Trends in Industrial Engineering Regarding the Use of Artificial Intelligence for Continuous Process Improvement

Adriel Ríos Díaz[1]; María García Sandoval[1]
[1]*Polytechnic University of Puerto Rico, San Juan, Puerto Rico*, ríos_141514@students,pupr.edu, margarcia@pupr.edu

Abstract- Artificial intelligence (AI) is increasingly used in continuous improvement, but evidence is distributed across application areas, technologies, and study designs. This review maps reported applications in Industrial Engineering through Scanning, Skimming, and Mapping. EBSCO and Emerald searches produced 138 records; 100 advanced to full-text assessment, and 23 met the problem-solution-impact eligibility rule. Process Improvement appeared in all retained studies, partly reflecting the review scope and inclusion criteria. Machine Learning and Decision Making each appeared in 86.96%, Quality Improvement in 82.61%, and Variability in 78.26%; these attributes exceeded the study-specific 70% threshold for predominant trends. Deep Learning appeared in 39.13% and was classified as emerging. Reclassification at 65%/25% and 75%/35% left these six labels unchanged, although several other attributes changed category. The complete coded matrix identifies the 23 studies and their recorded attributes. These frequencies describe the selected literature; they do not establish comparative effectiveness or population-wide adoption. The findings inform proposed curricular and professional recommendations, which require separate evaluation. Incomplete search documentation and the absence of a documented formal quality appraisal or independent agreement analysis limit reproducibility and confidence in the classifications.

Keywords- Artificial intelligence; continuous improvement; Industrial Engineering; Machine Learning; systematic literature review.

I. INTRODUCTION

Industrial Engineering is concerned with the design and improvement of integrated systems involving people, materials, information, equipment, and energy [1], [2]. Its established improvement approaches, including Lean, Lean Six Sigma, statistical quality control, operations research, and process analysis, seek to reduce waste, control variability, improve flow, and increase the reliability of operational decisions [3]. These methods depend on disciplined problem definition, valid measurement, and repeated comparison between current and desired performance.

Digital transformation is changing how this work is performed. Sensors, connected systems, cloud platforms, and large operational datasets allow organizations to observe processes at a frequency and scale that were previously difficult to achieve. Artificial intelligence (AI) can extend this digital infrastructure through prediction, classification, pattern recognition, optimization support, and automated interpretation. In Industrial Engineering contexts, such capabilities may contribute to quality management, maintenance, forecasting, scheduling, logistics, simulation, inspection, and process diagnosis [4]-[6].

The growth of AI applications does not automatically provide a clear roadmap for engineering practice. The literature uses overlapping labels for application areas, AI technologies, and operational problems. Some studies emphasize model accuracy, whereas others emphasize time, defects, cost, or decision quality. Evidence is also distributed among applied research, reviews, conceptual work, and case studies. Consequently, a reader may encounter many examples without being able to determine which uses are already predominant, which remain emerging, and which operational objectives receive the greatest attention.

A. Problem and Purpose

This fragmentation creates a practical and educational problem. Practitioners need to connect AI selection to a measurable process need rather than adopt a technique because it is fashionable. Students and early-career engineers need an evidence-based understanding of where AI fits within established Industrial Engineering reasoning. A systematic synthesis can clarify those relationships while preserving an important distinction: publication frequency indicates concentration of research attention, not comparative technical superiority or causal effectiveness.

The purpose of this study is to identify and interpret current trends in the use of AI for continuous process improvement within Industrial Engineering. The review emphasizes three linked elements in every retained study: a defined industrial problem, an AI-based solution that was actually applied, and a reported operational or performance impact. This problem-solution-impact rule was used to distinguish substantive applications from papers that mentioned AI only as background or future potential.

B. Research Questions and Contributions

The study addresses three research questions. RQ1 asks which continuous-improvement application areas appear most frequently. RQ2 asks which AI technologies are reported most often. RQ3 asks which operational problems are most commonly addressed. The paper contributes a structured screening summary, a literature-matrix structure for comparing heterogeneous evidence, a descriptive trend classification, and an interpretation of the findings for engineering education and practice.

Unlike a technology-centered review, the analysis begins with the operational purpose of the application. This orientation reflects the role of Industrial Engineering: the relevant question is not only whether an algorithm performs well, but whether it improves a system outcome, supports a defensible decision, or strengthens a repeatable improvement process. The paper therefore treats AI as one component of an engineering intervention rather than as an isolated product.

II. CONCEPTUAL BACKGROUND

A. Continuous Improvement and Intelligent Analytics

Continuous improvement is a recurring effort to understand current performance, identify sources of waste or variation,

implement changes, and verify whether those changes produce sustainable gains. Traditional tools remain essential because they provide process context, operational definitions, causal reasoning, and a baseline against which improvement can be evaluated [1], [3]. AI contributes most meaningfully when it strengthens one of these functions, for example by detecting a pattern earlier, estimating a future state, prioritizing an intervention, or processing information that exceeds manual analytical capacity.

Machine Learning is particularly compatible with data-rich improvement problems because it can learn relationships from historical observations and generate predictions or classifications for new cases. Feature engineering connects domain knowledge to model inputs and therefore remains an important bridge between industrial systems and AI methods [5]. Deep Learning can extend this capability when complex data representations are required, especially for images, signals, or high-dimensional patterns, but it generally demands more data, computational resources, and attention to interpretability.

A high-performing model is not equivalent to an improved process. Model metrics must be translated into an operational consequence, such as fewer defects, reduced cycle time, lower variability, improved service, lower cost, or better risk identification. This translation requires a defined baseline, appropriate validation data, and an explanation of how the prediction will change a decision or action. These conditions informed the eligibility rule used in the present review.

B. Industry 4.0 and Industry 5.0 Context

Industry 4.0 emphasizes automation, connectivity, cyber-physical integration, and the use of digital information across operations [7]. In that environment, AI can transform continuous data streams into forecasts, anomaly signals, classifications, or recommended decisions. The technology is therefore closely connected to the visibility and responsiveness expected in digitally integrated systems.

