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Algorithmic Risk Governance in Organizational Change: An Artificial Intelligence Framework for Predictive Decision Making in Enterprise Systems

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ABSTRACT

The accelerating digitization of enterprises has fundamentally transformed how organizational change is initiated, evaluated, approved, and governed. Change Advisory Boards, traditionally designed as expert-driven governance mechanisms for assessing technological and operational changes, now face unprecedented complexity, uncertainty, and interdependence driven by digital platforms, cloud infrastructures, cyber–physical systems, and globally distributed supply chains. In this environment, conventional qualitative and checklist-based change management practices are increasingly insufficient for anticipating cascading risks, financial exposure, and systemic failures. This article develops a comprehensive theoretical and analytical framework for Artificial Intelligence–driven predictive risk scoring in Change Advisory Board decision making, synthesizing insights from enterprise risk management, financial risk analytics, supply chain resilience, and machine learning research. Drawing on the emerging paradigm of algorithmic governance, the study situates AI-based CAB decision support as a critical extension of ISO 31000 risk management principles, COSO internal control frameworks, and enterprise IT governance models. Particular emphasis is placed on the predictive risk scoring approach articulated by Varanasi, which conceptualizes CAB decisions as probabilistic risk optimization problems that can be learned, updated, and refined through historical change data and continuous organizational feedback loops (Varanasi, 2025). The article advances a multidimensional interpretation of CAB risk that integrates technical, financial, operational, compliance, and reputational dimensions into a unified predictive architecture. Through extensive theoretical elaboration and comparative analysis with supply chain risk management, financial default prediction, and intelligent early warning systems, the study demonstrates how machine learning–driven risk intelligence enables a shift from reactive change governance toward anticipatory, data-informed, and resilience-oriented decision making. The findings suggest that AI-enhanced CABs not only improve approval accuracy and reduce failure rates but also create new forms of organizational learning, strategic foresight, and governance transparency. However, the article also critically examines ethical, epistemological, and institutional limitations associated with algorithmic risk scoring, including bias propagation, model opacity, and over-reliance on automated judgment. By situating CAB predictive analytics within broader debates on digital governance and enterprise resilience, this work contributes a foundational scholarly framework for understanding how AI reshapes the future of organizational change management in complex socio-technical systems.

INTRODUCTION

The governance of organizational change has long occupied a central position in both information systems management and enterprise risk theory. From the earliest days of mainframe computing to contemporary cloud-based infrastructures, organizations have relied on structured decision bodies to evaluate whether proposed changes should be approved, deferred, modified, or rejected. The Change Advisory Board, or CAB, emerged as a core institutional mechanism within information technology service management, particularly through the widespread diffusion of ITIL and related governance standards. Historically, CABs were designed to provide expert judgment over the risks and benefits of proposed changes, drawing on technical expertise, business priorities, and compliance requirements. However, the accelerating complexity of digital enterprises has gradually eroded the sufficiency of purely human-centered, qualitative, and experience-based change governance, a transformation that has been extensively documented in both enterprise governance literature and risk management research (De Haes and Van Grembergen, 2009; COSO, 2013).

In modern organizations, changes no longer occur in isolated technical silos. A single modification to a software platform may propagate across cloud services, financial reporting systems, customer interfaces, and supply chain coordination mechanisms, generating what Ivanov and colleagues have conceptualized as ripple effects in complex networks (Ivanov et al., 2019). These ripple effects are not merely technical phenomena; they are deeply entangled with financial exposure, regulatory compliance, and reputational risk, thereby transforming CAB decisions into high-stakes governance acts. In this context, traditional CAB processes that rely on static risk matrices, manual impact assessments, and limited historical memory struggle to anticipate nonlinear consequences, a limitation that parallels broader challenges in supply chain risk management and financial risk modeling (Ho et al., 2015; Baryannis et al., 2019b).

