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Original Research Article

Artificial Intelligence in Accounting and Financial Reporting Opportunities and Challenges for Saudi Arabian Organisations under Vision 2030

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Abstract: This review examines how artificial intelligence (AI) is reshaping accounting and financial reporting and considers the implications for organisations operating in Saudi Arabia under Vision 2030. It uses a structured integrative review informed by PRISMA 2020 reporting principles and the bibliometric-systematic approach of Marzi *et al*., [1], drawing on peer-reviewed studies published from 2020 to 2025. The evidence clusters around five applications: transaction processing, estimation and forecasting, misstatement detection, assurance and narrative disclosure. Reported opportunities include greater efficiency, deeper analysis and stronger fraud screening; the principal constraints concern explainability, ethical accountability, data governance, auditors' reliance on AI outputs and professional skills. Saudi-specific evidence remains limited and concentrated in banking, leaving corporate reporting, auditing and sustainability disclosure underexamined. The review develops an integrative framework that links AI capabilities and accounting functions to Vision 2030 enablers and proposes a prioritised research agenda. It also offers staged recommendations for preparers, auditors, regulators and educators.

Keywords: Artificial Intelligence, Accounting, Financial Reporting, Auditing, Vision 2030, Saudi Arabia.
JEL Classification: M41, M42, O33, G38.

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1. INTRODUCTION

Accounting technologies have progressed from double-entry ledgers to enterprise resource planning systems. The current wave differs because machine learning, natural language processing and robotic process automation do more than accelerate bookkeeping; they begin to perform judgement-laden tasks such as estimating provisions, flagging suspicious entries and reading management commentary [2, 3]. Evidence from the profession shows that change is uneven. Large audit firms have invested heavily, yet practitioners in many settings still describe adoption as early-stage and experimental [4, 5].

Saudi Arabia provides an important setting for studying this transition. Vision 2030 places digital transformation and economic diversification at the centre of national policy [6], and the National Strategy for Data and AI issued by the Saudi Data and Artificial Intelligence Authority [7], gave AI an explicit institutional home. Reporting entities meanwhile face converging pressures: International Financial Reporting Standards, mandatory electronic invoicing administered by the tax authority, a deepening capital market, and rising expectations around sustainability disclosure. These pressures create demand for faster, more reliable and more transparent financial information, which is precisely

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what AI promises and precisely where its risks are most consequential.

Despite this convergence, Saudi scholarship has approached AI mainly through adoption studies in banking, education and public administration [8-11]. Research on AI in accounting proper has been conducted largely in North America, Europe and East Asia, and it seldom considers institutional features such as state-led digital strategy, concentrated ownership or a developing assurance market. Practitioners and regulators in the Kingdom therefore lack a consolidated reading of what the international evidence implies for their own conditions.

The aim of this study is to synthesise research published between 2020 and 2025 on AI in accounting and financial reporting and to translate its findings into an evidence-informed appraisal for Saudi organisations pursuing Vision 2030 objectives. Five objectives follow from this aim:

- To chart the principal AI applications reported across bookkeeping, estimation, reporting, assurance and disclosure;
- To distil the organisational and professional opportunities these applications create;
- To diagnose the ethical, technical, regulatory and human-capital challenges that constrain adoption;
- To interpret the findings against Vision 2030 programmes and Saudi institutional conditions; and
- To propose an integrative framework and a prioritised research agenda.

Four questions operationalise these objectives. RQ1: Which AI applications dominate recent accounting and reporting research? RQ2: What opportunities do they offer preparers, auditors and regulators? RQ3: Which challenges limit responsible adoption? RQ4: How do these opportunities and challenges map onto the Saudi Vision 2030 context?

The paper integrates dispersed accounting, auditing and information-systems evidence and relates it to a national policy setting that has received little attention in accounting scholarship. It also identifies where evidence is missing instead of assuming that results transfer across jurisdictions.

The remainder of the paper is organised as follows. Section 2 clarifies concepts and the Saudi institutional setting. Section 3 explains the review protocol. Section 4 reports the evidence by accounting function and then examines opportunities, challenges and the state of Saudi research. Section 5 interprets the findings against Vision 2030, presents the framework and sets out a staged pathway, and Section 6 draws implications and a research agenda before Section 7 concludes.

