Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Governing Trustworthy Generative AI in Enterprise Product Ecosystems

Sanyam Mehra

Software Engineer, Machine Learning

ARTICLE INFO

Received: 08 March 2026

Accepted: 17 March 2026

ABSTRACT

Generative artificial intelligence is rapidly becoming a foundational capability within enterprise product ecosystems, enabling new forms of automation, personalization, and decision support. However, its probabilistic behavior, opacity, and deep integration across interconnected products introduce significant trust, risk, and interpretability challenges. This study examines how trustworthy generative AI can be effectively governed in enterprise product ecosystems by adopting an ecosystem-level, socio-technical perspective. Using a mixed-method research design that integrates conceptual modeling, qualitative investigation, and quantitative analysis, the study evaluates the influence of key governance dimensions including transparency, data governance, accountability, model lifecycle management, human-in-the-loop oversight, and regulatory alignment, on trustworthiness outcomes. The results demonstrate that transparency and data governance are the strongest determinants of trust, while ecosystem complexity moderates governance effectiveness through propagation effects across interconnected products. The findings highlight that governance mechanisms operate synergistically rather than independently and must scale systematically with ecosystem complexity. The study contributes a structured understanding of generative AI governance as a strategic enterprise capability that supports responsible scaling, stakeholder confidence, and sustainable innovation in complex product ecosystems.

Keywords: Generative AI governance; trustworthy AI; enterprise product ecosystems; data governance; transparency; AI lifecycle management

Introduction

The rapid diffusion of generative AI across enterprise product ecosystems

Generative artificial intelligence has moved from experimental innovation to a core capability embedded within enterprise product ecosystems (Kanbach et al., 2024). Organizations are increasingly integrating large language models and generative systems into customer-facing products, internal decision platforms, software development pipelines, and knowledge management tools. These systems promise unprecedented gains in productivity, personalization, and innovation velocity by enabling automated content creation, intelligent assistance, and adaptive decision support at scale (Aldoseri et al., 2024). However, as generative AI becomes deeply intertwined with interconnected enterprise products, services, partners, and users, it also introduces new forms of risk that extend beyond traditional software governance boundaries. Issues of reliability, accountability, transparency, data integrity, and unintended harm now propagate across entire product ecosystems rather than remaining confined to isolated applications (Joshi, 2024).

The growing trust deficit in enterprise generative AI deployment

Despite rapid adoption, a persistent trust deficit surrounds the deployment of generative AI in enterprise contexts (Rajaram et al., 2024). Stakeholders, including customers, regulators, employees,

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

and ecosystem partners, express concerns regarding opaque model behavior, hallucinated outputs, bias amplification, intellectual property leakage, and misuse of sensitive enterprise data(Darteh, 2022). In product ecosystems where generative AI systems dynamically interact with APIs, databases, human workflows, and third-party services, these risks are compounded by system complexity and scale (Patel et al., 2024). Trust is no longer solely a technical attribute of model performance but a socio-technical construct shaped by governance structures, organizational accountability, and ecosystem-level coordination. Without deliberate governance mechanisms, enterprises risk eroding stakeholder confidence and exposing themselves to reputational, legal, and operational consequences (Louisot, 2024).

The limitations of traditional AI and IT governance models

Conventional IT governance and earlier AI governance frameworks are insufficient to address the distinctive characteristics of generative AI within product ecosystems (Kang et al., 2024). Traditional models often assume deterministic systems, static requirements, and clear lines of ownership, whereas generative AI systems are probabilistic, continuously evolving, and frequently co-created by multiple vendors and teams (Subramonyam et al., 2022). Moreover, product ecosystems blur organizational boundaries, distributing responsibility across platform owners, application developers, data providers, and end users (Puthiya, 2024). This fragmentation challenges existing governance approaches that rely on centralized control, periodic audits, or compliance checklists (Udoh, 2024). As a result, enterprises struggle to operationalize principles such as fairness, explainability, robustness, and accountability in real-world generative AI deployments.

