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RESEARCH ARTICLE

INTEGRATING APPLIED AI WITH ENTERPRISE RESOURCE PLANNING SYSTEMS FOR INTELLIGENT MANUFACTURING DECISION SUPPORT IN SAUDI ARABIA

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Abstract

Artificial intelligence is increasingly used as a decision-making layer surrounding enterprise resource planning systems, although the evidence is still scattered throughout the areas of manufacturing analytics, digital twins, supply - chain intelligence and enterprise information systems. The present review looks at how applied artificial intelligence can be combined with ERP-based architectures in order to enhance intelligent decision support for manufacturing in Saudi Arabia. A selective integrative review draws on thirty peer - reviewed publications from 2020 to 2025 with verified bibliographic records. The corpus combines direct manufacturing evidence with contextual studies of ERP, technology adoption and decision governance. The evidence was categorised according to decision level, data source, integration method, AI capability, operational outcome and governance need. Official PMI guidance, outside the scholarly corpus, informs a CPMAI-based governance adaptation. The synthesis suggests that ERP can provide a foundation for AI when it serves as a governed enterprise context layer that links together finance, procurement, inventory, production and supply-chain records with data from manufacturing execution, the industrial Internet of Things and digital twins. Forecasting, scheduling, maintenance, quality, inventory and resilience decisions can then be supported through machine learning, explainable analytics and optimisation, on the condition that the results of the models are incorporated into accountable human workflows. For Saudi manufacturers, the review identifies potential constraints in data quality, interoperability, process ownership, cybersecurity, skills and decision governance. The paper proposes an integrative AI-ERP decision-support architecture and a staged maturity pathway for evaluation in Saudi manufacturing.

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Governance is specified through CPMAI-aligned lifecycle reviews, named decision owners, ERP transaction authorisation, audit records and reapproval following material change. These controls are conceptual proposals requiring validation. The review also identifies key research areas relating to the long-term realisation of value,

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cross-sector generalisability, Arabic-enabled interfaces, explainability, industrial data sovereignty and the measurement of human-AI decision quality.

Introduction:-

Manufacturers are shifting from isolated automation to decision environments in which operational, commercial and managerial information has to be constantly interpreted. Enterprise resource planning (ERP) systems still play a central role in this shift since they bring together the records of finance, procurement, inventory, sales, human resources and production within a single transactional framework. In industrial companies in Saudi Arabia, survey evidence links ERP capability with organisational performance and strategic decision-making, indicating that the value of ERP depends to a large extent on how integrated information is turned into managerial action [1]. Further research suggests that the benefits of ERP differ depending on the quality of its implementation, the level of organisational readiness and the ability to link up enterprise information with innovation and open digital practices [2], [3].

Applied artificial intelligence (AI) is transforming the role of ERP by incorporating predictive, diagnostic and prescriptive functions into workflows that use enterprise data. A review of machine learning in ERP describes a shift from rules and dashboards to machine-learning models that are able to forecast demand, recognise process anomalies, recommend inventory actions and prioritise managerial attention [4]. Research into Industry 4.0 also places ERP as an element of a broader digital production ecosystem in which shop-floor systems, connected equipment, cloud services and advanced analytics share information across the limits of the organisation [5].

This is especially important for Saudi Arabia. The National Industrial Development and Logistics Program (NIDLP), a Vision 2030 realisation programme, identifies localisation, productivity, Fourth Industrial Revolution adoption and supply security as priorities in its 2021–2025 delivery plan [6, pp. 13, 42, 46]. Saudi automotive and cement studies describe sector-specific implementation conditions and differences in readiness [7], [8]; they do not establish a national estimate of digital maturity. Post-implementation ERP research in Saudi Arabia also identifies integration, user adoption, training and support challenges [3]. Saudi manufacturers therefore need a framework that shows where AI should connect to ERP, which decisions are appropriate for augmentation, and what organisational safeguards are needed before recommendations are put into practice.

The reviewed literature addresses different parts of the integration problem. Research into ERP focuses on enterprise integration and effectiveness; that concerning manufacturing and AI centres on algorithms and applications at the shop floor; studies of digital twins stress cyber-physical synchronisation; and those on supply chains look at forecasting, resilience as well as optimisation. These separate perspectives leave a managerial question: how can AI be incorporated into ERP-based manufacturing systems to improve decisions while maintaining coherent governance, consistent data and human accountability?

The review deals with this issue by bringing together the evidence that was published between 2020 and 2025 and by explaining it in the context of the Saudi industrial environment. To begin with, it treats ERP as a governed enterprise context layer for AI. Secondly, rather than discussing the subject only in terms of technology, it links AI applications to strategic, tactical and operational decision-making levels. Thirdly, it suggests an implementation route on which data readiness, interoperability, explainability and human oversight all develop together. This approach is meant to help researchers who are working on digital manufacturing and those who are designing decision-support systems that are capable of scaling past experimental pilot projects.

The governance component is developed using the Cognitive Project Management in AI (CPMAI) methodology associated with PMI Certified Professional in Managing AI (PMI-CPMAI). PMI describes an iterative lifecycle connecting business purpose, data, model development, evaluation and operational use [9, pp. 5, 9–12]. This paper adapts that life-cycle to the authority required to turn an AI recommendation into an ERP-controlled action. The contribution is a proposed governance design for manufacturing workflows, not evidence that adopting the methodology alone improves performance.

Review Perspective and Research Gap:-

One transition is from using ERP primarily for transaction processing to using it as an information backbone. The ML–ERP review and Industry 4.0 chapter describe opportunities to connect enterprise information with analytics and production systems [4], [5]. The second change is a shift from descriptive reporting to predictive and prescriptive reasoning. AI is capable of detecting nonlinear patterns, estimating future states and producing ranked

actions, but the reliability of its recommendations depends in part on the definitions of the data and the process logic that go with them [10], [11]. These decisions also cross functional boundaries: decisions relating to production, maintenance or quality now have an impact on procurement, working capital, customer commitments, energy use and supply-chain risk.

