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Governance and Explainability of Advanced Decision-Support Systems in Saudi Manufacturing: Integrating IFRS, Audit Controls and Management Accountability

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Abstract-** Advanced decision-support systems are increasingly embedded in forecasting, costing, inventory, procurement, maintenance, quality, and financial reporting across manufacturing. Their value, however, depends on whether recommendations can be understood, challenged, reconciled with accounting requirements, and assigned to accountable managers. This review develops an integrated governance framework for Saudi manufacturing that connects explainable artificial intelligence, International Financial Reporting Standards (IFRS), audit controls, and management accountability. Evidence published from 2020 to 2025 was synthesized across auditing, accounting information systems, responsible artificial intelligence, internal audit, financial reporting, and Saudi digital-transformation research. The literature indicates that predictive accuracy alone is insufficient in high-consequence decisions. Decision-support outputs require traceable data lineage, version-controlled models, explanations suited to user roles, control evidence, and explicit approval authority. Explainability is most useful when it clarifies influential drivers, uncertainty, alternative scenarios, and conditions under which a recommendation should not be followed. IFRS alignment requires an additional accounting-policy layer so that model outputs affecting inventory, impairment, provisions, useful lives, revenue, or estimates remain consistent with recognized accounting judgments and evidence. Auditability depends on reproducible inputs, logged overrides, access controls, validation, and retained documentation. The proposed framework therefore separates analytical recommendation from management authorization while linking both through a controlled evidence chain. For Saudi manufacturing, the framework supports Vision 2030 objectives by combining digital productivity with stronger reporting reliability, governance discipline, local analytical capability, and defensible executive decision-making.

***Keywords:** artificial intelligence; explainability; decision-support systems; IFRS; audit controls; management accountability; manufacturing; Saudi Arabia; Vision 2030; model governance*

I. INTRODUCTION

Saudi manufacturing is moving toward more data-intensive operating models in which enterprise systems, industrial platforms, analytics, and artificial intelligence increasingly influence decisions that once depended mainly on periodic reports and managerial experience. Advanced decision-support systems can estimate demand, optimize production, detect anomalies, recommend maintenance, prioritize working capital, forecast cash requirements, and identify cost or margin deterioration. Research on accounting and auditing shows that artificial intelligence can expand analysis beyond samples and retrospective review toward continuous monitoring, anomaly detection, and decision support [1,2,5,6]. The same shift creates a governance problem: an accurate model can still produce an inappropriate business decision when its data are incomplete, its explanation is misleading, its accounting treatment is inconsistent, or its recommendation is accepted without accountable human judgment.

The problem is particularly important in manufacturing because operational and financial decisions are tightly coupled. A production forecast changes inventory purchasing; maintenance recommendations influence asset utilization and useful-life assumptions; quality predictions affect scrap and warranty estimates; procurement analytics influence supplier commitments; and cost models can shape pricing, product mix, and capital allocation. When algorithms become embedded in these workflows, management needs to know not only what the model predicts but why the prediction matters, which data and assumptions produced it, how uncertainty was treated, and who is authorized to approve the resulting action. Studies of AI-enabled audit and financial reporting repeatedly identify transparency, explainability, bias, privacy, reliability, professional skepticism, and overreliance as material concerns [3-4,10-13].

This review argues that governance should be designed around an evidence chain rather than around the algorithm alone. The chain begins with controlled source data and accounting definitions, passes through validated models and intelligible explanations, and ends with documented management decisions, control performance, and audit evidence. IFRS considerations are integral because model outputs may influence judgments and estimates that enter financial statements. Research examining AI-supported IFRS implementation similarly warns that weak standards knowledge, legal conflict, and absent AI governance can undermine sound application [19]. The purpose of this paper is therefore to develop a manufacturing-focused framework in which analytical sophistication strengthens rather than bypasses management accountability.

II. AIM, OBJECTIVES AND REVIEW QUESTIONS

The aim is to develop an integrated governance framework for advanced decision-support systems used by Saudi manufacturing organizations, with particular emphasis on explainability, IFRS-consistent judgment, audit controls, and management accountability.