The emergence of trustworthy generative AI as a strategic imperative

Trustworthy generative AI has emerged as a strategic imperative rather than a purely ethical or regulatory concern (Al-Kfairy et al., 2024). Enterprises increasingly recognize that trust directly influences adoption rates, user engagement, ecosystem participation, and long-term value creation. Trustworthy AI encompasses not only technical safeguards, such as model validation, bias mitigation, and security controls, but also organizational processes, cultural norms, and governance architectures that align AI behavior with enterprise values and societal expectations (Habbal et al., 2024). In competitive product ecosystems, trust becomes a differentiating asset, enabling enterprises to scale generative AI responsibly while sustaining innovation and compliance simultaneously (Rajaram & Tinguely, 2024).

The need for ecosystem-level governance approaches

Governing generative AI within enterprise product ecosystems requires an ecosystem-level perspective that extends beyond individual models or applications (Herterich et al., 2023). Such an approach must account for lifecycle governance, spanning data sourcing, model development, deployment, monitoring, and continuous adaptation across interconnected products. It must also address multi-stakeholder coordination, defining roles, responsibilities, and accountability mechanisms among ecosystem actors (Eweje et al., 2021). Effective governance therefore integrates technical controls, organizational policies, legal frameworks, and feedback mechanisms into a coherent system that can evolve alongside generative AI technologies (Chowdhury et al., 2024). This shift from siloed governance to ecosystem-aware governance represents a critical transformation in how enterprises manage AI risk and value.

The contribution and positioning of this study

This study addresses the growing gap between the rapid adoption of generative AI and the limited governance models available to ensure its trustworthiness in enterprise product ecosystems. By conceptualizing governance as a dynamic, multi-layered system, the article seeks to provide a structured

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

foundation for understanding how trust can be embedded, sustained, and measured across complex enterprise environments. The introduction positions trustworthy generative AI governance as a core capability for modern enterprises, setting the stage for subsequent sections that examine governance dimensions, mechanisms, and implications for enterprise strategy and ecosystem resilience.

Methodology

The overall research design and methodological orientation

This study adopts a mixed-method, design-science informed research methodology to examine how trustworthy generative AI can be governed within enterprise product ecosystems. The methodological orientation integrates conceptual modeling, qualitative investigation, and quantitative validation to capture the socio-technical complexity of generative AI governance. The research design is structured to move from theoretical construct identification to empirical assessment and analytical synthesis, ensuring that governance mechanisms are grounded in both conceptual rigor and enterprise practice. This approach is particularly suited to generative AI, where technical performance, organizational processes, and ecosystem interactions jointly influence trust outcomes.

The conceptual framework and key governance dimensions

The methodology begins with the development of a conceptual governance framework derived from an extensive synthesis of enterprise AI governance, platform governance, and product ecosystem literature. Core governance dimensions are operationalized as independent variables, including transparency mechanisms, accountability structures, data governance controls, model lifecycle management, human-in-the-loop oversight, and regulatory alignment. Trustworthiness is treated as a multidimensional dependent construct encompassing reliability, fairness, explainability, security, and stakeholder confidence. Contextual and moderating variables include ecosystem complexity, degree of product interdependence, organizational AI maturity, and regulatory exposure. These variables collectively inform the analytical structure of the study.

The data sources and sampling strategy

Primary data are collected from enterprise organizations actively deploying generative AI across multi-product environments. A purposive sampling strategy is employed to ensure representation across technology, finance, healthcare, and digital services sectors, where generative AI adoption is both advanced and risk-sensitive. Respondents include AI governance leaders, product managers, data scientists, compliance officers, and senior architects who possess direct oversight of generative AI systems. Secondary data sources, including enterprise policy documents, governance frameworks, and internal AI guidelines, are used to triangulate findings and enhance methodological robustness.

