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Original Research Article

From Dashboards to Agentic Intelligence: A Framework for AI Agents in Enterprise Business Intelligence Modernization under Saudi Vision 2030

Choudhry Bilal Mazhar[1]*, Tahani Muneer Algethami[2]
[1]Digital Analytics and AI Lead, Arabian Agricultural Services Company (ARASCO), Riyadh, Saudi Arabia
[2]BI and Analytics Administrative, Arabian Agricultural Services Company (ARASCO), Riyadh, Saudi Arabia

***Corresponding Author**
Choudhry Bilal Mazhar
Digital Analytics and AI Lead, Arabian Agricultural Services Company (ARASCO), Riyadh, Saudi Arabia

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Abstract: Enterprise business intelligence has traditionally depended on dashboards that visualize historical and near-real-time data for human interpretation. Although dashboards remain essential for transparency and performance monitoring, they often require decision makers to detect anomalies, interpret root causes, and translate insights into action. This paper proposes an agentic artificial intelligence framework for enterprise business intelligence modernization, shifting BI from passive reporting toward autonomous, governed, and decision-oriented intelligence. The study uses a conceptual design methodology supported by literature on agentic AI, enterprise analytics, decision intelligence, and national digital transformation priorities. The proposed framework integrates five layers: unified data foundation, semantic and KPI governance, agent orchestration, human-in-the-loop decision control, and performance assurance. It explains how AI agents can monitor business metrics, detect exceptions, generate contextual explanations, recommend actions, and support executive decision-making while preserving governance, accountability, and responsible AI controls. From a business and economic perspective, the framework links analytics modernization to productivity improvement, cost optimization, working-capital visibility, faster management response, and measurable return on AI investment. The framework is positioned for Saudi enterprises aligned with Vision 2030, where data and AI are central enablers of economic diversification, operational efficiency, and digital maturity. The paper contributes a practical modernization model for organizations seeking to evolve from descriptive dashboards to agentic intelligence ecosystems.

Keywords: Agentic AI, Business Intelligence, Enterprise Analytics, Decision Intelligence, AI Governance, Microsoft Fabric, Power BI, Saudi Vision 2030.

INTRODUCTION

Business intelligence has become a core capability for modern enterprises because it converts operational, financial, commercial, and supply-chain data into measurable insight. For many organizations, BI maturity has progressed from static reports to interactive dashboards, self-service analytics, governed semantic models, and cloud-based data platforms. Gartner defines analytics and

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BI platforms as solutions that help organizations model, analyze, and share data while increasingly supporting governance, interoperability, and AI-enabled automation [1]. However, the dominant operating model remains largely human-dependent. Dashboards inform users, but users must still identify issues, ask follow-up questions, interpret business context, and initiate action. This gap limits the ability of enterprises to respond quickly to changing conditions, especially when business operations are complex, data volumes are increasing, and executive expectations for real-time decision support are rising.

The business case for agentic BI is also economic. Enterprises invest heavily in data platforms, reporting teams, and dashboard portfolios, but value is often constrained when insights are not converted into timely action. Generative AI has been estimated to generate substantial productivity and economic value across business functions, with McKinsey identifying significant annual value potential from generative AI use cases [2]. Agentic BI can improve the economics of analytics by reducing repetitive analysis effort, shortening decision cycles, improving exception management, and increasing the reuse of governed data assets. In sectors with complex supply chains and operating-cost pressure, such as agriculture, food production, logistics, and shared services, faster insight-to-action cycles can support margin protection, inventory efficiency, procurement savings, service-quality improvement, and better capital allocation.

Agentic artificial intelligence introduces a new direction for BI modernization. Unlike conventional analytics systems that wait for user interaction, agentic AI systems can reason over goals, plan multi-step tasks, use enterprise tools, collaborate with other agents, and act within defined governance boundaries. In an enterprise analytics environment, this means that AI agents can continuously monitor KPIs, detect anomalies, summarize drivers, recommend corrective actions, and escalate decisions to accountable business owners. Recent enterprise research describes agentic AI as a shift from isolated productivity support to process reinvention, while analytics platforms are increasingly embedding generative AI and conversational experiences into governed data environments [3-5]. This direction also extends prior work on multi-agent enterprise operating models, where the movement from isolated AI assistants toward governed AI workforces was presented as a necessary step for scalable enterprise AI adoption [6].

The relevance of this transformation is particularly strong for Saudi organizations under Vision 2030. The Saudi Data and AI Authority emphasizes that data and artificial intelligence contribute directly and indirectly to a large portion of Vision 2030 objectives, while the National Strategy for Data and AI seeks to position the Kingdom among global leaders in data-driven economies [7, 8]. For industrial and service organizations, this creates a strategic need to move beyond reporting efficiency toward intelligent decision ecosystems that support governance, productivity, risk management, and economic diversification.

