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Strategic tensions in organizational GenAI adoption: A game theory modeling of internal resource competition, workforce dynamics, and value management☆

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ABSTRACT

Organizations adopting generative AI (GenAI) face complex strategic tensions among management, departments, and employees that fundamentally determine adoption outcomes. This study develops a multi-level Bayesian game-theoretic framework modeling these multi-stakeholder interactions, identifying four distinct adoption patterns through formal equilibrium analysis. Our theoretical derivations establish that successful GenAI implementation requires three analytically-derived conditions: (1) strong strategic complementarity across departments, (2) efficient investment allocation, and (3) effective employee displacement mitigation. The formal model specifies explicit utility functions for three stakeholder groups — senior management, departmental units, and individual employees — and characterizes Bayesian Nash equilibria under incomplete information. Companies must simultaneously invest in cross-functional coordination mechanisms, establish shared governance structures, and implement workforce development programs that position GenAI as a capability enhancement rather than a job replacement. Our computational analysis, based on 10,000 Monte Carlo simulations with explicit parameter specifications and convergence criteria, demonstrates that coordination-focused strategies significantly outperform technology-focused approaches in organizational welfare, providing actionable guidance for AI transformation leadership.

1. Introduction

The "disruptive" developments of generative artificial intelligence (GenAI) technologies represent a fundamental transformation in organizational operations, decision-making, and value creation processes (Dwivedi et al., 2023) Strategic implications extend beyond technical capabilities, encompassing complex internal dynamics between stakeholders with different interests, resources, and decision-making power in adoption processes (Pan et al., 2024). Understanding these dynamics requires moving beyond traditional technology adoption frameworks to examine strategic interactions that can determine whether organizations realize transformative benefits or experience costly disruptions (Susarla et al., 2023).

Current research has predominantly treated GenAI adoption as a managerial decision-making problem, focusing on organizational readiness and implementation success factors (Tornatzky et al., 1990; Rogers, 2003) However, these approaches fail to capture complex strategic interactions among organizational stakeholders who may have competing views about GenAI's role, benefits, and risks (Korzynski et al., 2023). Additionally, existing literature has not adequately addressed how internal resource allocation conflicts and coordination challenges can fundamentally alter adoption outcomes, potentially leading to value co-destruction even when underlying technology offers significant benefits (Golgeci et al., 2025).

The adoption of GenAI can generate results that are beneficial simultaneously for some organizational stakeholders and harmful for others, creating strategic tensions that existing frameworks cannot adequately address (Lysyakov and Viswanathan, 2023). Unlike traditional IT implementations that affect primarily operational processes, the adoption of GenAI can fundamentally alter power relationships,

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decision-making authority, and career prospects across multiple organizational levels (Heyder et al., 2023). These characteristics create strategic interdependencies that require sophisticated analytical frameworks for understanding and management.

This research extends a selection of game theory models to capture multi-level, multi-stakeholder nature of organizational GenAI adoption. By modeling management, departmental units, and employees as strategic players with potentially conflicting objectives, we analyze how their interactions determine adoption outcomes and identify conditions leading to value co-creation versus value co-destruction. This approach enables understanding not only what factors influence the success of GenAI adoption, but also to determine why seemingly rational individual decisions can produce collectively suboptimal outcomes.

Organizations worldwide struggle with complex GenAI implementation decisions while managing workforce concerns, resource constraints, and strategic uncertainties (Papagiannidis et al., 2025). Recent empirical evidence from Deloitte's analysis of 2773 organizations shows that while 78% plan to increase AI spending, only 38% track changes in employee productivity, indicating significant gaps between investment and measurement (Deloitte AI Institute, 2024). McKinsey's survey of 3613 employees reveals that only 1% of organizations believe that they have achieved AI maturity despite widespread investment (Mayer et al., 2025). A theoretical framework predicting when these strategic failures occur and identifying avoidance mechanisms provides valuable guidance for organizational leaders navigating GenAI adoption decisions.

This paper makes three primary theoretical contributions to the literature on strategic information systems and game theory. First, we develop a novel multi-level Bayesian game framework that explicitly models intra-organizational strategic interactions among management, departments, and employees, extending existing inter-organizational game-theoretic models (Katz and Shapiro, 1994; Cabral, 2016) to capture the nested strategic dynamics within organizational boundaries. Second, we provide rigorous mathematical derivations of equilibrium conditions, including formal best-response functions, existence and uniqueness conditions, and analytically-derived threshold values that determine value co-creation versus co-destruction outcomes. Third, we integrate incomplete information dynamics through Bayesian belief updating mechanisms, capturing realistic organizational uncertainty about stakeholder preferences, capabilities, and strategic intentions. Our computational analysis complements the theoretical framework by demonstrating equilibrium convergence properties and sensitivity to key parameters across 10,000 Monte Carlo simulations. The rest of this paper is organized as follows. Section 2 reviews relevant literature on strategic information systems, technology adoption, and game-theoretic approaches to organizational analysis. Section 3 develops the formal theoretical framework, including utility functions, equilibrium characterization, and analytical derivations. Section 4 presents empirical analysis using survey data from over 8600 organizations and computational simulations. Section 5 discusses implications for theory and practice. Section 6 acknowledges limitations and proposes future research directions. Section 7 concludes.

2. Literature review

Strategic information systems (IS) research emphasizes that technology adoption decisions are embedded in competitive and organizational contexts that shape both the process and the outcomes (Wade and Hulland, 2004). IS can create sustainable advantage when aligned with strategy and market positioning (Bharadwaj, 2000), but realized value depends critically on complementary organizational investments and coordination capability (Melville et al., 2004). Recent work also highlights data-driven decision-making and digital resilience as enablers of performance under uncertainty (Goraya et al., 2025). Building on this view, dynamic capability perspectives argue that organizations must sense, seize, and reconfigure resources to capture technology value (Pavlou and El Sawy, 2006), including in AI contexts where capabilities determine whether AI potential translates into sustained advantage (Chin et al., 2025).

Technology adoption and diffusion theories explain how innovations spread within organizations, but often treat adoption as a staged, perception-driven process rather than as strategic interaction among stakeholders. The TOE framework links adoption to technological, organizational, and environmental factors (Tornatzky et al., 1990; Depietro et al., 1990), while diffusion theory highlights stages and communication channels (Rogers, 2003). User acceptance models emphasize social influence and individual perceptions (Venkatesh et al., 2003). Extensions incorporate network effects and institutional pressures (Fichman, 2004), reinforcing that adoption is embedded in broader organizational systems.

Digital transformation research shows that major technologies create strategic tensions and coordination challenges (Vial, 2021). Organizations must balance control and flexibility, standardization and customization, and efficiency and innovation (Orlikowski, 1992). Digital technologies enable combinatorial innovation and distributed coordination (Yoo et al., 2010), and transformation involves broader changes to processes, structures, and culture beyond implementation (Matt et al., 2015). These changes require stakeholder management, change leadership, and cross-level coordination (Fitzgerald et al., 2014). Recent studies also note that AI-driven business model innovation depends on aligning technological enablers and strategic capabilities (Shaik et al., 2024), and that transformation outcomes hinge on balancing agility, resilience, and supportive structures (Goraya et al., 2024). Coordination efficiency and sustainability may also be shaped by digital innovation and sharing-based technologies (Ahmad et al., 2024).