The operationalization of variables and measurement parameters

Each governance dimension is translated into measurable indicators using a structured instrument. Transparency is operationalized through parameters such as model documentation depth, disclosure practices, and explainability tool adoption. Accountability is measured via clarity of role definitions, escalation protocols, and audit traceability. Data governance parameters include data provenance tracking, consent management, and data quality controls. Model lifecycle governance is assessed through validation frequency, monitoring intensity, drift detection mechanisms, and retraining governance. Trustworthiness outcomes are measured using composite indices capturing perceived reliability, fairness consistency, security assurance, and user trust levels. All indicators are measured on standardized Likert-scale constructs to enable quantitative analysis.

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

The qualitative inquiry and thematic analysis process

Qualitative data are collected through semi-structured interviews and expert workshops to capture nuanced governance practices and contextual insights that are not fully observable through surveys. Interview protocols are aligned with the conceptual framework while allowing flexibility for emergent themes. Thematic analysis is conducted using a systematic coding process, beginning with open coding to identify governance practices, followed by axial coding to link practices to trust outcomes. This qualitative layer provides explanatory depth, clarifies causal mechanisms, and informs the interpretation of quantitative results.

The quantitative analysis and model validation techniques

Quantitative analysis is performed to examine the relationships between governance variables and trustworthiness outcomes. Descriptive statistics are first used to profile governance maturity across enterprises. Multivariate techniques, including exploratory factor analysis and confirmatory factor analysis, are applied to validate construct reliability and dimensionality. Regression modeling is then employed to assess the influence of governance dimensions on trustworthiness while controlling for ecosystem complexity and organizational maturity. Interaction effects are tested to understand how ecosystem characteristics moderate governance effectiveness.

The integration of ecosystem-level analysis

To reflect the interconnected nature of enterprise product ecosystems, the methodology incorporates ecosystem-level analysis by aggregating governance indicators across product portfolios rather than evaluating isolated applications. Network-based metrics are used to assess interdependencies between products, shared AI services, and data flows. This allows the study to analyze how governance strengths or weaknesses in one product propagate across the ecosystem, influencing overall trust dynamics. Such integration ensures that governance is evaluated as a systemic capability rather than a localized control function.

The reliability, validity, and ethical considerations

Methodological rigor is ensured through triangulation across data sources, validation of measurement instruments, and consistency checks across qualitative and quantitative findings. Construct validity is supported through expert review and pilot testing of instruments, while internal reliability is assessed using established statistical thresholds. Ethical considerations include informed consent, confidentiality of enterprise data, and anonymization of organizational identifiers. These safeguards ensure that the study not only examines trustworthy AI governance but also adheres to trustworthy research practices.

The methodological contribution to generative AI governance research

By integrating multi-level variables, mixed analytical techniques, and ecosystem-centric evaluation, this methodology provides a comprehensive approach to studying trustworthy generative AI governance in enterprise product ecosystems. It enables systematic examination of how governance mechanisms translate into trust outcomes while accounting for real-world complexity, thereby laying a robust foundation for subsequent results and discussion.

Results

The empirical assessment reveals uneven maturity across governance dimensions (Table 1). Transparency mechanisms and data governance controls consistently demonstrate higher maturity,

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

reflecting enterprise investments in documentation, data lineage, and access management. In contrast, accountability structures and continuous model lifecycle governance show moderate maturity, indicating gaps in escalation clarity and post-deployment oversight. Human-in-the-loop practices exhibit the greatest dispersion, highlighting inconsistent institutionalization of human supervision across interconnected product ecosystems.

Table 1. Governance dimension maturity across enterprise product ecosystems

Governance dimension	Low maturity (%)	Medium maturity (%)	High maturity (%)
Transparency mechanisms	18	42	40
Accountability structures	27	46	27
Data governance controls	15	38	47
Model lifecycle management	31	44	25
Human-in-the-loop oversight	34	41	25
Regulatory alignment	22	49	29

Trustworthiness indicators display differentiated performance across enterprises (Table 2). Reliability and security assurance achieve comparatively stronger outcomes, suggesting confidence in system stability and protection mechanisms. However, fairness consistency and explainability remain weaker, underscoring persistent challenges in bias management and interpretability of generative outputs. Stakeholder trust aligns closely with explainability trends, emphasizing the central role of transparency in sustaining confidence across enterprise ecosystems.