This research aims to develop a practical framework for integrating agentic AI into enterprise BI modernization. The scope includes the data foundation, semantic governance, agent roles, decision workflows, responsible AI controls, and expected business outcomes. The novelty of the work lies in positioning BI dashboards not as final reporting products but as interaction points within a broader agentic intelligence architecture. The proposed framework is designed to guide enterprises that use modern analytics platforms such as Microsoft Fabric and Power BI while aligning with national digital transformation priorities. It builds conceptually on previous research that framed national data governance dashboards as governance operating systems rather than static reporting screens [9], and on prior work proposing an Autonomous Decision Assurance Layer for validating AI-generated recommendations before execution [10].

Experimental Section

This study follows a conceptual framework design methodology. The method does not involve laboratory chemicals, clinical subjects, animals, or human participant experiments. Instead, it synthesizes current enterprise AI, BI, data governance, and decision intelligence concepts into a repeatable implementation model. The methodology includes four steps: identifying limitations in traditional BI operating models; reviewing emerging agentic AI and analytics platform capabilities; defining architectural layers for an agentic BI ecosystem; and validating the framework through enterprise use-case scenarios relevant to industrial organizations.

The proposed framework assumes an enterprise environment with integrated data sources, such as enterprise resource planning systems, operational systems, lakehouse or warehouse storage, governed semantic models, and BI consumption layers. Microsoft Fabric and Power BI are used as representative platform examples because Microsoft describes Fabric as an integrated analytics platform with Copilot experiences that help users transform and analyze data, generate insights, and create reports [4, 5]. The framework, however, is platform-adaptable and can be applied to other enterprise analytics environments where governed data, semantic models, and AI orchestration capabilities are available. Its governance assumptions are also consistent with the NIST AI Risk Management Framework, which emphasizes governance, mapping, measurement, and management of AI risks across the AI lifecycle [11].

To keep the framework economically measurable, the study also considers business-value indicators that can be assessed before and after agentic BI adoption. These include reduction in manual reporting hours, decrease in executive response time, improvement in forecast accuracy, faster anomaly resolution, savings from early risk detection, reduction in duplicated reports, and improved utilization of existing analytics investments. These indicators provide a practical basis for evaluating agentic BI not only as a technology upgrade but also as a business-performance and productivity-improvement initiative.

The framework was developed using five design principles. First, agents must operate on trusted and governed enterprise data rather than disconnected extracts. Second, business logic must be represented through semantic models, KPI definitions, and ownership rules. Third, agent autonomy must be controlled through approval thresholds and human-in-the-loop checkpoints. Fourth, the agentic layer must produce explainable outputs that can be reviewed by business and technical stakeholders. Fifth, continuous monitoring must be established to measure adoption, accuracy, value realization, and risk. These design principles align with international responsible AI guidance that emphasizes transparency, explainability, robustness, safety, accountability, privacy, and human-centered oversight [11-13].

RESULTS AND DISCUSSION

The proposed agentic BI modernization framework consists of five layers, as illustrated in Figure 1. The first layer is the unified data foundation, where data from ERP, finance, procurement, HR, operations, customer, and external sources are ingested, cleaned, modeled, and made available through governed lakehouse or warehouse structures. This layer determines the quality of all downstream agent outputs. If enterprise data is incomplete, inconsistent, or delayed, agentic intelligence may generate misleading explanations or recommendations. Therefore, data quality, lineage, access control, and refresh governance are prerequisites for reliable agentic BI.

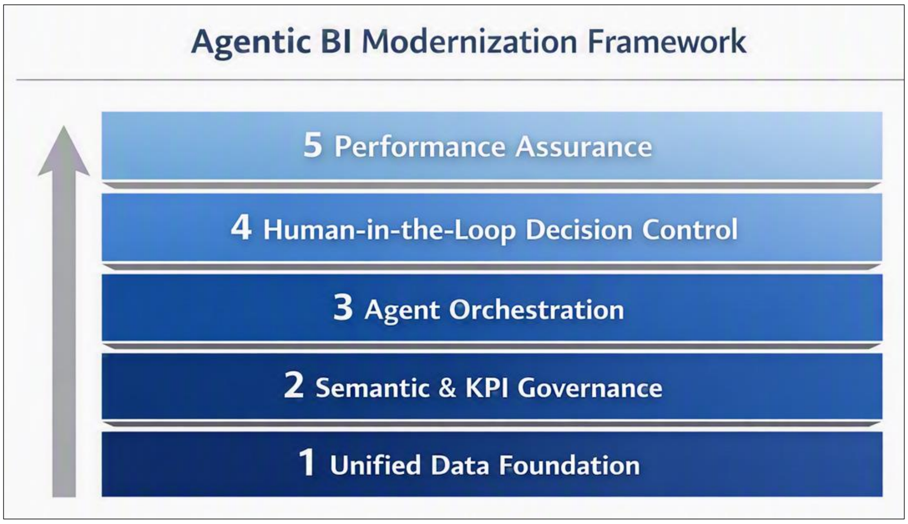

Figure 1: Agentic BI modernization framework showing the five layers required to move enterprise analytics from governed data foundations toward performance-assured decision intelligence.