Industry 5.0 broadens the discussion by emphasizing human centricity, resilience, and sustainability [8], [9]. This perspective is important because continuous improvement decisions often affect workers, customers, process stability, and long-term organizational capability. Human oversight, transparent evaluation, and responsible assignment of decision authority are therefore not secondary concerns. They determine whether an AI-supported improvement remains aligned with engineering objectives and organizational values.

C. Need for an Evidence Map

Prior work has described AI applications across branches of Industrial Engineering and has considered how intelligent tools can support analytical and modeling tasks [4]-[6]. However, the rapid increase in publications makes periodic mapping necessary. An evidence map does not replace a meta-analysis or an implementation study; it organizes what is being studied, how often attributes co-occur, and where the literature appears concentrated or sparse.

The map developed here uses nonexclusive categories. A single study may involve Machine Learning, support Decision Making, address Variability, and contribute to both Process Improvement and Quality Improvement. This structure reflects real engineering projects more accurately than mutually exclusive categories, but it also means that percentages should not be added together. The analytical focus is the presence of each attribute within the 23-study sample.

III. METHODOLOGY

A. Review Design

The study combines the systematic identification, selection, and synthesis logic described by Carrera-Rivera et al. [10] with the structured literature-review sequence of Machi and McEvoy [11]. The comparative matrix was adapted from the organizing logic illustrated by Singh et al. [12]. As shown in Fig. 1, the review proceeded through Scanning, Skimming, and Mapping. Each phase narrowed the evidence. Appendix A reproduces the recorded study-level classifications, and Section VII identifies limitations in the review documentation.

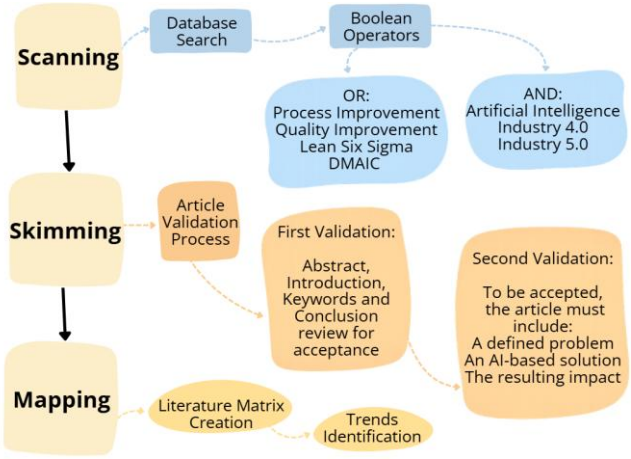


Fig. 1. Scanning, Skimming, and Mapping workflow used in the review.

B. Search Strategy and Scope

EBSCO and Emerald were used as the primary databases to identify literature on artificial intelligence applied to continuous improvement within Industrial Engineering. The search strategy combined process improvement, quality improvement, Lean Six Sigma, and DMAIC using OR. These terms were connected to technology-related terms using AND. Table I summarizes the database-specific search configurations.

TABLE I
SEARCH LOGIC USED DURING THE SCANNING PHASE

Concept block	Terms	Operator
Improvement	Process improvement; quality improvement; Lean Six Sigma; DMAIC	OR
Technology	Artificial intelligence; Industry 4.0; Industry 5.0	OR
Final logic	Improvement block with technology block	AND

In EBSCO, the All-fields option was selected for each search row. The selected filters were Available in Library Collection, Full text, Peer-reviewed publications, and Last 5 years. In Emerald, the Journal Articles filter was selected. The searched fields and publication-date filters for Emerald are not specified in the available search documentation.

The exploratory compilation covered publication years 2017 through the first quarter of 2026 to describe the

distribution of retrieved literature over time. The final mapping focused on studies published from 2021 through the first quarter of 2026. Earlier records contributed to the scanning overview but were not retained in the final literature matrix. This publication coverage describes the compiled dataset; the Last 5 years limiter identifies the EBSCO configuration reported above.

The Emerald query returned 97 results, whereas the compiled dataset contained 51 Emerald records. The relationship between these counts remains undocumented. A complete log identifying all search execution dates, the configurations used for the 2026 updates, and the duplicate-removal procedure and count is also unavailable. These gaps limit the reproducibility of the search and compilation process. Coverage was limited to EBSCO and Emerald; therefore, the retrieved frequencies should not be interpreted as representing the entire engineering and AI literature.

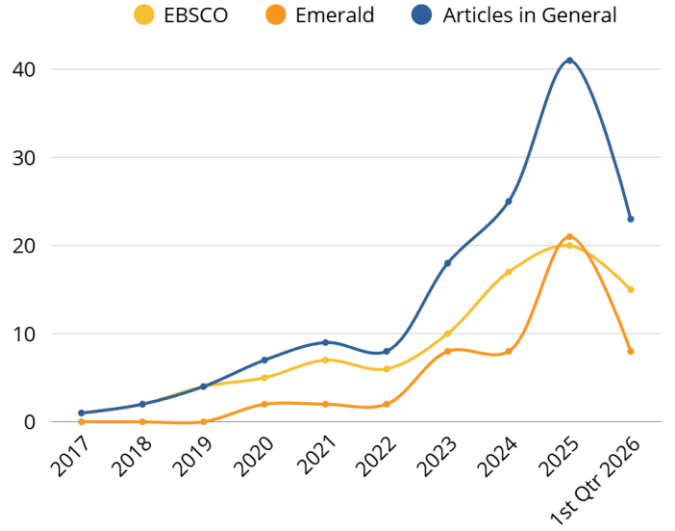


Fig. 2. Records retrieved from EBSCO and Emerald by publication year; 2026 includes the first quarter only.

C. Screening and Eligibility

Skimming was conducted in two levels. The first validation reviewed the abstract, introduction, keywords, and conclusion to evaluate scope, source relevance, date, and whether AI was substantively connected to the study. This pass reduced the 138 retrieved records to 100 articles for full-text evaluation. The second validation examined the complete article and required three elements: a clearly defined industrial problem, an AI-based solution that was applied rather than merely mentioned, and a resulting operational or performance impact.

First-stage exclusions totaled 38: AI mentioned without application (16), publication outside the defined period (7), content outside scope (6), source-quality requirements not met (5), and no substantive AI involvement (4). EBSCO contributed 22 of these exclusions and Emerald 16, leaving 65 and 35 records, respectively, for full-text assessment.