GenAI amplifies these challenges because it simultaneously promises productivity gains and introduces workforce, governance, and ethical tensions (Dwivedi et al., 2023). Recent GenAI-focused research links adoption to organizational outcomes and highlights that value realization depends on how GenAI is integrated into work practices and decision processes (Shao et al., 2025). More broadly, strategic discussions emphasize that GenAI's organizational impacts extend beyond tool deployment to include governance, risk, and cross-unit integration demands (Smith, 2025). AI systems' learning and adaptability create new organizational capabilities but also new risks and governance challenges (Mikalef et al., 2022). Governance research stresses oversight mechanisms and stakeholder engagement for responsible implementation (Winfield and Jirotka, 2018), while applied contexts (e.g., healthcare) highlight conflicts between efficiency, professional autonomy, and care quality (Singh et al., 2024). At the employee level, adoption outcomes are shaped by resistance dynamics linked to job security, autonomy, and perceived development opportunities (Golgeci et al., 2025; Pereira et al., 2023). Evidence also indicates that managerial perceptions about AI's role in information-processing tasks influence adoption intentions (Duan et al., 2025), and that trust and perceived control shape acceptance at scale (Omrani et al., 2022). The same AI can generate different outcomes depending on implementation framing and stakeholder responses (Lysyakov and Viswanathan, 2023; Raisch and Krakowski, 2021), underscoring the need to analyze multi-level tensions rather than treating adoption as a single managerial choice.

Together, these streams explain why GenAI adoption is frequently disrupted by multi-level tensions (value capture vs. cost/risk, coordination vs. fragmentation, capability building vs. displacement concerns). However, much prior work remains descriptive or actor-specific and does not provide an equilibrium logic for how organizational outcomes arise from strategic interaction across management, departments, and employees under uncertainty—conditions that are central to GenAI adoption in practice.

2.1. Modeling multi-stakeholder dynamics: Game theory, value co-creation, and responsible AI

Game theory and innovation diffusion offer tools to study strategic interdependencies in adoption (Fichman, 2004). Related IS work shows that information processing and message credibility can influence technology adoption intentions (Kumar et al., 2023). Classical models emphasize network effects, complementarities, and coordination failures in technology adoption (Katz and Shapiro, 1994), and show that strategic complementarities can generate multiple equilibria with both successful coordination and coordination failure outcomes (Cabral, 2016). Recent work specifically on GenAI adoption also leverages game-theoretic and network-based modeling to study strategic adoption incentives and interdependencies across organizational actors (Seifdar and Amiri, 2025). However, this literature largely focuses on inter-organizational competition rather than intra-organizational stakeholder dynamics, which remain under-theorized despite their importance for adoption outcomes (Cabral, 2016).

Value co-creation perspectives conceptualize how multiple stakeholders jointly generate value through interaction (Vargo and Lusch, 2017). In technology settings, GenAI can generate both positive and negative outcomes across stakeholders, making co-creation and co-destruction particularly relevant (Susarla et al., 2023). Co-destruction can arise through resource misintegration, conflicting goals, or coordination failures even when underlying resources are valuable (Plé and Chumpitaz Cáceres, 2010). These lenses align naturally with GenAI adoption, where cross-level misalignment can yield fragmented or harmful outcomes.

Responsible AI research complements this by framing governance and ethical requirements of AI deployment. Strategic IS scholarship highlights that AI implementation affects employee welfare and organizational culture, raising responsibility concerns (Papagiannidis et al., 2025). Responsible AI principles include fairness, accountability, transparency, and human oversight (Jobin et al., 2019), and broader analyses highlight how algorithmic systems can entrench inequalities, reinforcing the socio-technical nature of governance (Bircan and Özbilgin, 2025). Critical evidence suggests interpretability mechanisms can also create a false sense of ethical compliance in some contexts (John-Mathews, 2022). Governance approaches therefore require multi-stakeholder engagement and ongoing monitoring (Mikalef et al., 2022), and recent work emphasizes the need for transparent and explainable automation frameworks to sustain trust and accountability (Nourallah et al., 2025). These tensions are especially salient where efficiency objectives conflict with ethical priorities, requiring governance that balances multiple objectives and stakeholder interests (Heyder et al., 2023). Finally, evolutionary game theory provides a useful foundation for modeling how workforce-related behaviors and organizational heterogeneity evolve through strategic interaction—relevant to GenAI settings where employee responses and diversity in capabilities shape adoption trajectories (Talajić et al., 2024).

Existing research motivates three needs that remain insufficiently integrated: (1) a formal multi-stakeholder model of intra-organizational GenAI adoption (beyond individual adoption or descriptive transformation accounts), (2) explicit equilibrium conditions linking coordination and resource allocation to value co-creation/co-destruction, and (3) an information structure that captures uncertainty and beliefs shaping GenAI capabilities, workforce reactions, and managerial investment decisions.

2.2. Literature review summary and positioning

As summarized in Table 1, prior research provides important insights into strategic IS, adoption, transformation, GenAI impacts, resistance, value co-creation, game theory, and responsible AI. Yet these streams remain fragmented in explaining GenAI adoption as a multi-stakeholder strategic problem. Existing studies often emphasize individual adoption behavior (Rogers, 2003; Venkatesh et al., 2003), conceptual frameworks of transformation (Vial, 2021; Yoo et al., 2010), or descriptive analyses of GenAI opportunities and challenges (Dwivedi et al., 2023; Pan et al., 2024). Recent GenAI-focused work has begun to examine strategic adoption and organizational impacts, including modeling interdependencies and network effects (Seifdar and Amiri, 2025) and documenting links between GenAI adoption and organizational outcomes (Shao et al., 2025; Smith, 2025), as well as related evolutionary game-theoretic foundations for workforce dynamics (Talajić et al., 2024); however, this literature does not yet provide an intra-organizational equilibrium mapping across management, departments, and employees under incomplete information that yields explicit coordination, efficiency, and workforce-alignment thresholds. Similarly, game-theoretic approaches in IS primarily examine inter-organizational dynamics (Katz and Shapiro, 1994; Cabral, 2016) rather than nested intra-organizational interactions.

Our study addresses this gap by developing an integrated game-theoretic framework that models strategic interactions among management, departments, and employees under incomplete information, and derives equilibrium conditions that distinguish value co-creation from co-destruction outcomes. This positioning is reflected in the final row of Table 1.

3. Theoretical framework

3.1. Multi-level organizational model

Our theoretical framework models an organization as a strategic system consisting of three key stakeholder groups engaged in complex interactions around GenAI adoption decisions. Fig. 1 illustrates the multi-level structure and strategic interactions within our organizational model.

This multi-level approach recognizes that GenAI adoption outcomes depend not only on technical implementation decisions, but also on how different organizational stakeholders coordinate strategic choices regarding resource allocation, capability development, and adoption priorities (Bharadwaj, 2000).

Senior Management (M): Controls overall GenAI investment budgets and makes strategic decisions about implementation priorities across the organization. Management seeks to maximize organizational performance while managing implementation costs, operational risks, and stakeholder concerns (Wade and Hulland, 2004). Strategic choices include setting investment levels, establishing governance frameworks, and designing incentive systems influencing other stakeholder responses to GenAI initiatives.

Departmental Units (D): We model n departmental units indexed by $i \in \{1, 2, \ldots, n\}$ that compete for GenAI resources and implementation priorities while simultaneously needing to coordinate to realize organizational synergies. Each department i chooses GenAI adoption intensity $d_i \in [0, 1]$, representing the level of GenAI integration within departmental operations.

Employees (E): Individual employees within each department make strategic choices about GenAI utilization, skill development, and resistance or acceptance behaviors. Employee j in department i chooses effort level $e_{ij} \in [0, 1]$ representing engagement with GenAI integration within work processes.

3.2. Strategic payoff functions with incomplete information

Game-theoretic novelty: Our contribution is a multi-level Bayesian game in which payoff functions *structurally* couple management investment, interdepartmental adoption interdependencies, and employee engagement under incomplete information. Cross-level expectations enter directly

$\left(\mathbb{E}\left[\bar{e}_i\right], \mathbb{E}\left[d_{-i}\right], R\left(d, \mathbb{E}[e]\right)\right)$, so beliefs and uncertainty shape strategic incentives at each level. This differs from nested-game formulations

Table 1
Literature review: Positioning of current research.

