© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722404

Big Data, Artificial Intelligence, and Machine Learning Integration for Smart Business and Industrial Innovation in Saudi Arabia

ADNAN ANWAR SHAIKH
ORCiD: 0009-0006-8457-3499

Abstract- Saudi Arabia's economic diversification agenda has elevated data-intensive innovation to a strategic priority, extending beyond a narrow information-technology focus. This review analyzes how big data analytics, artificial intelligence, and machine learning function as an integrated capability system for smart business and industrial innovation in the Kingdom. In contrast to studies that examine the performance effect of individual technologies, this review focuses on the conversion process by which heterogeneous data are transformed into predictions, decisions, automated actions, and repeatable organizational learning. A structured integrative review was carried out using 30 core academic and Saudi policy sources published between 2020 and 2025. The evidence was organized into five themes: technology integration architecture, business innovation, industrial applications, organizational capabilities, and Saudi institutional conditions. The synthesis demonstrates that big data analytics provides the data engineering and sense-making foundation, machine learning generates adaptive predictive intelligence, and artificial intelligence embeds this intelligence into decision and business workflows. Performance improvements are most significant when technical integration is complemented by strategic agility, domain expertise, data culture, executive sponsorship, and responsible governance. In Saudi Arabia, national data and AI policy, digital infrastructure, localization objectives, and expanding industrial ecosystems create strong conditions for adoption, while talent shortages, fragmented legacy data, model risk, privacy requirements, and uneven small-firm readiness remain major constraints. This paper describes an integrated innovation stack and a Saudi digital innovation flywheel to illustrate how firms can progress from data readiness to scalable business and industrial outcomes. The review concludes with managerial priorities and a research agenda for sector-specific, longitudinal, and governance-aware studies.

Keywords: big data analytics; artificial intelligence; machine learning; smart business; industry 4.0; innovation; saudi arabia; vision 2030

I. INTRODUCTION

Digital transformation is shifting the basis of competition from the mere ownership of physical assets to the ability to integrate data, algorithms, organizational knowledge, and rapid execution. Big data analytics (BDA), artificial intelligence (AI), and machine learning (ML) are frequently discussed as separate technologies; however, in real-world contexts, they are interdependent. BDA establishes the architecture for ingesting, integrating, governing, and analyzing high-volume and high-velocity information. ML transforms historical and streaming data into statistical predictions or classifications. AI incorporates these outputs into decision support, automation, optimization, and increasingly generative or agentic workflows. This interdependence is critical because significant investment in platforms does not guarantee innovation unless analytical outputs are translated into altered decisions, processes, products, or customer experiences (Mikalef et al., 2020; Yasmin et al., 2020; Mikalef and Gupta, 2021).

The reference study by Alghamdi and Agag (2023) delivers a valuable foundation for understanding Saudi manufacturing. It demonstrates that AI-powered big data analytics is positively correlated with tactical agility and innovation performance, and that organizational and surrounding factors influence value realization. While this empirical logic is revealing, a wider review is necessary because the current innovation environment encompasses more than the relationship between analytics, agility, and market turbulence. Modern firms increasingly deploy

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722404

integrated technology stacks that combine cloud or edge computing, Internet of Things data, enterprise systems, ML models, computer vision, optimization, and AI-assisted human decision making. The strategic issue is not whether BDA or AI is effective in isolation, but how organizations configure an integrated data-to-action system that generates sustainable business and industrial capabilities (Jagatheesaperumal et al., 2022; Oesterreich et al., 2022).

Saudi Arabia offers a distinctive setting for this question. The National Strategy for Data and AI (NSDAI) positions data and AI as instruments of national competitiveness, investment, talent development, research, and sector transformation, with explicit attention to energy, mobility, health, education, and government (SDAIA, 2020). At firm level, the same agenda intersects with industrial localization, smart manufacturing, logistics modernization, digital finance, new urban developments, and entrepreneurial growth. Research on Saudi organizations also shows that the assimilation of AI depends on managerial attention and institutional arrangements, not only on technical availability (Alshahrani et al., 2022). For small and medium-sized enterprises, digital transformation opportunities coexist with gaps in awareness, capability, and preparation (Tripathi and Singh, 2024).

This review considers this context by synthesizing recent evidence published between 2020 and 2025. It conceptualizes BDA, ML, and AI as components of a layered innovation architecture and evaluates both the technical mechanisms and organizational conditions that enable value creation. The analysis adopts an interdisciplinary approach, embracing insights from information systems, innovation management, operations, industrial engineering, supply-chain research, and Saudi policy. The resultant framework is designed to support scholars investigating digital capability formation and managers determining investment priorities, governance strategies, and pathways from pilot projects to scaled innovation.

II. AIM, OBJECTIVES AND REVIEW QUESTIONS

The objective of this study is to provide an integrative explanation of how BDA, AI, and ML can be combined to facilitate smart business and industrial innovation in Saudi Arabia. This approach differs from conventional technology-adoption reviews by focusing on capability integration and value conversion rather than adoption intent or a singular performance trajectory. The review is guided by five objectives: mapping the functional relationships among data infrastructure, analytics, ML, and AI; synthesizing evidence on business and industrial use cases; identifying organizational capabilities that translate technical potential into innovation; examining Saudi policy, regulatory, talent, and ecosystem conditions; and formulating a research agenda that connects technology maturity with measurable innovation outcomes.