The second validation retained 23 studies: 18 from EBSCO and five from Emerald. The 77 full-text exclusions comprised 33 articles without an applied AI-based solution, 31 without a clearly defined problem, and 13 outside the research scope. These reported categories account for all 77 exclusions. Table II traces the recorded selection stages; its retrieval count is not presented as a verified post-deduplication total.

TABLE II
DETAILED SCREENING FLOW

Review stage	Records	Share of initial (%)
Recorded database retrieval	138	100.00
Excluded in first validation	38	27.54
Advanced to full-text assessment	100	72.46
Excluded after full-text assessment	77	55.80
Retained in final matrix	23	16.67

D. Data Extraction and Mapping

The review used Article Review and Data Extraction Forms to record bibliographic information, study context, the problem, AI application, reported impact, and limitations. The literature matrix organized the coded attributes into three dimensions: Application Area, Type of AI Used, and Problem Addressed. Appendix A presents the complete 23-study matrix with an individual reference for each study.

Application-area codes included Process Improvement and Quality Improvement together with more specific improvement frameworks when explicitly reported. Technology codes distinguished Machine Learning, Deep Learning, and other intelligent or vision-related methods. Problem codes captured the operational issue addressed, including Decision Making, Variability, defects, inspection, time reduction, cost reduction, manual inspection, and risk management or prediction. A marked matrix cell denotes the recorded presence of an attribute; each attribute is counted once per study. Evidence-location fields support individual codes where completed. The matrix is reproduced without a new assessment of the original publications.

E. Trend Classification and Interpretation

The categories were nonexclusive. Attribute prevalence was calculated as the number of retained studies carrying that code divided by 23 and multiplied by 100. Predominant trends required at least 70%; emerging attributes required at least 30% but less than 70%; limited presence meant less than 30%. For n = 23, these classes correspond to 17-23, 7-16, and 0-6 studies, respectively. Classification used the unrounded proportion. The labels describe frequency, not statistical significance, effect size, or causal importance.

The 70% cutoff was adapted from the consensus criteria discussed by Alkrides [13] and Gladysz et al. [14]. Those studies used agreement thresholds in Delphi-based work, not prevalence thresholds for literature-review trends. The adaptation is therefore a study-specific operational choice, not a validated universal SLR standard. The 30% boundary was likewise selected operationally to distinguish noticeable from limited presence. Sensitivity was examined by reclassifying the same matrix at upper/lower cutoffs of 65%/25% and 75%/35%, without changing any study or code.

Interpretation followed three safeguards. First, counts were treated as evidence of attention, not effect size. Second, over-

lapping categories were discussed as connected parts of an intervention rather than competing alternatives. Third, 2026 values were identified as first-quarter observations so that the apparent publication pattern would not be mistaken for a complete calendar-year comparison.

IV. RESULTS

A. Retrieved Compilation

The database search produced 138 records. EBSCO contributed 87 and Emerald contributed 51. The combined yearly totals were 1 in 2017, 2 in 2018, 4 in 2019, 7 in 2020, 9 in 2021, 8 in 2022, 18 in 2023, 25 in 2024, 41 in 2025, and 23 in the first quarter of 2026. As Fig. 2 shows, the increase accelerated after 2022, with 107 of the 138 retrieved records (77.54%) appearing from 2023 through early 2026.

The initial compilation contained several evidence forms. Applied Research Papers represented 31.9%, Literature Review Papers 25.4%, Theoretical Research Papers 17.4%, Conceptual Articles 12.3%, Case Studies 8.0%, Editorial Articles 2.9%, and Technical Papers 2.2%. The mixture shows that interest in AI and improvement is not limited to implemented industrial projects. It also reinforces why the final eligibility rule required an applied solution and reported impact: publication type alone could not establish the level of operational evidence.

B. Final Sample Profile

The first validation excluded 38 records, and full-text evaluation excluded another 77, leaving 23 studies (16.67% of the initial retrieval). Two were published in 2021, none in 2022, three in 2023, three in 2024, eight in 2025, and seven during the first quarter of 2026. Thus, 15 of 23 retained studies (65.22%) appeared in 2025 or early 2026. Fig. 3 visualizes the distribution; the 2026 count is partial-year evidence, not a forecast for the complete year.

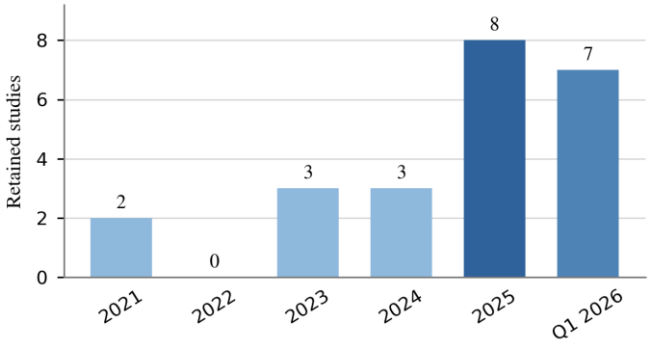


Fig. 3. Publication-year distribution of the 23 studies retained in the final literature matrix.

C. Predominant and Emerging Attributes

Process Improvement appeared in all 23 retained studies (100.00%). Its universal presence partly follows from the search scope and eligibility rule and should not be interpreted as an independently discovered trend across all AI research. Machine Learning and Decision Making each appeared in 20 studies (86.96%). Quality Improvement appeared in 19 studies (82.61%), and Variability appeared in 18 (78.26%). Each of these attributes exceeded the 70% rule and was classified as predominant. Deep Learning appeared in nine studies (39.13%) and was classified as emerging.