A significant gap appears where these transitions meet. Although a good deal of the manufacturing literature deals with what AI is capable of predicting, a similar amount of the ERP literature focuses on the kind of information the enterprise platform is able to integrate. Within the reviewed corpus, less attention is given to the organisational processes by which a prediction becomes a governed manufacturing decision. For instance, a model might accurately predict machine failure, but its operational value would still be restricted if the recommendation could not be brought into line with work-order priorities, spare-parts availability, production commitments and financial constraints inside the ERP system. In the same way, a demand forecast only becomes actionable when it is connected to material requirements, capacity, supplier lead times and service targets.

Studies of the Saudi automotive and cement sectors identify organisational and technical requirements for Industry 4.0 adoption [7], [8]. Alsaadi's literature-based modelling of adoption challenges provides broader manufacturing context [12], rather than direct evidence from a Saudi-firm sample. Within this corpus, AI-ERP integration receives limited attention as a distinct manufacturing decision framework. The Saudi environment includes large process industries, a growing discrete manufacturing sector, objectives relating to localisation, and companies which vary greatly in their level of digital maturity. It is therefore necessary to have a framework which is focused on decision-making and that connects the enterprise's context, industrial data, AI services, governance and quantifiable effects while permitting a step-by-step approach to adoption.

Aim and Objectives:-

This review seeks to synthesise evidence published between 2020 and 2025 on the integration of applied artificial intelligence with ERP-based manufacturing systems and to establish a decision-support framework for evaluation in industrial organisations in Saudi Arabia. The analysis is guided by four objectives: first, to outline the AI-supported manufacturing decisions at the strategic, tactical and operational levels; second, to identify the data, interoperability and governance conditions that influence the extent to which AI recommendations can be implemented via ERP; third, to examine the main opportunities and constraints inside the context of Saudi manufacturing; and fourth, to suggest a staged architecture, CPMAI-based decision-governance model and research programme aimed at progressing from predictive assistance to governed prescriptive decision support. Throughout the review, emphasis is placed on decision quality and the conditions required for implementation rather than on comparing different machine-learning algorithms.

Methodology:-

An integrative review approach was adopted because the research question spans information systems, operations management, manufacturing engineering and supply-chain management. The review draws on a selected corpus of 30 peer-reviewed publications [1]–[5], [7], [8], [10]–[32] with publication years from 2020 to 2025. It combines empirical studies, reviews and conceptual contributions to develop a decision-support framework; it does not estimate an average effect of AI-ERP integration. Publication years follow the cited journal issue or proceedings, which may differ from the year of online-first publication.

The thematic scope covers four areas: enterprise systems (enterprise resource planning or ERP); artificial intelligence (artificial intelligence, machine learning, predictive analytics or optimisation); manufacturing (manufacturing, production, Industry 4.0, digital twins or industrial systems); and decision support (planning, scheduling, forecasting, quality, maintenance or resilience). Database-specific search strings, search dates, retrieval totals, duplicate-removal counts and screening decisions are not documented. The corpus is therefore treated as a selective integrative synthesis. Its coverage cannot be reproduced as a systematic database search, and no claim of exhaustive retrieval is made. The selected corpus brings together complementary evidence streams used in the framework: ERP and enterprise analytics; manufacturing AI and digital twins; supply-chain resilience; Saudi industrial adoption; and human-AI decision governance. This describes the corpus's conceptual coverage rather than a reconstructed search or screening procedure.

The corpus consists of English-language, DOI-identifiable scholarly publications relevant to AI-enabled enterprise or manufacturing decisions. Saudi-specific ERP and Industry 4.0 studies provide contextual evidence even when they do

not evaluate AI–ERP integration directly. The conceptual SME ERP–BI framework [13] and ERP recruitment study [14] are retained only as contextual contributions, not as evidence of manufacturing performance gains. The official NIDLP delivery plan [6] is an additional policy source, outside the 30- publication scholarly corpus. PMI’s CPMAI v7 and updated PMI-CPMAI examination content outlines, consulted on 4 October 2026, provide formal professional guidance for the CPMAI governance extension [9], [33]. These documents are outside the 30-publication scholarly corpus and are not empirical studies of manufacturing performance. The six- phase lifecycle is mapped to AI–ERP decisions, then review evidence, accountable roles and transaction-release rules are specified as design propositions. This interpretive mapping has not been tested with practitioners or plant data. These distinctions separate policy objectives and methodology guidance from empirical findings.

The synthesis is organised around six analytical dimensions. The first of these was the level of decision-making, which was classified as strategic, tactical or operational. The second dimension related to the enterprise context and included ERP modules and the associated planning procedures. The third dimension referred to the operational data source, for example manufacturing execution systems (MES), the industrial Internet of Things (IIoT), sensors, quality records or digital twins. The fourth dimension was concerned with AI capabilities, namely prediction, anomaly detection, classification, recommendation, optimisation and explanation. The fifth dimension was the reported or proposed outcome, such as schedule adherence, quality, asset availability, inventory, resilience or decision speed. The sixth dimension was governance requirement and this included explainability, access control, human approval, data stewardship and model monitoring. Table I summarises the review scope, analytical dimensions and reporting limitations.

The analysis focuses on how an analytical output could become an ERP-controlled action, such as a maintenance recommendation becoming a work order or a forecast informing material planning. A bibliographic and targeted source-to-claim verification was completed on 2 October 2026 using DOI registration records and publisher or official-source records. This check concerned the cited corpus and did not extend the publication window or constitute a new systematic search. Evidence is interpreted according to study design, setting, whether an outcome was measured or proposed, and relevance to manufacturing. For example, the semiconductor field study [18] supports a specific quality application, while conceptual and cross-domain sources support possible mechanisms rather than proven effects. No standardised risk-of-bias score or independent duplicate appraisal is reported. The resulting architecture, decision matrix and maturity pathway are the author’s conceptual synthesis and require empirical validation.

Thematic Synthesis:-

A recurring theme across the reviewed literature is that the value of manufacturing AI depends on how analytical outputs are connected to data, operational decisions and organisational controls [4], [10], [17], [21]–[24]. The following sections examine ERP as enterprise context, AI-supported planning and control, industrial data integration, supply-chain resilience and human–AI governance. Their implications for Saudi manufacturing are developed as a synthesis, rather than as a finding shared by every source.

