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Enterprise AI Transformation Through Modern Data Platforms

Saurabh Mishra[1]
[1]*Pt Ravishankar Shukla University, Raipur, C.G., India.*
Emails: *saurabhkumar.mishra@gmail.com*[1]

Abstract

The shift towards enterprise AI transformation driven by modern data platforms has emerged as a has become a major research and practical challenge for organizations seeking to create value from AI not just relying on standalone algorithms, but on managed, scalable, and actionable data ecosystems. This review critically evaluates peer-reviewed journal literature published in the last decade (2015-2026) related to AI capability, big data analytics capability, data governance, machine learning operations, digital transformation, and organizational value creation. The literature surveyed shows that data platforms play a role in enterprise AI transformation, by providing integrated data access, scalable analytics capabilities, establishing data governance, managing the data model lifecycle, and connecting technical architecture and enterprise change. There is, however, some empirical evidence that is not equally consistent. While previous research clearly shows correlations between analytics capability and performance, the limited number of journal articles that focus on production AI systems, platform modularity, lineage, feature management, monitoring and cross-functional operating models as coupled transformation mechanisms suggests an opportunity for further exploration. Further longitudinal studies are needed at both architectural and organizational levels. Enterprise AI transformation using modern data platforms is more of a socio-technical capability development exercise than a mere technological migration.

Keywords: *AI capability; data governance; data platforms; digital transformation; MLOps; organizational performance.*

1. Introduction

Modern data platforms are at the core of enterprise AI transformation, which is about how to scale AI-enabled operations by uniting disparate data, analytical assets and model experimentation within a single organization. According to digital transformation research, digital transformation is a reconfiguration of value creation, the organization, and interaction mediated by technology rather than an event of the adoption of digital technology [1]. For this narrower topic, modern data platforms are important because enterprise AI demands accessible, governed, and computationally tractable data foundations in transactional systems, analytical stores, and metadata layers, in model pipelines, and in operational applications. AI is also a source of organizational problems, such as integration of knowledge, responsibility, redesign of work, and policy alignment, besides being an infrastructural issue, a point highlighted by the AI scholarship [2]. There is a current research state that is useful, but incomplete convergence of information systems, operations management, analytics capability research, data governance, and software engineering. The effects of organizational performance arising from bringing together data, talent, technology, and managerial coordination into a coherent capability bundle is identified through AI capability research [3]. Research on data governance also suggests that rights and responsibilities, standards and decision rules for data assets are essential to trustworthy AI [4]. Both streams converge on a fundamental thesis that modern data platforms only support enterprise transformation to AI when accompanied by architectural scalability with governance and coordination, and value-oriented management action. A major gap is the limited study of the complete enterprise platform stack as an integrated phenomenon. Big data analytics capability studies can be relied on for good evidence of strategic alignment, analytics resources and performance, but tend to obfuscate platform design decisions like data product ownership, real-time serving, metadata

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control, lineage, and feature reuse, as well as model monitoring. On the other hand, the literature on machine learning operations covers lifecycle architectures and assurance issues but provides relatively few examples of evidence of outcomes at a higher level of the enterprise. While digital transformation it can also leave more depth of organizational interpretation, it can also leave the material data platform underspecified. To this end, this review adopts a multidisciplinary and scholarly approach to the study of enterprise AI transformation via modern data platforms. The goal of this document is to provide interpretation of the peer-reviewed journal evidence regarding the role data platforms play in enabling the formation of AI capabilities, value creation, AI governance, operationalization, and organizational change. The review focuses on comparison between studies, not a general description of technologies. Special focus is paid to the reported studies that conceptualize the use of modern data platforms as technical infrastructure, organizational capacity, governance mechanism or transformation architecture.

