

The AI productivity-governance frontier: A theoretical model for enterprise value creation under agentic automation

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Abstract

Artificial intelligence (AI) adoption is accelerating, yet enterprise value remains uneven because technical capability often outpaces organizational redesign, workforce adaptation, and governance maturity. This paper develops an original theoretical model, the AI productivity-governance frontier (PGF), to explain why the same agentic AI capability can generate measurable value in one organization but produce negligible or negative returns in another. Using integrative theoretical modelling, the study synthesizes recent empirical evidence on generative AI productivity, enterprise adoption, AI risk management, labor-market exposure, and prior conceptual work by Kwan Hong TAN on AI-form organizations, AI stakeholder recognition, and temporal displacement-adaptation equilibrium. The resulting PGF model formalizes AI value as the interaction between automation-augmentation gains, learning spillovers, decision velocity, scalability, and institutional absorptive capacity, offset by governance drag, risk externalities, and identity-coordination costs. The paper proposes six testable propositions and a practical maturity pathway moving from experimental AI use to validated autonomy. The central argument is that sustainable AI value does not increase monotonically with either automation intensity or governance intensity. Instead, organizations approach maximum value when they design human-AI work systems that combine use-case fit, accountable autonomy, adaptive reskilling, and proportionate assurance. The contribution is threefold: a formal value equation for enterprise AI, a governance-sensitive interpretation of AI productivity heterogeneity, and an implementation framework for managers, policymakers, and researchers studying AI-enabled business transformation.

Keywords: Artificial intelligence; Agentic automation; Business transformation; Productivity; AI governance; Digital economy

1. Introduction

Artificial intelligence has entered a phase in which organizational impact can no longer be understood as a simple extension of software automation. Generative and agentic systems increasingly draft, reason, classify, code, search, summarize, recommend and coordinate across multi-step workflows. Reports tracking AI adoption now describe AI as a rapidly diffusing business capability rather than a peripheral digital tool [1,2]. Enterprise surveys also show that many organizations are moving from exploratory pilots to structured value-capture programmes, although maturity remains uneven across strategy, talent, operating model, data, technology and adoption practices [3].

This creates a central puzzle for business and economics. If AI tools can raise task productivity, reduce search costs and accelerate decision cycles, why do many firms still fail to convert pilots into measurable profit-and-loss outcomes? The question matters because the answer determines whether AI becomes a broad productivity technology, a narrow augmentation tool, a source of market concentration, or a managerial fashion with intermittent local benefits. Evidence

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already points to all four possibilities. Studies of customer support, writing tasks, software development and consulting show substantial productivity effects in selected contexts [5-8]. At the same time, business reports indicate that many enterprise pilots remain trapped in prototype mode, unable to deliver measurable financial returns [4].

This paper argues that the contradiction is not primarily a contradiction in the evidence. It is a contradiction in the unit of analysis. AI productivity studies often measure task-level performance, whereas managers and policymakers are concerned with system-level value. The task may improve while the organization fails to redesign incentives, decision rights, risk controls, training pathways, data flows or customer-facing processes. Conversely, heavy governance can reduce risk but also suppress experimentation, learning and speed. AI value therefore depends on a frontier condition: organizations must reach a zone in which technical autonomy, human judgment and governance assurance reinforce rather than neutralize one another.

The proposed contribution is the AI productivity-governance frontier (PGF), a theoretical model that explains sustainable AI value as the net effect of productivity gains, learning spillovers, decision velocity, scalability, institutional absorptive capacity, governance costs, risk externalities and identity-coordination costs. The model extends task-based economic accounts of automation and new work [21,22], while integrating recent organizational perspectives on the AI-form organization, AI as a stakeholder-like actor in value creation, and temporal adaptation in labor markets [13-17]. The paper is positioned as an original theoretical research article because it develops a formal construct system, propositions and managerial implementation pathway rather than merely reviewing prior studies.