ERP as the backbone for enterprise decision-making:-

ERP contributes to intelligent manufacturing since it incorporates the commercial and organisational background against which operational decisions are taken. The master data of ERP cover products, bills of materials, suppliers, cost objects, inventories, customers and accounting structures; its transactions document commitments and constraints which are frequently missing from shop-floor analytics. Research into ERP and business performance indicates that integration is able to enhance information consistency and operational coordination, although the benefits rely on complementary organisational capabilities [1], [2]. Evidence obtained after the implementation in Saudi Arabia supports this by demonstrating that the value of ERP is limited when the processes, the users and the technical interfaces are still misaligned [3].

ERP-supported decisions can incorporate production conditions from MES, IIoT platforms or digital twins when suitable interfaces are available. Jawad and Balázs review machine-learning integration with ERP, including prediction and data-driven optimisation [4]. Zheng and Khalid propose a conceptual framework for ERP–business-intelligence adoption in SMEs [13]; this provides adoption context but does not establish manufacturing AI outcomes. Strang and Sun evaluate NLP-assisted recruitment of ERP specialists using online candidate data [14]. Their study is a cross-domain illustration of AI-supported enterprise work, not evidence that AI improves production planning or shop-floor control.

An AI service has to employ the same definitions for the terms item, location, customer priority, resource and time horizon as those used by the planning process it is feeding information to. A model using an external data lake may produce operationally invalid recommendations if its master- data definitions differ from those in ERP. The ERP layer thus functions as a governed context boundary since it defines what the organisation considers to be a valid object, transaction and authorised action. This supports scalable AI since the recommendations can be traced back to enterprise records and then converted into controlled workflows.

Table I Review Scope And Analytical Framework

Element	Specification
Review design	Selective integrative review focused on decision architecture and implementation conditions.
Publication window	2020–2025, using the cited journal issue or proceedings year.
Thematic scope	ERP; AI and machine learning; manufacturing and Industry 4.0; planning, quality, maintenance and resilience.
Search traceability	Search dates, database-specific strings, retrieval totals, deduplication and screening counts are not documented; exhaustive coverage is not claimed.
Scholarly corpus	30 English-language, DOI-identifiable scholarly publications [1]–[5], [7], [8], [10]–[32], including reviews, empirical studies and conceptual work.
Contextual evidence	Saudi ERP and sector studies; SME ERP–BI adoption [13] and recruitment [14]. Official policy [6] and PMI methodology guidance [9], [33] are additional to the 30 scholarly publications.
Analytical dimensions	Decision level; enterprise context; operational data source; AI capability; reported or proposed outcome; governance requirement.
Evidence interpretation	Study design, setting, observed versus proposed outcomes and relevance inform claim strength. No standardised risk-of-bias score or independent duplicate appraisal is reported.
Verification and synthesis	Corpus checks completed 2 October 2026; PMI sources consulted 4 October 2026. Narrative synthesis and interpretive lifecycle mapping; architecture, governance and maturity pathway require empirical validation.

Source: Author's review design and analytical synthesis.

The use of AI in decisions relating to planning, control and quality:-

At the strategic level, AI can enhance capacity scenarios, supplier portfolio decisions, localisation choices, and investment planning by combining an organisation's historical data with probabilistic forecasts. It has, however, been pointed out by human-AI research that strategic decisions involve ambiguity and changing objectives; algorithms are most beneficial when they increase the amount of evidence available to managers rather than giving them a single seemingly objective answer [10]. Reviews of the use of AI in making innovation decisions also show a tendency towards rationalisation, although they do note that judgement, the way a situation is framed and organisational politics still have an influence [11]. At the tactical level, AI is especially pertinent to sales and operations planning, material requirements, production scheduling, inventory targets and the allocation of workforce. Research on business analytics associates organisational data-driven culture with innovation and performance [15]. For manufacturing planners, this suggests that analytical evidence needs to be understood and used in routine decisions. In the process industries, industrial AI is able to combine domain knowledge, process models and data-based learning in order to assist with optimisation inside complex physical constraints [16]. As shown in more general reviews of Industry 4.0, machine learning is being applied to planning, predictive maintenance, quality inspection, process control and resource optimisation, although repeated obstacles include data availability, interoperability, cybersecurity and skills [17]. Taken together, these studies suggest that tactical AI should be linked to the regular planning cycles and exception-management procedures rather than be provided as a standalone dashboard.

At the operational level, the corpus includes applications with measurable signals and outcomes. A semiconductor manufacturing study used explainable AI to prioritise process-quality improvements and tested the selected actions in a field experiment [18]. This supports a specific quality-management application, rather than a general claim that explainability always improves performance. Approaches based on knowledge graphs are able to represent the entities and relationships involved in manufacturing in a way that supports adaptive control, thus linking physical changes with decision rules [19]. Moreover, machine-learning models can estimate overall equipment effectiveness and detect patterns that are related to production loss [20]. The proposed framework connects these applications to ERP or MES workflows. For example, a predicted defect could trigger a quality

review and an authorised inventory hold, a maintenance risk could prompt preparation of a work order, and an OEE forecast could inform scheduling or staffing. These workflow examples are design proposals, not outcomes demonstrated by all three studies.

Decisions that have stable objectives, receive frequent feed-back and are based on high-quality data can enable a higher level of automation. However, decisions which involve conflicting strategic priorities, ethical trade-offs or unusual events need more extensive human interpretation. Table II presents the author's synthesis of illustrative use cases in relation to ERP context, AI capability and governance requirements. The table illustrates the fact that the output of AI should be given in the form of a decision object — for example, a forecast, a risk score, a recommended action or the result of a constrained optimisation — so that it can be examined and carried out using the existing enterprise controls.

Connecting ERP with MES, IIoT and digital twins:-

Vertical connectivity is essential for AI-ERP integration since the ERP system by itself usually does not have the level of detail needed for manufacturing intelligence. A digital twin keeps a representation of an asset or process in sync with operational data and thus enables functions including monitoring, diagnosis, simulation and optimisation [21]–[24]. In actual manufacturing systems, the twin or IIoT layer offers high-frequency state information, the MES provides the context relating to production execution, and the ERP supplies the enterprise constraints and consequences. Intelligent decision support appears when there is coherent exchange of information between these layers.