2. Literature Review

The AI transformation in enterprises via modern data platforms literature can be grouped into three related clusters: analytics capability and performance, AI-specific value creation, and governance-lifecycle control. Early capability-oriented work confirmed that value of data is not just in the volume of data, but in bundles of technological, human, and intangible resources [5]. Empirical research following these initial studies related the big data analytics capability to firm performance using dynamic capabilities [6] and demonstrated that strategic alignment enhances the relationship between analytics capability and operational outcomes [7]. The evidence from systematic review further buttressed this perspective, using big data analytics capability as a multi-dimensional construct comprising infrastructure, management, data culture and talent [8]. A second cluster is a combination of platform-based analytics and innovation and strategic value. Results show that the big data analytics capabilities have both direct and indirect impacts on innovation, mediated by dynamic capabilities, which means that the impact of big data analytics on enterprise AI transformation is related to the ability to sense, learn, and recombine tasks instead of automating them. Another approach comes from strategic value research, which states that integration of decisions, organisational redesign and appropriation mechanisms are needed for analytics value creation [10]. The results suggest a deterministic view of contemporary data platforms is incorrect. While the modernization of platforms seems to be the prerequisite for scale with AI, it must be accompanied by new decision processes, accountability mechanisms, and managerial routines that transform the analytical outputs into altered enterprise actions. A third group focuses on governance, value of AI and lifecycle assurance. Research on data governance connects trustworthy AI to stewardship, responsibility, quality, interoperability, and institutionalized decision rights [11]. AI business value reviews uncovered consistent issues that prevent AI investments from becoming measurable benefits for the organization [12]. The automation–augmentation paradox is emphasized by management theory, suggesting a balance between substitution and complementation with human judgment in the AI transformation process [13]. There are several points from the empirical and conceptual research on AI transformation leadership that can be highlighted as essential for the successful implementation of AI in the enterprise: AI transformation leadership requires disciplined prioritization and operational embedding, as well as organizational learning, instead of unrealistic expectations [14]. In addition, MLOps and assurance studies extend the view with a production focus, highlighting four key components of production AI platforms: deployment and monitoring, reproducibility, lifecycle governance, and risk controls [15, 16] shown in Table 1.

Table 1 Summary of key findings

Ref	Focus	Key Findings
[5]	Big data analytics capability construct	Analytics value arises from data, technology, talent, and intangible organizational resources rather than platform assets alone.

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[6]	Big data analytics and firm performance	Dynamic capabilities mediate the relationship between analytics capability and performance improvement.
[7]	Analytics capability and strategic alignment	Alignment between analytics capability and business strategy improves performance effects in operational contexts.
[8]	Systematic review of analytics capabilities	The literature treats analytics capability as a multi-layer capability involving infrastructure, people, management, and culture.
[9]	Analytics capability and innovation	Analytics capability supports innovation through dynamic capabilities and environmental responsiveness.
[10]	Strategic value from analytics	Analytics value depends on appropriation, organizational integration, and decision-process transformation.
[11]	Data governance for trustworthy AI	Trustworthy AI requires data ownership, stewardship, quality controls, and governance accountability.
[12]	AI and business value literature	AI value creation is limited by weak operational embedding, poor measurement, and fragmented organizational adoption.
[13]	Automation–augmentation paradox	AI creates managerial tension between replacement logics and human–machine complementarity.
[14]	AI transformation leadership	Realistic AI transformation requires prioritization, iterative learning, and operational integration.
[15]	Machine learning operations architecture	MLOps formalizes pipelines, deployment, monitoring, versioning, and feedback loops for production AI.
[16]	Assurance of machine learning lifecycle	AI assurance requires controls across data, model development, deployment, monitoring, and maintenance.

As can be seen in Table 1, there is more empirical evidence for analytics capability and performance, while direct evidence from journals on elements of modern AI platforms is less substantive. The reviewed studies all confirm that enterprise AI transformation is about more than just technology modernization, they're just they differ in emphasis. In the context of capability studies, the resources and alignment are highlighted; in the context of governance studies, the responsibility and control are highlighted; in the context of MLOps studies, the operational reliability is highlighted. The primary constraint is fragmentation; that is, studies seldom consider platform architecture, platform governance, platform lifecycle practices, and enterprise performance in an empirical design together.