The research objective is to answer the following question: under what organizational and institutional conditions does agentic AI generate sustainable enterprise value rather than isolated task efficiency? The paper advances six propositions and offers a practical maturity model for enterprise AI deployment. Its intended contribution is relevant to managers redesigning work, economists studying productivity diffusion, and policymakers concerned with equitable AI adoption in the digital economy.

2. Materials and methods

This study uses integrative theoretical modelling. The method is appropriate where a phenomenon is empirically visible but theoretically under-specified, as is the case with uneven AI value realization across firms. The aim is not to estimate a coefficient from a new dataset, but to synthesize empirical regularities into a coherent explanatory model that can guide later empirical testing.

The conceptual material was selected from five evidence streams. First, recent AI adoption and economy reports were used to establish the macroeconomic and enterprise context [1-4,9,10,25]. Second, causal or quasi-causal productivity studies were used to identify the conditions under which generative AI affects output, speed and quality [5-8]. Third, AI risk-management literature was used to specify the governance dimension of enterprise AI deployment [12]. Fourth, task-based labor economics and dynamic capability theory were used to connect firm-level redesign with labor-market adaptation [18,21-23]. Fifth, selected papers by Kwan Hong TAN were used to extend the model into the domains of sensemaking, stakeholder recognition, human-capital adaptation and temporal complementarity [13-17,19].

The modelling process followed four steps. Step 1 identified recurring empirical tensions: high individual task gains versus uneven enterprise value; rapid adoption versus low integration depth; automation efficiency versus augmentation learning; and governance necessity versus governance drag. Step 2 translated these tensions into constructs: automation-augmentation gain, learning spillover, decision velocity, scalability, institutional absorptive capacity, governance drag, risk externality and identity-coordination cost. Step 3 specified directional relationships among the constructs through a value equation and a frontier curve. Step 4 derived six propositions that can be tested using future surveys, field experiments, archival performance data, workflow analytics, or mixed-method case comparisons.

The paper therefore treats theory building as a disciplined research method. Model quality is assessed by parsimony, explanatory breadth, falsifiability and managerial usefulness. The model is parsimonious because it explains diverse AI outcomes through a limited set of interacting constructs. It has explanatory breadth because it accounts for both productivity successes and pilot failures. It is falsifiable because each proposition can be operationalized using measurable indicators such as cycle time, error rates, human validation frequency, governance latency, reskilling intensity and profit-and-loss impact. It is managerially useful because it converts abstract AI governance debates into an implementation pathway.

3. Results and discussion

3.1. The adoption-productivity paradox

The first result of the synthesis is the identification of an adoption-productivity paradox. AI adoption can spread rapidly while measurable business value remains concentrated. This resembles earlier information-technology productivity puzzles but differs in one crucial respect: generative AI is easy to access at the individual level but difficult to institutionalize at the organizational level. A worker can use a public chatbot within minutes; an enterprise must redesign data access, confidentiality rules, procurement, workflow integration, validation protocols, performance metrics and accountability structures.

Empirical evidence supports this distinction. Generative AI improved customer support productivity substantially, with the largest gains among novice and lower-skilled workers [5]. In professional writing tasks, AI reduced completion time and improved measured quality [6]. In software development experiments, coding assistants improved productivity under field conditions, but effects varied across workers and settings [7]. Consulting experiments showed a jagged frontier: AI improved performance on tasks within its capability range but could reduce correctness when users applied it beyond that range [8]. These findings imply that AI value is not a property of the tool alone. It is co-produced by task fit, user skill, validation design and organizational integration.

The paradox becomes sharper when firm-level reports are considered. Enterprise surveys highlight increasing AI use and growing interest in agentic systems [3]. Yet the GenAI Divide report found that many pilots generated no measurable return because they were insufficiently embedded in workflows, data systems and decision processes [4]. This is not evidence that AI lacks economic potential. Rather, it suggests that AI creates option value quickly but realized value only after complementary organizational investments are made.

3.2. Construct definitions

The PGF model contains eight constructs. The first five are value-enabling constructs and the final three are value-eroding constructs. The model deliberately separates task productivity from sustainable enterprise value because many AI initiatives fail during translation from individual efficiency to organizational performance.