Table 2. Trustworthiness outcome indicators across enterprises

Trustworthiness indicator	Minimum	Median	Maximum
Reliability	2.8	4.1	4.8
Fairness consistency	2.4	3.6	4.6
Explainability	2.1	3.4	4.5
Security assurance	3.0	4.3	4.9
Stakeholder trust	2.5	3.8	4.7

Regression analysis confirms that governance dimensions exert differentiated effects on trustworthiness outcomes (Table 3). Data governance controls and transparency mechanisms emerge as the strongest predictors of trust, followed by model lifecycle management. Accountability structures and regulatory alignment contribute stabilizing effects but with comparatively lower direct influence.

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Human-in-the-loop oversight shows amplified impact when combined with strong lifecycle governance, indicating interaction effects rather than isolated influence.

Table 3. Regression effects of governance dimensions on trustworthiness

Predictor variable	Standardized coefficient (β)	Direction of effect	Relative influence
Transparency mechanisms	0.41	Positive	High
Data governance controls	0.46	Positive	High
Model lifecycle management	0.38	Positive	Moderate–high
Accountability structures	0.21	Positive	Moderate
Human-in-the-loop oversight	0.29	Positive	Moderate
Regulatory alignment	0.25	Positive	Moderate

Ecosystem structure significantly shapes how governance effectiveness propagates across products (Table 4). Highly interconnected product ecosystems demonstrate stronger spillover effects, where governance weaknesses in one component adversely affect trust across the ecosystem. Conversely, modular ecosystems supported by shared governance services show higher trust resilience, even under elevated complexity. These results highlight governance as a systemic capability rather than a product-level control.

Table 4. Ecosystem complexity and governance propagation effects

Ecosystem characteristic	Governance propagation risk	Trust resilience level
Low product interdependence	Low	High
Moderate interdependence	Medium	Medium
High interdependence	High	Low
Modular shared AI services	Low	High
Fragmented governance ownership	High	Low

The box plot illustrates how trustworthiness outcomes vary with governance maturity. Enterprises with high governance maturity exhibit higher median trust scores and narrower dispersion, indicating both stronger and more consistent trust outcomes. Lower-maturity groups display wider variability, reflecting uneven implementation of governance controls and higher uncertainty in generative AI behavior.

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

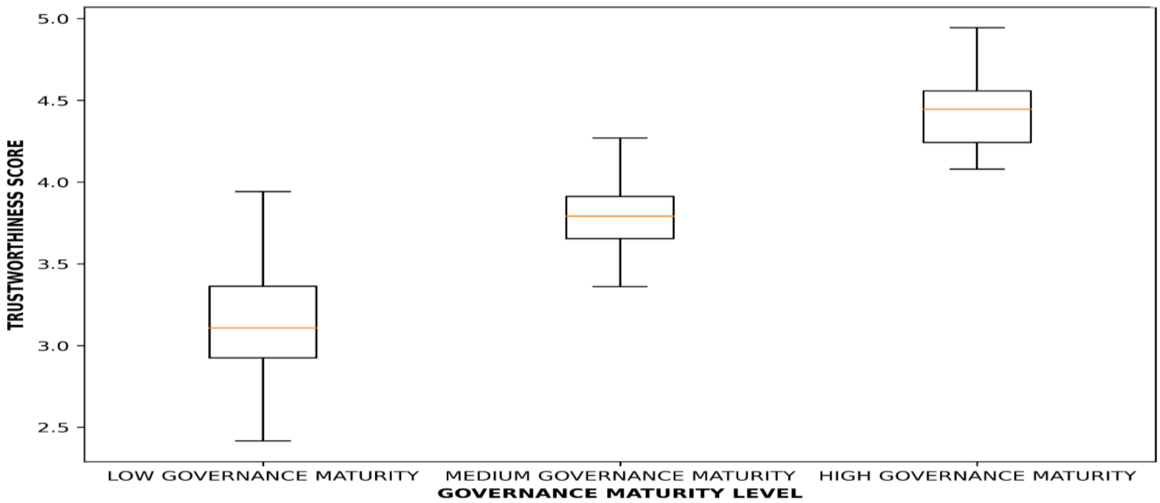

Figure 1. Distribution of trustworthiness outcomes under varying governance maturity