The synthesis is structured around three review questions. First, what mechanisms enable the combined BDA-ML-AI stack to convert raw organizational and industrial data into innovation outcomes? Second, which managerial, human, governance, and sustainability factors facilitate or hinder this conversion? Third, how does the Saudi Arabian context influence implementation priorities throughout manufacturing, supply chains, services, and emerging digital businesses? These questions go beyond basic correlations between digital investment and performance, supporting a process-oriented perspective in which sensing, learning, decision-making, action, and feedback are continuous.

III. CONCEPTUAL FOUNDATION: FROM DIGITAL RESOURCES TO INNOVATION CAPABILITIES

The resource-based view and dynamic capabilities perspective remain useful foundations to understand digital innovation, but they need a socio-technical interpretation. Data platforms, cloud services, algorithms, sensors, and computing capacity are resources that can be purchased. Competitive advantage arises when firms combine them with scarce complementary assets, including domain knowledge, high-quality proprietary data, cross-functional routines, customer understanding, and managerial judgement. Mikalef et al. (2020) show that analytical resources affect competitive performance through dynamic and managerial capabilities, while Brinch et al. (2021) emphasize firm-level capabilities involved in extracting value from big data. This distinction explains why similar technology portfolios can produce sharply different outcomes.

Dynamic capability logic frames BDA as a sensing infrastructure, ML as an adjustable learning mechanism, and AI as a means of seizing and reconfiguring opportunities through decision support and automation. Organizational flexibility is one bridge between these layers and innovation. Saudi evidence indicates that BDA-AI strengthens agility and innovation performance (Alghamdi and Agag, 2023), while broader evidence links AI assimilation to organizational and customer agility (Fosso Wamba, 2022). Yet agility is not automatic. Analytical insight must reach actors with authority, models must be interpretable enough for appropriate use, and processes must be redesigned so that decisions can change at the pace of new information.
A complementary socio-technical lens highlights interaction among technical systems, people, tasks, organizational structures, and institutional rules. Oesterreich et al. (2022) find that the business value of big data analytics represents both social and technical factors. AI research similarly stresses the automation-augmentation paradox: algorithms can substitute for some tasks while simultaneously increasing the importance of human framing, exception handling, creativity, and accountability (Raisch and Krakowski, 2021). For innovation management, AI can expand search, experimentation, and recombination, but its effects depend on the design of human and machine collaboration (Haefner et al., 2021).

These perspectives support the integrated stack proposed in Figure 1. The lowest layer is a governed data foundation connecting operational technology, enterprise applications, customers, suppliers, and external data. BDA transforms that raw material into accessible information and features. ML generates predictions, anomaly signals, recommendations, and optimized parameters. AI then orchestrates decisions across human and automated workflows. The upper layer is not "AI" itself but innovation outcomes such as faster product development, higher asset reliability, service personalization, supply-chain resilience, resource efficiency, and new business models. Governance and human capability flank every layer because weak data quality, insecure integration, poor incentives, or inadequate skills can break the conversion chain.

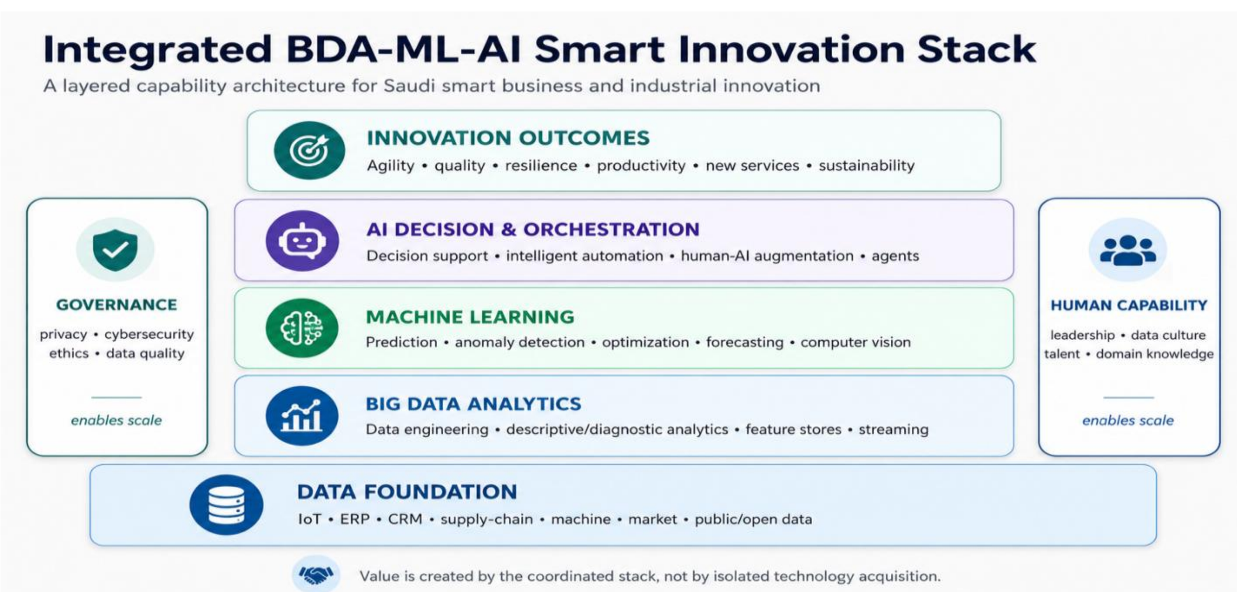

Figure 1. Integrated BDA–ML–AI smart innovation stack for Saudi organizations.