Table 1 Core constructs of the AI productivity-governance frontier model

Construct	Definition	Expected managerial indicator
Automation-augmentation gain (A)	Immediate improvement in task speed, quality or cost through AI-supported automation or human augmentation.	Cycle-time reduction, output quality, cost per transaction, defect rate
Learning spillover (L)	Improvement in human capability as AI exposes workers to exemplars, feedback and procedural knowledge.	Skill progression, reduced novice-expert gap, improved training throughput
Decision velocity (D)	Increase in the speed and breadth of managerial sensing, analysis and response.	Decision lead time, scenario coverage, time from signal to action
Scalability (S)	Capacity to replicate AI-enabled workflows across units without linear increases in cost or risk.	Reuse rate, process standardization, deployment replication, marginal cost decline
Institutional absorptive capacity (I)	Ability of the organization and its environment to absorb AI through skills, culture, incentives, infrastructure and regulation.	AI literacy, data readiness, managerial support, governance maturity, labor-market support
Governance drag (G)	Delay, friction or cost introduced by approval, audit, documentation and assurance processes.	Approval latency, compliance burden, redundant checkpoints
Risk externality (R)	Expected cost of AI failures imposed on the firm, customers, workers or society.	Hallucination incidents, privacy breaches, bias harms, reputational loss
Identity-coordination cost (O)	Psychological and coordination costs created when workers experience role ambiguity, loss of status or unclear human-AI accountability.	Resistance, disengagement, duplicated work, escalation conflict, role insecurity

3.3. Formal value equation

The PGF model expresses sustainable AI value as a net organizational effect rather than a simple productivity coefficient. The proposed value equation is:

$$\Delta V_{AI} = [(A + L + D) \times S \times I] - (G + R + O)$$

where ΔV_{AI} is net sustainable AI value; A is automation-augmentation gain; L is learning spillover; D is decision velocity; S is scalability; I is institutional absorptive capacity; G is governance drag; R is risk externality; and O is identity-coordination cost.

The multiplicative term $S \times I$ is important. A firm may generate strong local gains from AI, but if workflows cannot be scaled or the institution cannot absorb the change, net value remains localized. Similarly, a firm with strong governance and culture but weak use-case selection may absorb AI safely without realizing strategic advantage. The subtractive term recognizes that governance, risk and identity costs are not accidental side effects. They are endogenous to AI transformation and must be managed as part of the value model [20].