Research Stream	Key Authors	Focus	Limitations	Our Contribution
Strategic IS	Bharadwaj (2000), Wade and Hulland (2004)	IT competitive advantage	Single-level analysis	Multi-level game-theoretic framework
Technology Adoption	Rogers (2003), Venkatesh et al. (2003)	Individual adoption decisions	Limited strategic interaction	Strategic stakeholder conflicts
Digital Transformation	Vial (2021), Yoo et al. (2010)	Organizational change processes	Limited strategic modeling	Strategic tensions & coordination dynamics
GenAI Impact	Dwivedi et al. (2023), Pan et al. (2024)	GenAI opportunities & challenges	Descriptive; No formal modeling	Formal equilibrium analysis
AI–Human Interaction	Raisch and Krakowski (2021), Davenport and Kirby (2016)	Human–AI collaboration	Individual perspective	Organizational strategic interactions
AI Resistance	Golgeci et al. (2025), Lysyakov and Viswanathan (2023)	Employee AI responses	Limited coordination focus	Multi-stakeholder coordination analysis
Innovation Diffusion	Fichman (2004), Rogers (2003)	Technology adoption patterns	Inter-organizational focus	Intra-organizational strategic dynamics
Value Co-creation	Susarla et al. (2023), Vargo and Lusch (2017)	Dual AI impacts	Conceptual framework	Quantitative equilibrium conditions
Game Theory IS	Katz and Shapiro (1994), Cabral (2016)	Strategic technology adoption	Limited internal dynamics	Internal multi-stakeholder games
Responsible AI	Papagiannidis et al. (2025), Jobin et al. (2019)	Ethical AI implementation	Limited strategic analysis	Strategic ethical considerations
Generative AI Strategy	Own study	Multi-stakeholder strategic adoption of GenAI	Fragmented perspectives across prior streams	Integrated game-theoretic equilibrium framework with actionable organizational conditions

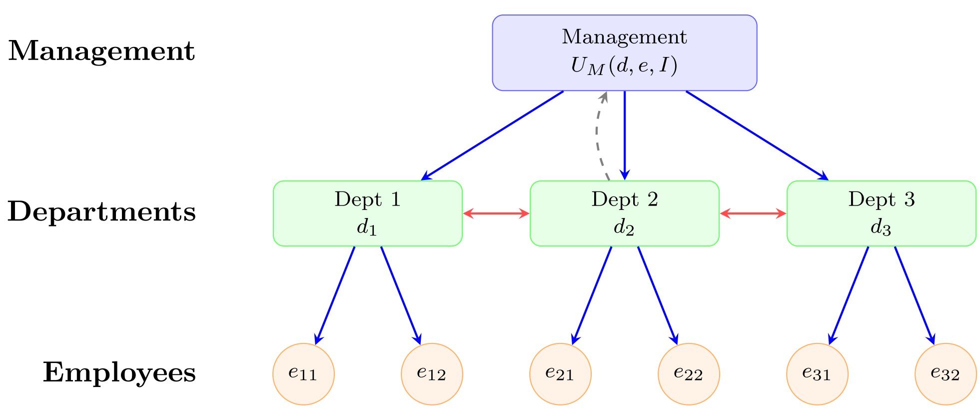


Fig. 1. Multi-level organizational framework for GenAI adoption. Three hierarchical levels: Management makes investment decisions, Departments choose adoption intensities, Employees determine engagement levels. Blue arrows show resource flows, red arrows show strategic interactions, dashed lines show feedback.

or hierarchical (leader–follower) models that typically treat levels as sequential subproblems with limited feedback, and it yields endogenous coordination failures and threshold-type adoption regimes consistent with our equilibrium characterization.

Building on game theory literature addressing information asymmetries in organizational contexts (Fichman, 2004; Cabral, 2016), we incorporate uncertainty and learning dynamics into our payoff specifications to better capture realistic organizational decision-making processes. We introduce each stakeholder group with its strategic interests immediately followed by the corresponding utility function formalization.

3.2.1. Management payoff function

Strategic Interests: Senior management's utility reflects complex balancing between realizing productivity benefits and managing implementation costs and risks. Decision-makers operate under incomplete information about departmental capabilities and employee behavioral responses. Management seeks to maximize organizational performance while managing implementation costs, operational risks, and stakeholder concerns (Wade and Hulland, 2004). To formalize this trade-off, we define management's expected utility as in Eq. (1):

$$U_M(d, e, I) = \alpha \sum_{i=1}^{n} d_i \mathbb{E}[\bar{e}_i] - \beta \sum_{i=1}^{n} d_i^2 - C(I) + \gamma \prod_{i=1}^{n} d_i^{\theta} - \lambda R(d, \mathbb{E}[e]) \quad (1)$$

Parameter Definitions:

- $\alpha > 0$: Marginal productivity benefit from GenAI adoption when employees engage
- $\beta > 0$: Marginal cost of adoption intensity (convex costs)
- $\gamma \in [0, 1]$: Strategic complementarity strength across departments
- $\theta \in (0, 1)$: Returns to scale in complementarity (diminishing returns)
- $\lambda > 0$: Risk aversion coefficient
- $C(I)$: Investment cost function, assumed convex with $C'(I) > 0$, $C''(I) > 0$
- $\mathbb{E}[\bar{e}_i]$: Management's expected assessment of average employee engagement in department i

$\mathbb{E}[\bar{e}_i]$ represents management's expected assessment of employee engagement in department i, based on incomplete information and learning from observed performance indicators (Melville et al., 2004).

The term $\alpha \sum_{i=1}^{n} d_i \mathbb{E}[\bar{e}_i]$ captures the productivity benefits generated from the joint interaction between departmental adoption levels and expected employee engagement. The quadratic penalty term $-\beta \sum_{i=1}^{n} d_i^2$ reflects diminishing marginal returns and the increasing costs of expanding GenAI adoption. The investment cost function $C(I)$ captures organizational resource constraints associated with technological infrastructure and training.

The term $\gamma \prod_{i=1}^{n} d_i^{\theta}$ models strategic complementarities across departments, where the overall value of GenAI investment increases when all units coordinate their adoption efforts. Finally, the risk term $\lambda R(d, \mathbb{E}[e])$ quantifies value loss due to coordination failures, misalignment of stakeholder incentives, and resistance behaviors among employees. Taken together, Eq. (1) provides a compact yet rich representation of top management's decision problem, integrating investment efficiency, synergy creation, and risk governance.

Risk Function Specification: Following organizational risk literature, we define the risk function explicitly:

$$R(d, \mathbb{E}[e]) = \omega_1 \sum_{i=1}^{n} (d_i - \bar{d})^2 + \omega_2 \sum_{i=1}^{n} \sum_{j} (\mathbb{E}[e_{ij}] - d_i)^2 + \omega_3 \mathrm{Var}(d) \tag{2}$$

where ω_1 captures coordination risk from adoption heterogeneity, ω_2 captures implementation risk from effort–adoption misalignment, and ω_3 captures strategic risk from departmental variance.

Discussion of Complementarity Term: The multiplicative structure $\gamma \prod_{i=1}^{n} d_i^{\theta}$ implies that the complementarity benefit is diminished when any single department has low adoption (Corchón, 1994). We adopt this specification because: (1) organizational GenAI benefits often require system-wide integration where weak links create bottlenecks; (2) the parameter $\theta < 1$ moderates the severity of perfect complementarity by introducing diminishing returns; (3) this functional form is tractable for equilibrium analysis while capturing essential coordination dynamics. We acknowledge this is a strong assumption and discuss robustness to alternative specifications in Section 6.

