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From Model-Centric to Data-Centric AI Governance: Strengthening Accountability, Transparency, and Equity

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Abstract: The emergence of data-centric governance paradigms in artificial intelligence (AI) reflects a paradigmatic shift away from traditional model-centric approaches toward frameworks that prioritize data quality, transparency, accountability, and compliance with socio-legal norms. This research article presents a comprehensive examination of data-centric governance models, with a particular focus on the integration of trustworthy AI principles into welfare management systems and other socio-technical domains. Drawing on interdisciplinary literature from computer science, policy studies, ethics, and data engineering, this work elaborates theoretical foundations, articulates methodological constructs, and critically evaluates the operational and governance challenges associated with data-centric AI. The article synthesizes insights from major scholarly contributions, including perspectives on anomaly detection in time series data, data augmentation strategies, quality profiling tools, and data traceability frameworks, to establish a cohesive narrative on how data-centric governance can reconcile innovation with ethical imperatives. Central to this discussion is the integration of frameworks that emphasize transparency, bias control, and policy compliance, as outlined by Uddandarao et al. (2026), within welfare management and beyond. The article also interrogates the broader implications of data-centric AI within contemporary socio-technical contexts, presents a critical discussion of empirical and theoretical debates, and proposes a forward-looking research agenda for advancing governance frameworks that align technological capabilities with societal expectations. Through an in-depth review, theoretical elaboration, and analytical interpretation of interdisciplinary research, this article contributes to both scholarly discourse and policy practice concerning trustworthy and equitable AI.

Keywords: Data-centric governance, trustworthy AI, transparency, bias control, welfare management, socio-technical systems, data ethics

Introduction

The rapid proliferation of artificial intelligence across diverse domains has transformed the landscape of socio-technical systems, heralding unprecedented opportunities for innovation while simultaneously exposing critical vulnerabilities in governance, accountability, and ethical practice. Historically, AI development has emphasized the refinement of algorithmic models—often at the expense of rigorous scrutiny of the data that underpins them. This model-centric paradigm, while facilitating early advances in machine learning performance, has generated significant challenges related to bias, opacity, and governance failures. Consequently, the research community has increasingly advocated for a data-centric approach to AI, wherein the quality, provenance, and governance of data are central to system reliability and ethical legitimacy (Jakubik et al., 2022; Motamedi et al., 2021; Miranda, 2021).

The theoretical underpinnings of data-centric AI draw from a long lineage of research in data management, information systems, and governance frameworks. Data quality has been recognized as a determinant of system performance and trustworthiness since the early development of database theory. As scholars such as Whang et al. (2023) have elucidated, the challenges inherent in collecting, curating, and validating data for machine learning extend beyond technical considerations to encompass socio-ethical dimensions that shape the outcomes of algorithmic decision-making. These dimensions implicate issues of fairness, accountability, and transparency, which are increasingly foregrounded in regulatory and governance discourses worldwide (Liang et al., 2022).

The present article is premised on the assertion that data-centric governance frameworks offer a robust pathway toward reconciling AI innovation with ethical imperatives and policy compliance. This assertion aligns with the arguments advanced by Uddandarao et al. (2026), who emphasize the role of trustworthy AI in strengthening transparency, bias control, and regulatory compliance within welfare management systems. Welfare management, as a sector, is particularly illustrative of the broader governance challenges in AI because it involves high-stakes decisions that affect vulnerable populations. The integration of data-centric governance in such contexts necessitates a critical exploration of both technical mechanisms and institutional frameworks that ensure AI systems are accountable, equitable, and aligned with public values.

This introduction lays the groundwork for a comprehensive exploration of data-centric governance by delineating the historical context, theoretical motivations, and scholarly debates that inform this emerging paradigm. The remainder of the article is organized as follows: the Methodology section explicates the conceptual and analytical approaches employed to synthesize interdisciplinary research; the Results section interprets key findings from the literature, emphasizing patterns, tensions, and unresolved questions; the Discussion section offers an extended theoretical interpretation, critically engaging with competing viewpoints and outlining directions for future inquiry; and the Conclusion synthesizes the core insights, articulating implications for both research and policy.

The shift toward data-centric governance must be situated within a broader historical evolution of AI research. The early decades of machine learning research, rooted in statistical pattern recognition and expert systems, privileged algorithmic accuracy and computational efficiency. As a result, data was often treated as a static input rather than a dynamic governance object subject to rigorous evaluation and refinement. This orientation began to shift as practitioners encountered the limitations of model-centric approaches, particularly in contexts where data heterogeneity, noise, and bias undermined system performance and legitimacy. Research on anomaly detection, such as that of Hegde (2022), highlighted the importance of robust data characterization for reliable AI outcomes. Similarly, tools such as Influenciæ (Picard et al., 2023) and Deepchecks (Chorev et al., 2022) emerged to trace the influence of individual data points and validate model behavior, respectively, underscoring the increasing recognition that data infrastructure must be engineered with the same rigor as algorithms.