Four objectives guide the review. First, it identifies governance mechanisms required to control data, models, user access, changes, and decision rights. Second, it evaluates how explainability can support managerial challenge, professional skepticism, documentation, and auditability rather than functioning as a purely technical visualization. Third, it examines how AI-assisted recommendations should interact with IFRS-based accounting judgments and manufacturing estimates. Fourth, it converts these findings into a staged implementation model suitable for digitally transforming Saudi manufacturers.

The review addresses three questions: RQ1, which governance and explainability controls make advanced decision-support outputs sufficiently transparent and auditable for management use? RQ2, how should IFRS requirements and audit evidence constrain or qualify AI-assisted manufacturing decisions? RQ3, how can responsibility be allocated so that automation improves speed and insight without diluting managerial accountability?

III. REVIEW METHODOLOGY

A structured integrative review was adopted because the topic spans accounting, auditing, information systems, artificial intelligence governance, financial reporting, and manufacturing management. The evidence window was limited to 2020-2025. Priority was given to peer-reviewed studies that addressed AI in auditing or accounting, explainability, internal control, auditability, financial reporting quality, governance, management judgment, or Saudi digital transformation. Saudi evidence was used for contextual claims, while international evidence was retained where the governance mechanism is transferable to manufacturing organizations.

The search logic combined terms related to artificial intelligence or advanced analytics with auditing, explainability, financial reporting, internal audit, governance, accountability, IFRS, and decision support. Studies were screened for clear relevance to at least one of four themes: model governance; explanation and human judgment; accounting and audit control; or organizational accountability. Methodological papers were included where they provided specific control, auditability, or explainability implications. The final synthesis used thirty DOI-resolvable references published within the stated period.

Analysis proceeded in two stages. Deductive coding classified evidence under data governance, model governance, explainability, IFRS alignment, audit controls, and management accountability. Inductive coding then identified recurring mechanisms, including data lineage, model versioning, override logging, role-based explanation, evidence retention, segregation of duties, professional skepticism, validation, monitoring, and escalation. Conflicting findings were retained. For example, AI may improve audit coverage and reporting quality [6,29], yet the

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literature also cautions that automation can change auditor judgment, create opaque dependencies, and encourage misplaced reliance [11,12,26].

The synthesis generated two outputs. The first is an evidence matrix linking governance risks to control objectives and management responsibilities. The second is a closed-loop decision-support architecture in which operational outcomes, audit findings, model drift, and management overrides feed back into standards, models, and control design. No invented primary data are presented; the contribution is a structured, testable conceptual framework derived from recent evidence.

IV. ADVANCED DECISION SUPPORT IN SAUDI MANUFACTURING

Manufacturing decision support sits at the intersection of operational technology and financial accountability. Systems may combine ERP transactions, production history, quality data, maintenance records, procurement information, sensor streams, and market signals to generate recommendations. Industry 4.0 research emphasizes the value of AI and big data for real-time analysis, prediction, and automation [2]. Saudi-focused accounting research likewise reports expanding interest in AI, cloud systems, and digital transformation, together with skills, infrastructure, and regulatory concerns [2,16-18,20-23,28].

The distinctive manufacturing issue is that operational recommendations can become accounting events. A production decision changes material consumption and inventory; predictive maintenance can affect shutdown plans, repair-versus-capitalize judgments, or asset-life expectations; anomaly detection can trigger investigations into scrap, fraud, or supplier performance; and demand models influence provisions and purchasing commitments. Consequently, governance cannot be split into a technical layer owned by data teams and a financial layer examined later by finance. Definitions, thresholds, and approval rules must be designed together.

Saudi manufacturers also operate within a national transformation agenda that rewards productivity, localization, advanced technology, and stronger institutional capability. Evidence from Saudi auditing and financial-reporting studies suggests that AI can improve efficiency and reporting quality, but adoption depends on readiness, skills, governance, and confidence in outputs [16-18,20-23,28-29]. A defensible operating model therefore treats advanced analytics as controlled decision infrastructure. Every material recommendation should have an identifiable business owner, defined purpose, approved data sources, validation status, explanation standard, and escalation path before it can affect production or reported financial outcomes.