3. Methodology

The methods used in the literature reflect the fragmented nature of enterprise AI transition on modern data platforms. Survey, measurement models, structural equation modelling and resource-based or dynamic-capability logic are commonly deployed in capability studies. This design can be applied to the generalisation of relationships between analytics capability and performance, as evidenced in the research on big data analytics capability [3], AI capability [5] and the innovation [6] [9]. Its strength is constructing clarity. Its drawback is architectural abstraction; things like data lineage, feature stores, semantic layers, Lakehouse governance, and real-time serving are typically not considered as concrete design features but rather as technology resources that exist behind the scenes. Review and conceptual

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studies use more encompassing interpretations. Strategic renewal, organizational restructuring, and value creation logics are the focal points of digital transformation reviews [17] and dynamic-capability research sees transformation as a process of iterative sensing, seizing, and reconfiguring [18]. This method allows researchers to link data platforms to enterprise change but can lead to reducing technical specificity. Conceptual specificity around automation and augmentation is added by the AI management studies [13] and control-oriented models for accountability, reproducibility, and lifecycle assurance are introduced by the data governance and MLOps studies [11], [15] and [16]. The methodological dilemma is obvious: enterprise-level theories reflect transformation; MLOps architectures reflect technical controls; and the former can be more about strategic transformation than the latter shown in Table 2.

Table 2 Method comparison

Ref	Method	Strengths	Limitations
[3]	Survey-based construct development and empirical testing	Connects AI capability with creativity and performance outcomes.	Treats platform architecture as part of a broad capability bundle.
[5]	Conceptual construct development	Clarifies tangible, human, and intangible analytics resources.	Provides limited direct evidence on modern platform implementation.
[6]	Empirical dynamic-capability model	Links analytics capability to firm performance through capability mediation.	Does not isolate data platform design variables.
[11]	Structured conceptual governance analysis	Specifies stewardship, accountability, and data control requirements for trustworthy AI.	Focuses more on governance logic than transformation outcomes.
[15]	Architecture-oriented MLOps review	Identifies deployment, monitoring, versioning, and pipeline components.	Limited direct testing of enterprise performance effects.
[16]	Lifecycle assurance review	Connects data, model, deployment, and monitoring controls.	Strong risk framing, weaker organizational change measurement.
[17]	Multidisciplinary review	Explains transformation as value creation and organizational reconfiguration.	Data platform mechanisms remain under-specified.
[18]	Longitudinal qualitative dynamic-capability analysis	Shows transformation as ongoing strategic renewal.	AI-specific data platform components are not central variables.

In Figure 1, a framework is provided to connect the modern data platform foundations to enterprise AI transformation outcomes, via governance and lifecycle control. It's important because the literature reviewed suggests that the value of AI comes from layers of capabilities that are connected to each other, not from singular model development efforts. The figure illustrates various stages of enterprise AI transformation, ranging from Data Platform Governance to AI Lifecycle Management, AI Decision Integration and AI Transformation Outcomes. The framework is based on the reviewed journal articles and the author's conceptual interpretation of AI capability, big data analytics capability, data governance, MLOps, assurance, and dynamic capabilities [3, 5, 11, 15, 16, 18].

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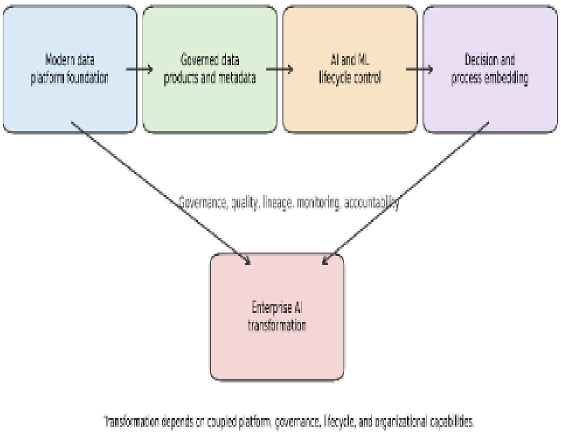

Figure 1 Conceptual framework for enterprise AI transformation through modern data platforms