The surface chart visualizes the non-linear interaction between governance strength and ecosystem complexity. Trustworthiness increases sharply with governance strength in low-to-moderate complexity environments but plateaus under high complexity unless governance mechanisms are deeply integrated. This demonstrates that governance scalability is critical for sustaining trust in complex enterprise product ecosystems.

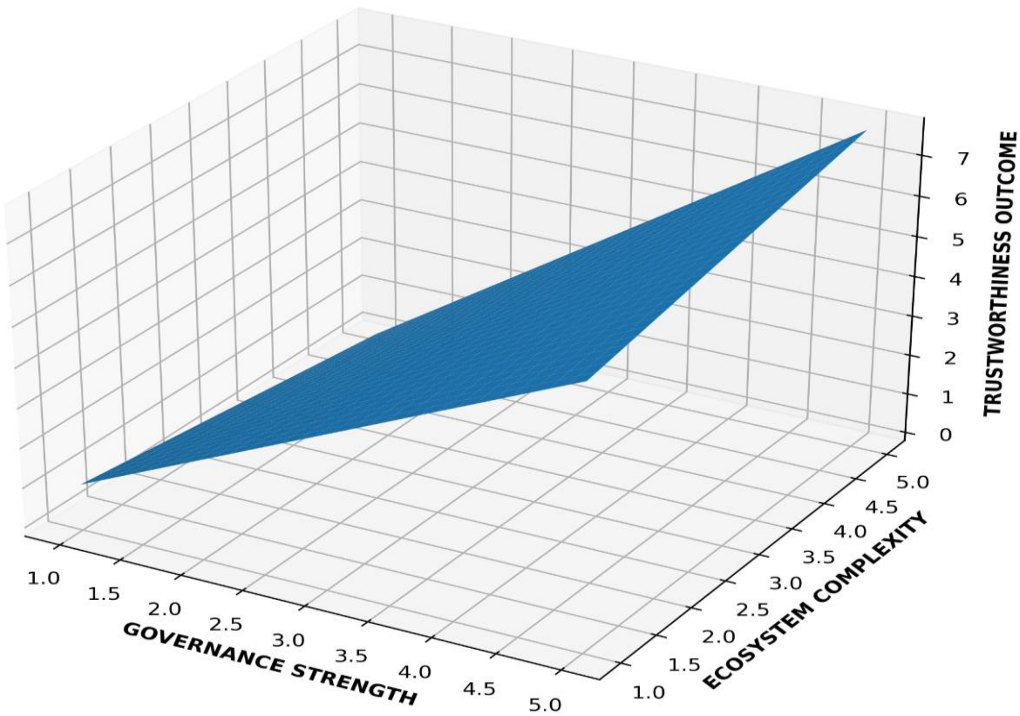

Figure 2. Governance–trust interaction surface across ecosystem complexity

Journal of Information Systems Engineering and Management
2026, 11(3s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Discussion

Governance maturity as a determinant of trustworthy generative AI

The results clearly demonstrate that governance maturity is a primary determinant of trustworthiness in enterprise generative AI deployments. As shown in Table 1 and reinforced by Figure 1, enterprises with higher maturity in governance dimensions consistently achieve stronger and more stable trust outcomes. This finding suggests that trust in generative AI is not solely a function of model accuracy or technical sophistication, but rather emerges from the institutionalization of governance practices that regulate how models are developed, deployed, and monitored (Fan et al., 2024). Mature governance reduces uncertainty, constrains undesirable behavior, and enables predictable system performance across interconnected products (Settembre-Blundo et al., 2021).