IV. REVIEW METHODOLOGY

A structured integrative review design was adopted because the topic spans heterogeneous empirical methods and disciplinary traditions. The purpose was not to estimate a single pooled effect size, but to compare mechanisms, contexts, and implementation conditions across business and industrial research. The review window was restricted to 2020-2025 to capture the recent convergence of Industry 4.0, advanced analytics, AI assimilation, cloud-connected operations, and post-pandemic digital acceleration. The attached 2023 Saudi study was used as an anchor for terminology and contextual framing, while the review deliberately moved beyond its empirical model to include ML, smart production, supply-chain resilience, AI-enabled innovation, SMEs, and governance.

Search concepts combined terms for technology and outcome: "big data analytics", "artificial intelligence", "machine learning", "predictive analytics", "smart manufacturing", "Industry 4.0", "innovation performance", "organizational agility", "supply-chain resilience", "digital transformation", and "Saudi Arabia". Candidate literature was identified through publisher-indexed and DOI-verifiable searches, with priority given to peer-reviewed journals commonly indexed in Scopus or Web of Science across Elsevier, Springer, Emerald, IEEE, and comparable scholarly publishers. Official Saudi sources were retained where institutional strategy or regulation could not be represented adequately by journal literature. No claim is made that the review reproduces a full database-export protocol; rather, it is a transparent integrative synthesis centered on recent, high-relevance evidence.

Studies were included when they were published between 2020 and 2025, addressed BDA, AI, or ML in an organizational or industrial setting, and offered evidence or theory relevant regarding innovation, performance, agility, resilience, adoption, smart production, or digital business. Studies were excluded when they were pre-2020, purely algorithmic without organizational implications, duplicated another report, or lacked a clear connection to business or industrial value. Thirty core sources were retained for synthesis, including Saudi-specific research and national policy documents. Each source was coded for technology focus, unit of analysis, mechanism of value creation, outcome, enabling condition, constraint, and relevance to the Saudi context.

The thematic synthesis proceeded in three stages. First, evidence was grouped into technology layers: data foundation and analytics, ML intelligence, and AI-supported decision or automation. Second, application evidence was separated into smart business and manufacturing domains to avoid treating customer-facing and asset-intensive innovation as identical. Third, cross-cutting conditions were coded into business agility, leadership, talent, data culture, governance, ecosystem support, and regulatory responsibility. Contradictory findings were preserved rather than harmonized artificially. This approach is consistent with the central insight of recent digital-transformation research that technology value is contingent, processual, and organization-specific (Verhoef et al., 2021; Borges et al., 2021).

Table 1. Evidence synthesis of representative studies (2020–2025).

Study	Context	Technology focus	Core finding / review relevance
Mikalef et al. (2020)	Cross-industry firms	BDA capability	Dynamic and operational capabilities convert analytics resources into competitive performance.
Ghasemaghaei & Calic (2020)	Firm innovation	Big data	Data volume alone does not guarantee innovation; quality and use matter.

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722404

Mikalef & Gupta (2021)	Organizations	AI capability	AI capability is linked with organizational creativity and performance.
Escobar et al. (2021)	Manufacturing	Quality 4.0 / big data	Industrial value depends on data quality, integration and analytical capability.
Alshahrani et al. (2022)	Saudi public sector	AI assimilation	Managerial attention and organizational structures shape AI assimilation.
Fosso Wamba (2022)	Firms	AI assimilation	Organizational and customer agility mediate AI-performance effects.
Alghamdi & Agag (2023)	Saudi manufacturing	AI-powered BDA	Strategic agility links analytics use and innovation performance.
Zamani et al. (2023)	Supply chains	AI + BDA	Integrated analytics supports resilience through sensing and response.
Tripathi & Singh (2024)	Saudi SMEs	Digital transformation	SME readiness and awareness remain uneven despite new opportunities.
Babina et al. (2024)	Firm-level innovation	AI	AI investment is associated with firm growth and product innovation.

V. THEMATIC SYNTHESIS AND FINDINGS

The reviewed evidence converges on a central proposition: integration quality matters more than the possession of any single technology. Big data capability improves the breadth, timeliness, and granularity of organizational sensing, but more data can also introduce noise, inconsistency, and governance burden. Ghasemaghaei and Calic (2020) caution that big data is not automatically better data for innovation. ML adds value when firms transform governed datasets into features that can support prediction or optimization, while AI adds value when model outputs are embedded in executive or operational action. Therefore, maturity should be assessed across the whole pipeline from data provenance to decision impact, not by counting models, dashboards, or AI licenses.

Manufacturing evidence makes this architecture particularly visible. Smart production systems generate continuous signals from machines, quality stations, maintenance histories, energy meters, and production plans. ML can recognize anomalies, estimate remaining useful life, identify defect patterns, forecast throughput, or recommend process settings. AI can then combine those predictions alongside scheduling rules, maintenance constraints, inventory availability, and operator judgement to coordinate action. Reviews of smart production and Quality 4.0 emphasize that manufacturing value increasingly depends on combining data engineering with ML, computer vision, and decision systems rather than deploying isolated analytics (Cioffi et al., 2020; Escobar et al., 2021; Jagatheesaperumal et al., 2022).