Table II Representative AI-ERP Manufacturing Decision-Support Matrix

Decision domain	ERP / enterprise context	Applied AI capability	Decision output	Human governance / control
Demand & S&OP	Orders, forecasts, inventory, service targets	Forecasting, scenario modelling	Demand range; exception priorities	Approved planning policy; planner sign-off; bias and drift review
Production scheduling	Orders, routings, capacity, due dates	Constraint optimisation, learning	Feasible schedule alternatives	Frozen-zone checks; schedule authority; versioned override record
Predictive maintenance	Assets, work orders, spares, cost	Failure prediction, anomaly detection	Risk score; intervention window	Engineering approval; work-order authority; escalation limits
Quality management	Lots, specifications, supplier and customer records	Classification, explainable detection	Defect risk; quarantine or inspection action	Explanation; quality authority; hold/release audit
Inventory & procurement	Materials, suppliers, lead times, working capital	Lead-time and risk prediction	Safety stock; reorder; sourcing option	Delegated spend limits; supplier due diligence; ERP approval
Supply-chain resilience	Purchase orders, plants, customers, alternatives	Risk sensing, simulation	Affected dependencies; response scenarios	Named response owner; cross-functional approval; scenario traceability
Energy / sustainability	Production volumes, cost centres, asset data	Optimisation, pattern analysis	Energy-intensity or operating recommendations	Approved operating envelope; change authority; constraint checks

Source: Author's synthesis based on [4], [10], [16]–[20], [26]–[29]. The decision outputs and controls are illustrative design proposals, not a set of empirically validated AI-ERP deployments. Lifecycle review and transaction-authority rules are specified in Section VI. S&OP = sales and operations planning.

For instance, a predictive-maintenance model might take into account vibration, temperature and operating-load signals from the equipment, but the decision to carry out an intervention will also be influenced by the production schedule, the level of spare parts in stock, the availability of technicians, the warranty status and the customer delivery obligations. A connected architecture is thus able to determine not only the probability of failure but also the business impact of different maintenance windows. Data from the sensors and from vision systems can detect process drift, while records from the ERP system and the quality-management system establish which batches are affected, how the inventory is to be disposed of, supplier claims and customer exposure.

A smart-manufacturing framework study identifies information flows, equipment data acquisition, management platforms and production visibility as implementation priorities [25]. A literature-based model of Industry 4.0 adoption challenges highlights workforce skills and technological infrastructure [12], and studies carried out specifically in the automotive and cement manufacturing sectors show that localisation and digital transformation involve coordinated changes in the technology, the workforce and the way operations are carried out [7], [8]. On this basis, the proposed framework recommends that companies with limited sensor coverage or inconsistent master data start with enterprise forecasting and exception analytics; those plants which have a mature MES and IIoT system can then move on to closed-loop recommendations; only organisations that have reliable interfaces and good governance should attempt adaptive prescriptive control.

Fig. 1 presents the proposed layered architecture: the data starts out in operational assets and enterprise transactions, is then harmonised via integration and master-data controls, and is subsequently interpreted by AI services. The recommendations are displayed through a decision workbench, which is distinguished by means of strategic, tactical and operational time horizons. CPMAI-based decision governance applies across these layers through lifecycle review and operational authority, as detailed in Section VI. Identity, cybersecurity, model ownership, traceability and approval rules are design requirements from the outset. The architecture is deliberately designed to be modular so that Saudi manufacturers can take on the various components depending on their level of maturity while still maintaining a common decision logic.

Supply-chain intelligence and resilience:-

The literature on the use of AI in supply-chain management lists forecasting, sourcing, inventory control, logistics and risk management as key areas of application [26], [27]. A review of post-COVID-19 supply-chain resilience identifies potential roles for AI in visibility, scenario assessment and response, while noting implementation challenges [28]. Decision frameworks concerning resilience describe how AI can help organisations to detect disruptions, assess various options and co-ordinate their actions rather than just predict a single event [29].

AI-ERP intelligent manufacturing decision architecture

Enterprise context and operational signals are translated into governed decision objects.

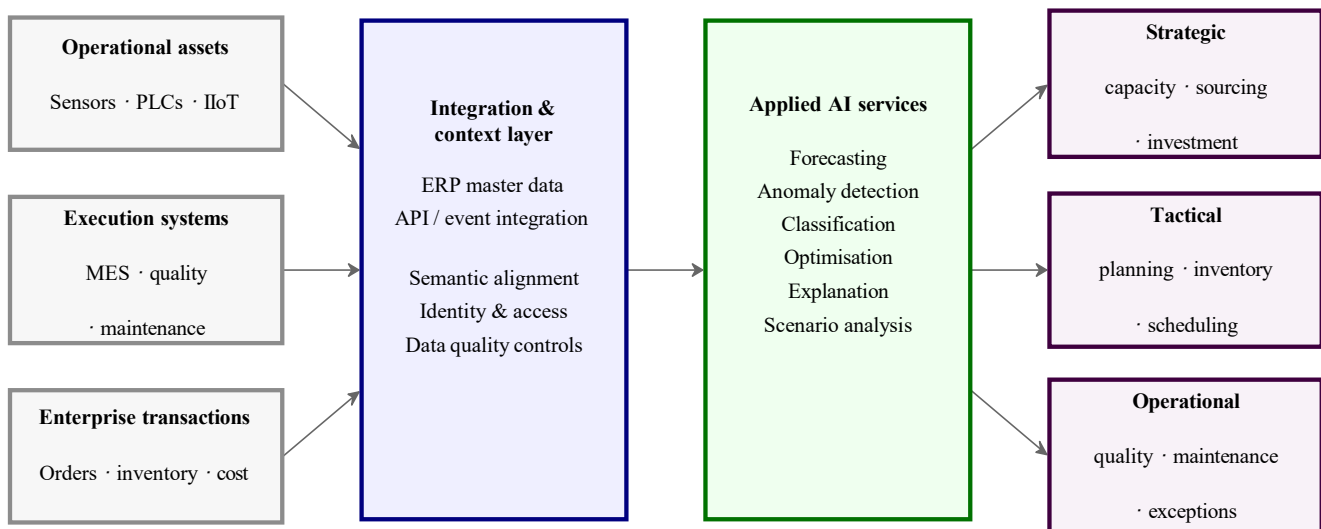


Fig. 1. Proposed layered AI-ERP architecture with CPMAI-based lifecycle review and ERP transaction authority spanning the technical layers. Source: Author's synthesis based on [4], [5], [10], [16], [17], [21]–[25]. The governance extension adapts PMI guidance [9], [33]; the architecture has not been empirically validated.