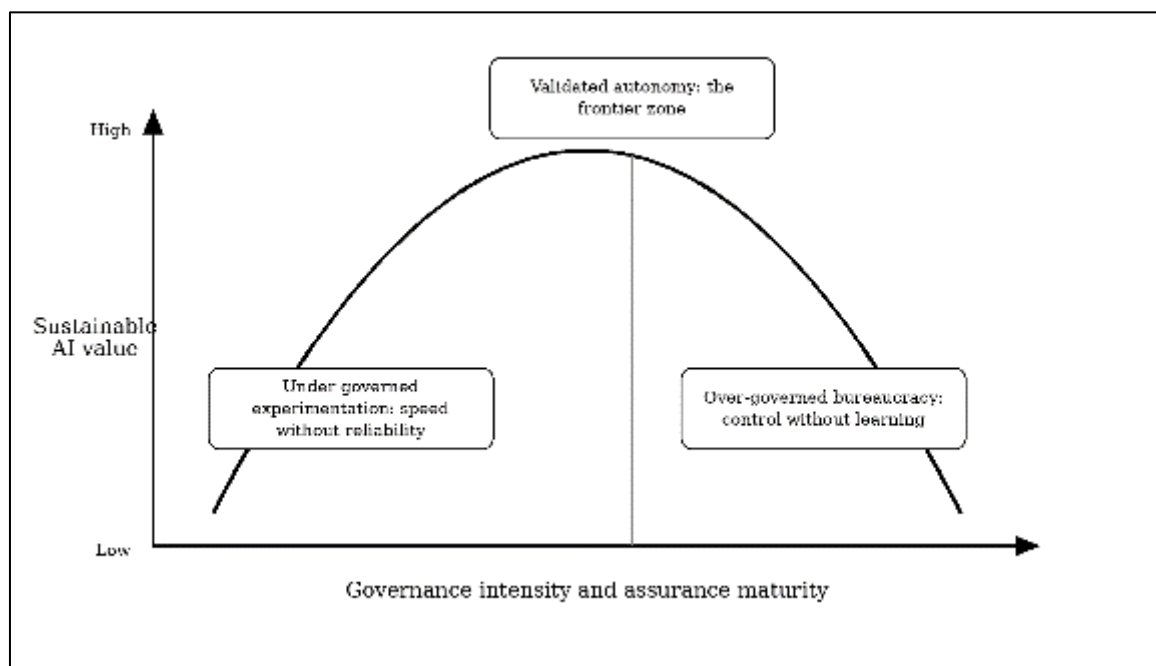


Figure 1 The AI productivity-governance frontier. Sustainable AI value rises when governance increases from under-controlled experimentation to validated autonomy, but falls when governance becomes bureaucratic overconstraint

3.4. The frontier logic

The frontier logic proposes that sustainable AI value is maximized neither at minimum governance nor at maximum governance. At low governance intensity, organizations may move quickly and produce visible prototypes, but they accumulate hidden risks: data leakage, hallucinated outputs, biased decisions, unclear accountability and employee distrust. These risks may not appear in pilot metrics but can destroy value when AI is scaled to customer-facing or high-consequence workflows.

At excessive governance intensity, organizations may avoid visible errors but suppress learning. If every AI experiment requires multiple approvals, static documentation and centralized review, workers will either abandon AI or use unsanctioned tools outside formal oversight. This creates shadow AI use, weakens organizational learning and leaves management without reliable evidence about where AI actually works. The PGF therefore defines the optimum as validated autonomy: clear use-case boundaries, risk-tiered assurance, human validation where needed, continuous monitoring, and enough freedom for workers to adapt AI to real workflows.

This interpretation helps reconcile the automation-augmentation paradox [24]. When AI is treated purely as automation, management tends to optimize for substitution and cost reduction. This can produce resistance and fragile

gains. When AI is treated purely as augmentation, management may understate accountability and risk. The frontier position integrates both: AI automates bounded tasks, augments human judgment in ambiguous contexts, and becomes subject to proportionate governance as autonomy increases.

3.5. Six propositions

- **Proposition 1: Task fit precedes technology fit.** AI initiatives will generate higher sustainable value when organizations select use cases based on task decomposability, error tolerance, data availability and verification feasibility rather than generic enthusiasm for AI capability.
- **Proposition 2: Learning spillovers moderate productivity gains.** The productivity impact of AI will be larger and more durable when AI use is designed to improve human capability rather than merely to accelerate output.
- **Proposition 3: Governance has an inverted-U relationship with AI value.** Insufficient governance increases risk externalities, while excessive governance increases drag; sustainable value peaks at proportionate, risk-tiered governance.
- **Proposition 4: Institutional absorptive capacity explains firm heterogeneity.** Organizations with higher AI literacy, data readiness, psychological safety, adaptive leadership and regulatory clarity will convert similar AI tools into higher net value.
- **Proposition 5: Identity-coordination costs mediate resistance.** Workers will be more likely to adopt AI productively when roles, accountability and career pathways are clarified, reducing ontological insecurity and status threat.
- **Proposition 6: Enterprise AI value is temporal, not instantaneous.** Short-term pilots should be evaluated alongside medium-term workflow redesign and long-term labor adaptation, because displacement and reinstatement effects unfold at different speeds.

3.6. Operating model

The PGF model can be translated into a seven-part operating model. The model begins with use-case fit because not all tasks are suitable for high-autonomy AI. It then moves to human-AI work design, governance architecture and institutional absorptive capacity. These mediating conditions determine whether task gains become productivity gain, economic resilience and sustainable value.