The rise of Artificial Intelligence and machine learning has fundamentally altered the epistemic foundations of risk assessment across multiple domains. In finance, predictive models now estimate credit defaults, loan behavior, and market volatility with a level of granularity and adaptability unimaginable in earlier eras (Anand et al., 2022; Suhadolnik et al., 2023). In engineering and safety science, machine learning systems identify early warning signals and complex interactions that escape human intuition (Hegde and Rokseth, 2020; Paltrinieri et al., 2019). In supply chain management, AI-driven analytics are increasingly used to forecast disruptions, optimize resilience, and evaluate strategic trade-offs under uncertainty (Belhadi et al., 2021; Fan et al., 2015). These developments collectively suggest that risk is no longer primarily an object of static classification but a dynamic, data-driven phenomenon that can be continuously inferred, updated, and optimized through intelligent algorithms.

Within this broader transformation, the application of AI to Change Advisory Board decision making represents a particularly significant yet underexplored frontier. While CABs have always functioned as risk assessment bodies, they have historically lacked the analytical infrastructure necessary to transform large volumes of historical change data into actionable predictive intelligence. Varanasi's conceptualization of AI for CAB decisions directly addresses this gap by framing change approval as a predictive risk scoring problem in which machine learning models estimate the likelihood and impact of adverse outcomes based on past change performance, contextual variables, and evolving organizational patterns (Varanasi, 2025). This approach redefines CAB governance from a deliberative committee model toward an algorithmically augmented decision environment in which human judgment is informed by probabilistic foresight rather than retrospective experience.

The theoretical significance of this shift extends far beyond IT service management. From the perspective of enterprise governance, predictive risk scoring introduces a new form of internal control in which risk is monitored not only through compliance checklists and audits but also through continuous statistical inference, aligning closely with the COSO framework's emphasis on dynamic risk assessment and control activities (COSO, 2013). From the standpoint of ISO 31000, which conceptualizes risk management as an integrated, structured, and iterative process, AI-enabled CABs represent a technological embodiment of these principles, operationalizing risk identification, analysis, and evaluation in real time (ISO 31000:2018). Moreover, when viewed through the lens of financial risk analytics, CAB predictive scoring resembles credit scoring, default prediction, and early warning systems, thereby situating change management within a broader ecosystem of algorithmic governance (Arora et al., 2022; Song et al., 2024).

Despite these convergences, scholarly research has yet to fully theorize how AI-driven risk scoring reshapes the epistemology, ethics, and institutional dynamics of CAB decision making. Existing studies on supply chain risk, financial analytics, and enterprise governance provide valuable insights into the technical capabilities of machine learning, yet they rarely address the specific socio-technical context of organizational change governance (Giannakis and Louis, 2016; Pereira Gaspar et al., 2020). Conversely, traditional IT governance literature often treats CABs as procedural structures rather than data-intensive decision systems, thereby overlooking the transformative potential of predictive analytics (De Haes and Van Grembergen, 2009). This fragmentation creates a significant literature gap at the intersection of AI, risk theory, and change governance, a gap that this article seeks to address through an integrative and deeply elaborated analytical framework.

The central problem that motivates this research is therefore not simply whether AI can improve CAB decisions, but how predictive risk intelligence fundamentally alters the meaning of governance, accountability, and organizational learning in change management. When machine learning models assign numerical risk scores to proposed changes, they effectively translate complex socio-technical uncertainties into quantifiable expectations, a process that echoes long-standing debates in financial economics and safety science about the limits and dangers of quantification (Karasan, 2021; Paltrinieri et al., 2019). Proponents argue that such models enhance objectivity, consistency, and foresight, reducing human bias and enabling proactive risk mitigation (Varanasi, 2025; Valli, 2024). Critics, however, warn that algorithmic risk scores may obscure causal reasoning, embed historical inequities, and create new forms of governance opacity that undermine trust and accountability (Alagic et al., 2024).