4. Discussion

The reviewed studies indicate that enterprise AI transformation facilitated by modern data platforms is most easily understood in terms of capability accumulation, rather than the direct conversion of technology to performance. Empirical studies have consistently uncovered positive associations between analytics capability and firm-level or process-level performance, with the direct causal mechanism between the two being indirect. Big data analytics resources are valuable only when coupled with dynamic capabilities [6] and when aligned to strategy [7] and when transformed into innovation routines [9]. This is significant because the justification for investing in this kind of platform is frequently based on promises of instant automation, productivity, or prediction benefits. Instead, the literature indicates value is realised through the reconfiguration of the organization, access to data, managerial interest, analytical capability and embedding of decision-making processes. Platform modernization is thus an enabling condition for which the value is contingent on complementary resources. The best comparative result in the literature is for platform-based analytics with strategic and operational alignment. Research on analytics capability shows that infrastructure is needed but not sufficient; intangible resources, data-driven culture, management support, and analytical talent have been found to repeatedly impact results [5, 8]. This finding challenges common enterprise narratives that treat cloud migration, data lake implementation, or tool consolidation as transformation in themselves. While a modern platform can create less friction, establish more uniformity in pipelines, and enhance compute flexibility, capability studies suggest that, alone, they do not drive AI transformation. The platform without governance and process integration is just a repository instead of an operating layer of enterprise AI. In governance studies, it is found that the value of the data platform is tied with accountability. Data stewardship, data quality management, decision rights and institutionalized control over data assets are necessary for trustworthy AI [11]. Enterprise AI transformation should not be measured only by model accuracy, infrastructure scale, or deployment frequency. The governance of platform determines the extent to which the system can be audited, compliant, reused, and accepted by organizational stakeholders. The same point highlights one of the shortcomings of the numerous analytics-performance studies that have been done: They have included items related to governance, but have not differentiated between formal governance mechanisms, metadata practices, the enforcement of policies, and runtime monitoring. This results in more evidence for governance importance than for which governance designs lead to better outcomes for AI transformation. Another contradiction highlighted by the value literature is that of the AI modeler and the AI user. Though frequently touted as engines of automation, AI systems often create an automation–augmentation paradox of automation-augmentation in management research [13]. Therefore, enterprise AI transformation is a design decision, between replacing human decision activity or augmenting expert judgment through the use of modern data platforms. The availability of data within data platforms impacts this decision; how the model results are integrated into the workflow and how the feedback is collected for model improvement. A platform capable of reusability, lineage, monitoring and feedback can help facilitate augmentation by making the output of the AI more transparent and revisable. A narrow deployment-speed platform can strengthen automation with little supervision. Therefore, the maturity of the platform should be evaluated, not only in terms of technical scale, but

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also its capability to support responsible human–AI partnership.Technical differences between platform approaches are most clearly evidenced by MLOps and assurance studies, both of which focus on production. The architectures of MLOps include versioning, pipeline orchestration, continuous training, deployment, monitoring, and feedback controls [15]. Assurance research extends the lifecycle to include concerns about risk, validation and maintenance throughout data, model and operational phases [16]. These studies change the focus from analytics capability as possession to AI capability as continuous operation. This is important as there's a need for consistent model behaviour once deployed to support enterprise AI transformation. When input distributions, business processes, or feedback loops change, the model trained on the central data may become inaccurate. Monitoring, data lineage, data reproducibility, and incident response are not only required for data storage and computation in modern data platforms but are essential.

Table 3 **Results comparison**

Ref	System / Context	Metric / Basis of Comparison	Outcome
[6]	Firm-level big data analytics capability	Dynamic capability mediation and firm performance relationship	Analytics capability improves performance through dynamic capability development.
[7]	Big data analytics capability in strategic alignment context	Alignment between analytics capability and business strategy	Stronger alignment is associated with improved firm performance.
[9]	Analytics capability and innovation context	Innovation outcomes mediated by dynamic capabilities	Analytics capability supports innovation when adaptive capabilities are present.
[10]	Strategic business value from analytics	Value creation and appropriation framework	Analytics value depends on organizational integration and decision transformation.
[11]	Trustworthy AI data governance context	Governance roles, accountability, and data control mechanisms	Governance is positioned as a prerequisite for reliable and accountable AI.
[12]	AI business value literature	Review-based evidence on AI value mechanisms	Value realization is constrained by fragmented adoption and weak operational embedding.
[15]	Production ML platform architecture	Deployment, monitoring, versioning, and pipeline control	MLOps converts models from experiments into maintainable production assets.
[16]	ML lifecycle assurance context	Data, model, deployment, and monitoring assurance requirements	Assurance must span the full lifecycle rather than final model validation alone.