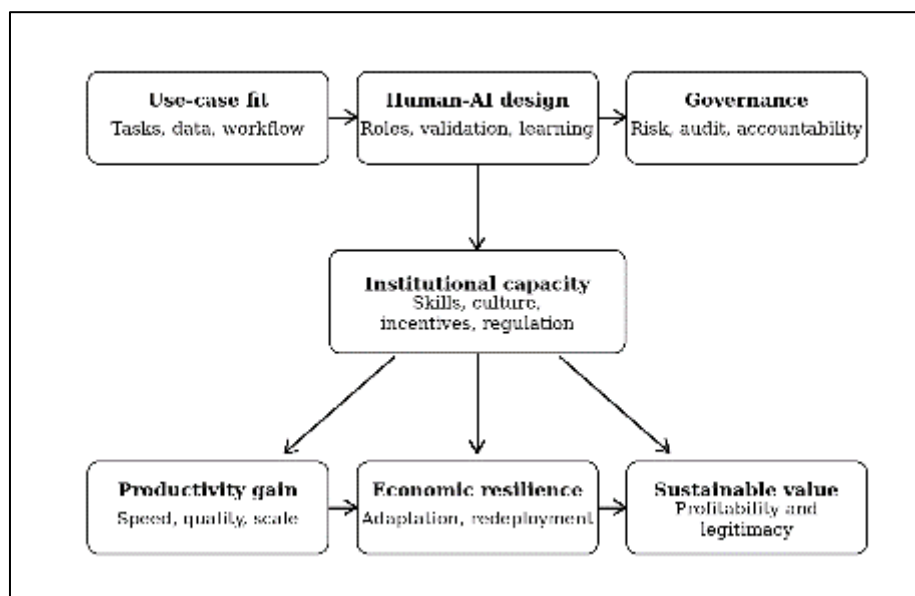


Figure 2 PGF operating model for enterprise AI value creation. The model connects use-case selection, human-AI design and governance architecture to productivity, resilience and sustainable value through institutional absorptive capacity

3.7. Maturity pathway

The PGF maturity pathway has four levels. The levels are not merely technological; they describe the organizational capacity to convert AI capability into accountable value.

Table 2 Maturity pathway for moving from AI experimentation to sustainable value

Maturity level	Dominant pattern	Risk if unmanaged	Recommended managerial move
Level 1: Ad hoc experimentation	Individuals use AI informally for drafting, search or ideation.	Shadow AI, data leakage, uneven quality, no learning record.	Create basic acceptable-use rules and identify high-value use cases.
Level 2: Assisted workflows	Teams embed AI into bounded tasks with human checking.	Local gains remain disconnected from performance metrics.	Measure speed, quality and error outcomes; codify reusable workflows.
Level 3: Validated autonomy	AI performs structured workflow components with risk-tiered oversight.	Governance may become too heavy or too narrow.	Use proportional assurance, monitor drift and clarify accountability.
Level 4: Adaptive AI-form capability	AI, human expertise and governance become an integrated operating capability.	Identity costs, labor displacement and strategic dependency.	Invest in reskilling, role redesign, stakeholder governance and temporal transition planning.

3.8. Managerial and economic implications

For managers, the PGF model suggests that the first AI question should not be which tool to buy, but which organizational bottleneck is being redesigned. AI should be evaluated against business processes, not just model features. A technically impressive system that does not alter workflow, decision speed, customer experience or cost structure may create activity without value.

Second, governance should be designed as an accelerator of trustworthy scaling rather than a defensive brake. A risk-tiered model allows low-risk internal ideation to proceed quickly while imposing stronger assurance on high-consequence decisions. This aligns with AI risk-management guidance that treats trustworthiness as a managed organizational process rather than a one-time compliance statement [12].

Third, the model implies that AI training should move beyond prompt tips. Workers need role-specific judgment: when to delegate, when to verify, when to escalate, and when to refuse AI output. This is especially important because overconfidence and reduced critical effort can weaken the quality of AI-assisted decisions in knowledge work [11].