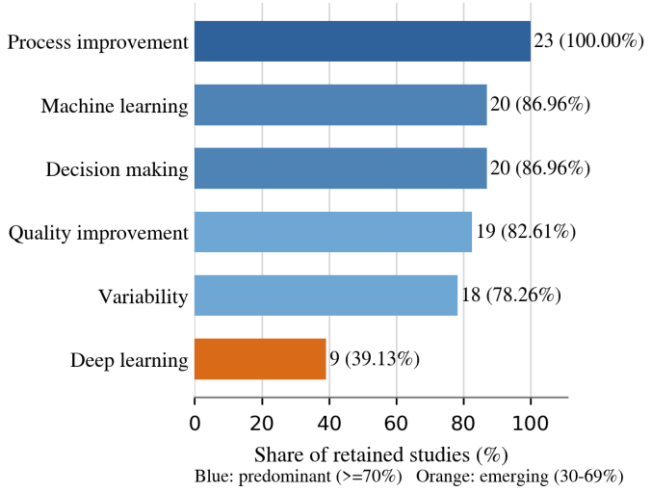


Fig. 4. Most frequent attributes identified in the final sample (n = 23).

TABLE III
FINAL TREND CLASSIFICATION

Attribute	Count	Percent	Class
Process Improvement	23	100.00	Predominant
Machine Learning	20	86.96	Predominant
Decision Making	20	86.96	Predominant
Quality Improvement	19	82.61	Predominant
Variability	18	78.26	Predominant
Deep Learning	9	39.13	Emerging

Note: categories are nonexclusive; percentages are calculated using n = 23. Process Improvement was also embedded in the review scope.

D. Relationships Among the Attributes

The leading categories should be read together. Process Improvement defines the broad purpose shared by the sample, while Machine Learning identifies the most frequently reported technical family. Decision Making and Variability describe common operational problems or decision contexts, and Quality Improvement identifies a major application area. A single study can therefore contribute to several leading frequencies when, for example, a Machine Learning model detects process behavior, supports a quality decision, and reduces exposure to variation.

This overlap explains why the percentages sum to more than 100%. It also prevents a misleading interpretation in which application areas, methods, and problems are treated as interchangeable categories. The evidence instead describes a layered structure: an organization has an improvement objective, selects an intelligent analytical capability, applies it to an operational problem, and evaluates a reported consequence.

The predominance of Machine Learning is consistent with the data-oriented character of many improvement problems. Historical process observations can be used to identify patterns, estimate outcomes, or classify conditions that warrant attention. Deep Learning was recorded less frequently than Machine Learning and was classified as an emerging attribute. In this study, emerging attributes are those present in 30% to

less than 70% of the retained studies and are interpreted as having the potential to become established trends in the coming years. This classification reflects their current frequency within the reviewed literature, while their possible development into established trends would require confirmation through future literature updates.

E. Areas with Less Documented Presence

Beyond the attributes in Table III, Quality Control, Defects, and Inspection each appeared in 16 studies (69.57%); Time Reduction in 15 (65.22%); Risk Management and Prediction in 14 (60.87%); Cost Reduction in eight (34.78%); and Manual Inspection in seven (30.43%). All were classified as emerging because their frequencies were at least 30% but below 70%. Within this study, emerging attributes are interpreted as having the potential to become established trends over time.

Lean Six Sigma appeared in four studies (17.39%), DMAIC in three (13.04%), and Scrap in five (21.74%), placing them in the limited presence category. The other technology categories also had limited presence: Internet of Things, Machine Vision, and Computer Vision each appeared in six studies (26.09%); Natural Language Processing in five (21.74%); Generative AI in four (17.39%); Fuzzy Logic and Metaheuristics in three each (13.04%); and Evolutionary Algorithms in two (8.70%). Appendix A retains these categories as coded, including the enabling technology Internet of Things.

These frequencies describe the explicit presence of attributes within the retained studies. Limited presence does not establish that an attribute is ineffective or lacks future potential. Similarly, the emerging category identifies attributes considered potential future trends, whose development would require assessment through subsequent updates of the literature review.

F. Sensitivity to the Classification Thresholds

At alternative upper/lower thresholds of 65%/25% and 75%/35%, the five predominant attributes in Table III remained predominant, and Deep Learning remained emerging. Other attributes were sensitive to these adjustments. At 65%/25%, Quality Control, Defects, and Inspection (16/23 each), and Time Reduction (15/23), were reclassified as predominant; Internet of Things, Machine Vision, and Computer Vision (6/23 each) were reclassified as emerging. At 75%/35%, Cost Reduction (8/23) and Manual Inspection (7/23) were reclassified from emerging to limited presence. All remaining classifications were unchanged.

These changes illustrate how attributes within the same category can have different levels of documented presence. Quality Control, Defects, and Inspection, each at 69.57%, were close to the original 70% threshold for predominant attributes. Cost Reduction (34.78%) and Manual Inspection (30.43%) were closer to the 30% boundary separating emerging attributes from those with limited presence. Reporting their counts and unrounded proportions alongside the category labels preserves these differences and helps explain why some attributes are more sensitive to the selected thresholds.

The classifications of the six attributes highlighted in Table III were stable under both alternatives, providing consistency for their interpretation within the tested scenarios. The changes among other attributes resulted from applying different thresholds to the same 23 studies, with their recorded frequencies remaining unchanged. Within this study, emerging attributes represent potential future trends, and the sensitivity analysis shows how their designation depends on the selected classification boundaries. Their possible development into established trends would require examination through future literature updates that assess changes in their documented presence over time.

V. DISCUSSION

A. AI as a Support Layer for Improvement

The combined results present AI primarily as an analytical and predictive support layer around established improvement goals. The universal presence of Process Improvement in the retained sample is partly a consequence of the study scope, but the accompanying frequencies show how that purpose is operationalized. Machine Learning supplies the most common technical capability, while Decision Making, Quality Improvement, and Variability identify the engineering contexts in which the capability is used.

This result argues against technology-first implementation. Selecting an algorithm before defining the process problem can produce an accurate model with little operational value. A problem-first sequence begins with the decision to be improved, establishes the current baseline, assesses whether suitable data exist, chooses an appropriate method, validates performance, and translates the output into an operational action. That sequence remains consistent with traditional continuous-improvement discipline even when the analytical technique changes.

B. Quality, Variability, and Decision Making

The strong presence of Quality Improvement and Variability indicates that AI is often applied where process consistency and conformance matter. Intelligent models can help identify nonlinear relationships, detect conditions associated with defects, prioritize inspection, or estimate future performance. However, these capabilities should complement rather than bypass process knowledge, measurement-system evaluation, sampling logic, and statistical interpretation.

