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AI ETHICS IN BUSINESS SCENARIOS: CORPORATE LEAP FORWARD, GOVERNANCE STRATEGIES, AND ACTIONABLE RISK FRAMEWORKS

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Abstract: As generative AI is integrated into core business processes such as marketing, risk control, recruitment, and customer service, enterprises face ethical and compliance risks, including bias and discrimination, privacy breaches, insufficient explainability, and unclear attribution of responsibility, while experiencing leaps in efficiency. This paper takes "AI Ethics in Business Applications" as its research object, drawing on the empirical paradigm of "time structure alignment + interval summary comparison" from the appendix paper. It selects publicly available reports on enterprise AI adoption rates and policy governance signals as samples to construct a reproducible descriptive empirical framework. On the one hand, it depicts the phased leaps in enterprise AI adoption rates from 2017 to 2025; on the other hand, it proposes actionable control points for business management based on AI governance frameworks (OECD AI Principles, NIST AI RMF). The study finds that enterprise AI adoption accelerated significantly around 2024, with generative AI penetration increasing even faster. Simultaneously, discussions on AI-related legislation and governance on the policy side are also on the rise, suggesting that enterprises need to upgrade "ethical governance" from a passive task of compliance departments to an integral part of their business strategy and risk management system. Finally, this article presents actionable governance guidelines to help companies reduce ethical risks and enhance trust while pursuing growth and innovation.

Keywords: AI ethics; Business applications; Governance; Risk management; Trustworthy AI

1 INTRODUCTION

In business contexts, the value of AI is often described as "cost reduction and efficiency improvement [1]" and "better decision-making [2]." However, when algorithms are used for credit assessment, fraud prevention, dynamic pricing, talent screening, and content recommendation, model outputs directly impact customer opportunities, employee rights, and brand reputation, thus inherently carrying ethical and governance attributes [3]. Unlike traditional information systems, machine learning models often rely on large-scale data and statistical correlations, and their results may be automatically executed without sufficient explanation, continuously reinforcing existing biases through feedback loops [4]. This forces companies to answer a set of more managerial questions: Which business processes should incorporate "human-in-the-loop" approaches? How to establish accountability chains for high-risk decisions? And, in the context of rapidly evolving global policies, how can companies use quantifiable metrics to assess and audit the risk exposure of AI systems?

In actual business operations, algorithmic decision-making is often embedded in highly competitive and performance-oriented organizational environments [5]. Its impact is not limited to a single technical level but is amplified through organizational processes. Once algorithmic outputs are institutionalized into standard operating procedures, such as automated approvals, risk scoring thresholds, or recommendation ranking rules, the space for individual managers to intervene in decision outcomes is significantly reduced. This "technology-mediated" decision-making model means that ethical risks no longer appear in the form of explicit conflicts but accumulate continuously within daily operations, increasing the difficulty for companies to identify and correct them [5-6].

Internal incentive mechanisms within business organizations can also unintentionally amplify algorithmic risks [5-7]. When companies use efficiency improvement, cost control, or conversion rate maximization as core performance indicators, algorithmic systems are often evaluated based on "effectiveness" rather than "reasonableness." In the absence of clear ethical constraints and governance structures, even if a model performs well statistically, it may still produce systemic biases in terms of fairness, interpretability, or attribution of responsibility [7-8]. Once these biases are deployed on a large scale, they can evolve into reputational risks, compliance risks, and even long-term trust losses.

Based on this, this paper understands "AI ethics" as: introducing constraints on individual rights, social equity, and sustainable impacts beyond the company's objective functions (growth, efficiency, profit), and transforming these constraints into enforceable control mechanisms through organizational processes. The research objective of this paper is not to make value judgments on AI applications, but to construct a structured and reproducible analytical path using publicly available data: using time series to characterize the changing rhythm of enterprise adoption rates, and then using interval aggregation to map "adoption leaps" to upgrades in "governance requirements".

2 EMPIRICAL RESEARCH

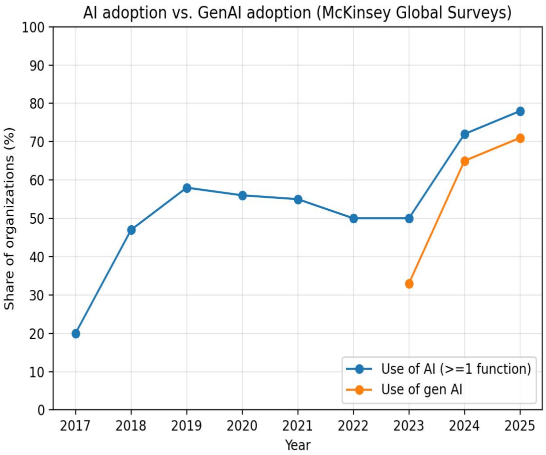

Figure 1 Temporal Alignment: AI adoption vs. GenAI Adoption (2017-2025)