The second layer is semantic and KPI governance. In traditional reporting, dashboards frequently embed business definitions inside individual reports, which creates inconsistency across departments. Agentic BI requires a stronger semantic layer because agents must reason over shared definitions of revenue, cost, inventory, production efficiency, supplier performance, compliance status, and service levels. This layer includes certified datasets, measures, dimensions, hierarchies, data ownership, and business glossary definitions. It enables AI agents to answer questions and generate recommendations based on consistent enterprise meaning rather than raw tables alone.

The third layer is agent orchestration. This layer defines specialized AI agents that perform analytics tasks within controlled scopes. A monitoring agent tracks KPI movement and detects unusual patterns. A diagnostic agent investigates possible root causes by comparing time periods, departments, products, suppliers, or locations. A narrative agent converts analytical findings into executive summaries. A recommendation agent suggests actions based on defined rules, historical patterns, and organizational policies. An escalation agent routes critical issues to accountable owners. Together, these agents form a coordinated analytical workforce that supports decision cycles rather than merely producing visual outputs.

Table 1: Agent roles in the proposed agentic BI modernization framework

Agent Role	Primary Function	Business Value
KPI Monitoring Agent	Tracks business indicators and detects anomalies.	Improves responsiveness and reduces manual monitoring effort.
Diagnostic Agent	Investigates drivers behind performance changes.	Accelerates root-cause analysis across departments.
Narrative Agent	Generates executive summaries and contextual explanations.	Improves clarity for leadership and non-technical users.
Recommendation Agent	Suggests corrective actions based on rules, history, and targets.	Supports faster and more consistent decision-making.
Escalation Agent	Routes high-risk issues to responsible owners.	Strengthens accountability and operational follow-up.

The fourth layer is human-in-the-loop decision control. Full autonomy is not appropriate for many enterprise decisions because actions may affect cost, compliance, customers, employees, suppliers, or operational continuity. Therefore, the framework defines levels of autonomy. At the lowest level, the agent only observes and summarizes. At the intermediate level, it recommends and prepares actions for approval. At the advanced level, it may execute predefined low-risk actions under policy limits. Human approval remains mandatory for strategic, financial, regulatory, or high-impact decisions. This approach balances efficiency with accountability and responsible AI governance.

The fifth layer is performance assurance. Enterprises should evaluate agentic BI using both technical and business metrics. Technical metrics include data freshness, response accuracy, hallucination rate, source traceability, latency, and security incidents. Business metrics include decision-cycle reduction, user adoption, issue-resolution time, forecast accuracy improvement, and measurable financial or operational impact. This layer is important because enterprise leaders are increasingly expected to translate AI investments into measurable outcomes rather than experimentation alone [2, 3]. Deloitte's enterprise AI research also highlights that AI success depends on movement from ambition to activation, production deployment, governance maturity, and business reimagination rather than isolated experimentation [3-14].

Economically, the most important contribution of agentic BI is the conversion of analytics from a cost center into a decision-value engine. Traditional dashboards often measure what has already happened, while agentic BI enables earlier detection of unfavorable trends, automated prioritization of exceptions, and faster managerial intervention. This can support tangible value creation through reduced operational leakage, improved demand and supply planning, better procurement control, lower compliance exposure, and more disciplined use of capital. For executive management, the value proposition is not only better visibility but also improved decision velocity, stronger accountability, and a clearer link between analytics investments and enterprise performance outcomes.

Table 2: Business and economic value indicators for agentic BI modernization

Value Dimension	Expected Business Impact	Suggested Indicator
Productivity	Reduced manual reporting and repetitive analysis effort.	Reporting hours saved per month.
Decision Velocity	Faster identification, explanation, and escalation of business issues.	Average issue detection-to-action time.
Cost Optimization	Earlier detection of spend leakage, process inefficiencies, and operational exceptions.	Verified savings or avoided cost.