2. Conceptual Background and Institutional Context

2.1 Defining AI in the Accounting Value Chain

AI encompasses several techniques, each with distinct implications for accounting. Robotic process automation executes predefined rules on structured data, which makes it comparatively transparent and easy to test. Supervised and unsupervised machine learning detect patterns that analysts have not specified in advance, while natural language processing converts text, such as contracts, earnings calls and management commentary, into analysable data [12, 13]. Generative systems add a further layer by drafting, summarising and explaining. The distinction matters because assurance and control requirements scale with opacity: a bot whose logic can be inspected poses a different risk from a neural model whose reasoning cannot [14].

Across the accounting value chain these techniques map onto five recurring functions. At the transactional layer they extract, classify and match documents. At the estimation layer they forecast quantities such as credit losses, claims reserves or impairment indicators. At the reporting layer they assemble statements, reconcile disclosures and monitor compliance. At the assurance layer they select samples, test populations and score risk. At the communication layer they read, and increasingly shape, narrative disclosure. This five-function view structures the evidence reported in Section 4.

A further distinction concerns who benefits from a given application. Some tools serve preparers inside the entity, such as automated journal testing and cash application. Others serve external parties, including auditors who screen full ledgers and investors who mine disclosures for signals. The same underlying model may therefore raise different questions depending on its user: internal control for management, evidence sufficiency for the auditor, and fair presentation for the reader. Keeping this multiplicity in view prevents the review from treating adoption as a uniform phenomenon and helps explain why enthusiasm and anxiety coexist within a single organisation.

2.2 Theoretical Lenses

Adoption research in this field draws mainly on three families of theory. Technology–organisation–environment reasoning explains why organisations with stronger infrastructure, awareness and external pressure adopt sooner, a pattern reported for Saudi small and medium-sized

enterprises by Baabdullah *et al.,* [8]. Institutional perspectives emphasise regulatory and normative pressure, which is salient where a central authority sets digital direction. Professional and ethics lenses, finally, examine how automation redistributes judgement and accountability between people and systems [15, 16]. Rather than commit to one theory, the review uses them as sensitising devices when interpreting why findings may or may not travel to the Saudi setting.

2.3 The Saudi Policy and Reporting Environment

Vision 2030, launched in 2016, seeks to diversify the economy away from hydrocarbons and to build a vibrant society, a thriving economy and an ambitious nation, with digital government and a stronger financial sector among its operational levers [6]. Its realisation programmes, including the National Transformation Program and the Financial Sector Development Program, translate these ambitions into measurable targets. The National Strategy for Data and AI, issued under SDAIA [7], added capability goals for talent, data governance and ecosystem development.

For accountants, the practical environment has several distinctive features. Listed entities and many large firms report under International Financial Reporting Standards endorsed through the Saudi Organization for Chartered and Professional Accountants. The tax authority has progressively required structured electronic invoicing and its integration with government systems, which generates machine-readable transaction data at scale. A personal data protection regime has also emerged, and public authorities are encouraging sustainability reporting. Evidence from other Saudi sectors indicates that infrastructure, organisational culture and managerial attention condition AI assimilation [9], and that governance and ethical concerns accompany enthusiasm in banking [11]. These features suggest fertile ground for AI in reporting, but also reasons for caution.

3. METHODOLOGY

3.1 Review Design

Because the objective is to integrate heterogeneous evidence rather than to estimate a pooled effect, the study adopts a structured integrative review. The design combines three established strands of guidance. Reporting follows the PRISMA 2020 principles for transparent documentation of search, selection and synthesis [17]. Procedural rigour follows the SPAR-4-SLR protocol, which organises a review into assembling, arranging and assessing stages [18]. Analytical logic draws on the bibliometric–systematic approach that pairs descriptive mapping of a literature with qualitative interpretation of its content [1-19]. Meta-analysis was judged inappropriate because the included studies differ in design, outcome and unit of analysis.