A supplier risk score only becomes actionable if the system is able to identify the purchase orders, materials, plants, customer commitments and alternative suppliers in question. A demand anomaly is significant only when it affects inventory exposure, capacity utilisation or cash requirements. Qureshi et al. examine Industry 4.0 use in Logistics 4.0 through an extended theory of planned behaviour, with attention to subjective norms, attitudes and perceived behavioural control [30]. This supports attention to adoption conditions; it does not demonstrate that an integrated technology portfolio out-performs individual tools. While AI can assist with make-or-buy analysis, supplier development, safety-stock positioning and import-risk scenarios, the recommendations should be linked to ERP records so that the localisation objectives can be assessed alongside the implications for cost, quality, lead time and service.

A survey of manufacturing firms in developing countries associates perceived reliability, competitive pressure and user confidence with willingness to adopt AI in human-capital supply-chain practices [31]. These are adoption relationships, not measured improvements in manufacturing decision quality. Planners, engineers and managers should know when a model is reliable, what data it is based on, and how to challenge the recommendations it makes. Technical integration may deliver little value if its users go around it, accept its advice without question, or keep their own spreadsheets which then become the actual source of operational decisions.

Human-AI decision governance:-

The key difference between analytics and decision support lies in the matter of accountability. Although AI can lessen the mental effort on people and detect complicated patterns, it may also lead to automation bias, hide problems in the data, and make it unclear who is responsible. Studies concerning the combination of human and artificial intelligence suggest that tasks should be allocated in a complementary way: machines are appropriate for carrying out high-volume pattern recognition and applying specified rules consistently, while humans are still needed for making sense of the context, setting goals, and dealing with new or value-related situations [10]. The semiconductor quality study illustrates how model explanations can help identify process-improvement priorities [18]. In the proposed framework, explanations also support expert review of recommendations against process knowledge; they do not by themselves establish that a model is correct or unbiased.

Decision rights should therefore be the basis on which governance is built, not simply model correctness. In each workflow involving AI, it is necessary to determine who owns the source data, who owns the model, who has the authority to approve or override a recommendation, what evidence must be shown, and what takes place when confidence drops below a specific threshold. The audit trails should include the model version, a snapshot of the input, the recommendation, the user's response and the actual outcome. This kind of information enables accountability and learning since organisations can compare the predicted effects with the actual effects over time.

This review proposes advisory operation followed, where justified, by bounded automation. In advisory operation, AI ranks options and a person authorises the resulting action. In bounded automation, only approved actions within validated limits may execute; exceptions require review by the designated authority. A failed control should hold the proposed transaction and invoke an approved fallback procedure. Greater autonomy is not treated as an obligatory maturity outcome. Each use case must specify permitted actions and escalation conditions; the evidence does not establish one suitable mode for most Saudi firms. Bandhana and Vokříněk survey multi-agent-system and MES integration, emphasising practical industrial problems, integration challenges and human-machine collaboration [32]. The recommendation to judge progress by decision quality rather than maximum autonomy is the present review's synthesis, not a comparative result established by that survey.

Pmi-Cpmai-Based Decision Governance:-

Lifecycle Reviews and Decision Ownership:-

PMI's CPMAI v7 examination outline identifies a six-phase methodology and iteration to earlier phases [9, pp. 9–12]. The updated PMI-CPMAI examination outline addresses responsible AI, business alignment, approval records, model governance and operational monitoring [33, pp. 6–12]. Table III adapts the lifecycle to manufacturing decisions. The proposed AI-ERP adaptation uses this structure to distinguish approval of a decision-support capability from authorisation of each business transaction. The checkpoints, role assignments and transaction controls below are the author's manufacturing-specific design; they are not a PMI-prescribed ERP configuration or a certification claim.

The six lifecycle phases should be distinguished from the five competency domains in the September 2025 examination outline [33, p. 5]. This paper uses the phases to organise iterative delivery and the updated domains to inform re- sponsibilities across that lifecycle; the two structures are not interchangeable.

At each checkpoint, a named accountable owner records a decision to proceed, revise, hold or stop, together with the evidence and unresolved conditions. Approval applies to a defined process, site, item or asset population, model– policy version and operating envelope. It should not be assumed to transfer to another plant or decision domain. The executive sponsor owns the business case and accepts residual business risk; a process owner is accountable for the live decision workflow. The AI project manager coordinates reviews and changes, while data owners, the analytics lead and ERP/OT system owners supply evidence within their responsibilities. Engineering, quality and procurement retain their existing domain authority. Validation should be reviewed separately from model development where practicable, and technical deployment permission should not confer business transaction authority.

For each use case, the proposed decision charter should translate these responsibilities into a versioned authority matrix specifying who recommends, reviews, approves, executes and monitors each action. Release criteria should be agreed before evaluation and address business benefit, error conse- quences, data readiness, privacy, security and relevant bias or fairness risks. A failed mandatory criterion should prevent release even when average predictive accuracy is acceptable. The review record should identify any residual risk accepted, its accountable owner and the conditions that require renewed review.

ERP Transaction Authority and Exception Handling:-

The central operating rule is that a model recommendation is a proposal until the enterprise workflow permits its execution. Each proposal should carry a unique decision identifier and reference the affected order, material, asset, batch or planning period. Before posting, the workflow should check the autho- rised model–policy version, input freshness, applicable site and process, feasibility constraints and the approver’s delegated authority. Automated release requires an explicit permission covering the action type and its limits; an unrecognised case should be held for review. Existing segregation of duties should also apply to AI-initiated actions, so that a developer or integration account cannot grant itself purchasing, quality- release or production authority.