The scholarly debate on data-centric AI encompasses several key themes. One central theme involves the reconfiguration of engineering practices to prioritize data at every stage of the development lifecycle (Polyzotis & Zaharia, 2021). This reconfiguration challenges conventional workflows that emphasize model optimization, advocating instead for iterative cycles of data curation, quality assessment, and augmentation. Another theme interrogates the ethical implications of data governance, particularly with respect to bias, fairness, and inclusion. Mehrabi et al. (2021) and Holstein et al. (2019) offer comprehensive surveys of fairness challenges in machine learning, revealing how unexamined data practices can perpetuate inequities. These works catalyze discussions on how data governance frameworks must integrate ethical frameworks to mitigate systemic biases and ensure equitable outcomes.

Despite growing scholarly interest, significant gaps remain in conceptualizing governance models that operationalize data-centric principles within institutional contexts. Few studies have systematically addressed how governance structures interact with legal frameworks, socio-cultural norms, and policy compliance mechanisms. This lacuna is particularly pronounced in welfare management systems, where data-centric governance intersects with public accountability, resource allocation, and social justice concerns. The work of Uddandarao et al. (2026) represents a pioneering effort to bridge this gap; however, their analysis also reveals the need for broader theoretical elaboration on governance mechanisms that can be generalized across sectors. This article seeks to address this gap by synthesizing interdisciplinary insights into a cohesive governance framework that foregrounds data quality, transparency, and trustworthiness as foundational pillars of ethical AI.

Methodology

The methodological foundation of this research is grounded in an interdisciplinary literature synthesis that integrates theoretical and empirical insights from computer science, data engineering, ethics, and policy studies. Recognizing the multifaceted nature of data-centric governance, this study adopts a qualitative meta-analytical approach that systematically synthesizes existing research, identifies conceptual patterns, and interprets disagreements and convergences in scholarly discourse. The analytical strategy was guided by the following principles: comprehensiveness, contextualization, and reflexivity.

The first phase of the methodology involved a comprehensive survey of literature on data-centric AI, trustworthy AI governance, and socio-technical systems. Sources were selected based on their relevance to core themes of data quality, transparency, bias mitigation, governance frameworks, and policy compliance. Key contributions included foundational works on data-centric AI methodologies (Jakubik et al., 2022; Motamedi et al., 2021), empirical studies on data quality and governance challenges (Whang et al., 2023; Aldoseri et al., 2023), and ethical analyses of bias and fairness in AI (Mehrabi et al., 2021; Holstein et al., 2019). The inclusion of Uddandarao et al. (2026) provided a focal anchor for discussions on trustworthy AI within welfare management contexts.

The second phase involved thematic coding and synthesis of the literature. Textual content from selected works was coded according to themes such as data governance principles, transparency mechanisms, bias control strategies, institutional frameworks, and policy implications. This thematic coding enabled the identification of cross-cutting patterns and tensions across disciplinary boundaries, facilitating an integrated conceptual framework. For example, the analysis of data profiling tools like ydata-profiling (Clemente et al., 2023) was contextualized within broader debates on data quality governance and ethical accountability.

A critical component of the methodology was the integration of theoretical lenses from science and technology studies (STS) to interpret how socio-technical values influence governance practices. STS frameworks emphasize that technological artifacts, including AI systems, are not neutral but are imbued with social, political, and ethical values. This perspective informed the analytical interpretation of governance models, particularly regarding how institutional norms, legal frameworks, and public accountability shape design and deployment practices.

Limitations of this methodological approach stem primarily from its reliance on published literature, which may reflect disciplinary biases and gaps in empirical evidence. For instance, while there is substantial research on technical aspects of data quality and model validation, fewer studies provide in-depth empirical evidence on governance implementations within public sector systems. Moreover, the rapidly evolving nature of AI research means that analyses may lag behind emerging practices in industry and policy arenas. Despite these limitations, the qualitative synthesis approach offers a robust foundation for conceptualizing comprehensive governance frameworks.

Results

The synthesis of interdisciplinary literature reveals several key findings that elucidate the contours of data-centric governance and its implications for trustworthy AI. First, there is broad consensus that data-centric paradigms shift the focus of AI development from algorithmic performance to data quality, governance, and ethical accountability. Jakubik et al. (2022) argue that the data-centric approach fundamentally reorients engineering workflows, emphasizing iterative cycles of data curation and validation. This shift

prioritizes mechanisms that ensure the integrity, completeness, and relevance of datasets, thereby reducing the risk of biased or unrepresentative inputs that can compromise system fairness and reliability. The literature underscores that this orientation is particularly critical in high-stakes domains such as welfare management, healthcare, and financial services, where data errors or biases can directly affect human wellbeing (Uddandarao et al., 2026; Liang et al., 2022; Hegde, 2022).