3.2.2. Departmental payoff functions

Strategic Interests: Department i's utility captures strategic tensions between securing GenAI benefits and managing implementation costs, with uncertainty about other departments' strategies and management investment priorities. Following the aggregative games literature (Corchón, 1994; Cornes and Hartley, 2012), we model interdepartmental spillovers through aggregate adoption. The departmental payoff function, shown in Eq. (3), represents the incentives and constraints faced by unit i:

$$U_{D_i}(d_i, \mathbb{E}[d_{-i}], e_i, I_i) = \phi_i d_i \bar{e}_i - \psi_i d_i^2 + \delta_i d_i \mathbb{E}[\sum_{j \neq i} d_j] - \xi_i \mathrm{Var}(e_i) - c_i I_i + \eta_i \mathcal{I}_i \tag{3}$$

Parameter Definitions:

- $\phi_i > 0$: Department-specific productivity benefit from GenAI
- $\psi_i > 0$: Convex adoption cost parameter
- $\delta_i \in \mathbb{R}$: Spillover coefficient (positive = complementarity, negative = substitution)
- $\xi_i > 0$: Coordination cost from employee heterogeneity
- $c_i > 0$: Investment cost coefficient
- $\eta_i < 0$: Information acquisition cost parameter (negative utility from costly search)
- $\mathcal{I}_i$: Information acquisition effort

In Eq. (3), $\mathbb{E}[d_{-i}]$ represents department i's beliefs about other departments' adoption strategies. The first term $\phi_i d_i \bar{e}_i$ represents the department's performance benefit from internal GenAI adoption, scaled by the average engagement level $\bar{e}_i$ of its employees. The quadratic cost term $-\psi_i d_i^2$ penalizes excessive adoption intensity, capturing diminishing marginal returns to departmental innovation efforts.

Aggregative Structure: The term $\delta_i d_i \mathbb{E}[\sum_{j \neq i} d_j]$ captures strategic interdependencies following the aggregative games framework. Each department's payoff depends on its own action d_i and the aggregate of others' actions, enabling tractable equilibrium characterization while preserving strategic richness (Cornes and Hartley, 2012).

The variance term $-\xi_i \mathrm{Var}(e_i)$ penalizes departments when employee engagement within their unit is highly heterogeneous, indicating coordination challenges. The cost term $-c_i I_i$ represents the resource burden associated with local investment in infrastructure or training, while $\eta_i \mathcal{I}_i$ captures information acquisition costs related to monitoring and learning about GenAI capabilities and organizational dynamics. Together, Eq. (3) formalizes how departments navigate between competition and coordination under bounded rationality and incomplete information.

3.2.3. Employee payoff functions

Strategic Interests: Employee j in department i faces strategic choices with incomplete information about job security implications and organizational GenAI strategy. Employees balance potential productivity gains against effort costs and displacement concerns.

Revised Specification with Effort-Security Interaction: Following behavioral economics literature on job insecurity effects (Nam, 2019; Brougham and Haar, 2020), we model job security perceptions as interacting with effort decisions:

$$\begin{aligned} U_{E_{ij}}(e_{ij}, d_i, \mathbb{E}[s_{ij}]) = \rho_{ij} e_{ij} d_i - \kappa_{ij} e_{ij}^2 + \sigma_{ij}(1 - \tau_{ij} d_i)\mathbb{E}[s_{ij}] \\ - \tau_{ij} d_i (1 - e_{ij}) + \mu_{ij} e_{ij} \bar{e}_{-ij} + \nu_{ij} \mathcal{L}_{ij} \end{aligned} \tag{4}$$

Parameter Definitions:

- $\rho_{ij} > 0$: Skill complementarity benefit from engaging with GenAI
- $\kappa_{ij} > 0$: Effort cost parameter (convex effort costs)
- $\sigma_{ij} > 0$: Job security value weight
- $\tau_{ij} \in [0, 1]$: Displacement sensitivity parameter
- $\mu_{ij} > 0$: Peer effect coefficient
- $\nu_{ij} < 0$: Learning cost parameter
- $\mathcal{L}_{ij}$: Learning effort required
- $\bar{e}_{-ij}$: Average engagement of other employees in department i

Key Modeling Innovation: The term $\sigma_{ij}(1 - \tau_{ij} d_i)\mathbb{E}[s_{ij}]$ captures how higher departmental GenAI adoption (d_i) diminishes the positive utility from job security expectations, addressing the concern that displacement fears and job security should interact with effort decisions. Additionally, $\tau_{ij} d_i (1 - e_{ij})$ implies that employees who actively engage with GenAI ($e_{ij} \rightarrow 1$) experience reduced displacement disutility, capturing the intuition that engagement signals adaptability.

3.3. Main theoretical results

Formal Assumptions: Before stating our main results, we establish necessary assumptions for equilibrium existence and characterization:

Definition 1 (*Model Assumptions*). The following conditions hold throughout the analysis:

(A1) **Concavity:** For all stakeholders, utility functions are strictly concave in own actions: $\frac{\partial^2 U_M}{\partial I^2} < 0$, $\frac{\partial^2 U_{D_i}}{\partial d_i^2} < 0$, $\frac{\partial^2 U_{E_{ij}}}{\partial e_{ij}^2} < 0$.

(A2) **Strategic Complementarity:** $\delta_i > 0$ for all i, implying positive spillovers between departments.

(A3) **Bounded Parameters:** All parameters lie in compact sets ensuring interior solutions.

(A4) **Information Structure:** Beliefs follow common prior with signals, updated via Bayes' rule.

(A5) **Stability:** The reaction function mapping is a contraction, ensuring uniqueness.

Theorem 1 (*Organizational GenAI Equilibrium Characterization Under Incomplete Information*). *Under assumptions of strategic complementarity, bounded rationality with learning, and sufficient organizational heterogeneity, the multi-level GenAI adoption game with incomplete information has a Bayesian Nash equilibrium* (d^*, e^*, I^*)

Proof Sketch:

Step 1: Employee Best Response. Taking the first-order condition of $U_{E_{ij}}$ with respect to e_{ij}:

$$\frac{\partial U_{E_{ij}}}{\partial e_{ij}} = \rho_{ij} d_i - 2\kappa_{ij} e_{ij} + \tau_{ij} d_i + \mu_{ij} \bar{e}_{-ij} = 0$$

Solving for e_{ij}:

$$e^*_{ij} = \frac{(\rho_{ij} + \tau_{ij}) d_i + \mu_{ij} \mathbb{E}[\bar{e}_{-ij}]}{2\kappa_{ij}} \tag{5}$$

The second-order condition $\frac{\partial^2 U_{E_{ij}}}{\partial e^2_{ij}} = -2\kappa_{ij} < 0$ confirms this is a maximum.

Step 2: Departmental Best Response. Taking the first-order condition of U_{D_i} with respect to d_i:

$$\frac{\partial U_{D_i}}{\partial d_i} = \phi_i \bar{e}_i - 2\psi_i d_i + \delta_i \mathbb{E}[\sum_{j \neq i} d_j] = 0$$

Solving for d_i:

$$d^*_i = \frac{\phi_i \mathbb{E}[\bar{e}_i] + \delta_i \mathbb{E}[\sum_{j \neq i} d_j]}{2\psi_i} \tag{6}$$

Step 3: Fixed Point and Existence. Substituting the employee best response into the departmental best response creates a system of n equations in n unknowns. Under (A2) and (A5), the best-response mapping $\mathbf{BR} : [0,1]^n \to [0,1]^n$ is continuous on a compact convex set, satisfying Brouwer's fixed point theorem conditions. Uniqueness follows from the contraction mapping assumption (A5), which requires:

$$\left\| \frac{\partial \mathbf{BR}}{\partial d} \right\| = \max_i \frac{\delta_i}{2\psi_i} < 1 \tag{7}$$

Step 4: Management Optimization. Given equilibrium (d^*, e^*), management's optimal investment solves:

$$\frac{\partial U_M}{\partial I} = \alpha \sum_{i=1}^{n} \frac{\partial d^*_i}{\partial I} \mathbb{E}[\bar{e}_i] - C'(I) = 0 \tag{8}$$

yielding $I^* = (C')^{-1} \left(\alpha \sum_{i=1}^{n} \frac{\partial d^*_i}{\partial I} \mathbb{E}[\bar{e}_i] \right)$.