For Saudi industrial firms, the implication is practical. High-capital sectors such as energy, petrochemicals, mining, utilities, and advanced manufacturing can create large value from small improvements in uptime, yield, energy intensity, quality, and safety. However, the economic case depends on reliable sensor coverage, contextualized asset data, integration with maintenance and enterprise systems, and engineering validation. An ML model that predicts failure but cannot trigger a work order, access spare-parts information, or explain its confidence to reliability engineers remains an experiment rather than an innovation capability. Industry 4.0 readiness research in Saudi manufacturing similarly identifies adoption challenges that go beyond technology acquisition (Alsaadi, 2022).

Supply chains reveal a second integration pattern. BDA provides end-to-end visibility by combining demand, inventory, supplier, transport, production, and external risk data. ML supports demand forecasting, lead-time estimation, disruption prediction, route optimization, and inventory classification. AI can use these signals for exception management, scenario planning, prescriptive recommendations, or semi-automated replanning. Zamani et al. (2023) synthesize evidence linking AI and big data analytics with supply-chain resilience, while Qureshi et al. (2024) connect Industry 4.0 technologies to ecologically sustainable manufacturing supply chains. The strategic benefit is not simply lower cost; it is the ability to recognize disturbance earlier and reconfigure operations before service or production deteriorates.

In smart business, the same stack is oriented toward customers, markets, and knowledge-intensive decisions. Consumer and transaction data can be examined to identify micro-segments, product affinities, churn risks, or unmet needs. ML models transform these patterns into forecasts and propensity scores, while AI can personalize content, prioritize sales actions, support pricing, automate regular service, or augment product design. Mariani and Fosso Wamba (2020) show how big-data analytics companies contribute to innovation in consumer-goods settings, and Olabode et al. (2022) link BDA capability to market performance through business-model circumstances and competitive intensity. The mechanism is strongest when analytics changes how firms experiment and assign resources, rather than simply reporting past performance.

Marketing and commercial innovation also illustrate the importance of assimilation. Hossain et al. (2022) associate marketing analytics capability and AI adoption with competitive advantage in manufacturing. BDA can discover weak market signals, but strategic value appears when teams act on them quickly, test alternatives, and learn. This is consistent with evidence that analytical capability can strengthen business agility and creativity (Alyahya et al., 2023). In Saudi Arabia, these capabilities are relevant not only to large incumbents but also to digitally enabled SMEs pursuing scalable customer acquisition, effective operations, and service differentiation. Tripathi and Singh (2024) nevertheless show that awareness and preparation for digital transformation remain uneven, suggesting that shared platforms, advisory support, and capability-building can matter as much as access to tools.

AI has a distinct contribution to innovation because it changes both task execution and the search space for new solutions. Mikalef and Gupta (2021) conceptualize AI capability as an organizational capability linked to creativity and performance, while Babina et al. (2024) provide firm-level evidence connecting AI investment with growth and product innovation. AI can expand the number of alternatives considered, accelerate pattern recognition, support simulation, and reduce the marginal cost of some knowledge tasks. At the same time, the automation-augmentation paradox means that indiscriminate substitution can reduce learning or create brittle operations (Raisch and Krakowski, 2021). High-value designs keep humans responsible for objectives, exceptions, contextual judgement, and consequences.

Organizational capability repeatedly acts as the transformation mechanism between technical potential and innovationYasmin et al. (2020) show that BDA capability is multidimensional, and Wamba-Taguimdje et al. (2020) demonstrate that AI-based transformation projects can create business value when embedded in wider organizational change. Leadership must define which decisions matter, where uncertainty is costly, and which processes can be redesigned. Data teams must work with operational and commercial specialists so that model features reflect causal realities rather than convenient database fields. Incentives must also reward evidence-based learning; otherwise managers may protect legacy routines even when analytics reveals better alternatives.

Business agility is especially relevant in Saudi Arabia's rapidly changing markets. The attached study finds that strategic responsiveness mediates the relationship between AI-powered BDA and innovation performance (Alghamdi and Agag, 2023). Fosso Wamba (2022) similarly shows that organizational and customer agility mediate AI assimilation effects. These results indicate that technology is most valuable when it shortens the cycle from signal to coordinated response. An integrated stack should therefore be evaluated by decision latency, experimentation speed, reconfiguration capacity, and learning quality, not solely by model correctness. A highly accurate forecast delivered after planning decisions are locked can have less business value than a slightly less accurate forecast embedded in a responsive process.

Governance is part of innovation architecture rather than a compliance layer added after deployment. Saudi organizations handling personal or sensitive information must comply with for the Personal Data Protection Law, which establishes obligations around processing and safeguarding of personal data (SDAIA, 2023). For industrial systems, cybersecurity, model integrity, access controls, data lineage, and safe human override are important. AI also introduces fairness, explainability, accountability, and monitoring questions, where decisions affect people or safety-critical operations (SDAIA, 2025). Governance can accelerate adoption when it gives managers clear risk boundaries, approved data pathways, documentation standards, and escalation procedures instead of requiring every project to renegotiate basic controls.