By situating AI-based CAB decision making within these broader scholarly debates, this article advances a comprehensive theoretical framework that integrates enterprise governance, financial risk analytics, and supply chain resilience into a unified model of predictive change management. The objective is not merely to describe technological tools, but to critically analyze how they reconfigure power, knowledge, and responsibility within organizations. In doing so, the study responds to calls in the risk management and AI literature for more holistic and interdisciplinary approaches to algorithmic decision systems (Baryannis et al., 2019b; Hegde and Rokseth, 2020).

The remainder of this article develops this argument through an extensive methodological, analytical, and theoretical exposition grounded exclusively in the provided scholarly references. The methodological section elaborates how predictive risk scoring for CABs can be conceptualized and evaluated through qualitative synthesis and comparative literature analysis, following established practices in systematic risk research (Pereira Gaspar et al., 2020; Ho et al., 2015). The results section interprets the implications of AI-driven risk scoring for change approval accuracy, organizational resilience, and financial stability, drawing on empirical patterns reported across machine learning and risk analytics studies (Suhadolnik et al., 2023; Anand et al., 2022). The discussion section offers a deep theoretical interpretation of these findings, engaging with competing scholarly perspectives on algorithmic governance, risk epistemology, and enterprise control, while also identifying limitations and directions for future research (Varanasi, 2025; De Haes and Van Grembergen, 2009). Through this sustained and elaborated inquiry, the article aims to establish predictive risk intelligence for CABs as a foundational paradigm in the evolving landscape of digital enterprise governance.

METHODOLOGY

The methodological foundation of this study is grounded in an interpretive and integrative research design that synthesizes theoretical, empirical, and conceptual insights from the extensive body of literature on artificial intelligence, risk management, enterprise governance, and financial analytics. Given that predictive risk scoring for Change Advisory Board decisions is an emergent domain that spans multiple disciplinary traditions, a purely empirical or purely technical methodology would be insufficient to capture its complexity. Instead, this research adopts a literature-driven analytical methodology that aligns with established approaches in supply chain risk management, financial risk modeling, and enterprise governance research, where conceptual integration and theoretical generalization play a central role (Ho et al., 2015; Pereira Gaspar et al., 2020).

At the core of this methodology lies a structured synthesis of the provided reference corpus, which includes foundational frameworks such as ISO 31000 and COSO, applied machine learning studies in finance and engineering, and domain-specific analyses of supply chain and organizational risk. These sources are treated not as isolated empirical findings but as components of a coherent theoretical system through which AI-based CAB decision making can be understood. This approach mirrors the methodology used in systematic literature reviews of risk management and artificial intelligence, where the goal is to identify patterns, causal logics, and conceptual convergences across diverse empirical contexts (Baryannis et al., 2019b; Hegde and Rokseth, 2020).

The methodological logic proceeds from the premise that Change Advisory Board decisions are a specialized form of organizational risk assessment. According to ISO 31000, risk assessment involves identifying, analyzing, and evaluating uncertainty in relation to objectives, a definition that maps directly onto the CAB's mandate to approve or reject changes based on their anticipated impact on service continuity, compliance, and business performance (ISO 31000:2018). By conceptualizing CAB activity as a risk management process, the study is able to draw on a wide range of machine learning–based risk assessment methodologies developed in finance, safety science, and supply chain management. For example, credit default prediction models, loan approval classifiers, and early warning systems for financial distress all rely on historical data, feature extraction, and probabilistic inference to estimate the likelihood of adverse outcomes (Arora et al., 2022; Anand et al., 2022; Song et al., 2024). These methodological principles are directly transferable to the evaluation of change risk in organizational contexts, as argued by Varanasi, who explicitly frames CAB decisions as predictive risk scoring problems (Varanasi, 2025).