For economists, the PGF model suggests that AI productivity diffusion should be studied at multiple levels. Task experiments reveal local capability. Firm-level performance reveals integration quality. Labor-market outcomes reveal temporal adaptation. National productivity data reveal whether complementary investments diffuse widely enough to affect aggregate output. This multi-level interpretation is consistent with task-based accounts of automation but adds governance and identity as mechanisms that shape adoption quality [21,22].

For policymakers, the model implies that AI readiness is not only a matter of infrastructure. Digital skills, labor-market mobility, competition policy, data governance, public-sector capability and social protection all affect institutional absorptive capacity. Countries that encourage AI adoption without complementary reskilling and assurance systems may experience concentrated gains and uneven adjustment.

3.9. Testable research agenda

The PGF model generates a research agenda that can be tested empirically. Future studies can operationalize each construct using measurable indicators and examine whether the proposed relationships explain variance in AI value realization across firms, sectors and countries.

Table 3 Testable research agenda derived from the PGF model

Proposition	Possible empirical design	Indicative variables
P1: Task fit precedes technology fit	Field experiment or matched use-case comparison	Task ambiguity, verification cost, error tolerance, performance change
P2: Learning spillovers moderate gains	Longitudinal worker-level panel	Training hours, AI feedback frequency, novice-expert productivity gap
P3: Governance has inverted-U effect	Cross-firm survey with performance linkage	Governance latency, assurance tiering, AI incident rate, value realization
P4: Absorptive capacity explains heterogeneity	Sectoral comparison or structural equation model	AI literacy, data readiness, leadership support, workflow modularity
P5: Identity costs mediate resistance	Mixed-method organizational case study	Role clarity, psychological safety, adoption frequency, resistance narratives
P6: AI value is temporal	Three-wave panel or difference-in-differences design	Pilot value, workflow redesign, job redeployment, P&L impact

Limitations

This paper is a theoretical research article and does not claim to provide new survey or experimental estimates. Its contribution lies in model development, construct integration and proposition generation. The model should therefore be treated as a structured hypothesis system rather than a validated predictive instrument.

A second limitation is that the model abstracts from sector-specific regulatory differences. AI deployment in finance, healthcare, education, manufacturing and public administration faces different risk thresholds and accountability regimes. Future research should calibrate the frontier curve by sector.

A third limitation is that the model focuses on enterprise value and institutional adaptation. It does not fully model broader societal externalities such as energy consumption, geopolitical AI sovereignty, market concentration or cultural impacts. These factors can be integrated in later versions by expanding the risk externality and institutional absorptive capacity constructs.

4. Conclusion

Artificial intelligence creates value only when capability becomes organized, governed and absorbed. The AI productivity-governance frontier explains why high technical capability and rapid adoption do not automatically produce sustainable business value. AI gains are amplified by automation-augmentation effects, learning spillovers, decision velocity, scalability and institutional absorptive capacity; they are reduced by governance drag, risk externalities and identity-coordination costs. The central implication is that firms should not choose between speed and governance. They should design validated autonomy: enough freedom for experimentation and learning, enough assurance for trustworthy scaling, and enough human-centered redesign to preserve agency, expertise and accountability. In this sense, the future of enterprise AI is not merely artificial intelligence deployment, but the design of intelligent institutions capable of learning with machines.

Compliance with ethical standards

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Disclosure of conflict of interest

Kwan Hong TAN declares that there are no financial or non-financial conflicts of interest in connection with this paper.

Statement of ethical approval

The present research work does not contain any studies performed on animals or human subjects by the author

Statement of informed consent

Not applicable. This study does not involve individual participants.