3.2 Search Strategy and Eligibility

The search protocol was specified before evidence was examined. Two index sources were designated, Scopus and the Web of Science Core Collection, so that coverage of accounting, auditing and information-systems journals would be complementary rather than dependent on a single database [20]. Search strings combined technology terms with accounting terms, and a second string added Saudi and Gulf context terms to capture regional evidence. Boolean operators were used to balance breadth and precision [21]. Table 1 reports the protocol and eligibility criteria.

Table 1: Review protocol and eligibility criteria

Protocol element	Specification
Review type	Structured integrative review using bibliometric–systematic logic
Reporting and procedure	PRISMA 2020 reporting principles; SPAR-4-SLR stages (assembling, arranging, assessing)
Sources searched	Scopus; Web of Science Core Collection
Period and language	2020–2025; English
Core search string	("artificial intelligence" OR "machine learning" OR "robotic process automation" OR "natural language processing") AND (accounting OR "financial reporting" OR audit* OR disclosure)
Context string	AND ("Saudi Arabia" OR "Gulf Cooperation Council" OR "Vision 2030")
Inclusion criteria	Peer-reviewed journal articles analysing an AI-enabled accounting, reporting, assurance or disclosure task; or evidence on AI adoption, readiness and governance in Saudi Arabia
Exclusion criteria	Conference papers, book chapters and editorials; studies mentioning AI only incidentally
Contextual material	National Strategy for Data and AI [7]
Synthesis method	Thematic coding by five accounting functions; opportunity and challenge themes; comparison with Vision 2030 programmes

Source: Author's elaboration, informed by Page *et al.,* [17] and Paul *et al*., [18].

Eligibility decisions were taken at two levels. Title and abstract screening removed records that mentioned AI only incidentally, for instance as a general digitalisation backdrop, while full-text assessment retained studies that analysed an AI-enabled accounting, reporting, assurance or disclosure task. One official policy document, the national data and AI strategy, was admitted as contextual material rather than empirical evidence. The sources cited in this article, 30 in total, form the evidence base: accounting and auditing studies carry the analytical weight, Saudi studies supply institutional context, and methodological papers support the design [22].

3.3 Quality Appraisal and Synthesis

Each study was appraised for relevance to the research questions, clarity of design, transparency of data and consistency between claims and evidence. Journals were considered in terms of indexing and disciplinary standing, though conceptual contributions were not excluded solely on ranking grounds, since conceptual work is influential in a field that is still forming. Extracted information covered technology, accounting function, setting, method, principal finding and stated limitation. Synthesis proceeded thematically: codes were first assigned inductively, then grouped under the five functions introduced in Section 2.1 and under cross-cutting opportunity and challenge themes, and finally compared against Vision 2030 programme objectives. Figure 1 depicts the sequence.