V. GOVERNANCE ARCHITECTURE AND DECISION RIGHTS

A practical governance architecture begins by separating five responsibilities: business ownership, data stewardship, model ownership, control assurance, and decision authorization. Business owners define the decision and acceptable risk. Data stewards maintain source definitions, lineage, quality thresholds, and access. Model owners develop, validate, version, and monitor analytical logic. Finance, risk, internal audit, or control functions test whether governance requirements are operating. Authorized managers remain responsible for the decision itself. This separation reduces the risk that the team building a model also defines its success criteria, approves its deployment, and accepts its recommendations without independent challenge.

Research on AI governance in auditing supports this layered approach. Governance, human factors, strategy, and data infrastructure are recurring priorities when AI enters audit processes [7-9]. IT-audit research similarly identifies logs, standards, data governance, explainability, and specialized competencies as essential to the auditability of AI-driven processes [25]. Ethical auditing literature emphasizes responsibility, transparency, data security, and the need to preserve professional judgment [4]. These findings are highly transferable to manufacturing decision systems because both environments require evidence that automated recommendations are controlled rather than merely technically functional.

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Decision rights should be proportional to consequence. Low-risk recommendations, such as prioritizing routine production reports, may be accepted automatically within approved thresholds. Higher-risk decisions affecting major inventory write-downs, plant shutdowns, large capital expenditure, supplier disqualification, or financial estimates should require named approvers and independent review. The governance record should capture the recommendation, explanation, model version, relevant data period, confidence or uncertainty, user action, any override, and the reason for that override.

Model change governance is equally important. Retraining, new data sources, threshold changes, feature changes, and accounting-policy changes can alter behavior even when the user interface remains unchanged. Each material change should therefore trigger documented testing and, where appropriate, renewed approval. Governance effectiveness should be measured through indicators such as unresolved validation findings, overdue model reviews, unauthorized changes, override concentration, explanation failures, control exceptions, and model-performance drift rather than through adoption rates alone.

Table 1. Governance risks, control evidence and assurance questions for advanced decision support.

Governance domain	Primary risk	Required evidence	Management control	Assurance question
Data & lineage	Incomplete or transformed data drives misleading recommendations.	Source mapping, quality results, timestamps, reconciliations.	Named data steward; approved definitions; access control.	Can inputs be reproduced and reconciled to authoritative systems?
Model lifecycle	Unvalidated or changed logic is used outside its approved purpose.	Model card, tests, version history, drift results, change approvals.	Independent validation; risk tier; review frequency.	Was the deployed model approved and still performing within tolerance?
Explainability	Users accept outputs they cannot challenge or misunderstand.	Drivers, uncertainty, limitations, alternatives, explanation logs.	Role-based explanation standard; escalation conditions.	Does the explanation support informed skepticism rather than cosmetic transparency?
IFRS & financial reporting	Operational analytics silently determine material accounting judgments.	Policy mapping, materiality, assumptions, ledger reconciliation, review evidence.	Finance-owned judgment and reporting-date assessment.	Is the analytical output appropriate evidence for the accounting conclusion?
Decision accountability	Automation diffuses responsibility or hides overrides.	Approver identity, decision record, override rationale, execution outcome.	Explicit decision rights; segregation; escalation.	Can a named manager defend the action and its evidence?

VI. EXPLAINABILITY AND MODEL ASSURANCE

Explainability is valuable when it supports a specific decision responsibility. In auditing, explainable AI has been proposed as a means of linking machine-learning outputs to audit documentation and evidence requirements, including the use of local and global techniques that show influential variables or alternative outcomes [3]. The central governance

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question is not whether a system can generate an explanation, but whether the explanation is faithful enough to the model, understandable to the user, stable enough for comparison, and relevant to the decision being made.

Different stakeholders require different explanations. A production manager may need the operational drivers of a schedule recommendation; a controller may need the effect of volume, price, yield, and overhead assumptions on a forecast; an auditor may need traceability from a flagged transaction to the underlying data and model logic; and an executive may need scenario ranges, uncertainty, and materiality. A single technical explanation cannot satisfy all of these purposes. Role-based explanation should therefore be part of system design.