Value Dimension	Expected Business Impact	Suggested Indicator
Asset Utilization	Greater reuse of governed datasets, semantic models, and BI investments.	Reuse rate of certified analytics assets.
Risk and Compliance	Improved visibility into policy breaches, control gaps, and high-risk trends.	Number of early warnings resolved before escalation.

For Saudi enterprises, the framework supports Vision 2030 by improving organizational agility, digital maturity, and evidence-based decision-making. SDAIA's national strategy emphasizes data and AI as foundations for economic and social value creation, including governance, innovation, talent development, and ecosystem growth [7, 8]. Agentic BI can help organizations operationalize these priorities by embedding intelligence directly into daily management routines. In industrial contexts, such as agriculture, food supply, manufacturing, logistics, and shared services, agentic BI can support cost monitoring, procurement performance, inventory optimization, safety compliance, workforce planning, and executive performance reviews. The sectoral relevance of this approach is consistent with earlier research on AI-driven cybersecurity analytics dashboards for critical-infrastructure protection, which argued that real-time executive dashboards require telemetry, governance evidence, responsible AI controls, and human oversight to support trusted decision-making [15]. Table 2 summarizes the main business and economic indicators that enterprises can use to assess the value of agentic BI modernization.

However, implementation challenges must be addressed. Data silos, unclear ownership, weak semantic governance, insufficient AI literacy, security risks, model bias, and overreliance on automated recommendations can reduce trust. Enterprises should begin with controlled use cases, such as anomaly detection, automated narrative summaries, or procurement spend monitoring, before expanding to autonomous recommendations. The staged transition from traditional dashboards to governed action is summarized in Figure 2. A phased roadmap is recommended: establish data governance, certify semantic models, deploy assistive analytics agents, introduce recommendation workflows, and finally enable controlled autonomous actions for low-risk processes.

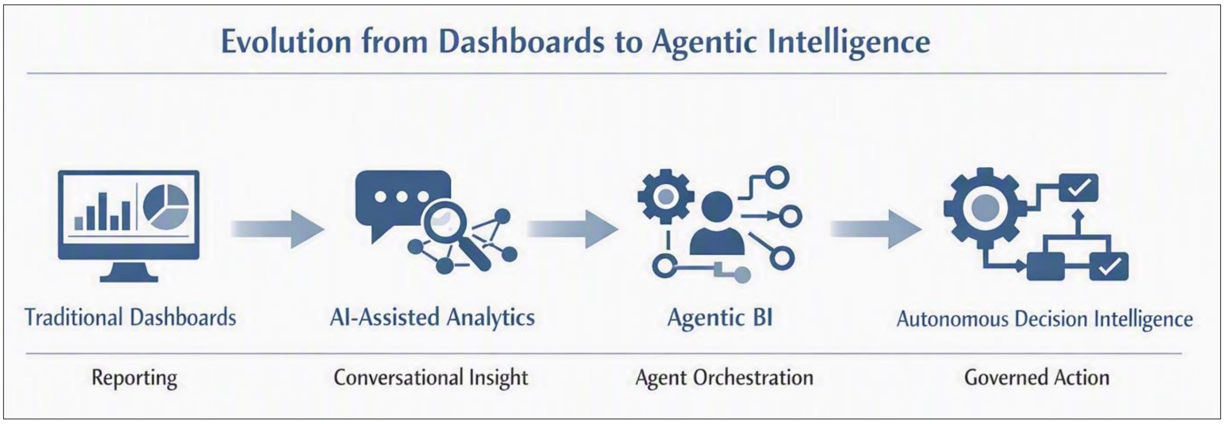

Figure 2: Evolution from traditional dashboards to agentic intelligence, highlighting the progression from reporting to conversational insight, agent orchestration, and governed action

CONCLUSION

This paper proposed a framework for agentic AI in enterprise BI modernization. The main finding is that the next stage of BI maturity is not limited to richer dashboards or faster reporting; it is the transformation of dashboards into governed decision-intelligence ecosystems supported by specialized AI agents. The proposed five-layer model combines data foundation, semantic governance, agent orchestration, human-in-the-loop control, and performance assurance. This structure enables enterprises to increase responsiveness, improve decision quality, strengthen accountability, and align analytics modernization with responsible AI principles. From a business and economic perspective, the framework also supports productivity improvement, cost optimization, faster managerial response, better use of analytics investments, and clearer measurement of AI-driven value creation.

The study contributes a practical and Vision 2030-aligned model for organizations seeking to move from descriptive reporting toward autonomous and explainable analytics. Future research should test the framework through empirical case studies, measure adoption outcomes across departments, and compare agentic BI maturity across sectors. Further work should also explore governance models for AI agents, quantitative ROI measurement, and the impact of agentic analytics on executive decision behavior.

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