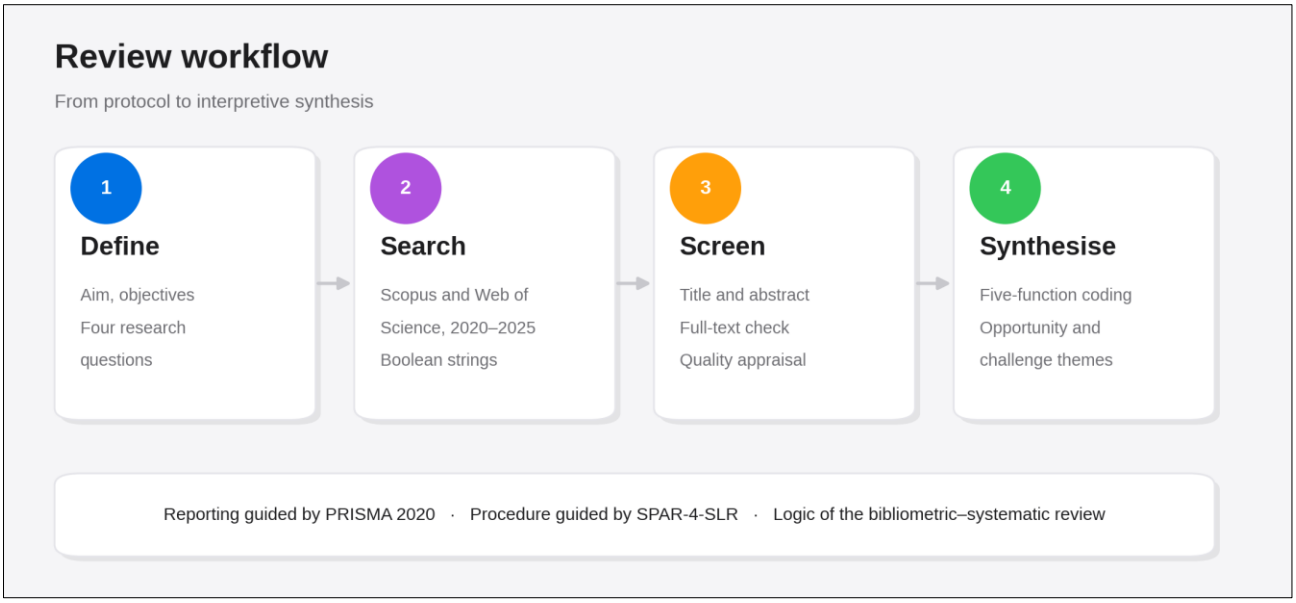


Fig. 1: Review workflow from protocol to interpretive synthesis. Source: Author's elaboration.

Coding rules were fixed in advance. A study was assigned to a function when its central task, rather than its incidental setting, matched the function definitions given in Section 2.1. A finding was recorded as an opportunity when the study reported or argued for a benefit to accuracy, efficiency, timeliness, insight or capability, and as a challenge when it reported or argued for a constraint, risk or cost. Where a study addressed several functions it was coded under each, and contradictory findings were retained and discussed instead of being averaged away. These rules keep the interpretation traceable, which matters in a field where terminology is not yet standardised.

Two cautions apply. First, the review reports the procedure rather than a numerical screening tally, so it should be read as an interpretive synthesis and not as an exhaustive census. Second, thematic judgements retain a subjective element, which is mitigated by explicit coding rules and by anchoring each theme in at least two independent sources.

4. FINDINGS

4.1 Evidence by Accounting Function

Transaction processing. The most mature applications automate repetitive work. Rule-based robotic process automation can handle invoice matching, reconciliations and data entry when inputs are structured and stable, and a task-selection framework developed for audit settings stresses that suitability depends on rule clarity, digital inputs and volume [14]. Studies of the profession similarly report that routine tasks are the first to be absorbed, with accountants moving toward review and exception handling [23, 5].

Estimation and forecasting. Machine learning has shown measurable value in judgemental estimates. Using insurance claims data, Ding *et al.*, [2],

demonstrate that learned models can produce loss estimates closer to realised outcomes than those prepared by management, which suggests a role as a benchmark for reserves and provisions. The implication for expected credit loss modelling, fair value measurement and impairment testing is evident, although the opacity that supports accuracy also complicates the explanation owed to auditors and users.

Misstatement detection. Bertomeu *et al.,* [24], show that models trained on financial and auditor-related variables identify material misstatements out of sample more effectively than conventional benchmarks. Such tools allow regulators and audit committees to prioritise scrutiny, yet their outputs are probabilistic and require human interpretation, a point echoed in the wider accounting-technology literature [12].

Assurance. At the firm level, Fedyk *et al*., [25], associate AI investment with higher audit quality, indicated by fewer restatements, and with a reallocation of staffing away from junior roles. Process-level work shows how automation can extend testing from samples to full populations, but also that auditors must decide how much weight to give algorithmic output [14]. Evidence on adoption in practice remains mixed, with Bakarich and O'Brien [4], describing use that is limited relative to the rhetoric surrounding it.

Narrative disclosure. Cao *et al.,* [3], find that managers adjust the wording and tone of corporate disclosure when machines are among its readers. This implies that AI changes both how reports are analysed and how they are written. For preparers this introduces a strategic dimension, because linguistic choices acquire market consequences when algorithms parse sentiment at scale. Sustainability disclosure is a natural extension: it is text-intensive, hence amenable to language models, and ESG reporting has been linked to sustainability performance [26]. Table 2 consolidates the evidence by function.