Authority should follow consequence as well as decision frequency. Strategic sourcing and investment choices remain management decisions. Tactical schedule and inventory pro- posals require the relevant planning or procurement authority and checks on frozen periods, capacity, service commitments and financial limits. Operational recommendations may be frequent but still consequential: releasing a quality hold or altering a safety-related maintenance action should remain with the authorised domain role. Bounded automation is a possible mode for validated routine actions, not a general exemption from enterprise controls. Numeric limits and re- view frequency must be set for the plant and use case; this conceptual framework does not prescribe universal thresholds. For example, a failure-risk prediction may generate a pro- posed maintenance intervention. The workflow checks asset identity, available spares, production commitments and the approved operating envelope; engineering reviews the inter- vention and the responsible planner authorises the work order. A resulting purchase requisition follows the separate procure- ment approval route. If the schedule or stock position changes after approval, the system should revalidate the proposal before posting. Duplicate-message protection and reconciliation of ERP responses should prevent an interface retry from creating duplicate orders. This example is a proposed workflow, not a reported deployment outcome.

An override should record the authorised person, reason, affected transactions and expiry or review condition. It should remain within existing engineering, quality and financial au- thority; an override of an AI recommendation should not bypass a mandatory enterprise control. Unresolved conflicts between the recommendation and those controls should be escalated to the designated process owner before execution.

Decision Evidence, Monitoring and Change Control:-

The audit record should connect the decision identifier to source-data and master-data versions, the prediction or scenario, uncertainty, feasible alternatives, model and policy versions, the authority rule, approvals and override reasons. It should also retain the ERP transaction identifier, execution status and subsequent business outcome. Recommendation, approval, posting and physical execution are distinct events; recording each prevents a technically successful model re- sponse from being counted as an implemented decision. Ac- cess controls, timestamps and change history should make this evidence reviewable while respecting the organisation’s data- retention and access policies.

Table Iii Proposed Ai-Erp Governance Checkpoints Mapped To The Cpmal Lifecycle

CPMAI phase	Proposed decision checkpoint	Required AI-ERP evidence	Proposed accountable owner
1. Business understanding	Is the use case justified, and which decisions may be delegated?	Decision charter; current-process baseline; business KPIs; cost of error; permitted actions; risk limits; named process owner and acceptance criteria.	Executive sponsor, with the process owner.
2. Data understanding	Can enterprise and operational records support the intended decision?	ERP/MES/IIoT source register; access rights; master-data meaning; ownership; latency and coverage; missingness; cross-system linkage and usage constraints.	Data owner, with ERP and OT system owners.
3. Data preparation	Are decision-time inputs trustworthy and reproducible?	Versioned dataset; reconciled identifiers, units and timestamps; lineage; quality exceptions; leakage checks; temporal evaluation split.	Data owner, supported by data engineering.
4. Model development	Is the candidate consistent with the approved decision problem?	Model and policy versions; baseline; feature rationale; uncertainty; constraint tests; reproducibility; limits for unfamiliar operating conditions.	Analytics lead for evaluation submission, without live-action authority.
5. Model evaluation	Does the complete recommendation-to-action workflow meet release criteria?	Holdout and scenario tests; business and technical results; explanation usability; privacy, security and relevant bias checks; authority and interface tests; shadow-mode evidence; residual risks.	Process owner, with independent review and relevant domain approval.
6. Model operationalization	Can the approved workflow operate within controlled limits?	Release record; ERP roles and approval rules; transaction linkage; monitoring and escalation triggers; incident and fallback tests; change and retirement plan.	Operations/process owner; system owners control technical deployment.

Source: Author's AI-ERP adaptation of the CPMAI phases [9], [33]. Evidence and role assignments are proposed controls, not validated outcomes or mandatory PMI requirements.

Monitoring should cover model behaviour and workflow performance: data freshness, calibration or prediction error, constraint breaches, failed or duplicate transactions, approval latency, override patterns and the use-case business KPIs. A critical control breach should suspend the affected automatic actions and alert the designated owner. Supplier changes, new product families, altered routings, ERP configuration changes or deterioration in outcomes should reopen the relevant lifecycle reviews. Retraining or changing an optimisation objective requires applicable validation and release approval before renewed live use. Fallback may mean manual planning or the last approved policy; already executed transactions require established cancellation or corrective procedures, rather than an assumed automatic reversal. Feedback should distinguish outcome evidence from human acceptance and account for interventions that change the observed data.

Proposed Integrative Framework For Saudi Manufacturing:-

The synthesis proposes a five-stage maturity pathway, as illustrated in Fig. 2. The stages are a design heuristic rather than an empirically validated sequence. They describe organisational capability, whereas CPMAI describes the lifecycle of each AI initiative. Each selected use case should therefore repeat the relevant CPMAI reviews at its current maturity level; the six phases are not a sixth stage or a replacement for this five-stage pathway. The first stage involves building a reliable data foundation; companies standardise their master data, make clear who is responsible for each process, eliminate duplicate records and determine the decisions for which the ERP data are adequate. The aim here is to ensure that trustworthy information is available for use in high-value scenarios. Business understanding first establishes the decision charter and baseline, while data understanding and preparation supply the evidence for readiness approval. The second stage is connected execution, which consists of linking the ERP system to the MES, the quality systems, the maintenance platforms and to some IIoT sources via controlled interfaces, together

with the use of common identifiers and time standards so that the records at enterprise and operational levels can be matched.

In Stage 3, predictive decision support is introduced, with the models forecasting demand, lead time, quality risk, equipment condition or inventory exposure and the results being shown as ranked exceptions within the current planning procedures. Assessment of performance is based on business outcomes rather than just on the accuracy of the models. Development and evaluation reviews should cover both the recommendation and its ERP workflow, beginning with shadow operation before planner-approved live use. Stage 4 includes prescriptive optimisation, whereby the AI examines feasible alternatives under constraints such as capacity, service level, cost and risk, while human decision-makers still have to approve any actions that result from these. In Stage 5, governed adaptive operations may permit selected low-risk actions within approved policy bounds. Operationalization requires a named owner, tested transaction controls, monitoring, fallback and reapproval triggers. Progression to this stage is conditional on evidence and does not remove human accountability.