The Saudi national ecosystem changes the economics of integration. NSDAI identifies talent, investment, policy, research, and ecosystem development as coordinated national priorities (SDAIA, 2020). This alignment itself can lower uncertainty for firms by encouraging infrastructure investment, local capability development, and cross-sector experimentation. Alshahrani et al. (2022) nevertheless demonstrate that attention structures inside organizations continue to be decisive for AI assimilation. National ambition cannot substitute for firm-level ownership, portfolio discipline, data stewardship, or workflow redesign. The key managerial challenge is to translate ecosystem opportunity into repeatable internal capabilities without undertaking technology adoption for signaling purposes alone.

VI. SECTORAL CONSEQUENCES FOR SAUDI SMART BUSINESS AND INDUSTRY

In manufacturing and process industries, priority use cases should be selected where data frequency, decision repeatability, and economic consequence are high. Predictive maintenance, quality inspection, energy optimization, advanced process control, production scheduling, and root-cause analysis fit this pattern. Integration sequence should begin with trustworthy asset and process data, followed by operational analytics, supervised or unsupervised ML, and then AI-supported action. For plants with safety-critical operations, human validation and engineering constraints need to remain explicit. This approach converts AI from a stand-alone software project into a component of reliability, quality, and production-management systems.

Logistics and supply-chain organizations can focus on visibility and decision synchronization. Saudi Arabia's role as a regional logistics hub increases the value of combining port, warehouse, fleet, customs, inventory, demand, and supplier information. ML can forecast arrival times, congestion, demand, and disruption risk; AI can support dynamic allocation, routing, procurement decisions, and exception handling. Resilience research indicates that such value depends on cross-organizational data access and the ability to act on insights (Zamani et al., 2023). Governance agreements, data standards, and partner trust are therefore part of the technical architecture.

In banking, retail, e-commerce, and professional services, the challenge is balancing personalization and automation with privacy, trust, and human accountability. BDA and ML can improve fraud detection, credit-risk signals, customer segmentation, demand forecasting, and next-best-action decisions. AI can simplify communications and augment analytical work, but opaque or poorly monitored models may create reputational exposure. A responsible innovation portfolio should separate low-risk productivity tools from higher-impact decision systems, with proportionate validation and oversight. This portfolio approach is consistent with wider AI-management literature that treats governance as a design choice changing both value and risk (Bawack et al., 2022; Borges et al., 2021; Haefner et al., 2021). For SMEs, the most workable pathway may be modular rather than platform-heavy. Cloud analytics, managed ML services, standardized enterprise applications, and industry-specific AI tools can reduce fixed costs, but firms still require basic data hygiene and managerial clarity. A small company with consistent customer, inventory, and financial records can often gain more from one well-integrated forecasting or customer-retention use case than from a broad AI transformation program. Saudi ecosystem initiatives are able to support this segment using shared infrastructure, targeted training, sandboxes, and procurement pathways that reduce experimentation cost while protecting data protection.

Table 2. Saudi smart business and industrial innovation matrix.

Sector	Priority data	AI/ML applications	Value outcome	Critical capability
Manufacturing	Machine, quality, MES/ERP	Predictive maintenance, vision, process optimization	Uptime, yield, quality	OT/IT integration + engineering validation
Energy / process	Sensors, maintenance, process, emissions	Anomaly detection, forecasting, optimization	Reliability, efficiency, safety	High-integrity data + model assurance
Logistics	Fleet, warehouse, port, demand, supplier	ETA prediction, routing, disruption sensing	Resilience, service, inventory	Partner data standards + rapid replanning
Retail / e-commerce	Transactions, CRM, digital behavior	Personalization, churn, demand, service AI	Revenue, loyalty, speed	Consent, experimentation, customer analytics
Finance	Transactions, risk, customer, market	Fraud, risk signals, next-best action	Trust, productivity, risk control	Explainability + model governance
SMEs / services	Core ERP/CRM and operational records	Forecasting, service automation, copilots	Scalable growth, lower cost	Data hygiene + modular cloud adoption

VII. DISCUSSION: THE CAPABILITY CONVERSION GAP

The synthesis suggests a capability conversion gap between digital investment and innovation performance. This gap appears when an organization owns data platforms or AI tools but lacks the routines required to convert analytical signals into action. Four breaks are common: data are inaccessible or unreliable; models solve technically interesting but economically weak problems; decision rights and workflows are not redesigned; or learning is not captured after implementation. The gap explains why technology spending can exist alongside limited productivity gains and why organizational capabilities repeatedly mediate performance relationships in empirical studies (Mikalef et al., 2020; Wamba-Taguimdje et al., 2020; Fosso Wamba, 2022).

Figure 2 expresses the alternative as a flywheel. Data readiness enables ML intelligence; ML intelligence supports AI orchestration; orchestration becomes useful when it strengthens business agility; agility produces innovation and environmental sustainability outcomes; and measured outcomes generate new data and organizational learning. The cycle accelerates as firms standardize interfaces, governance, model operations, and experimentation routines. It slows when each project builds separate data pipelines, duplicates controls, or does not capture feedback. Saudi firms can therefore create advantage by industrializing the innovation process itself, not simply by acquiring more state-of-the-art algorithms.

The findings also challenge an overly deterministic reading of Vision 2030 digitalization. National infrastructure and policy can expand opportunity, but organizational heterogeneity remains substantial. Large industrial firms may have deep engineering data but slow legacy integration; digital-native businesses may move quickly but lack proprietary historical data; SMEs may face financing and skills constraints; public organizations may encounter attention and governance complexities (Alshahrani et al., 2022; Tripathi and Singh, 2024). Research and practice should therefore avoid a single maturity template and instead evaluate the bottleneck that prevents each organization from converting data into action.