Table 2: Synthesis of AI applications, opportunities, challenges and Vision 2030 links by accounting function

Function	AI technique	Opportunity	Principal challenge	Vision 2030 link
Transaction processing	Robotic process automation; document extraction	Capacity release and fewer reconciliation breaks [14]	Task suitability and role displacement [23]	Structured e-invoicing and digital government data
Estimation and forecasting	Supervised machine learning	Benchmarks for provisions and reserves [2]	Explaining model output to auditors and users	Financial Sector Development Program: competitiveness
Misstatement detection	Machine learning classification	Earlier identification of material misstatement [24]	Probabilistic output requires human interpretation [12]	Financial-sector transparency
Assurance and audit	Machine learning; process automation; analytics	Higher audit quality and wider testing [25]	Reliance on AI evidence [27]; ethics [28]	Talent and capability goals [7]
Narrative disclosure	Natural language processing; language models	Scalable analysis of ESG and narrative text [26]	Strategic wording for machine readers [3]; Arabic-language models	Sustainability agenda [6]

Source*: Author's synthesis of the reviewed studies.*

4.2 Opportunities

AI can increase productivity without necessarily reducing quality. Automating high-volume tasks releases capacity, and the firm-level evidence suggests that the released capacity need not come at the expense of audit quality [25, 14]. For Saudi preparers handling structured e-invoicing flows, the same logic implies shorter closing cycles and fewer reconciliation breaks.

AI can also improve analytical depth and timeliness. Learned models can benchmark management estimates and screen entire populations for anomalies instead of relying on samples [2-24]. Continuous monitoring becomes feasible, so that audit committees and regulators can examine risk during the reporting period rather than after it.

AI adoption is also changing professional roles. Studies converge on the expectation that routine work will shrink while analytical, advisory and technology-oversight roles expand [23, 5]. Education is a precondition: Qasim and Kharbat [13], argue that data analytics and AI content should enter accounting curricula so that graduates can question model output instead of merely operating it.

Transparent, traceable and timely reporting may strengthen stakeholder trust. Perceived

usefulness and understanding raise acceptance of AI-enabled financial services, while perceived risk depresses it [29]. Reporting that is demonstrably consistent, traceable and timely can reinforce confidence among investors and regulators, which aligns with national ambitions for a competitive financial sector [10].

Language models may also support sustainability and non-financial reporting. Language models can extract, classify and cross-check narrative and quantitative sustainability information, thereby narrowing the gap between financial and non-financial disclosure. Given the link between ESG reporting and sustainability performance [26], and the importance of sustainability to national policy [6], this application deserves early empirical attention.

4.3 Challenges

Explainability and model risk remain central constraints. The same flexibility that lets models outperform benchmarks makes their reasoning difficult to articulate [2]-24]. Accounting standards and audit methodologies assume that judgements can be documented and challenged, so a model that cannot be explained strains the evidential chain.

Ethical accountability is closely related. Munoko *et al*., [28], identify ethical issues at each stage of AI use in auditing, from design to deployment, and Lehner *et al*., [15], show that delegating decisions to algorithms can blur professional responsibility. Zhang *et al*., [16], reach comparable conclusions for managerial accounting, noting risks of bias and unclear liability. Frameworks for responsible AI that combine ethical, sustainability, legal and innovation-management dimensions have been proposed as a response [30].

Auditors' reliance on AI-generated evidence creates a separate challenge. Commerford *et al*., [27], found that auditors may respond differently to contradictory evidence depending on whether it comes from an AI system or a human specialist. When AI evidence challenged management's estimates, auditors proposed smaller adjustments than when similar evidence came from a human specialist. This suggests that auditors may give less weight to AI-generated evidence when evaluating management's estimates, particularly when those estimates are based on relatively objective inputs. Auditors should therefore consider the source of the evidence carefully, assess all relevant information, and use their professional judgement before reaching a final conclusion.