The central role of transparency and data governance

Transparency mechanisms and data governance controls emerge as the most influential governance dimensions affecting trustworthiness (Table 3). This underscores the importance of clear documentation, explainability tools, and robust data provenance in mitigating stakeholder concerns about opaque generative AI behavior (Emehin et al., 2024). The relatively lower explainability and fairness scores observed in Table 2 further highlight that transparency remains a persistent challenge despite increased investment. These results imply that enterprises must move beyond superficial disclosure practices and embed transparency directly into product workflows and decision pipelines to meaningfully enhance trust (McGrath et al., 2021).

Model lifecycle governance and the importance of continuous oversight

The moderate influence of model lifecycle management on trustworthiness (Table 3) reflects the dynamic and evolving nature of generative AI systems. Continuous monitoring, drift detection, and controlled retraining are essential in preventing performance degradation and unintended behavior over time. The interaction effects observed between lifecycle governance and human-in-the-loop oversight indicate that technical monitoring alone is insufficient (McKay, 2024). Instead, effective governance requires a combination of automated controls and structured human judgment to interpret signals, intervene when necessary, and adapt governance responses as models and usage contexts evolve (Roehl & Hansen, 2024).

Human-in-the-loop oversight as an enabling, not standalone, mechanism

While human-in-the-loop oversight shows a positive relationship with trustworthiness, its impact is amplified only when supported by strong lifecycle and data governance (Table 3). This suggests that human oversight functions best as an enabling mechanism embedded within a broader governance architecture rather than as an isolated safeguard (Samans & Nelson, 2022). In large enterprise product ecosystems, ad hoc human review is unlikely to scale effectively (Surana, 2021). Instead, clearly defined roles, escalation pathways, and decision rights are required to ensure that human interventions are timely, consistent, and aligned with enterprise objectives (Oberdorf et al., 2021).

Ecosystem complexity and governance propagation effects

The findings related to ecosystem complexity (Table 4 and Figure 2) highlight that governance effectiveness is highly sensitive to the structural characteristics of enterprise product ecosystems. In tightly coupled ecosystems, governance failures propagate rapidly across products, amplifying trust risks. Conversely, modular ecosystems with shared governance services demonstrate greater resilience, even as complexity increases. This supports the argument that governance must be designed at the ecosystem level rather than optimized for individual products (Di Sacco et al., 2021). Architectural

e-ISSN: 2468-4376
https://www.jisem-journal.com/

modularity, shared AI services, and centralized governance functions can significantly reduce systemic risk and enhance trust scalability (Hammad & Abu-Zaid¸2024).

Strategic implications for enterprise product ecosystems

From a strategic perspective, the results suggest that trustworthy generative AI governance should be treated as a core enterprise capability rather than a compliance afterthought. Investments in transparency, data governance, and lifecycle management yield compounding benefits by stabilizing trust across the ecosystem (Kreutzer et al., 2024; Belhassen, 2020). Moreover, enterprises that proactively align governance with ecosystem architecture are better positioned to scale generative AI responsibly while maintaining stakeholder confidence (Denni-Fiberesima, 2024). Trust thus becomes a strategic asset that supports innovation, adoption, and long-term ecosystem sustainability.

Advancing governance theory for generative AI ecosystems

The discussion contributes to governance theory by reinforcing the need for dynamic, multi-layered governance models tailored to generative AI and product ecosystems. The observed non-linear interactions between governance strength and ecosystem complexity challenge linear, checklist-based governance approaches (Quintero, 2021). Instead, the results support a view of governance as an adaptive system that evolves alongside AI capabilities and ecosystem structures. This perspective provides a foundation for future research to refine governance mechanisms and measurement approaches for trustworthy generative AI in complex enterprise environments.