The pathway is intentionally cumulative because bypassing data and integration foundations can leave advanced models operationally fragile. On the other hand, holding back until enterprise data is perfect will delay useful experimentation. It is better therefore to adopt a portfolio strategy: start with decisions that have measurable results and involve accessible data, demonstrate value and establish governance, and then move on to problems that cut across functions. At all stages, six capabilities remain relevant: cybersecurity, data governance, interoperability, workforce skills, explainability and accountability. These capabilities must be regarded as design requirements and as categories for investment, not simply as compliance activities carried out after the technical deployment has taken place.

For Saudi organisations, the framework also accommodates sectoral diversity. Process industries may prioritise asset health, energy intensity and production stability; discrete manufacturers may emphasise scheduling, quality, inventory and supplier coordination; emerging local manufacturers may begin with procurement, demand and working-capital decisions before investing in dense shop-floor sensing. The architecture is intended to support different starting points while keeping a common progression from reliable context to governed intelligence.

Discussion:-

The review offers a decision-centred interpretation of AI–ERP integration. An approach that focuses on decision-making identifies which organisational decisions are repeatedly important, determines the information that sets those decisions' constraints, assesses which elements can be predicted or optimised, and considers how recommendations should be incorporated into accountable workflows. Many manufacturing decisions involve more than one system: a scheduling decision has an impact on inventory and delivery; a maintenance decision affects capacity and cost; and a supplier decision influences resilience, quality and working capital. The ERP system provides the enterprise-level consequences that make local predictions economically sensible.

The synthesis distinguishes data integration from decision integration: it is possible for an organisation to technically link together its ERP, MES and IIoT systems and yet still not improve its decisions if the responsibilities, thresholds and response methods remain unclear. On the other hand, a fairly simple model can provide considerable value when it is incorporated into a clearly defined exception process. This distinction offers one possible explanation for implementation difficulties described in ERP and Industry 4.0 research [1]–[4], [12]; the reviewed studies do not directly test this mechanism across Saudi manufacturing sectors. It also means that AI maturity should be evaluated in terms of the quality of the decisions reached and the actual operational outcomes achieved, not by how many models have been deployed.

From a theoretical point of view, the synthesis is based on a socio-technical approach to decision augmentation. AI capabilities, enterprise information, and human judgement are complementary rather than being substitutable resources. The proposed value mechanism consists of four elements: operational and enterprise data produce a contextual representation; AI then converts this representation into predictions or recommendations; governance decides whether the output is accepted and acted upon appropriately; and feedback from the actual outcomes improves both the model and the decision process. If there is a failure at any of these links, the realisation of value is weakened. The CPMAI-based adaptation makes the governance link observable through review decisions, approved operating scope, and traceable ERP transactions. Its proposed mechanism is that explicit authority and evidence reduce the gap between a technically plausible recommendation and an operationally permitted action. This mechanism

brings together ERP, manufacturing AI, digital-twin, and supply-chain perspectives but has not been empirically established by this review.

The first point from a managerial standpoint is to establish the decision prior to choosing the model. The use-case charter should identify who is responsible for the decision, how often the decision needs to be made, the current sources of information, the cost of an error, the actions that are allowed, and the measurable outcome. Secondly, the ERP team and the manufacturing-technology team should share responsibility for the architecture. If AI is developed completely outside the framework of enterprise governance, there will probably be duplicated data and inconsistent business rules. If it is kept entirely within the ERP system, high-frequency industrial data may not be accessible. A federated architecture with controlled interfaces is therefore more realistic.

Third, organisations must assess AI using operational and financial criteria. Although measures such as forecast error, classification accuracy, or model fit are necessary, they are not enough; relevant ones are schedule stability, unplanned down-time, scrap, inventory turns, service level, expediting cost, maintenance effectiveness and decision-cycle time. Fourth, change management should concentrate on decision routines. Finally, senior leaders should differentiate between automation and intelligence; their objective should not be maximum autonomy but rather better, faster, and more consistent decisions within appropriate control.

Research Agenda and Limitations:-

Longitudinal studies are needed to assess whether AI-ERP systems lead to ongoing operational and financial benefits after the initial novelty effect and as the implementation support fades away. Comparative studies in Saudi Arabia should examine the differences between the petrochemical, metals, food, pharmaceutical, automotive and other manufacturing sectors. The structure of each sector is likely to affect the availability of data, the frequency of decisions, regulatory limitations and the economic value of automation.

Maturity pathway for governed AI-ERP decision support:-

Five capability stages; iterative CPMAI lifecycle reviews govern each use case.