The first methodological step involves defining the conceptual variables that constitute CAB risk. Drawing on enterprise governance theory and supply chain risk management, CAB risk is decomposed into technical, operational, financial, compliance, and reputational dimensions, reflecting the multidimensional nature of modern organizational change (De Haes and Van Grembergen, 2009; Ivanov et al., 2019). This decomposition is supported by the literature on supply chain risk, which demonstrates that disruptions are rarely confined to a single domain but instead propagate across interconnected networks of activities and stakeholders (Giannakis and Louis, 2016; Belhadi et al., 2021). By adopting this multidimensional risk ontology, the methodology ensures that AI-based CAB models are evaluated not merely on technical performance but on their capacity to capture the full spectrum of enterprise exposure.

The second methodological step involves mapping these risk dimensions onto machine learning constructs. In financial risk analytics, variables such as income stability, repayment history, and macroeconomic conditions are used as features to predict default probabilities and loan performance (Suhadolnik et al., 2023; Karasan, 2021). In the context of CAB decisions, analogous features include change type, system criticality, historical failure rates, dependency structures, and timing relative to business cycles. Although this article does not implement or test a specific algorithm, it draws on the methodological insights of Braga et al., who emphasize the importance of robust confidence intervals and uncertainty estimation in machine learning–based effort and risk prediction (Braga et al., 2008). This emphasis is crucial for CAB governance, where decisions must be justified not only by point estimates but by transparent representations of uncertainty.

The third methodological component concerns validation and interpretability. In financial and safety-critical domains, machine learning models are increasingly evaluated not only on predictive accuracy but also on their capacity to support explainable and auditable decision making (Alagic et al., 2024; Paltrinieri et al., 2019). This concern is especially salient for CABs, which operate within regulatory and governance frameworks such as Sarbanes–Oxley and COSO that require traceability, accountability, and control over decision processes (Lander, 2002; COSO, 2013). Therefore, the methodological framework adopted in this study emphasizes the alignment between predictive risk scoring and enterprise governance principles, ensuring that AI outputs can be integrated into formal control systems rather than functioning as opaque black boxes.

Finally, the methodology incorporates a critical reflexive dimension that examines the limitations and potential biases of AI-driven risk scoring. Drawing on comparative studies of machine learning in credit risk and mental health–integrated loan approval, the research acknowledges that predictive models are shaped by historical data distributions and may reproduce structural inequities or erroneous correlations (Alagic et al., 2024; Suhadolnik et al., 2023). By embedding this awareness into the methodological design, the study avoids a purely technocratic interpretation of AI and instead situates predictive CAB systems within broader socio-technical and ethical debates.

Through this integrative and theoretically grounded methodology, the article constructs a comprehensive analytical lens for understanding AI-enabled CAB decision making. This approach is consistent with the interdisciplinary traditions of supply chain risk research, financial analytics, and enterprise governance, all of which emphasize the need to bridge quantitative modeling with organizational and institutional analysis (Baryannis et al., 2019b; De Haes and Van Grembergen, 2009). The following section applies this methodological framework to derive and interpret the results of AI-driven predictive risk scoring in change management contexts.

RESULTS

The application of predictive risk intelligence to Change Advisory Board decision making yields a series of interrelated outcomes that reshape how organizations perceive, evaluate, and manage change-related uncertainty. These results, derived from a synthesis of machine learning–based risk analytics, supply chain resilience research, and enterprise governance theory, indicate that AI-enhanced CABs operate not merely as faster or more automated versions of traditional boards, but as fundamentally different epistemic systems that transform risk from a retrospective judgment into a forward-looking, continuously updated probability distribution (Varanasi, 2025; Paltrinieri et al., 2019).

One of the most significant results is the emergence of probabilistic foresight in change governance. Traditional CAB processes rely heavily on expert intuition, historical memory, and qualitative impact assessments, which are inherently limited by cognitive biases and incomplete information. In contrast, AI-driven risk scoring systems draw on large volumes of historical change data to estimate the likelihood that a proposed modification will lead to service disruptions, financial losses, or compliance violations. This mirrors the transformation observed in financial credit scoring, where machine learning models have replaced manual underwriting by identifying complex, nonlinear relationships among borrower characteristics and repayment outcomes (Anand et al., 2022; Suhadolnik et al., 2023). When applied to CABs, this predictive capability allows organizations to move from reactive crisis management to proactive risk mitigation, a shift that aligns with ISO 31000's emphasis on anticipatory risk evaluation (ISO 31000:2018).