Second, the analysis highlights that transparency mechanisms are central to trustworthy AI governance. Transparency, in this context, refers not only to the visibility of model architectures and decision-making processes but also to the traceability of data provenance, transformations, and the rationale behind feature selection. Tools such as Influenciæ (Picard et al., 2023) and Deepchecks (Chorev et al., 2022) operationalize these transparency mechanisms by enabling practitioners to track the influence of individual data points on model outcomes. Such tools allow organizations to detect anomalies, biases, and inconsistencies, ensuring that governance extends beyond procedural compliance to substantive accountability. Holstein (2024) reinforces the importance of domain expertise in interpreting transparency outputs, emphasizing that technical solutions alone cannot guarantee equitable outcomes without human oversight.

Third, bias control emerges as a critical dimension of data-centric governance. Several studies demonstrate that unexamined data collection and preprocessing practices perpetuate systemic inequities (Mehrabi et al., 2021; Holstein et al., 2019). Data augmentation and rebalancing strategies, such as those described by Song et al. (2024) and Zhu et al. (2024), mitigate imbalance and noise in datasets, thereby enhancing model fairness. Moreover, the literature emphasizes that bias is multidimensional, encompassing representational, measurement, and algorithmic forms, and that effective governance requires a holistic approach integrating data, model, and institutional interventions. In welfare management systems, bias control is particularly salient, as it ensures that resource allocation and service provision are equitable and do not inadvertently marginalize vulnerable populations (Uddandarao et al., 2026).

Fourth, policy compliance and regulatory integration are increasingly recognized as essential components of governance frameworks. AI governance cannot be decoupled from legal and ethical norms, particularly in contexts involving public service delivery and sensitive personal data. Studies such as those by Aldoseri et al. (2023) and Kumar et al. (2024) underscore that organizations must operationalize compliance not only through technical safeguards but also via organizational processes that embed legal requirements into data management practices. The Federal Reserve's guidance on model risk management exemplifies the regulatory expectations for traceability, documentation, and risk assessment in AI-enabled decision-making (Federal Reserve, 2011). Uddandarao et al. (2026) further highlight how welfare management systems can integrate governance frameworks that align operational procedures with policy mandates, ensuring accountability while fostering public trust.

Fifth, the literature identifies several challenges and limitations in implementing data-centric governance. One recurring theme is the tension between data quantity and quality. While large datasets are necessary for robust model training, the curation and annotation of high-quality data require substantial resources and domain expertise (Motamedi et al., 2021; Polyzotis & Zaharia, 2021). Additionally, technical debt arising from inconsistent data pipelines and inadequate governance processes can compromise system reliability, as detailed by Sculley et al. (2015). The dynamic nature of social data, especially in public-sector applications, introduces the problem of concept drift, necessitating continuous monitoring and updating of datasets (Gama et al., 2014). Finally, the integration of governance practices into existing institutional structures often encounters resistance due to cultural, operational, and knowledge barriers, underscoring the importance of change management and stakeholder engagement (Parashar et al., 2023; Holstein, 2024).

Despite these challenges, the literature demonstrates that well-designed data-centric governance frameworks produce measurable benefits in system performance, trustworthiness, and compliance. Empirical studies of healthcare analytics, financial AI systems, and public welfare platforms indicate that improvements in data quality, transparency, and bias mitigation correlate with enhanced predictive accuracy, equitable outcomes, and stakeholder confidence (Bertucci et al., 2022; Liang et al., 2022; Majeed & Hwang, 2023). Moreover, governance models that integrate iterative feedback mechanisms, domain expertise, and rigorous documentation foster adaptive capacity, allowing AI systems to respond to evolving societal and regulatory demands (Luley et al., 2023; Holstein, 2024).

Discussion

The theoretical interpretation of the results indicates that data-centric governance is not merely a technical or procedural adjustment but a paradigmatic reorientation in the conceptualization of AI development and deployment. Historically, AI research has privileged model-centric approaches, emphasizing algorithmic sophistication and computational efficiency. This emphasis produced advances in predictive performance but also revealed systemic vulnerabilities associated with biased data, opaque decision-making, and poor traceability (Jakubik et al., 2022; Motamedi et al., 2021). The transition to data-centric governance challenges this paradigm by asserting that the integrity, transparency, and ethical quality of data are as critical—if not more so—than the model architecture itself (Ng, 2021; Miranda, 2021).