Data quality and infrastructure are further constraints. Saudi public-sector evidence indicates that data infrastructure, cultural variables and organisational attention shape AI assimilation [9], and board-level evidence from banking reports infrastructure gaps and ethical concerns alongside strategic enthusiasm [11]. Readiness in terms of infrastructure and awareness also explains differences in AI adoption among Saudi enterprises [8].

Skills shortages may also delay adoption. Systematic evidence shows that emerging technologies are changing the competencies expected of accountants toward analytics, communication and judgement [5], yet curricula and professional training adjust slowly [13]. The national strategy's emphasis on talent development [7], is therefore directly relevant to accounting.

Cost and scale also affect adoption. Smaller organisations may lack the data volume, budget or specialist staff needed to build and validate models, and evidence on Saudi small and medium-sized enterprises suggests that readiness differs markedly between firms [8]. Vendor-supplied tools can lower entry barriers but shift dependency and validation burdens onto the buyer, who must still demonstrate that the system performs as intended.

Finally, regulatory clarity remains incomplete. Saudi authorities have advanced data and AI governance, but accounting-specific expectations on model validation, documentation and disclosure of AI use have not been articulated in the sources reviewed [10, 11].

4.4 The State of Saudi Evidence

Saudi studies in the evidence base address adoption, readiness and governance rather than accounting outcomes. Baabdullah *et al*., [8], connect AI readiness with organisational performance and customer interaction among business-to-business small and medium-sized enterprises. Alshahrani *et al*., [9], examine the assimilation of AI in public-sector bodies and highlight infrastructure and culture. Al-Baity [10], reviews AI in digital finance and proposes a framework, while Eskandarany [11], surveys bank directors on adoption obstacles and the role of governance. Noreen *et al.,* [29], add consumer perspectives on AI in banking that include the Saudi market.

Taken together, these contributions confirm that readiness, governance and trust are recurring themes, and they indicate that banking is the sector in which finance-related AI research is most developed. They do not, however, test AI tools on Saudi accounting data, examine how Saudi auditors use algorithmic evidence, or analyse AI-assisted disclosure by listed companies. These absences

define the evidence gap that the framework and agenda in Section 5 and Section 6 address.

5. DISCUSSION

5.1 Alignment with Vision 2030

The findings align with three Vision 2030 priorities. First, the Financial Sector Development Program seeks a more competitive and transparent financial system, and AI-enabled estimation, anomaly detection and disclosure analytics serve those aims directly [10]. Second, digital government and structured e-invoicing create standardised data streams, which are the raw material that rule-based automation and machine learning require. Third, the national data and AI strategy gives capability building a mandate [7], and accounting is a data-intensive profession in which such capability has immediate application.

The mapping also exposes asymmetries. Banking attracts research and policy attention, as the Saudi studies reviewed demonstrate, whereas corporate reporting, statutory audit, internal audit and sustainability disclosure are barely addressed. This asymmetry is not evidence that these areas are unimportant; it indicates that the knowledge base on which managers and regulators can rely is uneven.

Data protection adds a Saudi-specific consideration. Models trained on transaction, payroll or customer data must respect the personal data regime that has emerged in the Kingdom, and cloud-based tools raise questions about where data are stored and processed. These questions affect design choices such as anonymisation, access control and vendor selection, and they should be addressed before deployment because retrofitting controls is costlier than building them in.

5.2 An Integrative Framework

Figure 2 integrates the evidence. AI capabilities, comprising automation, machine learning, language processing and generative systems, act on five accounting functions and, when well governed, yield four families of value: efficiency, reporting quality, transparency and talent development. Vision 2030 enablers sit above this chain and raise its feasibility, whereas five constraints sit beneath it and erode its benefits unless managed. The framework is deliberately conditional: the same capability can produce either value or risk depending on explainability, oversight and skills.