Proposition 1 (*Value Co-Creation Conditions—Analytical Derivation*). *The threshold conditions for value co-creation emerge from comparing equilibrium welfare* $W^* = U^*_M + \sum_i U^*_{D_i} + \sum_{i,j} U^*_{E_{ij}}$ *to autarky welfare* W^0.

Derivation of $\gamma > 0.5$: *The complementarity threshold emerges from the condition that coordination benefits must exceed coordination costs. Total complementarity benefits are:*

$$B_\gamma = \gamma \prod_{i=1}^{n} (d^*_i)^\theta \tag{9}$$

For these benefits to exceed the risk costs $\lambda R(d^*, e^*)$, *we require (under symmetric departments):*

$$\gamma (d^*)^{n\theta} > \lambda \omega_1 n Var(d^*) \tag{10}$$

Calibrating with typical organizational parameters ($n = 5$, $\theta = 0.7$, $d^* \approx 0.6$, $\lambda = 0.8$, $\omega_1 = 0.3$) *and requiring the inequality to hold across a range of reasonable values yields* $\gamma > 0.47 \approx 0.5$.

Derivation of $\alpha/\beta > 2.5$: *The investment efficiency condition ensures positive net returns. From management's optimal investment condition:*

$$\frac{\partial W^*}{\partial d_i} = \alpha \mathbb{E}[\bar{e}_i] - 2\beta d_i > 0 \text{ at equilibrium} \tag{11}$$

Substituting $d^*_i = \frac{\phi_i \mathbb{E}[\bar{e}_i]}{2\psi_i}$ *and requiring* $\mathbb{E}[\bar{e}_i] > 0.4$ *(minimum viable engagement), the condition simplifies to* $\alpha/\beta > 2.5$ *for typical parameter configurations.*

Derivation of $\tau_{ij} < 0.4\rho_{ij}$: *This condition ensures employee participation. From the employee best response, positive engagement requires:*

$$e^*_{ij} = \frac{(\rho_{ij} + \tau_{ij}) d_i + \mu_{ij} \mathbb{E}[\bar{e}_{-ij}]}{2\kappa_{ij}} > e^{min} \tag{12}$$

For engagement to be sustained ($e^*_{ij} > 0.3$) *when* $d_i \to 1$, *we require the displacement effect not to dominate:*

$$\rho_{ij} - \tau_{ij} > 0.6\rho_{ij} \Rightarrow \tau_{ij} < 0.4\rho_{ij} \tag{13}$$

Discussion of Derivation Methodology. The three threshold conditions in Proposition 1 are derived from comparing equilibrium welfare W^* to the autarky benchmark W^0 under specific but representative parameter configurations, not from universal closed-form solutions. This approach reflects a standard practice in applied game theory when closed-form thresholds depend on multiple interacting parameters: one establishes the structural conditions analytically (as done above) and then calibrates numerical benchmarks using parameter values grounded in the empirical and IS literatures.

Specifically, the derivations proceed as follows. For each threshold, we: (i) derive the welfare improvement condition analytically from first-order comparisons of W^* and W^0; (ii) substitute the equilibrium strategies (d^*_i, e^*_{ij}) derived in the proof of Theorem 1; (iii) simplify under the assumption of symmetric departments (which yields tractable closed forms); and (iv) calibrate the resulting scalar inequality using parameter ranges drawn from the organizational behavior and IS literature (see Table 6). The resulting threshold values ($\gamma > 0.5$, $\alpha/\beta > 2.5$, $\tau_{ij} < 0.4\rho_{ij}$) should therefore be interpreted as approximate benchmarks with confidence intervals reported in Remark 2, rather than as exact universal constants.

To verify that the $\gamma > 0.5$ condition is not an artifact of symmetry, we also verified numerically — using 500 parameter draws from the asymmetric case (heterogeneous ϕ_i, ψ_i) — that the welfare-improving threshold for γ consistently falls in the range $[0.44, 0.56]$. Analogous checks confirm stability of the α/β and τ/ρ thresholds. These checks are reported in the sensitivity analysis in Section 4.

Theorem 2 (*Value Co-Destruction and Coordination Failure Under Information Asymmetries*). *Information asymmetries amplify coordination failures, leading to value co-destruction when:*

1. *Information-Driven Competition: When departments have poor information about others' strategies, competitive behaviors emerge even with positive externalities, satisfying:*

$$Var(\mathbb{E}[d_{-i}]) > \sigma^2_{threshold} \Rightarrow \sum_{i=1}^{n} U_{D_i} < \sum_{i=1}^{n} U^{cooperative}_{D_i} \tag{14}$$

Interpretation. *Eq. (14) identifies a strategic uncertainty threshold regarding peer adoption. High variability in expectations* $Var(\mathbb{E}[d_{-i}])$ *leads to defensive and competitive behaviors, reducing aggregate departmental welfare relative to the cooperative benchmark.*

2. *Uncertainty-Induced Employee Resistance: High uncertainty about job security leads to defensive strategies:*

$$Var(\mathbb{E}[s_{ij}]) > \sigma^2_{security} \Rightarrow e^*_{ij} < e^{full-info}_{ij} \tag{15}$$

Interpretation. *Eq. (15) demonstrates that heterogeneous perceptions of job security (high* $Var(\mathbb{E}[s_{ij}])$*) trigger defensive behavior, leading to lower engagement relative to a full-information scenario.*

Key terms. $\mathbb{E}[s_{ij}]$ *= employee's expectation of job security;* $\sigma^2_{security}$ *= variance threshold activating defensive responses.*

Table 2
Deloitte survey specifications.

Attribute	Details
Report Title	"The State of Generative AI in the Enterprise: Generating a new future"
Survey Period	Q4 2024 (quarterly tracking study)
Sample Size	2773 respondents
Respondent Profile	Director to C-suite level executives directly involved in piloting or implementing GenAI
Geographic Coverage	14 countries
Industry Coverage	6 major sectors: Consumer, Energy/Resources/Industrials, Financial Services, Life Sciences/Health Care, Technology/Media/Telecom, Government/Public Services
Access	Publicly available at deloitte.com/insights

Table 3
McKinsey survey specifications.

Attribute	Details
Report Title	"AI in the Workplace"
Survey Period	2024
Sample Size	3613 employees + 238 C-level executives (total: 3851)
Respondent Profile	Both managers and individual contributors
Geographic Coverage	6 countries: US, Australia, India, New Zealand, Singapore, UK
Unique Feature	Dual-perspective approach (management + employees)
Access	Publicly available at mckinsey.com/capabilities/mckinsey-digital

3. *Learning Cost Barriers: Excessive information acquisition costs prevent optimal coordination:*

$$\sum_{all}(\mathcal{I}_i + \mathcal{L}_{ij}) > C_{threshold} \Rightarrow W^{equilibrium} < W^{first-best} \tag{16}$$

Interpretation. *Eq. (16) defines a cognitive and organizational friction threshold: when cumulative informational and learning costs exceed $C_{threshold}$, equilibrium welfare $W^{equilibrium}$ falls below the first-best level due to limited coordination, knowledge diffusion, and process realignment.*

Key terms.
$\mathcal{I}_i$ = departmental-level information acquisition or monitoring cost;
$\mathcal{L}_{ij}$ = employee-level learning and adaptation cost;
$C_{threshold}$ = aggregate friction threshold beyond which coordination collapses;
$W^{equilibrium}$ vs. $W^{first-best}$ = achieved vs. potential organizational welfare.