One major theoretical implication of this shift concerns the conceptualization of trustworthiness in AI. Trust is traditionally construed as a function of algorithmic accuracy and performance metrics; however, the data-centric perspective expands this understanding to include procedural legitimacy, data provenance, and societal alignment (Uddandarao et al., 2026; Liang et al., 2022). In welfare management systems, trust is not solely a technical consideration but a socio-political construct shaped by perceptions of fairness, accountability, and transparency.

Therefore, governance frameworks must integrate mechanisms that enable both technical validation and public scrutiny, ensuring that AI outputs are credible and socially acceptable.

The integration of transparency mechanisms offers practical and theoretical benefits. Tools such as Deepchecks and Influenciæ operationalize data tracing and model validation, enabling practitioners to detect anomalies and biases before deployment (Chorev et al., 2022; Picard et al., 2023). Theoretically, these tools illustrate the concept of "traceable AI," wherein each decision can be linked to specific data inputs, enhancing accountability and facilitating compliance audits. Such frameworks reconcile the dual imperatives of innovation and governance, providing a robust mechanism for managing risk while preserving the flexibility of AI systems.

Bias control is equally central to the discussion, with theoretical debates emphasizing the multidimensional nature of algorithmic inequities. As Mehrabi et al. (2021) note, bias manifests not only in data representation but also through interactions between algorithms and social systems. Effective governance must, therefore, extend beyond technical mitigation to encompass institutional, regulatory, and societal interventions. In practical terms, welfare management systems illustrate this integration: bias-mitigating data pipelines, continuous auditing, and stakeholder engagement converge to produce equitable outcomes, while policy alignment ensures that AI interventions respect social norms and legal requirements (Uddandarao et al., 2026).

The literature further highlights the complexity of policy compliance within data-centric governance frameworks. Regulatory and ethical considerations introduce constraints that affect system design, operational workflow, and resource allocation (Aldoseri et al., 2023; Kumar et al., 2024). For example, compliance with privacy regulations requires sophisticated data anonymization, provenance tracking, and access control mechanisms. These mechanisms, in turn, influence data selection, preprocessing, and feature engineering, illustrating the intertwined nature of governance, technical design, and regulatory adherence. The Federal Reserve's supervisory guidance provides a canonical example, emphasizing the necessity of comprehensive documentation, validation, and risk assessment in model deployment (Federal Reserve, 2011).

Despite the benefits, limitations of data-centric governance must be acknowledged. Data curation, annotation, and continuous monitoring are resource-intensive activities that may pose barriers for organizations with limited capacity. Concept drift, arising from dynamic social, economic, and environmental factors, necessitates continuous updating of datasets and governance policies (Gama et al., 2014). Furthermore, institutional resistance, knowledge gaps, and cultural inertia can undermine implementation, highlighting the need for effective change management strategies and education of stakeholders (Parashar et al., 2023). Addressing these limitations requires integrated frameworks that combine technical tools, governance policies, and organizational strategies.

Looking forward, future research must explore several avenues to advance data-centric governance theory and practice. First, there is a need for longitudinal studies examining the impact of governance interventions on AI system performance, fairness, and societal outcomes. Second, methodological innovation is required to integrate dynamic data quality assessment, bias detection, and compliance monitoring into real-time operational workflows. Third, interdisciplinary research must investigate how socio-cultural, institutional, and political factors influence governance efficacy, thereby situating AI systems within broader societal contexts. Finally, the development of standardized frameworks, metrics, and best practices for data-centric governance will facilitate knowledge transfer, comparability, and policy harmonization across sectors.

In conclusion, the discussion demonstrates that data-centric governance represents a transformative approach to AI that foregrounds data quality, transparency, bias control, and policy compliance. By centering these dimensions, organizations can design AI systems that are not only technically robust but also ethically accountable and socially legitimate. Welfare management systems provide a paradigmatic context for this exploration, illustrating how governance frameworks can reconcile technological innovation with societal imperatives (Uddandarao et al., 2026). The theoretical, practical, and policy insights derived from this analysis offer a foundation for advancing the field, guiding both scholarly inquiry and applied practice in trustworthy AI.

Conclusion

This article has provided a comprehensive exploration of data-centric governance frameworks in AI, emphasizing transparency, bias control, and policy compliance within socio-technical systems. The findings indicate that prioritizing data quality and governance over mere algorithmic performance yields systems that are technically robust, ethically accountable, and socially legitimate. Key insights include the critical role of transparency tools, multidimensional bias mitigation strategies, and the integration of regulatory and institutional requirements into data pipelines. Theoretical contributions highlight a re-conceptualization of trustworthiness as an emergent property of socio-technical interactions rather than a solely technical attribute. While challenges such as resource constraints, concept drift, and institutional resistance remain, the study outlines a forward-looking agenda for research, policy, and practice. Overall, data-centric governance represents a foundational shift in AI scholarship and application, providing a pathway toward equitable, transparent, and accountable technological systems.

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