Table 3 indicates that empirical results focus on capability-performance relationships while platform studies of production give technical prescription (beyond performance) rather than performance estimates. This imbalance exists because a field can assert that capabilities in analytics and AI are important but provide limited and less reliable estimates of how particular platform capabilities impact cost, risk, speed, reuse, model reliability, or strategic agility. Figure 2 uses the evidence reviewed to create an article-level emphasis profile for each of the major capability dimensions. It's important

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because it indicates that enterprise AI transformation on the basis of modern data platforms is being investigated more from an analytics capability and governance perspective than from direct evidence of the production AI platform. Each dimension of enterprise AI transformation is quantified with the number of reviewed journal articles that significantly focus on it in relation to modern data platforms. he reviewed articles were coded by the author; counts indicate emphasis rather than effect size shown in Figure 2.

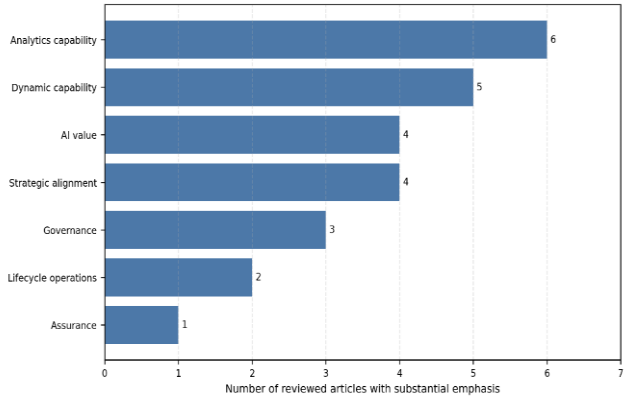

Figure 2 Evidence emphasis across reviewed journal studies

An observational bias is also present in the evidence distribution. The constructs and survey instruments for analytics capability and dynamic capability are well developed in the field of information systems studies. Compared to the other categories, lifecycle operations and assurance is less frequent, not because it is an inconsequential topic, but because journals focusing on production ML platforms are newer and tend to be more technical. This distribution had left enterprise AI transformation scholarship on an incomplete evidence base. The organizational side is more empirical and the platform-operations side more architectural and normative. The literature reviewed is presented as a comprehensive literature clusters in Figure 3. It's relevant because it puts different studies into context, as to why they may have different results regarding AI transformation. The figure depicts, in a qualitative way, the intensity of governance, the level of operationalisation and the level of value-link maturity in relation to main literature clusters. Reviewed journal articles with interpretation of the following topics: Analytics capability, governance, MLOps, assurance, AI management, and digital transformation [5] – [18] shown in Figure 3.

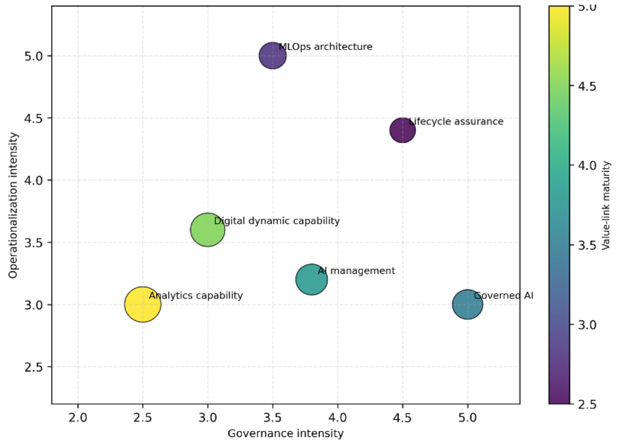

Figure 3 Comparative map of platform-transformation orientations in the reviewed literature