Decision Making appeared as frequently as Machine Learning. These equal frequencies do not establish that one attribute causes the other or that a supported decision necessarily improved. Relevant decisions may concern inspection, adjustment, scheduling, maintenance, release, allocation, or investigation. A model that does not change a decision may still provide insight, but its contribution to continuous improvement is harder to demonstrate. Future reporting should therefore specify the decision supported, the person or system responsible for acting, and the operational metric affected.

C. Human-Centered and Responsible Use

The movement toward Industry 5.0 strengthens the case for human-centered evaluation [8], [9]. Industrial systems combine technical and social elements, and AI-supported interventions can redistribute work, change authority, or introduce new failure modes. Responsible use requires attention to data quali-

ty, bias, interpretability, privacy, security, and the consequences of incorrect predictions. Human oversight is especially important when model outputs affect safety, employment, customer access, or high-cost operational decisions.

Human oversight does not mean that every decision must remain manual. It means that decision rights, escalation conditions, monitoring responsibilities, and acceptable error levels are explicitly designed. Industrial Engineering is well positioned to address this requirement because it integrates process design, human factors, quality, analytics, and organizational performance. AI implementation can therefore be evaluated as a system redesign rather than a software installation.

D. Meaning of the Recent Publication Concentration

The concentration of retained studies in 2025 and early 2026 shows that the final matrix is largely composed of recent literature. Eight studies were published in 2025 and seven during the first quarter of 2026, together representing 15 of the 23 retained studies (65.22%). This distribution provides context for interpreting the predominant and emerging attributes, whose frequencies mainly reflect recently documented applications. Since 2026 includes only its first quarter, comparisons with preceding years require consideration of unequal observation periods. Publication concentration alone also does not establish the maturity, continuity, or extent of industrial implementation.

The publication types identified in the initial compilation provide additional context. Applied Research Articles constituted the largest individual category, with 44 of the 138 records (31.9%). Literature Reviews, Theoretical Research Articles, and Conceptual Articles also represented substantial portions of the retrieved literature. This distribution shows that the compilation included contributions addressing applications, evidence synthesis, theoretical development, and conceptual discussion. Publication type helped characterize the retrieved material, while the eligibility criteria determined whether each study provided the evidence required for the final mapping.

The screening process reduced the initial compilation from 138 records to 100 articles for full-text assessment and ultimately to 23 retained studies. Requiring a defined industrial problem, an applied AI solution, and reported impact focused the matrix on studies connecting AI with operational improvement. The recent publication concentration should therefore be interpreted together with these selection conditions. Future updates using consistent search, eligibility, and coding criteria could examine whether the documented patterns persist and whether attributes currently classified as emerging become more consistently represented and develop into established trends.

VI. IMPLICATIONS FOR EDUCATION AND PRACTICE

A. Progressive Curricular Integration

Table IV presents the authors' proposed integration of AI competencies, informed by the descriptive mapping. It is not a curricular model validated by the 23 studies, and no curricular implementation or learning-outcome evaluation is reported. Students first need data literacy, statistical reasoning, and a clear understanding of measurement and variation. They can then learn how features are constructed, how models are trained and validated, and how predictive metrics differ from operational outcomes [5]. Advanced projects should require comparison with a baseline and discussion of interpretability, ethics, and human responsibility.

TABLE IV
AUTHORS' PROPOSED INTEGRATION OF AI COMPETENCIES

Curricular area	AI capability	Required evidence
Special Topics Area	Develop and validate AI competencies	Validated AI model with documented performance and limitations
Statistical Quality Control	Apply AI to defect detection and variability analysis	Measurable improvement compared with traditional quality-control methods
Production Planning and Control	Apply AI to forecasting, scheduling, and production decisions	Improved planning performance compared with an established baseline
Simulation and Process Design	Apply AI to simulation and scenario optimization	Sensitivity and robustness results across multiple scenarios
Lean Six Sigma	Integrate AI throughout the DMAIC phases	Measurable improvement from baseline to control using validated operational metrics
Capstone Project	Validate an end-to-end AI-supported solution in a real industrial project	Measurable, responsible, and sustainable operational improvement with human oversight

This proposed sequence would allow students to progressively develop, apply, integrate, and validate AI competencies while addressing established industrial engineering problems. In the Special Topics course, students would develop and validate AI models while documenting their performance and limitations. In Statistical Quality Control, they would apply AI to defect detection and variability analysis and compare the results with conventional quality-control methods. In Production Planning and Control, students would assess AI-assisted forecasting, scheduling, and decision support against an established analytical baseline [4]. In Simulation and Process Design, they would evaluate scenario-based and surrogate models through sensitivity and robustness analyses. Lean Six Sigma would then provide a structured environment for integrating AI throughout the DMAIC cycle and measuring improvement from baseline to control. Finally, the Capstone Project would culminate in an end-to-end, AI-supported intervention in a real industrial context, demonstrating measurable, responsible, and sustainable operational improvement under human oversight.

B. Guidance for Practitioners

For practice, the authors propose six connected actions informed by the evidence map: define the operational problem; establish a measurable baseline; evaluate data readiness and measurement quality; select a method appropriate to the available data and decision; validate both technical and operational performance; and design monitoring, escalation, and human

oversight. Skipping the early steps increases the risk that the project optimizes a model metric without improving the process.

Implementation should also distinguish a laboratory result from a field result. A model may perform well on historical or simulated data but degrade after deployment because of process conditions, product mix, sensor behavior, or work practices change. Continuous monitoring, periodic revalidation, and ownership of corrective action are therefore part of the improvement system. These responsibilities should be assigned before deployment rather than after performance declines.

C. Reporting Recommendations

Researchers and practitioners should report enough information to connect the AI method to the engineering result. At minimum, a study should describe the industrial context, problem definition, data source, data period, preprocessing, validation procedure, baseline, technical metric, operational metric, implementation setting, and important constraints. Claims of improvement should identify whether evidence came from simulation, historical testing, pilot deployment, or sustained field use.

This reporting discipline would make future comparisons more meaningful. It would also help distinguish improvements produced by the model from improvements produced by broader process changes. When several interventions occur together, authors should describe the contribution and timing of each component rather than attribute the entire result to AI.