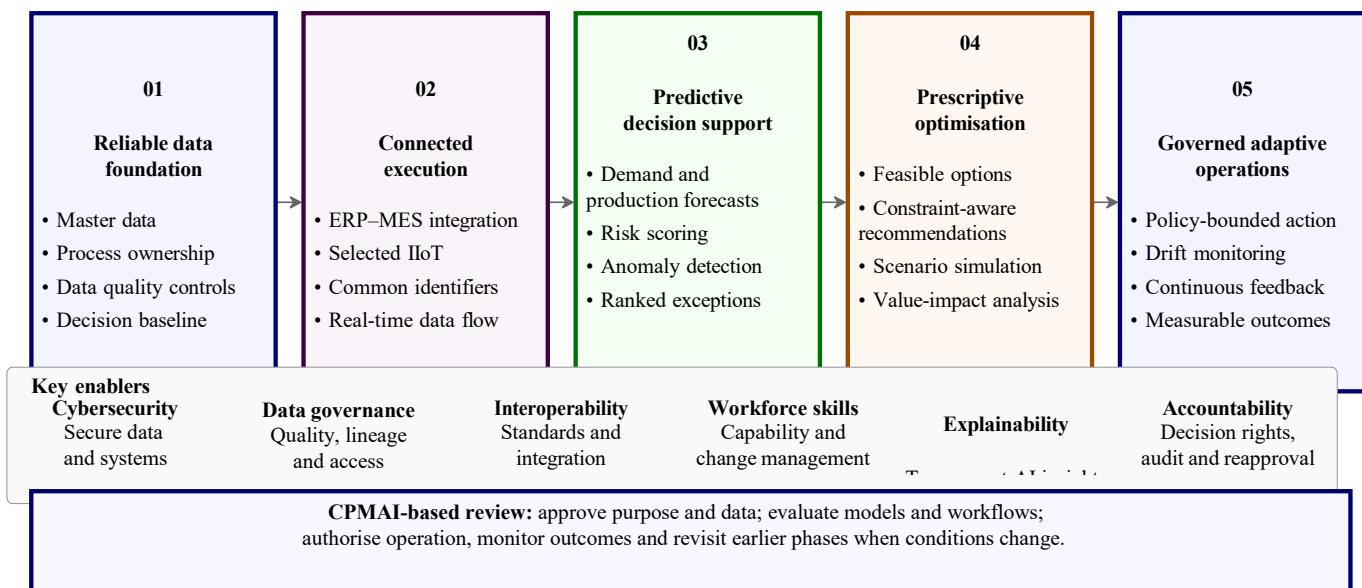


Fig. 2. Proposed five-stage capability pathway for AI-ERP decision support, with CPMAI lifecycle reviews applied to use cases at every stage. Source: Author's synthesis based on [1]–[4], [7], [8], [10], [12], [17], [25], [32]. The lifecycle governance adaptation follows [9], [33]; the maturity sequence is a design heuristic requiring empirical validation.

Research ought to directly assess the quality of decisions made by humans in collaboration with AI. The reviewed corpus gives limited attention to how planners and engineers make use of the recommendations, when they choose to override them, and whether such overrides lead to better outcomes. Controlled field studies could be carried out to compare the situations where only humans make decisions, where only AI makes decisions, and where decisions are

made collaboratively, while at the same time recording the level of confidence expressed, the use of explanations, and the time taken to make a decision. Explainability should be treated as an operational design variable rather than as a general ethical principle. Different types of decisions may call for different kinds of explanations: for example, feature contributions in the case of forecasts, counterfactuals when making quality decisions, scenario comparisons in the case of scheduling, or causal narratives when evaluating strategic choices.

Saudi-specific work is needed on Arabic-enabled decision interfaces, industrial data sovereignty, cloud-edge deployment, and cybersecurity for connected ERP-manufacturing environments. These issues may shape adoption even when the underlying algorithms are globally transferable. Research should investigate semantic interoperability. Knowledge graphs and shared manufacturing ontologies offer a possible route for connecting ERP master data with equipment, process, and quality concepts [19], but evidence on large-scale industrial maintenance of these structures is still limited.

The CPMAI-based governance contribution also requires a distinct evaluation. A prospective pilot could compare current planning practice, AI recommendations under existing approvals, and the same model and use case under the proposed lifecycle and transaction controls. Comparable product groups or phased introduction would help assess differences while retaining mandatory plant safeguards. Outcomes should include operational and financial KPIs, unauthorised-action attempts, traceability completeness, approval delay, exception-resolution time, override quality and governance effort. Holding the model and data preparation constant where feasible would help distinguish governance effects from technical improvements.

A before–after gain alone would not establish a causal CPMAI effect. For such a pilot, traceability completeness could be defined as the proportion of executed AI-assisted transactions linked to the required decision, approval and model records. Control effectiveness should distinguish blocked unauthorised attempts from unauthorised transactions actually posted, with each measured against a stated exposure denominator. Approval delay should be measured from recommendation availability to authorisation, and governance effort should include review and exception-handling time. These are proposed evaluation definitions, not observed results. The review has several limitations. The 2020–2025 publication window excludes earlier foundational studies and does not cover subsequent research. The English-language and DOI-based scholarly corpus may omit relevant non-English, professional or government evidence; the NIDL source [6] provides policy context and the two PMI sources [9], [33] provide methodology guidance, but neither resolves those coverage gaps. The absence of a reproducible search and screening record prevents assessment of selection bias or completeness, and no formal risk-of-bias appraisal is reported. The heterogeneous designs and outcomes do not support a pooled effect estimate. Direct Saudi-specific evidence on AI–ERP integration is limited within this corpus, so parts of the framework draw on adjacent manufacturing and supply-chain studies. The architecture, maturity pathway and governance adaptation therefore require empirical testing in specific sectors and organisations. The proposed role assignments and release rules have not been validated with Saudi stakeholders or assessed for CPMAI conformity. Professional guidance is not independent evidence of improved manufacturing outcomes, and the costs, staffing needs and approval delays introduced by the controls must be evaluated alongside their potential benefits.

Conclusion:-

The review suggests that applied AI can support manufacturing decisions when AI and ERP are designed as components of a governed decision architecture. ERP provides enterprise context, supports transactional integrity and controls workflow; industrial systems supply real-time information about the state; and AI offers prediction, anomaly detection, recommendations and optimisation. Realising manufacturing value depends on whether the data definitions are consistent, the interfaces are reliable, the recommendations are linked to authorised actions, and humans are given the appropriate level of visibility and accountability.

The review proposes a staged approach for Saudi manufacturers. Organisations should begin by setting up reliable master data and defining who is responsible for decisions, then link their enterprise and execution systems, introduce predictive assistance, move on to constrained optimisation, and only automate the decisions where data quality, policy limits and monitoring are well developed. This approach matches technical aspirations with the organisational realities found in the research on Saudi ERP and Industry 4.0. CPMAI-based reviews connect the decision charter, data readiness, model evaluation and operational release to named owners. ERP transaction controls then link each recommendation to its permitted action, approval evidence and outcome, with reapproval when conditions change. In this approach, AI supports large-scale analysis and pattern recognition, while people set objectives, manage exceptions and remain accountable for decisions.

Future research should examine how enterprise context, operational data, model design and governance interact to improve specific decisions over time. Managers should treat AI–ERP integration as a portfolio of decision capabilities. Developing architecture, governance and skills together can help ERP support accountable, explainable and adaptive man-ufacturing decisions.

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