Implementation sequencing is therefore a research and management issue in its own right. Firms often attempt AI before resolving data ownership, process integration, and measurement problems, producing prototypes that remain fragile in production. A stronger sequence defines the decision first, verifies data provenance, establishes a baseline, and increases model sophistication only after readiness is demonstrated.

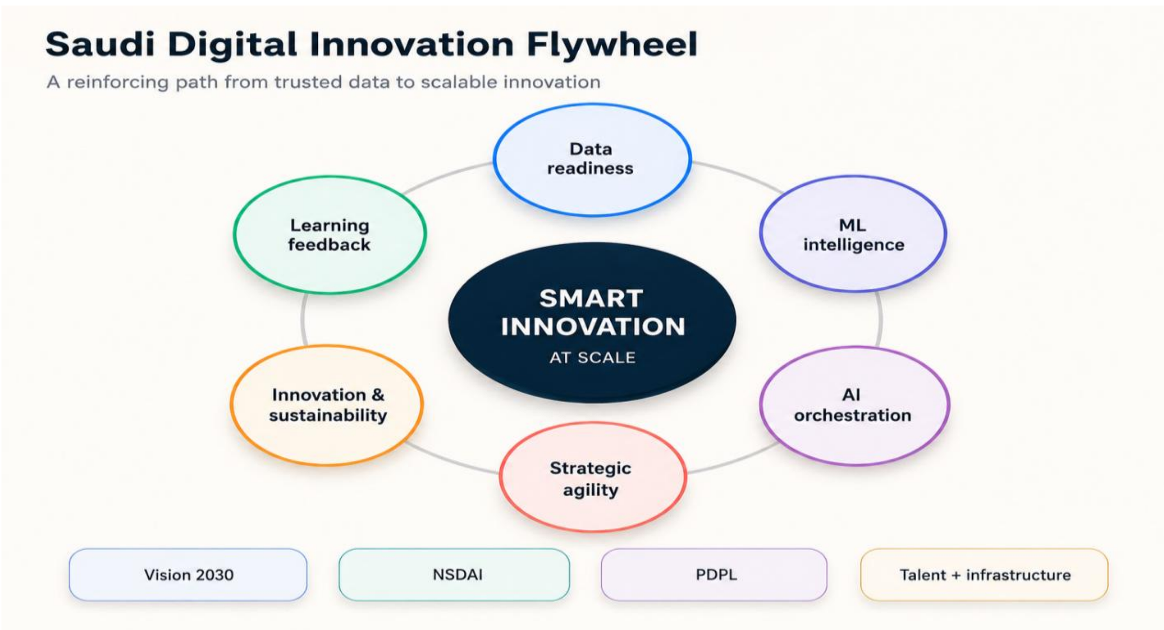

Figure 2. Saudi digital innovation flywheel: a reinforcing path from trusted data to scalable innovation.

VIII. MANAGERIAL AND POLICY IMPLICATIONS

Managers should begin with decision portfolios rather than technology portfolios. Each proposed use case should specify the decision to be improved, current decision latency, available data, responsible owner, economic or public-value metric, model risk, and integration pathway. This discipline prevents teams from starting with a fashionable algorithm and searching later for a problem. It also creates comparability across initiatives, allowing investment committees to balance quick wins, foundational data work, and planned options. Business cases should include the cost of data preparation, integration, monitoring, change management, and governance, not only model development.

Second, organizations should treat data products and ML models as managed operational assets. Data products need owners, quality thresholds, lineage, access policies, and service expectations. Models need documented training data, validation, drift monitoring, retraining triggers, human override, and retirement criteria. These practices increase reuse and reduce duplicated work. They also make responsible scale possible under Saudi privacy requirements and industry-specific controls. The objective is not bureaucracy; it is to turn experimentation into dependable infrastructure that business and industrial teams can trust.

Policy makers and ecosystem actors can support adoption by strengthening interoperable standards, trusted data-sharing mechanisms, sector sandboxes,

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1722404

applied research partnerships, and SME access to expertise. Regulation should remain risk-proportionate and clear enough to stimulate responsible experimentation. The PDPL creates an essential baseline for personal-data governance (SDAIA, 2023); complementary sector guidance may assist firms understand acceptable model use, audit expectations, and cross-border or cloud considerations. Public procurement can additionally encourage local innovation when evaluation criteria reward verifiable outcomes, interoperability, knowledge transfer, and lifecycle governance instead of isolated demonstrations.

IX. FUTURE RESEARCH AGENDA

Subsequent research should move beyond cross-sectional perceptions of AI adoption toward longitudinal evidence on capability accumulation. Studies could track how data quality, model deployment, decision latency, workforce routines, and innovation metrics evolve over several years. This would clarify whether organizational flexibility is a stable mediator, an outcome of repeated digital learning, or both. Sector comparisons are also needed because value mechanisms diverge between asset-intensive plants, financial services, logistics networks, public organizations, and digitally native SMEs. Saudi-specific longitudinal datasets would be especially valuable for distinguishing national ecosystem effects from firm-level managerial effects.
A second agenda concerns integration architecture. Studies frequently measure BDA or AI capability as a broad construct, while practitioners build modular stacks. Future studies should examine complementarities among data engineering maturity, feature reuse, ML operations, generative AI, edge intelligence, digital twins, and workflow automation. A key question is whether performance exhibits threshold effects: for example, whether AI orchestration adds little value until data lineage, model monitoring, and process integration reach a minimum maturity. Such work could produce more effective guidance than generic adoption scales.