VII. LIMITATIONS AND FUTURE RESEARCH

A. Limitations

The study has several limitations. First, the search relied primarily on EBSCO and Emerald, so relevant work indexed elsewhere may be absent. Second, the final sample contained 23 studies published from 2021 through the first quarter of 2026. Third, the categories were coded descriptively and were not used to estimate effect size or implementation quality. Fourth, the nonexclusive structure captures overlap but does not establish dependence among attributes. Fifth, first-quarter 2026 results cannot be compared directly with complete calendar years.

The first author conducted both screening stages, while the research advisor contributed to defining the eligibility criteria. Studies identified as falling outside the defined Industrial Engineering scope were excluded during full-text assessment. Article Review and Data Extraction Forms were used to document eligibility criteria, identified attributes, and supporting evidence. The form provides fields for the three inclusion checks, the final decision, and the evidence location for each coded attribute. After the initial matrix coding, GPT 5.6 Sol was used to assist in checking for potentially omitted attributes and suggesting justifications for their inclusion. This AI-assisted check did not constitute independent recoding by a second human reviewer. No inter-reviewer agreement statistic was calculated.

The threshold comparison in Section IV shows that the six headline labels are stable under the two alternative rules, while categories near the boundaries are sensitive to the cutoffs. This is a deterministic reclassification of the same 23 studies, not a test of coding accuracy or a statistical uncertainty analysis. The review does not rank algorithms, industries, or application outcomes; frequency cannot establish comparative effectiveness.

B. Research Agenda

Future reviews should expand database coverage, search gray literature under explicit quality criteria, and update the matrix after a complete 2026 publication cycle. Cross-tabulation can examine how technologies relate to industries, application areas, problems, study designs, and geographic contexts. A second independent coding pass and agreement analysis would further strengthen classification reliability.

Empirical research is also needed in organizations and geographically underrepresented regions. Such studies should compare baseline and post-implementation performance, document adoption barriers, examine worker and decision-maker experiences, and monitor results over time. Particular attention should be given to whether AI-supported improvements remain effective after process changes and whether benefits are distributed responsibly across stakeholders.

A final research priority is the relationship between AI and established improvement frameworks. Studies should make explicit whether AI supports problem definition, measurement, analysis, improvement selection, control, or several stages. This would clarify whether intelligent methods are being integrated into continuous-improvement systems or used as isolated analytical tools.

VIII. CONCLUSION

This review synthesized a scattered body of evidence on AI for continuous process improvement in Industrial Engineering. From 138 retrieved records, 100 advanced to full-text evaluation and 23 met the reported problem-solution-impact eligibility rule. Within this selected sample, Machine Learning, Decision Making, Quality Improvement, and Variability exceeded the operational threshold for predominant trends, while Deep Learning was emerging. Process Improvement appeared throughout the sample, partly reflecting the review scope and eligibility criteria.

Within the selected literature, the combined pattern suggests that AI is commonly used to strengthen established improvement objectives through analytical and predictive support. Its value depends on the quality of problem definition, data, validation, operational measurement, and the decision process surrounding the model. AI should therefore complement statistical foundations, engineering methods, and human judgment rather than replace them.

The mapping informs proposed curricular integration and a problem-first implementation sequence, but it does not validate either recommendation or establish broad industrial adoption. The complete matrix and explicit exclusion counts improve traceability. Reproducible search records, formal quality appraisal, independent coding, broader database coverage, and longitudinal field studies remain necessary to strengthen the conclusions and evaluate sustained performance.

IX. AI Use Disclosure & Author Responsibility Statement

GPT 5.6 Sol was used after the initial coding of the literature matrix to help identify potentially omitted attributes and suggest reasons for considering them. The first author personally checked these suggestions against the corresponding articles before incorporating supported changes into the matrix. Verification of the results reported from the included articles was completed by the first author. ChatGPT was also used to assist with drafting and revising manuscript passages in response to reviewer feedback.

The authors retain full responsibility for the final manuscript, including the accuracy of its findings and references, the originality of its text, and its overall integrity.

APPENDIX A

TABLE V
RECORDED ATTRIBUTES OF THE 23 INCLUDED STUDIES

Study and reference	Application area	AI or enabling technology	Problem addressed
Adnyana and Schwung (2026) [15]	PI, QI, QC	ML, NLP, GAI	DF, IN, VA, TR, DM, RM
Altuğ (2023) [16]	PI, QI, LSS, DMAIC	ML, DL	DF, IN, VA, SC, TR, DM, CR, RM
Benbarrad et al. (2021) [17]	PI, QI, QC	ML, DL, MV, CV	DF, IN, TR, DM, MI
Castillo et al. (2024) [18]	PI, QI, QC	IoT, ML, DL, MV, CV	DF, IN, SC, TR, CR, MI
Garg et al. (2021) [19]	PI, QI, QC	ML	DF, IN, VA, DM, RM
Gholami et al. (2026) [20]	PI	FL	VA, DM, CR, RM
Grech and Zammit (2026) [21]	PI, QI, LSS	ML, NLP	VA, DM, RM
Hoque et al. (2026) [22]	PI, QI, QC	IoT, FL	DF, IN, VA, SC, TR, DM, CR, RM
Köken et al. (2026) [23]	PI, QI, QC, LSS	ML, EA, MH	DF, IN, VA, SC, DM, RM
Lamdjad (2025) [24]	PI	IoT, ML	VA, TR, DM, RM
Lee et al. (2025) [25]	PI, QI, QC	ML, DL	DF, IN, VA, DM, RM
Mahfoud et al. (2025) [26]	PI, QI	ML, DL, NLP, GAI	IN, TR, DM
Moor et al. (2024) [27]	PI, QI, QC	ML, MV, CV	DF, IN, TR, DM, CR, MI
Nasr et al. (2025) [28]	PI, QI, QC	ML, FL, EA, MH	DF, VA, SC, TR, DM, RM
Nesterak et al. (2025) [29]	PI, QI, QC	ML, MV, CV	DF, IN, VA, TR, DM, CR, MI
Oancea et al. (2026) [30]	PI, QI, QC	IoT, ML, DL, NLP, GAI	DF, IN, VA, TR, DM, RM
Perez Colo et al. (2023) [31]	PI, QI, QC	ML, DL, MV, CV	DF, IN, VA, TR, DM, MI, RM
Profili et al. (2024) [32]	PI, QI, QC	ML, DL, MV, CV	DF, IN, MI
Raamets et al. (2025) [33]	PI, LSS, DMAIC	ML	VA, TR, DM
Saavedra Sueldo et al. (2025) [34]	PI	ML, MH	VA, TR, DM, CR
Gonzalez Santacruz et al. (2025) [35]	PI, QI, QC, DMAIC	IoT, ML	DF, IN, VA, DM, RM
Singh et al. (2023) [36]	PI, QI, QC	IoT	DF, IN, VA, CR, MI, RM
Watson-Hemphill (2026) [37]	PI, QI, QC	ML, DL, NLP, GAI	VA, TR, DM