The comparative map shows that there are no fully complete literature clusters on enterprise AI transformation from modern data platforms. Established analytics capability work includes the highest value maturity and the lowest production detail. While MLOps architecture provides a high level of insight on how to operate, the evidence of enterprise performance is less. Governance work provides greater accountability logic, but less empirical evidence of outcomes of transformation. Digital transformation studies are strategic and generally address platforms indirectly. The fragmentation accounts for the complementary but incomplete results reported. The major implication is methodological. For future research, cross-sectional surveys or technical architecture descriptions are not sufficient. To effectively modernize data platforms and enable enterprise AI transformation, designs need to be multi-level, weaving together platform capabilities, governance frameworks, lifecycle management, workforce adaptation and enterprise outcomes. Lineage availability, data product reuse, pipeline automation, model monitoring coverage, decision latency, incident recovery, and governance enforcement are examples of platform variables. Measures of outcomes should shift from perceived

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performance to cost of AI delivery, model degradation rate, time from experiment to production, regulatory auditability and realized process change. These measures would enable further benchmarking of investments in the modern data platform with real enterprise AI transformation.

5. Future Directions

Future studies for enterprise AI transformation using modern data platforms should tackle the capability evidence-to-platform-specific measure gap. Under alignment and dynamic capability conditions, existing research indicates that the platform attributes that lead to improved performance are those that provide analytics and AI capabilities [6, 7, 9] but the literature does not detail which platform attributes do so. Research and analysis should therefore be based on measurable constructs of platform maturity – for example, metadata completeness; lineage depth; feature re-use; automated data quality checks; deployment frequency; monitoring coverage; model rollback capability, and so forth. Longitudinal research is a second priority. Digital transformation and dynamic-capability studies view transformation as strategic renewal instead of as a one-time implementation [17], [18]. Research should examine enterprise AI platforms across pilot, scaling, production, and post-deployment learning stages. These designs would help determine if data platform modernization lowers the cost of delivering AI, enhances decision-making model reliability and alters decision-making processes over time or simply correlate capability maturity and perceptions of the model performance. The third priority is research on governance-sensitive MLOps. Literature on governance refers to stewardship and accountability for trustworthy AI [11] and MLOps and assurance studies refer to lifecycle controls [15], [16]. Future studies should examine how governance rules are implemented as code in platform pipelines, automated lineage capture, access control, validation gates, and monitoring escalation. Lastly, interdisciplinary efforts must involve information systems, software engineering, organizational design, operations management, and responsible AI research. The process of enterprise AI transformation is not just about cloud computing, data science skills, or formulating a strategy. The central research question is: How can platform architectures, AI lifecycle controls, and organizational decision routines be co-evolved to establish a lasting transformation capability.

Conclusion

Enterprise AI transformation is a socio-technical capability building process where the ability to access, control, govern and analyse data collectively influence value realization; where lifecycle control is also a key capability; and where organizational alignment is also key. The literature reviewed supports the idea that analytics and AI capabilities can help organizations achieve performance, innovation and strategic renewal, provided they are supported by the complementary managerial, human and governance resources. For this reason, modern data platforms are crucial as they can integrate and coordinate data products, metadata, model pipelines, monitoring and decision integration across the enterprise. The main scholarly significance of this review lies in linking previously divided research streams. Value creation, governance, production control, and organizational renewal are explained by analytics capability studies, governance studies, MLOps studies and digital transformation studies, respectively. There are still significant gaps as few studies have been able to measure platform architecture, AI lifecycle maturity, governance enforcement and enterprise outcomes together. The current evidence is therefore more robust on the relationships between broad capabilities and organizational performance than on the specific mechanisms of the platforms that enable scalable, trustworthy, and persistent AI transformation. More precise constructs of platforms, longitudinal designs and more integrated measures of platform technical reliability, organizational adoption and strategic value are needed to make future progress. The field will progress best if we consider modern data platforms as an operating architecture for enterprise AI instead of a neutral infrastructure.

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