A second major result concerns the integration of multidimensional risk into a single decision framework. Supply chain risk research has demonstrated that disruptions are rarely confined to one operational domain but instead propagate through interconnected networks, creating cascading effects that can amplify initial failures (Ivanov et al., 2019; Giannakis and Louis, 2016). AI-based CAB risk scoring systems capture this complexity by incorporating features that reflect technical dependencies, business criticality, and external environmental factors. As a result, CABs are able to evaluate proposed changes not only in terms of immediate technical impact but also in terms of their potential ripple effects on financial performance, customer satisfaction, and regulatory compliance. This multidimensional integration represents a significant advance over traditional risk matrices, which often treat different risk categories in isolation (Ho et al., 2015; Pereira Gaspar et al., 2020).

The results also indicate a substantial improvement in organizational learning. In conventional CAB environments, lessons from past change failures are often captured informally, through anecdotal knowledge or post-incident reports that may not systematically influence future decisions. By contrast, predictive risk scoring systems embed historical outcomes directly into the learning process of the algorithm, allowing each new change to update and refine the model's understanding of what constitutes high or low risk. This dynamic learning capability parallels the adaptive mechanisms observed in financial early warning systems, where models continuously recalibrate as new data become available (Song et al., 2024; Karasan, 2021). Varanasi emphasizes that such feedback loops are essential for transforming CABs into self-improving governance systems that evolve alongside organizational complexity (Varanasi, 2025).

Another important result relates to the consistency and transparency of decision making. Human-driven CAB processes are often criticized for variability, where similar changes may receive different outcomes depending on who is present, how risks are framed, or what organizational politics are at play. AI-based risk scoring introduces a standardized evaluative lens that applies the same underlying logic to every proposed change, thereby reducing arbitrary or inconsistent judgments. This mirrors findings in credit risk modeling, where machine learning classifiers provide more consistent loan approval decisions than manual review processes (Arora et al., 2022; Lohani et al., 2022). When integrated into CAB governance, this consistency enhances fairness and predictability, key principles in enterprise control frameworks such as COSO (COSO, 2013).

However, the results also reveal important tensions and limitations. One such tension arises from the potential for model bias and misrepresentation. Studies in financial and mental health–integrated credit risk have shown that machine learning models may inadvertently encode historical biases or spurious correlations, leading to unjust or inefficient decisions (Alagic et al., 2024; Suhadolnik et al., 2023). In the CAB context, this could manifest as systematic overestimation of risk for certain types of changes or business units, thereby constraining innovation and agility. This limitation underscores the need for governance structures that oversee not only change decisions but also the design, training, and validation of the predictive models themselves, a requirement that aligns with enterprise governance principles (De Haes and Van Grembergen, 2009; Lander, 2002).

Finally, the results suggest that AI-driven CABs contribute to enhanced organizational resilience. Supply chain research demonstrates that resilience is built not only through redundancy and flexibility but also through anticipatory analytics that enable organizations to prepare for and absorb shocks (Belhadi et al., 2021; Baryannis et al., 2019b). By providing early warnings about high-risk changes, predictive risk scoring allows organizations to allocate resources, schedule deployments, and design contingency plans more effectively. This proactive orientation transforms the CAB from a gatekeeping body into a strategic resilience engine, reinforcing the broader enterprise objective of sustaining performance under uncertainty (Varanasi, 2025; Ivanov et al., 2019).

Collectively, these results indicate that AI-based predictive risk scoring fundamentally reconfigures the role of the Change Advisory Board, enhancing foresight, learning, consistency, and resilience while also introducing new governance challenges related to bias, transparency, and accountability. These findings provide the empirical and conceptual foundation for the deeper theoretical interpretation developed in the following discussion section.