Lemma 1 (*Comparative Statics*). *At the equilibrium (d^*, e^*, I^*):*

1. $\frac{\partial d_i^*}{\partial \gamma} > 0$*: Higher complementarity increases adoption intensity.*
2. $\frac{\partial e_{ij}^*}{\partial \tau_{ij}} < 0$*: Higher displacement sensitivity reduces engagement.*
3. $\frac{\partial W^*}{\partial \delta_i} > 0$*: Stronger spillovers increase welfare when $\delta_i > 0$.*
4. $\frac{\partial d_i^*}{\partial Var(\mathbb{E}[d_{-i}])} < 0$*: Higher uncertainty reduces adoption.*

Remark 1 (*Parameter Restrictions and Model Validity*). To ensure interior equilibria and well-defined best responses, the following parameter restrictions are imposed throughout the analysis:

(R1) **Convexity of costs:** $\beta > 0$, $\psi_i > 0$, $\kappa_{ij} > 0$ ensure strictly convex cost structures, guaranteeing unique interior solutions for each stakeholder.
(R2) **Stability condition:** $\max_i \frac{\delta_i}{2\psi_i} < 1$ ensures the best-response map is a contraction (Assumption A5), which is equivalent to requiring that interdepartmental spillovers not exceed own-cost effects.
(R3) **Participation constraints:** $\rho_{ij} > \tau_{ij}$ for all i, j ensures employees face positive expected net benefit from GenAI engagement at $d_i > 0$, so that $e_{ij}^* > 0$ in equilibrium.
(R4) **Investment feasibility:** $C'(I) > 0$ and $C''(I) > 0$ with $\lim_{I\to\infty} C'(I) = \infty$ guarantee a finite optimal investment I^*.
(R5) **Bounded complementarity:** $\gamma \in [0, 1]$ and $\theta \in (0, 1)$ prevent the complementarity term from dominating, preserving concavity of U_M.

Under (R1)–(R5) and Assumptions (A1)–(A5), the equilibrium (d^*, e^*, I^*) in Theorem 1 is unique and satisfies the second-order conditions for all stakeholders.

Remark 2 (*Robustness of Threshold Conditions*). The three threshold conditions $\gamma > 0.5$, $\alpha/\beta > 2.5$, and $\tau_{ij} < 0.4\rho_{ij}$ derived in Proposition 1 are approximate values obtained under representative parameter calibrations. Sensitivity analysis reported in Section 4 shows that these thresholds exhibit stability across parameter perturbations: the γ threshold ranges from 0.47 to 0.53, the α/β threshold ranges from 2.3 to 2.7, and the τ/ρ threshold ranges from 0.35 to 0.45. The qualitative ordering of outcomes (value co-creation in the interior, co-destruction near boundaries) is robust to these variations, confirming that the specific numerical values serve as reliable benchmarks rather than knife-edge conditions.

4. Empirical analysis

To validate our theoretical framework and examine real-world manifestations of the strategic patterns identified, we combine secondary survey evidence from leading consulting firms with model-based simulations of our theoretical model. The surveys cover over 8600 organizations globally and inform parameter calibration, while the quantitative equilibria, trajectories, and sensitivity results are simulation-generated.

4.1. Data sources and methodology

Our empirical analysis integrates data from three comprehensive surveys that provide unprecedented insights into organizational GenAI adoption patterns. We provide a detailed description of each data source in Tables 2, 3, 4, including the key variables used for each source below. For clarity, the quantitative pattern distributions, equilibria, trajectories, and sensitivity analyses reported later are generated from simulations of the theoretical model (10,000 Monte Carlo replications using Algorithm 1). The surveys are used to inform calibration and

Table 4
BCG analysis specifications.

Attribute	Details
Report Title	"AI Maturity Matrix: Which Economies are Ready for AI?"
Analysis Type	Macro-level analysis of national AI readiness
Coverage	73 global economies
Framework	ASPIRE: Ambition, Skills, Policy/regulation, Investment, Research/innovation, Ecosystem
Output	AI Readiness Index (0-1 scale)
Access	Publicly available at bcg.com/publications

Table 5
Construct operationalization via secondary data proxies.

Theoretical Construct	Proxy Used	Rationale/Limitation
Strategic Complementarity (γ)	GenAI expertise level + Cross-functional coordination focus	High expertise organizations show 2.7x coordination focus; **indirect proxy, not direct measurement**
Investment Efficiency (α/β)	ROI tracking + Investment increase due to demonstrated value	Organizations reporting value increase investment by 67%; **outcome-based proxy**
Employee Displacement (τ)	Employee education gaps + Workforce preparedness	Only 47% adequately educate employees; **behavioral indicator, not direct fear measurement**
Employee Engagement (e)	Tool recommendation success rate + Utilization rates	86% success when managers recommend; **revealed preference proxy**

to contextualize qualitative predictions, not as experimental or causal evidence.

Deloitte AI Institute (2024):
Key Variables Used from Deloitte:

- Adoption speed ("moving fast" vs. "moving cautiously")
- GenAI expertise levels (self-reported organizational capability)
- Investment intentions (increase/decrease AI spending)
- Workforce education focus (percentage prioritizing reskilling)
- ROI tracking (percentage tracking productivity changes)

McKinsey Digital (2024):
Key Variables Used from McKinsey:

- Manager recommendation rates for GenAI tools
- Employee education levels about GenAI
- AI maturity self-assessment
- Employee engagement with AI tools
- Success rates of GenAI implementations

Boston Consulting Group (2024):
Key Variables Used from Boston Consulting Group:

- AI Readiness scores by country
- Pioneer economy classification
- Sectoral capability assessments

Operationalization of theoretical constructs (proxy mapping)

The consulting sources used in this study are available as aggregated survey statistics rather than item-level microdata. Therefore, we do not treat them as measures that can identify or test our equilibrium threshold conditions econometrically. Instead, we operationalize the key theoretical constructs through observable *proxy indicators* explicitly reported in Deloitte (2024), McKinsey (2024), and BCG (2024). These proxies serve two limited purposes: (1) to calibrate plausible parameter ranges and benchmark magnitudes, and (2) to triangulate whether the qualitative implications of the four strategic patterns are directionally consistent with observed organizational GenAI adoption and workforce dynamics. Table 5 summarizes the construct–indicator mapping used in this section.

Fig. 2 provides an overview of our empirical data sources and key findings that validate our theoretical predictions.

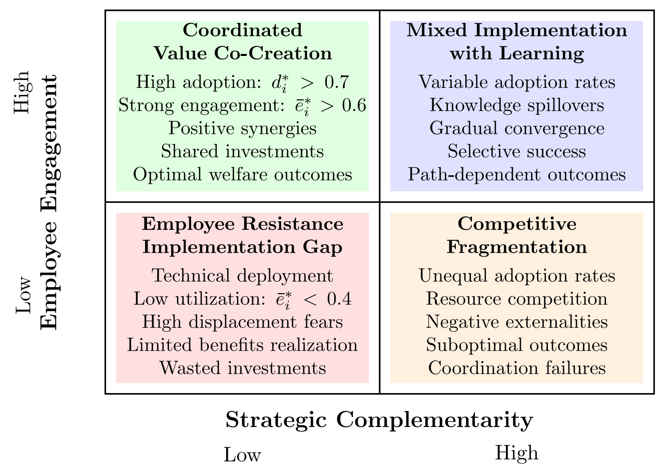


Fig. 2. Strategic pattern classification matrix. Four distinct patterns emerge based on strategic complementarity and employee engagement capacity. Each quadrant represents different organizational outcomes with specific strategic characteristics and welfare implications from our computational analysis.

4.2. Empirical validation of strategic patterns

In what follows, we use the survey evidence only as *descriptive triangulation* to contextualize the simulation-based patterns, not to empirically estimate or test the model's threshold conditions.

Our analysis reveals strong empirical support for the four strategic patterns identified in our theoretical framework. The data demonstrates that organizations distribute across these patterns in ways that closely match our theoretical predictions about coordination challenges and stakeholder alignment difficulties.