This study draws on two categories of publicly available metrics to support a reproducible analysis of AI adoption and governance trends in business contexts. The first category captures corporate AI adoption rates, derived from McKinsey Global Surveys and defined as the adoption of AI in at least one business function, with the adoption rate of generative AI included as a supplementary indicator. The second category reflects governance signals, measured using statistics from the Stanford AI Index on the number of AI-related laws enacted globally, which serve as a proxy for the strengthening of policy-level governance. Building on the methodological logic of the reference paper, the analysis adopts a two-step strategy that combines time-structure alignment with interval-based comparison. Specifically, annual changes in corporate AI adoption and governance signals are first aligned along the time dimension, as illustrated in Figures 1 and 2, and the study then divides the observation period into three phase windows to compare average adoption levels and their associated management implications. This approach does not attempt to infer the causal effects of specific laws or policies on adoption behavior, but instead emphasizes reproducible trend characterization and management-oriented interpretation.

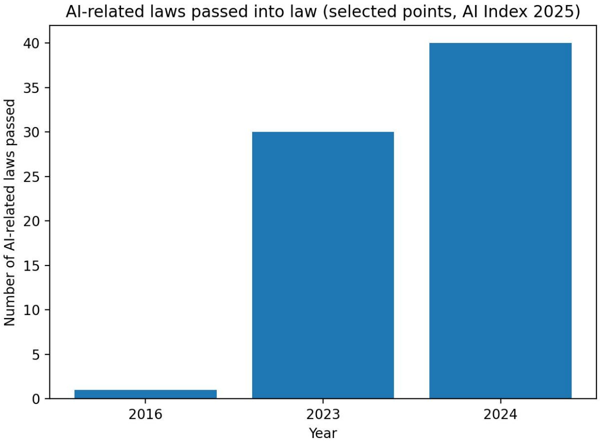

Figure 2 Policy Signal: AI-Related Laws Passed (Global, Selected Points 2016/2023/2024)

As shown in Figure 2, the AI Index indicates that the number of AI-related laws enacted globally has increased from single-digit levels in 2016 to 30 in 2023 and further to 40 in 2024, reflecting a clear acceleration in the pace of governance [5][9]. This upward trend suggests that regulatory attention to AI has shifted from exploratory discussion to more formalized and institutionalized rule-making, covering issues such as data protection, algorithmic accountability, and the use of automated decision-making systems. Rather than targeting isolated technologies, these regulatory developments increasingly address the systemic risks associated with large-scale AI deployment, thereby reshaping the external environment in which firms operate.

For businesses, such governance signals are rarely experienced as abstract policy changes but are instead transmitted into daily operations through concrete managerial channels. Regulatory expectations are often embedded in procurement and bidding requirements, cross-border data and model compliance obligations, and expanding audit and disclosure pressures imposed by partners, regulators, and investors. As a result, firms face a situation in which the rapid acceleration of AI adoption coincides with a rising density of regulatory constraints. This simultaneity requires companies to rely on auditable and traceable governance mechanisms, not only to demonstrate compliance ex post, but also to manage uncertainty proactively as AI systems become more deeply integrated into core business processes.

Table 1 Period Comparison of AI Adoption And Implied Governance Focus

Time window	Adoption level	Avg. AI use (%)	Avg. gen AI use (%)
P1 (2017-2019)	Medium	41.7	—
P2 (2020-2022)	Medium	53.7	—
P3 (2023-2025)	High	66.7	56.3

Table 1 aggregates the annual data into three analytical windows and reveals a clear evolution in both AI adoption patterns and the associated ethical governance focus. In the early diffusion stage between 2017 and 2019, AI adoption remained relatively limited, and ethical risks were primarily concentrated on foundational issues such as the legitimacy of data sources and legal authorization, the identification of potential biases, and the boundaries of model performance. As adoption entered a multi-functional deployment phase from 2020 to 2022, enterprises began to apply AI at scale in areas including risk control, marketing, and operations, shifting the emphasis of ethical governance toward cross-departmental responsibility allocation, the governance of third-party models and data, and the establishment of mechanisms for continuous monitoring. In the most recent period from 2023 to 2025, driven by the rapid diffusion of generative AI, governance challenges have further expanded beyond traditional concerns related to bias and privacy to include emerging issues such as hallucinations and misinformation, intellectual property protection, and content traceability, as well as the need for explainable and contestable automated decision-making mechanisms.

3 CONCLUSION

This paper constructs a reproducible descriptive framework based on publicly available data to explain the simultaneous upgrade of AI adoption and ethical governance in business settings. Corporate AI adoption accelerated significantly around 2024, with generative AI penetration increasing even faster, while at the same time the density of governance at the policy and legislative levels is also rising. Therefore, enterprises should upgrade AI ethics from “project-level compliance checks” to “operational-level risk governance systems” and implement it at operational control points. These control points include establishing a cross-functional AI governance committee with clearly defined responsibilities for product owners, business owners, compliance, and auditing; building traceable ledgers for training data and feature engineering while minimizing and limiting the use of sensitive data; conducting group assessments and differential impact analyses for high-impact decisions such as recruitment, credit granting, and insurance pricing and setting correction thresholds.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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