Explainability also needs control boundaries. Post-hoc methods can make complex models easier to interpret, but an explanation is not proof that the model is correct. It must be combined with validation, data-quality checks, out-of-distribution monitoring, sensitivity analysis, and comparison against business rules or simpler baselines. Recent field evidence identifies transparency, bias, privacy, robustness, and overreliance as continuing barriers to AI adoption in auditing [26]. Responsible-AI research likewise warns that trustworthiness should not be reduced to a single acceptable-risk label [10].

For manufacturing, a useful explanation package should include the purpose of the model, decision scope, major drivers, confidence or uncertainty, relevant counterfactuals, known limitations, and the conditions that require human escalation. Explanations should be retained when decisions are material because later reviewers need to reconstruct what management knew at the decision date. Model assurance then becomes a continuous process: validate before deployment, monitor after deployment, investigate drift and unusual overrides, and revise explanation rules when users repeatedly misunderstand or misuse outputs. This approach treats explainability as part of control evidence rather than as an optional visualization layer.

VII. IFRS ALIGNMENT IN MANUFACTURING DECISIONS

IFRS alignment matters because manufacturing analytics frequently influence estimates and judgments rather than merely operational choices. Inventory valuation and obsolescence, impairment indicators, provisions, expected costs, useful lives, residual values, capitalization decisions, revenue estimates, and segment or product profitability may all draw on forecasts or classification models. The accounting requirement remains a management responsibility even when a model supplies evidence.

Research connecting AI with financial reporting highlights this boundary. Financial executives may accept AI support but remain uncertain about how it should affect complex reporting judgments [14]. Protocol-analysis research has shown that weak IFRS knowledge, legal conflict, and the absence of an AI framework can adversely interact with standards implementation [19,30]. Saudi evidence also suggests that AI adoption can improve the quality and timeliness of financial information when organizational infrastructure and professional competence are adequate [22,29]. The implication is that governance must explicitly connect model outputs to the accounting policy they inform.

A controlled workflow should therefore identify, for each material use case, the relevant accounting judgment, responsible preparer, required evidence, review level, and documentation. Consider an inventory-obsolescence model. The system may estimate slow-moving stock risk using demand, age, yield, and product-lifecycle data. Management must still determine whether the output supports the applicable valuation conclusion, whether assumptions are reasonable at the reporting date, whether exceptional commercial facts are missing, and whether the evidence is sufficiently reliable. The same principle applies to asset impairment or useful-life estimates: predictive maintenance evidence can inform assumptions without replacing management's assessment.

The accounting-policy layer should also define prohibited uses. A model trained for operational

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optimization should not automatically become a financial-reporting model without validation for that purpose. Materiality thresholds, cut-off rules, master-data mappings, exchange rates, cost classifications, and estimation horizons should be controlled. Where model recommendations affect journals or disclosures, reconciliation to the general ledger and source systems should be retained. This design preserves the distinction between analytical insight and authoritative accounting treatment while allowing high-quality operational data to strengthen reporting judgments.

VIII. AUDIT CONTROLS AND EVIDENCE

Auditability requires that a reviewer can reconstruct how a material decision was produced and whether relevant controls operated. Research on AI in auditing shows clear efficiency benefits from broader data analysis, anomaly detection, and continuous monitoring [1,6,15]. Yet it also demonstrates that new technologies create additional control requirements around data, model behavior, transparency, access, and professional judgment [4,9,13,25].

For manufacturing decision-support systems, the minimum evidence chain should cover source data, transformations, model version, parameter settings, user identity, explanation output, approval, execution, and subsequent outcome. Data controls include completeness, interface reconciliation, master-data governance, timestamp integrity, and access restrictions. Model controls include independent validation, version control, test results, performance thresholds, drift monitoring, and formal retirement. Application controls include authorization, workflow segregation, exception handling, and protected audit logs. Financial controls add reconciliation to accounting records, evidence of review, and consistency with approved policies.

Override governance deserves special attention. Human override is necessary because models cannot observe every commercial, operational, or legal fact. However, uncontrolled overrides can conceal poor model quality, management bias, or attempts to bypass policy. Every material override should record the original recommendation, responsible manager, rationale, evidence, and outcome. Patterns such as repeated overrides by one plant, product, or manager should be analyzed because they may indicate either model weakness or control weakness.