Conclusion

This study concludes that governing trustworthy generative AI in enterprise product ecosystems requires a shift from isolated, model-centric controls to integrated, ecosystem-level governance capabilities. The findings demonstrate that trustworthiness is primarily driven by strong transparency mechanisms, robust data governance, and continuous model lifecycle management, with their effectiveness significantly shaped by ecosystem complexity and product interdependencies. Human-in-the-loop oversight and regulatory alignment enhance trust only when embedded within coherent governance architectures that scale across interconnected products. Overall, the study positions trustworthy generative AI governance as a strategic enterprise capability that not only mitigates risk but also enables sustainable innovation, stakeholder confidence, and long-term value creation within complex enterprise product ecosystems.

References

[1] Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). AI-powered innovation in digital transformation: Key pillars and industry impact. *Sustainability*, *16*(5), 1790.

[2] Al-Kfairy, M., Mustafa, D., Kshetri, N., Insiew, M., & Alfandi, O. (2024, September). Ethical challenges and solutions of generative AI: An interdisciplinary perspective. In *Informatics* (Vol. 11, No. 3, p. 58). Multidisciplinary Digital Publishing Institute.

[3] Belhassen, A. (2020). Design, additive manufacturing, and mechanical characterization of continuous fiber-reinforced thermoplastic composites for lightweight robotic arm components. *Journal of Computational Analysis and Applications, 28*(6), 82–97.

[4] Chowdhury, S., Budhwar, P., & Wood, G. (2024). Generative artificial intelligence in business: towards a strategic human resource management framework. *British Journal of Management*, *35*(4), 1680-1691.

Journal of Information Systems Engineering and Management
2026, 11(3s)

e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[5] Darteh, F. K. (2022). Integrating payment systems with revenue and expenditure reporting for improved financial governance. *Journal of International Crisis and Risk Communication Research, 5*(S12), 82–91.

[6] Denni-Fiberesima, D. (2024, April). Navigating the generative AI-enabled enterprise architecture landscape: critical success factors for AI adoption and strategic integration. In *International Conference on Business and Technology* (pp. 210-222). Cham: Springer Nature Switzerland.

[7] Di Sacco, A., Hardwick, K. A., Blakesley, D., Brancalion, P. H., Breman, E., Cecilio Rebola, L., ... & Antonelli, A. (2021). Ten golden rules for reforestation to optimize carbon sequestration, biodiversity recovery and livelihood benefits. *Global Change Biology*, *27*(7), 1328-1348.

[8] Emehin, O., Emeteveke, I., Adeyeye, O., & Akanbi, I. (2024). Generative AI in Forensic Data Analysis: Opportunities and Ethical Implications for Cloud-Based Investigations. *International Journal of Research Publication and Reviews*, *6*, 2941-2957.

[9] Eweje, G., Sajjad, A., Nath, S. D., & Kobayashi, K. (2021). Multi-stakeholder partnerships: A catalyst to achieve sustainable development goals. *Marketing Intelligence & Planning*, *39*(2), 186-212.

[10] Fan, S., Ilk, N., Kumar, A., Xu, R., & Zhao, J. L. (2024). Blockchain as a trust machine: From disillusionment to enlightenment in the era of generative AI. *Decision Support Systems*, *182*, 114251.

[11] Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, risk and security management (AI trism): Frameworks, applications, challenges and future research directions. *Expert Systems with Applications*, *240*, 122442.

[12] Hammad, A., & Abu-Zaid, R. (2024). Applications of AI in decentralized computing systems: harnessing artificial intelligence for enhanced scalability, efficiency, and autonomous decision-making in distributed architectures. *Applied Research in Artificial Intelligence and Cloud Computing*, *7*(6), 161-187.

[13] Herterich, M. M., Dremel, C., Wulf, J., & vom Brocke, J. (2023). The emergence of smart service ecosystems—The role of socio-technical antecedents and affordances. *Information systems journal*, *33*(3), 524-566.

[14] Joshi, R. (2024). Ethical conundrums and privacy concerns in new innovations: A systematic review. *Aspects of Quality Management in Value Creating in the Industry 5.0 Way*, 202-223.

