This systematic literature review was conducted and reported in accordance with the PRISMA 2020 reporting guideline [38]. The literature search, eligibility criteria, study selection procedure, methodological quality appraisal, data extraction, and synthesis methods are described in the manuscript to support transparency and reproducibility.

Clinical Trial Registration

Not applicable. This study is a systematic literature review and not a clinical trial.

Supplementary Materials

The supplementary material contains the study extraction matrix and item-level methodological quality appraisal supporting the findings of the review.

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