DISCUSSION

The implications of AI-driven predictive risk scoring for Change Advisory Board governance extend far beyond operational efficiency, touching on fundamental questions about how organizations conceptualize risk, authority, and knowledge in the digital age. At a theoretical level, the integration of machine learning into CAB decision making represents a paradigmatic shift from deliberative, human-centered governance toward hybrid socio-technical systems in which algorithmic inference and managerial judgment are co-constitutive. This transformation resonates with broader debates in enterprise governance, financial analytics, and safety science, all of which have grappled with the epistemological consequences of algorithmic risk assessment (De Haes and Van Grembergen, 2009; Paltrinieri et al., 2019; Karasan, 2021).

From the perspective of risk theory, predictive CAB systems instantiate a move from descriptive to inferential governance. Traditional CABs operate largely on descriptive risk information, such as checklists of potential impacts or narratives of past failures. AI-based systems, by contrast, generate probabilistic expectations about future outcomes, enabling what might be termed anticipatory governance. This aligns closely with Varanasi's argument that predictive risk scoring transforms CAB decisions into forward-looking optimization problems rather than backward-looking evaluations (Varanasi, 2025). Such a transformation echoes developments in financial risk management, where the shift from historical averages to predictive analytics has redefined how institutions perceive creditworthiness and systemic vulnerability (Song et al., 2024; Suhadolnik et al., 2023).

However, this inferential orientation also raises profound epistemological questions. When CAB members rely on algorithmic risk scores, they are implicitly delegating part of their judgment to statistical models whose internal logic may be opaque. Scholars of machine learning have long warned that high-performing models can be difficult to interpret, creating what is often described as a black box problem (Alagic et al., 2024; Karasan, 2021). In the context of enterprise governance, such opacity challenges the principles of accountability and auditability enshrined in frameworks like COSO and Sarbanes–Oxley, which require that decisions be traceable and justifiable (COSO, 2013; Lander, 2002). Thus, while predictive risk scoring enhances foresight, it simultaneously demands new forms of governance over the algorithms themselves.

The integration of AI into CABs also reconfigures organizational learning. In traditional settings, learning occurs through human reflection on past incidents, often mediated by post-implementation reviews or informal knowledge sharing. Predictive models, by contrast, operationalize learning as statistical updating, embedding past outcomes directly into future predictions. This mirrors the adaptive feedback loops observed in financial early warning systems and supply chain analytics, where models continuously recalibrate to changing environments (Belhadi et al., 2021; Song et al., 2024). From a theoretical standpoint, this represents a shift from episodic to continuous learning, aligning organizational change governance with cybernetic models of control and adaptation.

Yet this form of learning is not neutral. Because models learn from historical data, they may reproduce past organizational pathologies, such as risk aversion toward innovative changes or systemic underestimation of emerging threats. This phenomenon has been documented in credit risk modeling, where historical lending patterns can encode social and economic biases that persist in algorithmic decisions (Suhadolnik et al., 2023; Alagic et al., 2024). In CAB contexts, similar dynamics could constrain digital transformation by penalizing novel or unconventional changes, thereby creating a paradox in which AI designed to manage complexity inadvertently reinforces organizational inertia.

Another critical dimension concerns the relationship between predictive CAB systems and supply chain resilience. Contemporary organizations are embedded in extended networks of suppliers, partners, and platforms, making them vulnerable to cascading disruptions that originate far beyond their immediate control (Ivanov et al., 2019; Giannakis and Louis, 2016). By integrating external and internal data into change risk models, AI-enabled CABs can theoretically anticipate how a proposed modification might interact with these broader networks. This aligns with the concept of digital supply chain twins and risk analytics, which seek to simulate and forecast ripple effects before they materialize (Baryannis et al., 2019b; Fan et al., 2015). In this sense, predictive CAB governance becomes a microcosm of enterprise-wide resilience engineering.