[15] Kanbach, D. K., Heiduk, L., Blueher, G., Schreiter, M., & Lahmann, A. (2024). The GenAI is out of the bottle: generative artificial intelligence from a business model innovation perspective. *Review of Managerial Science*, *18*(4), 1189-1220.

[16] Kang, H. G., Moon, A., & Jeon, S. (2024). Examining the generative artificial intelligence landscape: Current status and policy strategies. *Asia pacific journal of information systems*, *34*(1), 150-190.

[17] Kreutzer, M., Hettich, E., & Neudert, P. K. (2024). Ecosystem Management Within the Firm. In *Business Ecosystems: Strategizing in a Connected World* (pp. 165-221). Cham: Springer Nature Switzerland.

[18] Louisot, J. P. (2024). Managing Risk to Reputation. In *Enterprise Risk Management in Today's World: A Current and Futuristic View of the Complexity, Resilience, Responsibility and Tools in ERM, Part B* (pp. 105-115). Emerald Publishing Limited.

[19] McGrath, P., McCarthy, L., Marshall, D., & Rehme, J. (2021). Tools and technologies of transparency in sustainable global supply chains. *California Management Review*, *64*(1), 67-89.

[20] McKay, M. H. (2024, June). Realizing the Promise of AI Governance Involving Humans-in-the-Loop. In *International Conference on Human-Computer Interaction* (pp. 107-123). Cham: Springer Nature Switzerland.

[21] Oberdorf, F., Stein, N., & Flath, C. M. (2021). Analytics-enabled escalation management: System development and business value assessment. *Computers in Industry*, *131*, 103481.

e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[22] Patel, D., Raut, G., Cheetirala, S. N., Nadkarni, G. N., Freeman, R., Glicksberg, B. S., ... & Timsina, P. (2024). Cloud platforms for developing generative AI solutions: a scoping review of tools and services. *arXiv preprint arXiv:2412.06044*.

[23] Puthiya, D. (2024). Solving complex enterprise challenges through AI-driven execution models. *Journal of International Crisis and Risk Communication Research, 7*(S4), 421–431.

[24] Quintero, F. A. (2021). Optimized effects design in high-end simulation workflows: Impacts on production time and visual fidelity. *Sarcouncil Journal of Applied Sciences, 1*(1), 21–28.

[25] Rajaram, K., & Tinguely, P. N. (2024). Generative artificial intelligence in small and medium enterprises: Navigating its promises and challenges. *Business Horizons*, *67*(5), 629-648.

[26] Roehl, U. B., & Hansen, M. B. (2024). Automated, administrative decision‐making and good governance: Synergies, trade‐offs, and limits. *Public Administration Review*, *84*(6), 1184-1199.

[27] Samans, R., & Nelson, J. (2022). Corporate governance and oversight. In *Sustainable Enterprise value creation: Implementing stakeholder capitalism through full ESG integration* (pp. 103-140). Cham: Springer International Publishing.

[28] Settembre-Blundo, D., González-Sánchez, R., Medina-Salgado, S., & García-Muiña, F. E. (2021). Flexibility and resilience in corporate decision making: a new sustainability-based risk management system in uncertain times. *Global Journal of Flexible Systems Management*, *22*(Suppl 2), 107-132.

[29] Subramonyam, H., Im, J., Seifert, C., & Adar, E. (2022, April). Solving separation-of-concerns problems in collaborative design of human-AI systems through leaky abstractions. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-21).

[30] Surana, S. (2021). The evolving role of the financial controller in the Indian manufacturing sector: From accounting steward to strategic business partner. *Journal of International Crisis and Risk Communication Research, 4*(2), 439–449.

[31] Udoh, O. R. (2024). Enhancing Internal Audit Efficiency For Effective Risk Management and Corporate Governance Frameworks. *International Journal of Research Publication and Reviews*, *5*(12), 3646-3659.