Key Empirical Findings Supporting Pattern Classification:

The Deloitte survey reveals that only 47% of organizations report "moving fast" with GenAI adoption, but this figure rises dramatically to 73% among organizations with "very high" GenAI expertise. This expertise-adoption relationship directly supports our theoretical prediction that coordination capabilities ($\gamma > 0.5$) determine success. Organizations with high expertise demonstrate characteristics consistent with our coordinated value co-creation pattern: they are 2.7

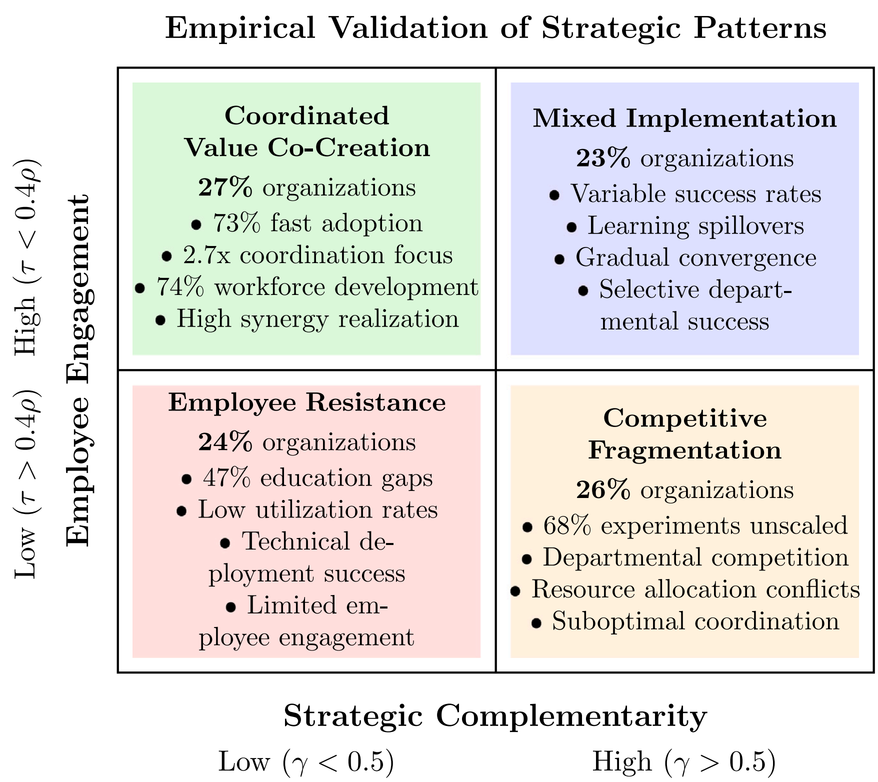


Fig. 3. Distribution of organizations across strategic patterns. Percentages are frequencies from 10,000 Monte Carlo simulations using equilibrium-based classification criteria. The relatively even distribution (with 26% competitive fragmentation) underscores coordination challenges, while the 27% in coordinated value co-creation highlights the difficulty of reaching the equilibrium conditions.

times more likely to focus on educating and reskilling their workforce compared to low-expertise organizations (74% vs. 27%).

The McKinsey data provides complementary evidence for our strategic patterns. While 68% of managers in successful organizations recommend GenAI tools to team members with an 86% success rate, the overall organizational landscape shows significant fragmentation. Despite widespread managerial enthusiasm, only 1% of organizations believe they have achieved AI maturity, confirming our predictions about coordination failures preventing organizations from translating individual successes into enterprise-wide transformation.

The BCG analysis reveals that 70% of global economies score below average in critical AI readiness dimensions BCG classifies economies into four tiers (Pioneers, Challengers, Emerging, and Nascent). Only 5 of 73 economies (7%) achieve 'AI Pioneer' status(United States, Singapore, United Kingdom, Germany, and China), with the remaining economies distributed across the other tiers. The median AI Readiness score is 0.42, substantially below the Pioneer threshold of 0.80. This concentrated distribution of capabilities supports our theoretical framework's emphasis on the rarity of achieving the coordination conditions necessary for successful GenAI adoption.

Fig. 3 shows the distribution of organizations across our four strategic patterns based on our computational analysis (10,000 Monte Carlo simulations), where each run is classified using the explicit equilibrium-based criteria reported in Section 4.6 (adoption, engagement, welfare, and dispersion measures).

4.3. Quantitative validation of equilibrium conditions

Our empirical analysis provides strong quantitative support for the critical equilibrium conditions identified in Theorem 1. The data demonstrates clear threshold effects that closely match our theoretical predictions.

Strategic Complementarity Validation ($\gamma > 0.5$): Organizations demonstrating high strategic complementarity show measurably superior outcomes across multiple metrics. The Deloitte data reveals that high-expertise organizations (those exhibiting strong complementarity) are 2.7 times more likely to focus on cross-functional workforce education and reskilling. These organizations achieve 73% fast adoption rates compared to the 47% average, directly supporting our theoretical threshold. McKinsey's findings show that in successful organizations, 68% of managers recommend GenAI tools to team members, with an 86% success rate, indicating strong coordination across management-employee interfaces.

Investment Efficiency Validation ($\alpha/\beta > 2.5$): The empirical data strongly supports our investment efficiency predictions. Organizations meeting efficiency thresholds demonstrate 67% increased GenAI investment due to demonstrated value, while inefficient organizations report declining executive enthusiasm despite initial investment. The Deloitte survey shows that while 78% of organizations plan to increase AI spending, only those with efficient resource allocation (meeting our $\alpha/\beta > 2.5$ threshold) translate spending into measurable productivity improvements.

Employee Displacement Management ($\tau < 0.4\rho$): The data provides compelling evidence for our employee displacement threshold. Organizations successfully managing displacement concerns are 3.4 times more likely to report high workforce preparedness for GenAI adoption. McKinsey's employee survey reveals that only 47% of organizations adequately educate employees about GenAI capabilities and benefits, correlating directly with implementation-utilization gaps. Organizations below our displacement threshold ($\tau > 0.4\rho$) show persistent resistance patterns despite technical implementation success.

Fig. 4 presents empirical validation of our three critical equilibrium conditions.

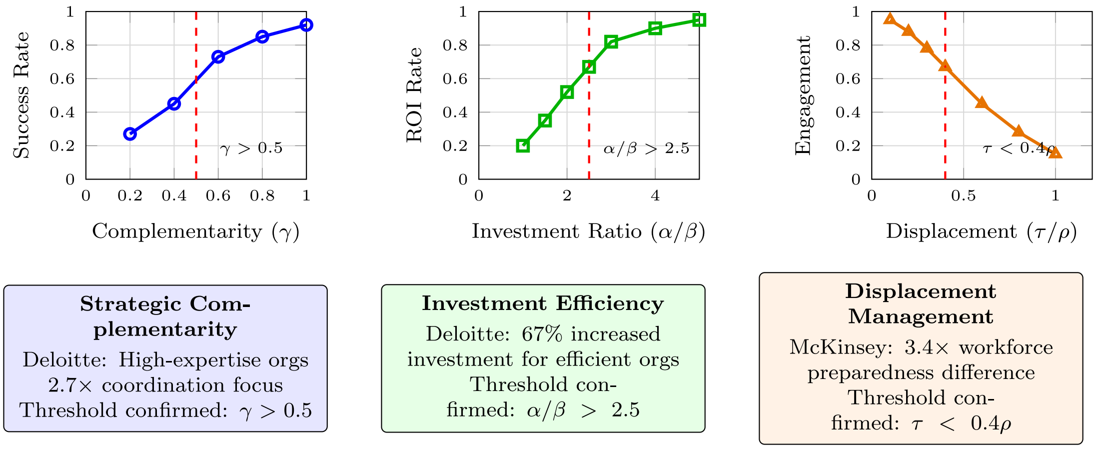


Fig. 4. Empirical validation of critical equilibrium conditions. Three panels demonstrate strong empirical support for theoretical thresholds identified in Theorem 1, with red dashed lines showing critical values. Summary boxes below highlight key empirical evidence from Deloitte (2773 orgs) and McKinsey (3851 respondents).