Codes denote recorded presence; an omitted code is unmarked in the source matrix, not proof that the attribute is absent in practice. The categories are nonexclusive.

Application area: PI = Process Improvement; QI = Quality Improvement; QC = Quality Control; LSS = Lean Six Sigma; DMAIC = Define, Measure, Analyze, Improve, Control.

Technology: IoT = Internet of Things; ML = Machine Learning; DL = Deep Learning; MV = Machine Vision; FL = Fuzzy Logic; NLP = Natural Language Processing; EA = Evolutionary Algorithms; MH = Metaheuristics; GAI = Generative AI; CV = Computer Vision.

Problem: DF = Defects; IN = Inspection; VA = Variability; SC = Scrap; TR = Time Reduction; DM = Decision Making; CR = Cost Reduction; MI = Manual Inspection; RM = Risk Management and Prediction.

REFERENCES

[1] A. R. Buendia Giribaldi, M. A. Rojas Quispe, L. H. Tosso Pineda, G. C. Quispe Gonzales, and E. M. Gutierrez Sulica, "Impact of the industrial engineer in the management of organizations," Journal of Scientific and Technological Research Industrial, vol. 2, no. 1, 2021, doi: 10.47422/jstri.v2i1.12.

[2] W. K. Holstein, "Industrial engineering: Process improvement, automation and optimization," Encyclopaedia Britannica, Jul. 26, 1999. [Online]. Available: https://www.britannica.com/technology/industrial-engineering

[3] V. Prajova, K. Lestyanszka Skurkova, F. Praj, and V. Bestvinova, "The importance of applying selected industrial engineering tools and methods in process improvement," MM Science Journal, pp. 7115-7121, Dec. 2023, doi: 10.17973/MMSJ.2023_12_2023073.

[4] S. Mardikar, A. Aldhuhayyan, and V. V. Prabhu, "Can the art of mathematical modeling in Industrial Engineering be automated by AI?" in Proc. 9th North American Conference on Industrial Engineering and Operations Management, Washington, DC, USA, 2024, doi: 10.46254/NA09.20240261.

[5] L. Budeli, "Application of feature engineering and artificial intelligence in industrial systems programs," PM World Journal, vol. 10, no. 2, Feb. 2021.

[6] S. Gonzalez Araque, "Estado del arte en la aplicacion de la inteligencia artificial en las ramas de la ingenieria industrial," undergraduate thesis, Universidad Catolica de Colombia, 2021.

[7] P. C. B. de Oliveira, E. G. Craveiro, J. P. Bezerra, E. dos S. Oliveira, and D. Nascimento-e-Silva, "What is Industry 4.0: A review of the literature using the conceptual bibliographic method," International Journal of Professional Business Review, vol. 8, no. 12, pp. 1-31, 2023, doi: 10.26668/businessreview/2023.v8i12.4171.

[8] N. Jafari, M. Azarian, and H. Yu, "Moving from Industry 4.0 to Industry 5.0: What are the implications for smart logistics?" Logistics, vol. 6, no. 2, Art. no. 26, 2022, doi: 10.3390/logistics6020026.

[9] D. R. Fogaça, M. Grijalvo, and M. Sacomano Neto, "What are Industry 4.0 and Industry 5.0 all about? An integrative institutional model for the new industrial paradigms," Administrative Sciences, vol. 15, no. 4, Art. no. 118, 2025, doi: 10.3390/admsci15040118.

[10] A. Carrera-Rivera, W. Ochoa, F. Larrinaga, and G. Lasa, "How-to conduct a systematic literature review: A quick guide for computer science research," MethodsX, vol. 9, Art. no. 101895, 2022, doi: 10.1016/j.mex.2022.101895.

[11] L. A. Machi and B. T. McEvoy, The Literature Review: Six Steps to Success, 4th ed. Corwin, 2022.

[12] B. Singh, S. K. Garg, and S. K. Sharma, "Value stream mapping: Literature review and implications for Indian industry," The International Journal of Advanced Manufacturing Technology, vol. 53, nos. 1-4, pp. 799-809, 2011, doi: 10.1007/s00170-010-2860-7.

[13] B. F. Alkrides, "Promoting sustainable urban walkability: A modified Delphi study on key indicators for urban walkability in Gulf Cooperation Council urban streets," Sustainability, vol. 17, no. 3, Art. no. 1179, 2025, doi: 10.3390/su17031179.

[14] B. Gladysz, C. Cimini, A. Lagorio, S. Mattsson, M. Pinzone, D. Romero, T. Ruppert, and P. Thorvald, "Technology adoption models for Operator 5.0 implementations: A harmonized framework," Computers & Industrial Engineering, vol. 217, Art. no. 112089, 2026, doi: 10.1016/j.cie.2026.112089.

[15] K. Adnyana and A. Schwung, "Benchmarking and validation of prompting techniques for AI-assisted industrial PLC programming," Machine Learning with Applications, vol. 23, Art. no. 100804, 2026, doi: 10.1016/j.mlwa.2025.100804.

[16] M. Altuğ, "Application of six sigma through deep learning in the production of fasteners," International Journal of Lean Six Sigma, vol. 14, no. 7, pp. 1376-1402, 2023, doi: 10.1108/IJLSS-08-2022-0191.