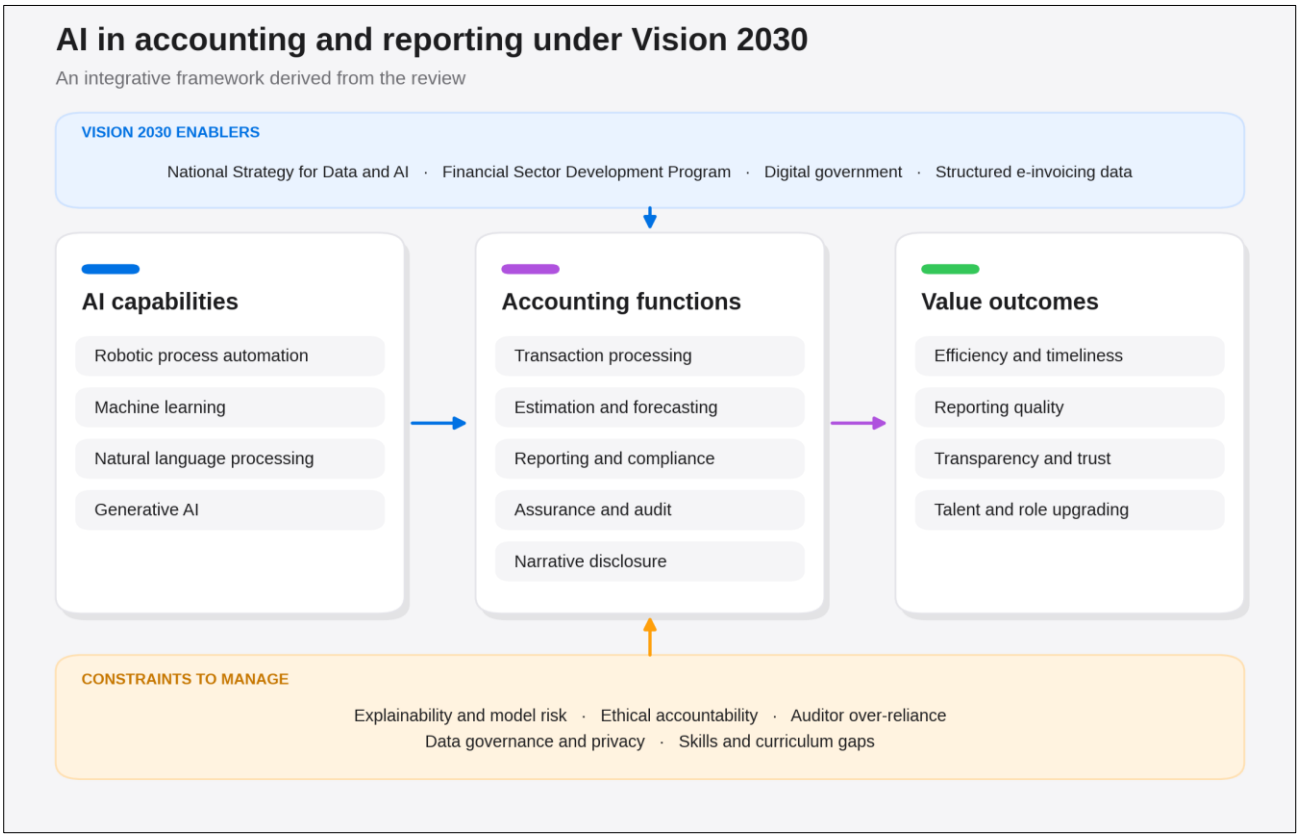


Fig. 2: Integrative framework linking AI capabilities, accounting functions, value outcomes, Vision 2030 enablers and constraints. Source: Author's elaboration

Three propositions follow. Proposition 1: where structured data are abundant and rules are clear, automation delivers early gains with limited ethical exposure. Proposition 2: where judgement is intensive, as in estimates and assurance, benefits depend on explanation and calibrated human oversight rather than on model accuracy alone. Proposition 3: policy-led infrastructure accelerates adoption only if matched by professional standards and education.

5.3 Transferability of International Evidence

Most evidence derives from competitive audit and capital markets in which firms invest to differentiate themselves [25]. In Saudi Arabia the impetus may come more from policy than from market rivalry, a pattern consistent with the strong role of state strategy in the Kingdom's digital agenda [6, 7]. This is an interpretation rather than an empirical finding of the reviewed studies, but it carries a practical consequence. If environmental pressure is the primary driver, as technology–organisation–environment reasoning would predict, then organisational readiness may lag behind policy ambition, and the gap should be monitored.