Third, responsible AI should be studied as a potential innovation capability rather than only a constraint. Strong governance may increase trust, shorten approval cycles, improve data reuse, and make high-impact applications easier to scale. Research could test how privacy-by-design, explainability, cybersecurity, auditability, and human monitoring interact with speed of experimentation. This question is highly relevant in Saudi Arabia as data-intensive sectors expand under a stronger government authority environment. Comparative studies across regulated and less-regulated sectors could reveal when governance accelerates rather than slows innovation.
Finally, research should measure innovation more precisely. Broad self-reported performance scales may obscure whether technology produces incremental process improvement, radical product innovation, new business models, sustainability gains, or endurance. Future studies should combine financial and operational indicators with innovation outcomes such as time-to-market, defect reduction, avoided downtime, service personalization, patents, new-product revenue, carbon intensity, and recovery time after disruption. Linking these outcomes to specific data and model designs would make causal claims more credible and help Saudi organizations benchmark the return on digital capability development.

X. CONCLUSION

BDA, ML, and AI should be understood as an integrated innovation system rather than three independent technology trends. BDA creates a governed information foundation; ML converts data into predictive and adaptive intelligence; AI embeds that intelligence into decisions, coordination, and automation. The reviewed evidence shows that this technical chain creates sustainable value only when combined with strategic responsiveness, domain knowledge, data culture, leadership, workflow redesign, and responsible governance. This conclusion extends the Saudi manufacturing logic of Alghamdi and Agag (2023) into a wider business and industrial architecture.

Saudi Arabia has strong enabling conditions for this integration through national strategy, digital infrastructure, industrial transformation, investment, and expanding data and AI capabilities. Yet opportunity should not be confused with automatic value. Firms must close the capability conversion gap by selecting economically meaningful decisions, building reusable data foundations, operationalizing models, developing human expertise, and measuring outcomes through feedback loops. The proposed innovation stack and flywheel provide a practical way to connect these actions. For researchers, the next step is to test these mechanisms longitudinally and across sectors; for managers, the priority is to turn data and algorithms into disciplined organizational learning at scale.

REFERENCES

[1] Alghamdi, O.A. and Agag, G. (2023), "Boosting Innovation Performance through Big Data Analytics Powered by Artificial Intelligence Use: An Empirical Exploration of the Role of Strategic Agility and Market Turbulence", Sustainability, Vol. 15, 14296. https://doi.org/10.3390/su151914296

[2] Alyahya, M., Aliedan, M., Agag, G. and Abdelmoety, Z.H. (2023), "Understanding the Relationship between Big Data Analytics Capabilities and Sustainable Performance: The Role of Strategic Agility and Firm Creativity", Sustainability, Vol. 15 No. 9, 7623. https://doi.org/10.3390/su15097623

[3] Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P.A. (2020), "Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities", Information & Management, Vol. 57 No. 2, 103169. https://doi.org/10.1016/j.im.2019.05.004

[4] Yasmin, M., Tatoglu, E., Kilic, H.S., Zaim, S. and Delen, D. (2020), "Big data analytics capabilities and firm performance: An integrated MCDM approach", Journal of Business Research, Vol. 114, pp. 1-15. https://doi.org/10.1016/j.jbusres.2020.03.028

[5] Ghasemaghaei, M. and Calic, G. (2020), "Assessing the impact of big data on firm innovation performance: Big data is not always better data", Journal of Business Research, Vol. 108, pp. 147-162. https://doi.org/10.1016/j.jbusres.2019.09.062

[6] Mariani, M.M. and Fosso Wamba, S. (2020), "Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies", Journal of Business Research, Vol. 121, pp. 338-352. https://doi.org/10.1016/j.jbusres.2020.09.012

[7] Brinch, M., Gunasekaran, A. and Fosso Wamba, S. (2021), "Firm-level capabilities towards big data value creation", Journal of Business Research, Vol. 131, pp. 539-548. https://doi.org/10.1016/j.jbusres.2020.07.036

[8] Oesterreich, T.D., Anton, E., Teuteberg, F. and Dwivedi, Y.K. (2022), "The role of the social and technical factors in creating business value from big data analytics: A meta-analysis", Journal of Business Research, Vol. 153, pp. 128-149. https://doi.org/10.1016/j.jbusres.2022.08.028

[9] Olabode, O.E., Boso, N., Hultman, M. and Leonidou, C.N. (2022), "Big data analytics capability and market performance: The roles of disruptive business models and competitive intensity", Journal of Business Research, Vol. 139, pp. 1218-1230. https://doi.org/10.1016/j.jbusres.2021.10.042

[10] Hossain, M.A., Agnihotri, R., Rushan, M.R.I., Rahman, M.S. and Sumi, S.F. (2022), "Marketing analytics capability, artificial intelligence adoption, and firms' competitive advantage: Evidence from the manufacturing industry", Industrial Marketing Management, Vol. 106, pp. 240-255. https://doi.org/10.1016/j.indmarman.2022.08.017

[11] Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance", Information & Management, Vol. 58 No. 3, 103434. https://doi.org/10.1016/j.im.2021.103434