Internal audit should evaluate both design and operating effectiveness. Testing can include sampling decision records, re-performing model inputs, checking access changes, comparing explanations with model behavior, reviewing validation independence, and assessing whether management actually challenges recommendations. Continuous controls can monitor unusual journal patterns, threshold changes, override concentration, stale models, and missing approvals. The objective is not to require auditors to rebuild every algorithm but to ensure that the decision-support process produces reliable, traceable, and reviewable evidence.

9. Management Accountability and Human Oversight

Accountability is weakened when organizations treat algorithmic output as an independent decision-maker. Management remains responsible for strategy, resource allocation, financial reporting, and control performance. The literature on auditor judgment provides a useful warning: automating apparently routine tasks can remove opportunities for deliberation and practical learning, while new technologies create new areas of uncertainty requiring judgment [11]. Studies of financial executives likewise show that managers do not automatically trust or incorporate AI outputs simply because the technology is available [14,27].

A governance framework should therefore specify who is accountable for accepting, rejecting, or escalating each class of recommendation. Accountability should follow authority: the manager who has authority to commit inventory, shut a line, recognize an estimate, or approve a capital project should also own the documented decision. Data scientists and system vendors are accountable for technical performance within their roles, but they should not absorb business accountability by default.
Human oversight must also be meaningful. Requiring a click on an approval screen is not sufficient if the user lacks the information, time, or competence to challenge the model. Effective oversight requires explanations, access to underlying evidence, training,

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comparison with alternative scenarios, and a practical right to override or pause automation. Governance metrics should therefore examine decision quality, escalation behavior, override outcomes, and post-decision learning. The goal is calibrated reliance: managers should neither ignore useful analytics nor defer to them automatically.

IX. INTEGRATED GOVERNANCE AND EXPLAINABILITY FRAMEWORK

The evidence supports a closed-loop framework with six connected layers. The first is controlled business and accounting data: ERP records, production transactions, master data, sensor evidence, costing logic, and policy definitions. The second is the analytical layer, where models are developed within an approved purpose, documented scope, and version-controlled lifecycle. The third is the explanation layer, which converts model behavior into role-specific drivers, uncertainty, limitations, and alternatives. The fourth is the accounting and control layer, where IFRS implications, materiality, reconciliations, segregation of duties, and authorization rules are applied. The fifth is management decision and execution. The sixth is assurance and learning, where outcomes, audit findings, exceptions, drift, and overrides feed back into data, models, policies, and controls.

This structure prevents three common governance failures. First, it prevents technical validation from being mistaken for business approval. A model may perform statistically while remaining unsuitable for an accounting or operational decision. Second, it prevents explanation from being mistaken for assurance. An intelligible output still requires valid data and control evidence. Third, it prevents human review from becoming ceremonial. Decision-makers receive defined evidence and remain explicitly accountable.

Table 1 converts these principles into control objectives, while Figure 1 shows the closed-loop architecture. The framework also supports tiering. Low-consequence models can use lighter documentation and automated approvals within narrow limits. High-consequence models require independent validation, enhanced explanations, finance or risk review, retained evidence, and senior authorization. The tier should be determined by financial materiality, safety and operational consequence, reversibility, regulatory exposure, and the degree of model autonomy.

The framework is intentionally technology-neutral. It can govern statistical forecasting, machine learning, anomaly detection, optimization, or generative decision support. What changes is the evidence required to demonstrate reliability. The consistent requirement is that every material recommendation remains traceable from controlled inputs to accountable action.

Operationalizing the framework requires a model-risk classification that is understandable outside the data-science function. A proposed classification uses five dimensions: decision consequence, financial materiality, reversibility, degree of autonomy, and model opacity. A forecasting model that only prioritizes a planner's attention may be low consequence even if technically complex, whereas a simpler rule that automatically posts a material provision can be high consequence because it directly changes reported results. Each tier should trigger a defined package of controls. Tier-one uses may require documented ownership, basic performance monitoring, and controlled access. Tier-two uses add independent validation, explanation standards, override logging, and periodic review. Tier-three uses require formal risk approval, finance or internal-control sign-off, scenario testing, enhanced documentation, and senior management authorization. This approach avoids the common mistake of classifying risk only by algorithm type.