[17] T. Benbarrad, M. Salhaoui, S. B. Kenitar, and M. Arioua, "Intelligent machine vision model for defective product inspection based on machine learning," Journal of Sensor and Actuator Networks, vol. 10, no. 1, Art. no. 7, 2021, doi: 10.3390/jsan10010007.

[18] M. Castillo, R. Monroy, and R. Ahmad, "A cyber-physical production system for autonomous part quality control in polymer additive manufacturing material extrusion process," Journal of Intelligent Manufacturing, vol. 35, pp. 3655-3679, 2024, doi: 10.1007/s10845-024-02389-0.

[19] P. Garg, A. Patil, G. Soni, A. Keprate, and S. Arora, "Machine learning-based abnormality detection approach for vacuum pump assembly line," Reliability: Theory & Applications, vol. 16, Special Issue 2(64), pp. 176-187, 2021.

[20] H. Gholami, X. Delorme, and A. Dolgui, "An intelligent data-driven model for sustainable-resilient supplier scrutiny and selection in sustainable reconfigurable manufacturing systems," International Journal of Production Research, vol. 64, no. 7, pp. 2591-2615, 2026, doi: 10.1080/00207543.2025.2581249.

[21] V. Grech and J. P. Zammit, "Enhancing safety management through occurrence reporting: Modelling and predictive analytics," Procedia Computer Science, vol. 277, pp. 2193-2202, 2026.

[22] M. R. Hoque, R. B. Noor, S. R. Tushar, M. M. Bappy, and M. G. S. Rayhan, "Improving the overall equipment effectiveness in the textile dyeing section through total productive maintenance: Implications for economic sustainability," International Journal of Productivity and Performance Management, 2026, doi: 10.1108/IJPPM-01-2025-0044.

[23] R. Köken, A. R. Firuzan, and İ. Yavuz, "Application of artificial intelligence-integrated Six Sigma methodology for multi-objective optimization in injection molding processes," Applied Sciences, vol. 16, Art. no. 1025, 2026, doi: 10.3390/app16021025.

[24] B. Lamdjad, "Edge AI-driven adaptive maintenance for manufacturing systems: Improving decision-making and reducing energy consumption," Journal of Intelligent Manufacturing and Special Equipment, 2025, doi: 10.1108/JIMSE-05-2025-0008.

[25] J. Lee, J. Jang, Q. Tang, and H. Jung, "Recipe based anomaly detection with adaptable learning: Implications on sustainable smart manufacturing," Sensors, vol. 25, Art. no. 1457, 2025, doi: 10.3390/s25051457.

[26] H. Mahfoud, M. Masmoudi, A. Hassani, and O. Moutaoukil, "AI chatbots for healthcare maintenance: Transforming total productive maintenance in the Industry 5.0 era," The TQM Journal, 2025, doi: 10.1108/TQM-10-2024-0394.

[27] M. Moor, M. Sarkans, T. Kangru, T. Otto, and J. Riives, "AI functionalities in cobot-based manufacturing for performance improvement in quality control application," Journal of Machine Engineering, vol. 24, no. 2, pp. 44-55, 2024, doi: 10.36897/jme/189169.

[28] M. M. Nasr, W. Ameen, A. Dabwan, and A. Al-Ahmari, "Machine learning-based multi-objective optimization for enhancing the performance of block support structures for electron beam additive manufacturing," Metals, vol. 15, Art. no. 671, 2025, doi: 10.3390/met15060671.

[29] J. Nesterak, M. Szelągowski, and P. Radziszewski, "Workplace performance measurement: Digitalization of work observation and analysis," Journal of Intelligent Manufacturing, vol. 36, pp. 3569-3585, 2025, doi: 10.1007/s10845-024-02419-x.

[30] A.-V. Oancea, L.-M. Ionescu, C. Rontescu, N. Ionescu, A. Misztal, A.-M. Bogatu, C. Ştirbu, D.-T. Cicic, and E.-M. Stanciu, "An intelligent framework for implementing AIAG-VDA FMEA and action priority (AP) assessment," Applied Sciences, vol. 16, Art. no. 2591, 2026, doi: 10.3390/app16052591.

[31] I. Perez Colo, C. Saavedra Sueldo, M. De Paula, and G. G. Acosta, "Intelligent approach for the industrialization of deep learning solutions applied to fault detection," Expert Systems with Applications, vol. 233, Art. no. 120959, 2023, doi: 10.1016/j.eswa.2023.120959.

[32] A. Profili, R. Magherini, M. Servi, F. Spezia, D. Gemmiti, and Y. Volpe, "Machine vision system for automatic defect detection of ultrasound probes," The International Journal of Advanced Manufacturing Technology, vol. 135, pp. 3421-3435, 2024, doi: 10.1007/s00170-024-14701-6.

[33] T. Raamets, K. Karjust, J. Majak, and A. Hermaste, "Implementing an AI-based digital twin analysis system for real-time decision support in a custom-made sportswear SME," Applied Sciences, vol. 15, no. 14, Art. no. 7952, 2025, doi: 10.3390/app15147952.

[34] C. Saavedra Sueldo, I. Perez Colo, M. De Paula, S. A. Villar, and G. G. Acosta, "Simulation-based metaheuristic optimization algorithm for material handling," Journal of Intelligent Manufacturing, vol. 36, pp. 1689-1709, 2025, doi: 10.1007/s10845-024-02327-0.

[35] E. Gonzalez Santacruz, D. Romero, J. Noguez, and T. Wuest, "Integrated quality 4.0 framework for quality improvement based on Six Sigma and machine learning techniques towards zero-defect manufacturing," The TQM Journal, vol. 37, no. 4, pp. 1115-1155, 2025, doi: 10.1108/TQM-11-2023-0361.

[36] J. Singh, I. S. Ahuja, H. Singh, and A. Singh, "Application of Quality 4.0 (Q4.0) and Industrial Internet of Things (IIoT) in agricultural manufacturing industry," AgriEngineering, vol. 5, pp. 537-565, 2023, doi: 10.3390/agriengineering5010035.

[37] K. Watson-Hemphill, "AI turns data into decisions: Enhancing continuous improvement work with actionable insights," Lean & Six Sigma Review, pp. 8-13, Feb. 2026.