[12] Wamba-Taguimdje, S.L., Fosso Wamba, S., Kala Kamdjoug, J.R. and Wanko, C.E.T. (2020), "Influence of artificial intelligence (AI) on firm performance: The business value

of AI-based transformation projects", Business Process Management Journal, Vol. 26 No. 7, pp. 1893-1924. https://doi.org/10.1108/BPMJ-10-2019-0411

[13] Raisch, S. and Krakowski, S. (2021), "Artificial Intelligence and Management: The Automation-Augmentation Paradox", Academy of Management Review, Vol. 46 No. 1, pp. 192-210. https://doi.org/10.5465/amr.2018.0072

[14] Verhoef, P.C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J.Q., Fabian, N. and Haenlein, M. (2021), "Digital transformation: A multidisciplinary reflection and research agenda", Journal of Business Research, Vol. 122, pp. 889-901. https://doi.org/10.1016/j.jbusres.2019.09.022

[15] Cioffi, R., Travaglioni, M., Piscitelli, G., Petrillo, A. and De Felice, F. (2020), "Artificial Intelligence and Machine Learning Applications in Smart Production: Progress, Trends, and Directions", Sustainability, Vol. 12 No. 2, 492. https://doi.org/10.3390/su12020492

[16] Escobar, C.A., McGovern, M.E. and Morales-Menendez, R. (2021), "Quality 4.0: a review of big data challenges in manufacturing", Journal of Intelligent Manufacturing, Vol. 32, pp. 2319-2334. https://doi.org/10.1007/s10845-021-01765-4

[17] Jagatheesaperumal, S.K., Rahouti, M., Ahmad, K., Al-Fuqaha, A. and Guizani, M. (2022), "The Duo of Artificial Intelligence and Big Data for Industry 4.0: Applications, Techniques, Challenges, and Future Research Directions", IEEE Internet of Things Journal, Vol. 9 No. 15, pp. 12861-12885. https://doi.org/10.1109/JIOT.2021.3139827

[18] Zamani, E.D., Smyth, C., Gupta, S. and Dennehy, D. (2023), "Artificial intelligence and big data analytics for supply chain resilience: a systematic literature review", Annals of Operations Research, Vol. 327 No. 2, pp. 605-632. https://doi.org/10.1007/s10479-022-04983-y

[19] Qureshi, K.M., Mewada, B.G., Kaur, S., Khan, A., Al-Qahtani, M.M. and Qureshi, M.R.N.M. (2024), "Investigating Industry 4.0 technologies in Logistics 4.0 usage towards sustainable manufacturing supply chain", Heliyon, Vol. 10 No. 10, e30661. https://doi.org/10.1016/j.heliyon.2024.e30661

[20] Alsaadi, N. (2022), "Modeling and Analysis of Industry 4.0 Adoption Challenges in the Manufacturing Industry", Processes, Vol. 10 No. 10, 2150. https://doi.org/10.3390/pr10102150

[21] Tripathi, A. and Singh, A. (2024), "SMEs Awareness and Preparation for Digital Transformation: Exploring Business Opportunities for Entrepreneurs in Saudi Arabia's Ha'il Region", Sustainability, Vol. 16 No. 9, 3831. https://doi.org/10.3390/su16093831

[22] Babina, T., Fedyk, A., He, A. and Hodson, J. (2024), "Artificial intelligence, firm growth, and product innovation", Journal of Financial Economics, Vol. 151, 103745. https://doi.org/10.1016/j.jfineco.2023.103745

[23] Fosso Wamba, S. (2022), "Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility", International Journal of Information Management, Vol. 67, 102544. https://doi.org/10.1016/j.ijinfomgt.2022.102544

[24] Bawack, R.E., Fosso Wamba, S., Carillo, K.D.A. and Akter, S. (2022), "Artificial intelligence in E-Commerce: a bibliometric study and literature review", Electronic Markets, Vol. 32, pp. 297-338. https://doi.org/10.1007/s12525-022-00537-z

[25] Borges, A.F.S., Laurindo, F.J.B., Spínola, M.M., Gonçalves, R.F. and Mattos, C.A. (2021), "The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions", International Journal of Information Management, Vol. 57, 102225. https://doi.org/10.1016/j.ijinfomgt.2020.102225

[26] Haefner, N., Wincent, J., Parida, V. and Gassmann, O. (2021), "Artificial intelligence and innovation management: A review,

framework, and research agenda", Technological Forecasting and Social Change, Vol. 162, 120392. https://doi.org/10.1016/j.techfore.2020.120392

[27] Alshahrani, A., Dennehy, D. and Mäntymäki, M. (2022), "An attention-based view of AI assimilation in public sector organizations: The case of Saudi Arabia", Government Information Quarterly, Vol. 39 No. 4, 101617. https://doi.org/10.1016/j.giq.2021.101617

[28] Saudi Data and Artificial Intelligence Authority (SDAIA) (2020), National Strategy for Data & AI, Riyadh, Saudi Arabia.

[29] Saudi Data and Artificial Intelligence Authority (SDAIA) (2023), Personal Data Protection Law (PDPL), as amended by Royal Decree No. M/148, Riyadh, Saudi Arabia.

[30] Saudi Data and Artificial Intelligence Authority (SDAIA) (2025), AI Ethics Principles, Regulatory Publication, Riyadh, Saudi Arabia.