Manufacturing organizations also need an explicit control bridge between operational metrics and financial assertions. For example, yield deterioration may feed both process-improvement decisions and inventory valuation; equipment-health forecasts may influence maintenance scheduling while also providing evidence relevant to useful-life or impairment assessments; and supplier-risk scoring may affect purchasing strategy, provisions, or commitments. The same source signal can therefore support different decisions with different accounting consequences. Governance should specify when

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information is merely operational evidence and when it becomes an input to a financial-reporting judgment. Once the second condition applies, finance-owned definitions, reporting-date relevance, materiality, review, and reconciliation requirements should be activated. This bridge prevents operational models from silently determining accounting outcomes without the controls normally expected around financial close.

Finally, governance should distinguish model performance from decision performance. A model can meet statistical thresholds while management decisions remain poor because users misunderstand the explanation, ignore constraints, or apply the output outside its intended scope. Conversely, a model with moderate predictive accuracy can create substantial value when it consistently prompts timely investigation. Monitoring should therefore combine model metrics with behavioral and control metrics: how often users request clarification, whether overrides improve outcomes, whether explanations are stable, how frequently recommendations lead to control exceptions, and whether decisions can be reconstructed after the fact. These measures turn governance into a learning system rather than a periodic compliance exercise.

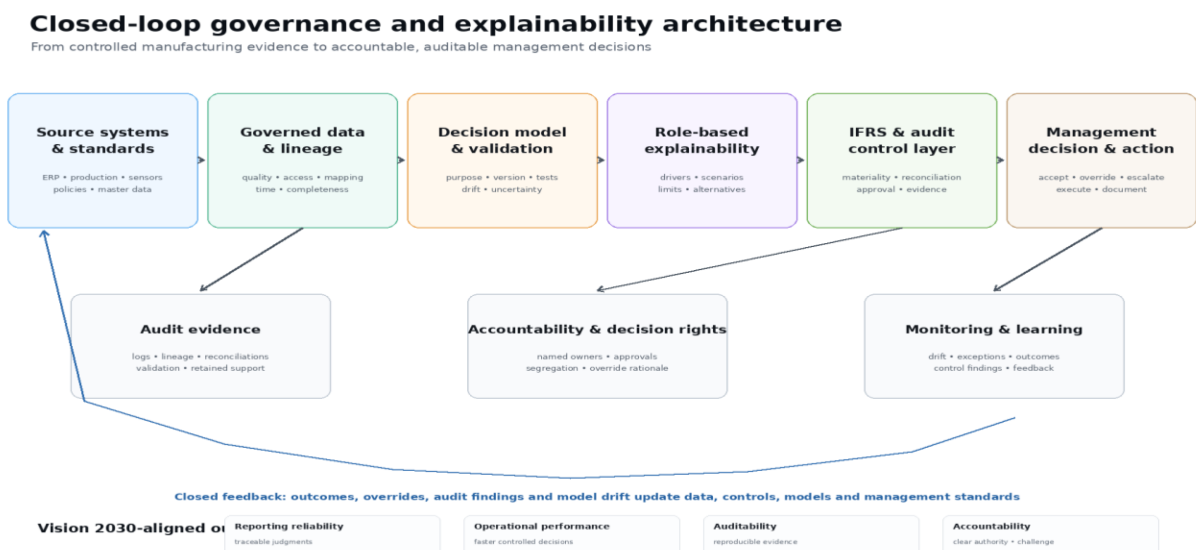

Figure 1. Closed-loop governance and explainability architecture for advanced manufacturing decision support.

X. VISION 2030 IMPLEMENTATION ROADMAP

Implementation should begin with use cases rather than a broad technology policy. Saudi manufacturers should inventory advanced decision-support applications and classify them by consequence, financial relevance, autonomy, and data sensitivity. High-risk uses should be prioritized for governance remediation.

Stage one establishes foundations: common data definitions, decision owners, model inventory, access rules, and accounting-policy mappings. Stage two introduces validation and explainability standards, including independent testing, approved performance measures, role-based explanations, and documented limitations. Stage three integrates audit controls: immutable logs, approval workflows, segregation of duties, journal or ledger reconciliation where relevant, override records, and evidence retention. Stage four adds portfolio monitoring, including model drift, control exceptions, repeated overrides, stale approvals, and changes in accounting policy. Stage five uses accumulated evidence to improve standards, training, and local analytical capability.