However, the complexity of such models also introduces new vulnerabilities. The more variables and dependencies are included in a predictive system, the greater the risk of overfitting, spurious correlations, and false confidence. Engineering risk assessment literature has emphasized that machine learning models must be rigorously validated and continuously monitored to avoid catastrophic mispredictions (Hegde and Rokseth, 2020; Braga et al., 2008). In CAB settings, a flawed risk model could lead to the approval of a change that triggers widespread failure or the rejection of a change that would have generated significant strategic value. This underscores the importance of maintaining human oversight and institutional checks on algorithmic authority, consistent with enterprise governance principles (De Haes and Van Grembergen, 2009).

The ethical implications of AI-based CAB decision making also warrant careful consideration. When risk scores influence which changes are approved, delayed, or denied, they indirectly shape organizational priorities, innovation trajectories, and even employee careers. In financial contexts, scholars have shown that algorithmic credit scoring can have profound social consequences, affecting who gains access to resources and opportunities (Arora et al., 2022; Anand et al., 2022). Similarly, in organizational change governance, predictive risk scoring could privilege certain departments, technologies, or strategic visions over others, potentially reinforcing power asymmetries within the enterprise. Addressing these ethical dimensions requires not only technical solutions such as explainable AI but also institutional mechanisms for oversight, appeal, and deliberation.

Despite these challenges, the theoretical and practical benefits of predictive CAB systems remain compelling. By aligning change governance with the principles of ISO 31000 and COSO, AI-based risk scoring offers a way to operationalize integrated, dynamic, and evidence-based risk management across the enterprise (ISO 31000:2018; COSO, 2013). It enables organizations to move beyond fragmented, reactive, and intuition-driven decision making toward a more coherent and resilient governance model. As Varanasi argues, the true value of AI in CAB contexts lies not in replacing human judgment but in augmenting it with a depth of historical and contextual insight that no individual or committee could achieve alone (Varanasi, 2025).

Future research should therefore focus on developing robust governance frameworks for predictive CAB systems, including standards for data quality, model validation, and ethical accountability. Comparative studies across industries and organizational contexts would further illuminate how AI-driven change governance interacts with different institutional cultures and risk appetites, building on the cross-sectoral insights provided by supply chain and financial analytics research (Belhadi et al., 2021; Valli, 2024). By continuing to integrate technical, organizational, and ethical perspectives, scholars and practitioners can ensure that predictive risk intelligence fulfills its promise as a transformative force in enterprise change management.

CONCLUSION

This article has advanced a comprehensive and theoretically grounded analysis of AI-driven predictive risk scoring in Change Advisory Board decision making, situating it within the broader landscapes of enterprise governance, financial risk analytics, and supply chain resilience. By synthesizing insights from machine learning, risk management standards, and organizational theory, the study demonstrates that predictive CAB systems represent not merely a technological upgrade but a profound reconfiguration of how organizations perceive, evaluate, and govern change. Drawing particularly on the framework articulated by Varanasi, predictive risk scoring emerges as a mechanism for transforming CABs into anticipatory, learning-oriented, and resilience-enhancing governance bodies capable of navigating the uncertainties of digital enterprises (Varanasi, 2025).

At the same time, the analysis highlights critical challenges related to model bias, interpretability, and ethical accountability, underscoring the need for robust institutional oversight and interdisciplinary research. As organizations continue to embrace AI across their operations, the governance of change will increasingly depend on the delicate balance between algorithmic foresight and human judgment. By embedding predictive risk intelligence within established frameworks such as ISO 31000 and COSO, enterprises can harness the power of AI while preserving the principles of transparency, responsibility, and strategic alignment that define effective governance (ISO 31000:2018; COSO, 2013). In this way, AI-enabled CABs can become not only more efficient but more just, adaptive, and resilient in an era of continuous transformation.

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