Language is a second transferability issue. Studies of disclosure analytics are built on English-language text [3], whereas Saudi reporting is bilingual. Arabic financial text may require dedicated models and validation, which turns a technical detail into a research priority.

5.4 A Staged Adoption Pathway

The evidence supports a phased adoption pathway. In the short term, organisations can concentrate on rule-based automation of structured flows, where logic is inspectable and ethical exposure is modest [14]. They should simultaneously establish data ownership, quality controls and an inventory of automated processes, because the later use of learned models depends on this foundation.

In the medium term, learned models can be introduced to benchmark estimates and screen transactions, provided that validation, documentation and human challenge are formalised. This is the stage at which findings on reliance on AI evidence become practical, since reviewers need guidance on when to accept, question or override model output [27, 15].

In the longer term, language models and generative tools may support drafting, disclosure review and sustainability reporting. Governance here should draw on responsible AI frameworks that combine ethical, legal, sustainability and innovation-management dimensions [30], and it should be coordinated with national data and AI direction [7]. Sequencing of this kind lets organisations capture early gains while building the controls that later stages demand.

6. Implications and Research Agenda

6.1 Implications for Practice and Policy

The implications differ for preparers, auditors, regulators and educators. Preparers should sequence adoption, beginning with rule-based automation on structured flows and moving to learned models only when validation, documentation and ownership are in place. Auditors should define how algorithmic output is weighed, train staff to challenge it, and record the reasoning behind reliance. Regulators and standard setters should consider guidance on model validation, documentation and disclosure of material AI use in reporting. Educators and professional bodies should embed analytics and AI oversight into curricula and continuing development.

These recommendations are intentionally modest in scope. They do not presume that every organisation should adopt every technology; they ask that each adoption decision be accompanied by evidence of fitness for purpose, a named owner and a plan for review. Such discipline is consistent with the professional scepticism on which accounting and assurance have traditionally relied, and it helps ensure that automation reinforces rather than weakens the credibility of financial information.

6.2 Research Agenda

Six research priorities emerge for the Saudi context:

- Empirical studies of how structured e-invoicing data improve audit analytics and reporting timeliness;
- Experiments on auditor reliance on AI output in Saudi assurance settings;
- Arabic and bilingual natural language models for sustainability and financial disclosure;
- Comparative research across Gulf Cooperation Council jurisdictions;
- Curriculum and competency studies within accounting programmes and professional bodies; and
- Governance of generative AI in drafting, reconciling and explaining financial information.

Each priority can be pursued with designs that suit the available data. Archival studies can exploit listed-company filings, field studies can follow implementation inside firms, and experiments can isolate judgement effects. Mixed-method programmes that combine these approaches, ideally across several Gulf jurisdictions, would allow findings to be compared and cumulated rather than

remaining isolated case reports. Transparent reporting of data sources and model settings should accompany studies.

7. CONCLUSION

This review synthesises recent evidence on AI in accounting and financial reporting and interprets it for Saudi organisations operating under Vision 2030. Evidence from 2020 to 2025 shows credible gains in estimation, misstatement detection, assurance quality and the processing of routine transactions, alongside persistent difficulties in explainability, ethical accountability, auditor reliance, data governance and skills. Saudi research addresses adjacent sectors but rarely accounting itself, so organisations should treat international findings as hypotheses to be tested locally rather than as settled guidance.

Managers should begin where evidence is strongest and risk is lowest and invest in the human and governance capabilities that make later stages safe. Policymakers should recognise that national AI ambition will translate into reporting quality only if professional standards, education and assurance practice evolve alongside infrastructure.

Three limitations qualify the conclusions. The review reports its procedure rather than a screening tally, so it is interpretive and not exhaustive. Restricting attention to English-language journal evidence omits Arabic-language and practitioner work. Finally, rapid change in generative AI means that the literature will move faster than any review can follow. Future work that combines systematic bibliometric counts with primary data from Saudi preparers, auditors and regulators would test and extend the framework presented here.

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