The implementation scorecard should combine technical and governance measures. Useful indicators include data-quality exceptions, validation findings,

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explanation acceptance, decision reversals, override success, unapproved model changes, audit issues, control failures, and time required to reconstruct a material decision. Financial and operational outcomes should also be tracked, but performance benefits should not be allowed to mask weak governance. Figure 2 summarizes the maturity pathway, and Table 2 links each stage to management evidence and expected outcomes.

This staged approach aligns digital productivity with institutional capability. It supports faster and more consistent decisions while reinforcing reliable financial reporting, accountable management, and auditable processes—capabilities directly relevant to competitive, technology-enabled manufacturing under Vision 2030.

A practical deployment sequence should also start with a small number of high-value use cases rather than attempting enterprise-wide certification at once. Suitable pilots include inventory-risk forecasting, production-cost variance analysis, maintenance prioritization, and exception-based financial review because each combines operational data with clear management ownership. During the pilot, organizations should measure not only accuracy and savings but also whether explanations are understood, whether approval steps are completed on time, whether users can reconstruct recommendations, and whether exceptions reach the correct authority. Lessons should then be embedded in standard model cards, approval templates, accounting-policy links, validation checklists, and training material before the next wave is scaled. This creates reusable governance assets and reduces dependence on individual experts. It also supports localization by developing finance, audit, engineering, and analytics capability inside the organization rather than relying entirely on external vendors. Over time, a central governance function can maintain common standards while plant and business teams retain responsibility for use-case-specific assumptions and decisions. Such a federated model combines consistency with operational knowledge and is better suited to diversified manufacturing groups than either fully centralized control or unrestricted local experimentation.

Table 2. Governance maturity stages, evidence gates and expected outcomes.

Maturity stage	Priority actions	Evidence gate	Key indicators	Expected outcome
1. Governance foundation	Inventory use cases; assign owners; classify risk; standardize data definitions.	Every material system has approved purpose, owner and data sources.	Inventory coverage; unresolved ownership; data exceptions.	Controlled scope and accountability.
2. Model assurance	Independent validation; version/change control; drift and performance monitoring.	High-risk models pass validation before use.	Validation findings; stale models; unauthorized changes.	Reliable analytical behavior.
3. Explainability & accounting	Role-based explanations; policy links; materiality and reconciliation controls.	Users can reconstruct drivers and finance approves reporting uses.	Explanation failures; reconciliation exceptions; policy gaps.	Defensible IFRS-linked judgment.
4. Integrated audit controls	Protected logs; approvals; override evidence; continuous exception monitoring.	Material decisions are reproducible from source to action.	Missing approvals; override concentration; audit issues.	Auditable execution.

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Maturity stage	Priority actions	Evidence gate	Key indicators	Expected outcome
5. Adaptive accountability	Portfolio monitoring; lessons from outcomes; skills, training and standards updates.	Governance improvements are driven by measured outcomes and findings.	Decision reversals; reconstruction time; repeated exceptions.	Trusted scaling and continuous learning.