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References

- [1] Sajadieh S, Fattorini L, Perrault R, Gil Y, Parli V, Santarlaschi L, et al. Artificial Intelligence Index Report 2026. Stanford, CA: Stanford Institute for Human-Centered Artificial Intelligence; 2026.
- [2] OECD/BCG/INSEAD. The adoption of artificial intelligence in firms: New evidence for policymaking. Paris: OECD Publishing; 2025. doi:10.1787/f9ef33c3-en.
- [3] Singla A, Sukharevsky A, Yee L, Chui M, Hall B, Balakrishnan T. The state of AI: How organizations are rewiring to capture value. New York: McKinsey and Company; 2025.
- [4] MIT NANDA. The GenAI Divide: State of AI in Business 2025. Cambridge, MA: Massachusetts Institute of Technology; 2025.
- [5] Brynjolfsson E, Li D, Raymond LR. Generative AI at Work. NBER Working Paper No. 31161. Cambridge, MA: National Bureau of Economic Research; 2023.
- [6] Noy S, Zhang W. Experimental evidence on the productivity effects of generative artificial intelligence. *Science*. 2023;381(6654):187-192.
- [7] Cui KZ, Demirer M, Jaffe S, Musolff L, Peng S, Salz T. The effects of generative AI on high-skilled work: Evidence from three field experiments with software developers. *Management Science*. 2026;0(0). doi:10.1287/mnsc.2025.00535.
- [8] Dell'Acqua F, McFowland E, Mollick ER, Lifshitz-Assaf H, Kellogg KC, Rajendran S, et al. Navigating the jagged technological frontier: Field experimental evidence of the effects of AI on knowledge worker productivity and quality. *Organization Science*. 2026. doi:10.1287/orsc.2025.21838.
- [9] Bick A, Blandin A, Deming DJ. The Rapid Adoption of Generative AI. NBER Working Paper No. 32966. Cambridge, MA: National Bureau of Economic Research; 2024.
- [10] Cazzaniga M, Jaumotte F, Li L, Melina G, Panton AJ, Pizzinelli C, et al. Gen-AI: Artificial Intelligence and the Future of Work. IMF Staff Discussion Note SDN/2024/001. Washington, DC: International Monetary Fund; 2024.
- [11] Lee HPH, Sarkar A, Tankelevitch L, Drosos I, Rintel S, Banks R, et al. The impact of generative AI on critical thinking. Microsoft Research; 2025.
- [12] National Institute of Standards and Technology. Artificial Intelligence Risk Management Framework (AI RMF 1.0). NIST AI 100-1. Gaithersburg, MD: NIST; 2023.
- [13] Tan KH. Beyond automation: Sensemaking, ontological insecurity, and the emergence of the AI-form organisation in the digital era. ResearchGate; 2026. doi:10.5281/zenodo.20069532.
- [14] Tan KH. Artificial Intelligence as Stakeholder: A Novel Framework for Ethical Recognition in Value-Creation Ecosystems. ResearchGate; 2025.
- [15] Tan KH. The Temporal Displacement-Adaptation Equilibrium: A Novel Framework for Understanding AI's Impact on Global Employment Markets. ResearchGate; 2025. doi:10.13140/RG.2.2.10642.98240.

- [16] Tan KH. The Paradox of Technological Displacement: A Novel Framework for Understanding AI and Automation's Impact on Human Capital Development and Labor Market Transformation. ResearchGate; 2025. doi:10.13140/RG.2.2.12851.54569.
- [17] Tan KH. Temporal Complementarity in Economic Transition: Reconciling Efficiency and Equity Through AI-Driven Automation and Climate Policy Integration. ResearchGate; 2025.
- [18] Teece DJ. Explicating dynamic capabilities: The nature and microfoundations of sustainable enterprise performance. *Strategic Management Journal*. 2007;28(13):1319-1350.
- [19] Weick KE. Sensemaking in organizations. Thousand Oaks (CA): Sage Publications; 1995. 231 p.
- [20] Williamson OE. The economic institutions of capitalism: Firms, markets, relational contracting. New York: Free Press; 1985. 450 p.
- [21] Acemoglu D, Restrepo P. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*. 2019;33(2):3-30.
- [22] Autor DH. Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*. 2015;29(3):3-30.
- [23] Eloundou T, Manning S, Mishkin P, Rock D. GPTs are GPTs: An early look at the labor market impact potential of large language models. *arXiv*. 2023.
- [24] Raisch S, Krakowski S. Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*. 2021;46(1):192-210.
- [25] OECD. The Effects of Generative AI on Productivity, Innovation and Entrepreneurship. Paris: OECD Publishing; 2025.