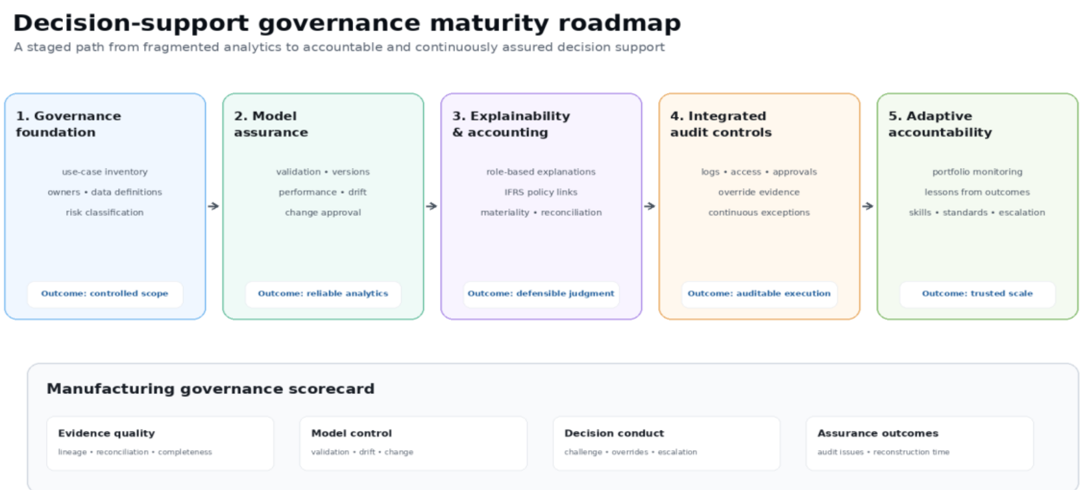

Figure 2. Decision-support governance maturity roadmap for Saudi manufacturing.

XI. DISCUSSION, RESEARCH GAPS AND IMPLICATIONS

The literature is mature enough to establish that AI can improve audit coverage, decision speed, and financial analysis, but less mature on how governance should operate when operational and accounting decisions converge. Explainability research has advanced rapidly [3,24], yet explanation quality is often evaluated technically rather than through the needs of controllers, plant managers, audit committees, or external auditors. More research is needed on whether explanations actually improve challenge behavior and reduce inappropriate reliance.

A second gap concerns IFRS-linked manufacturing applications. Existing work discusses AI and financial reporting, but fewer studies examine how predictive models influence specific estimates such as inventory obsolescence, useful lives, warranty provisions, or impairment assumptions in industrial settings. The interaction between model uncertainty and accounting materiality deserves direct study.

Third, accountability remains under-specified. AI governance frameworks often identify principles but do not define who signs off on a recommendation, who owns a failed model, or how responsibility should be shared when vendors, data teams, finance, and operations contribute to one decision. Saudi manufacturers provide a useful setting for future research because rapid digital investment is occurring alongside industrial expansion and stronger reporting expectations.

For practice, the implication is clear: organizations should govern decisions, not merely models. A technically strong model becomes defensible only when its data, explanation, accounting treatment, control evidence, and accountable approval form one coherent chain.

XII. LIMITATIONS AND FUTURE RESEARCH

This review synthesizes heterogeneous evidence and does not estimate pooled effect sizes. Much of the literature focuses on auditing and financial services rather than factory-level decision systems, so some governance mechanisms are transferred conceptually to manufacturing. The 2020-2025 window improves recency but excludes earlier foundational work.

Future studies should test the framework in Saudi manufacturing organizations using longitudinal case research, controlled decision experiments, and audit-file analysis. Priority topics include explanation effectiveness by management role, governance of generative systems, control design for model-driven journals, IFRS-sensitive estimation models, override behavior, and the relationship between model governance maturity and audit findings. Empirical work should also examine whether governance adds excessive friction or, when well designed, reduces rework and accelerates trusted decisions.

XIII. CONCLUSION

Advanced decision-support systems can strengthen Saudi manufacturing only when faster analytics are matched by stronger governance. The reviewed evidence shows that explainability, auditability, IFRS alignment, and management accountability are complementary rather than separate requirements. Explainability makes model outputs challengeable; audit controls make the decision process reconstructable; accounting-policy alignment prevents analytical recommendations from bypassing reporting requirements; and explicit decision rights preserve human responsibility.

The proposed framework links controlled data, validated models, role-based explanations, accounting and control rules, accountable management action, and continuous assurance in one feedback loop. It allows governance intensity to increase with materiality and consequence while preserving efficiency for lower-risk decisions. For Vision 2030, the benefit is not simply greater use of artificial intelligence. It is the creation of manufacturing organizations capable of using advanced analytics with disciplined judgment, reliable financial reporting, defensible audit evidence, and clear executive accountability. That combination is essential if digital transformation is to generate durable productivity and institutional trust. Governance maturity should therefore be treated as a manufacturing capability, measured through evidence quality, decision traceability, control reliability, and the organization's ability to learn systematically from exceptions, overrides, and outcomes. continuously. in practice.

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