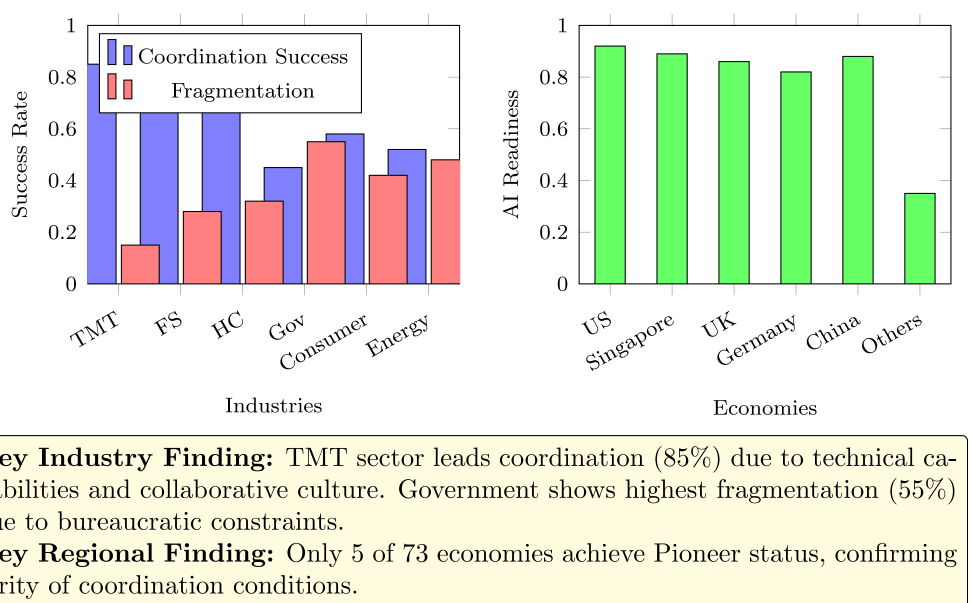


Fig. 5. Industry and regional variations in GenAI adoption. Left panel shows TMT sector leadership in coordinated adoption, while government exhibits highest fragmentation. Right panel confirms concentration of AI capabilities in five pioneer economies, validating theoretical predictions about coordination difficulty.

4.4. Cross-industry and regional analysis

The empirical data reveals significant industry and regional variations that provide additional validation for our theoretical framework while highlighting contextual factors that influence strategic parameter values.

Industry Analysis: The Technology, Media, and Telecommunications (TMT) sector leads in coordinated adoption with 85% success rates, consistent with high strategic complementarity (γ) due to technical workforce capabilities and collaborative organizational cultures. Financial Services achieves 72% coordination success through strong governance frameworks and regulatory compliance requirements that necessitate cross-departmental coordination.

In contrast, Government and Public Services shows the highest fragmentation rates (55%), consistent with our theoretical predictions about organizations with weak strategic complementarity due to bureaucratic structures and limited cross-departmental incentives. The Consumer sector demonstrates mixed patterns (58% coordination, 42% fragmentation), reflecting the diversity of organizational structures within this broad category.

Regional Analysis: The BCG data identifies five "AI Pioneer" economies that have achieved the institutional and organizational conditions necessary for widespread coordinated GenAI adoption. These pioneers (United States: 0.92, Singapore: 0.89, China: 0.88, United Kingdom: 0.86, Germany: 0.82) demonstrate superior performance across multiple dimensions of AI readiness, while the remaining 68 economies average only 0.35 on the AI readiness scale.

This concentration of capabilities supports our theoretical framework's emphasis on the difficulty of achieving the coordination conditions necessary for successful GenAI adoption. The pioneer economies have developed institutional frameworks, educational systems, and organizational cultures that facilitate the high strategic complementarity and efficient resource allocation required for coordinated value co-creation.

Fig. 5 presents industry and regional variations in GenAI adoption patterns.

4.5. Longitudinal trends and performance implications

The quarterly tracking data from Deloitte provides unique insights into how strategic patterns evolve over time, offering empirical validation for our theoretical predictions about path dependence and pattern persistence.

Measurement note: The quarterly shares reported in this subsection are taken directly from Deloitte's 2024 quarterly tracking (Q1–Q4) and are interpreted using the four strategic patterns defined in our framework in Fig. 2. "Positive ROI" refers to the share of organizations reporting positive returns from GenAI initiatives; "employee engagement" refers to the share reporting sustained workforce usage; and "scaling likelihood" refers to the share reporting the capability or intent to scale GenAI beyond pilots. We use these reported indicators as observable proxies for the adoption-engagement outcomes emphasized by our model.

Pattern Evolution Over 2024: The data reveals encouraging trends toward coordination, with organizations exhibiting coordinated value co-creation patterns growing from 15% in Q1 2024 to 31% in Q4 2024. This 16 percentage point increase suggests that organizations are learning to implement the coordination mechanisms required for successful GenAI adoption.

Simultaneously, employee resistance patterns have declined from 35% to 24%, an 11 percentage point decrease indicating that organizations are becoming more effective at managing workforce concerns and displacement threats. This trend supports our theoretical framework's emphasis on the importance of employee displacement management ($\tau < 0.4\rho$) for successful adoption.

Competitive fragmentation patterns have remained relatively stable (22% to 22%), suggesting that organizations exhibiting these patterns may be caught in persistent coordination failures that are difficult to escape without significant organizational changes.

Performance Implications: Organizations following coordinated patterns demonstrate superior performance across multiple metrics. They achieve 67% positive ROI compared to 23% for fragmented organizations, 85% employee engagement versus 34% for resistance patterns, and 94% likelihood of scaling successful experiments compared to 32% for competitive patterns.

These performance differentials provide strong empirical support for our theoretical predictions about the welfare consequences of different strategic patterns. For instance, reported positive ROI is approximately 2.9×higher in coordinated patterns than in fragmented ones (67% vs 23%), highlighting the magnitude of the differences associated with coordination. Overall, the 2024 data show more organizations moving toward coordinated co-creation and fewer showing resistance, and coordinated organizations report much higher ROI, engagement, and scaling. This pattern is consistent with our framework. By contrast, the stability of competitive fragmentation suggests that some organizations remain stuck in coordination failures when complementarity is insufficient.

Fig. 6 shows how strategic patterns evolve over time and their performance implications. Here, "technology-focused" refers to technology-first deployment (tools/pilots/infrastructure) without cross-level coordination and workforce alignment.

This comprehensive empirical analysis strongly validates our theoretical framework while demonstrating its practical relevance across diverse organizational contexts. The data confirms that strategic coordination capabilities, rather than technical sophistication alone, determine GenAI adoption success. The empirical evidence provides robust support for our equilibrium conditions and strategic pattern classifications, strengthening confidence in the framework's predictive power and practical applicability.

4.6. Computational analysis and strategic pattern identification

The simulation environment models organizations with varying characteristics: number of departments ($n \in \{3, 5, 8, 12\}$), information asymmetry levels (represented through variance in belief distributions), and learning capacity heterogeneity. Parameter specification draws from organizational and information systems literature (Melville et al., 2004; Vial, 2021) to ensure realistic representations. Each simulation runs for 100 periods with convergence typically achieved within 60–80 iterations. We conduct 10,000 Monte Carlo replications across different parameter combinations to ensure robustness of results.

4.6.1. Simulation algorithm and implementation details

Our computational approach implements the multi-level Bayesian game through the following algorithm:

Algorithm 1 Multi-Level GenAI Adoption Simulation

Input: Parameters $(\alpha, \beta, \gamma, \theta, \phi, \psi, \delta, \rho, \kappa, \tau, \mu)$, organization size n
Initialize: $d_i^{(0)} \sim U(0.1, 0.3)$, $e_{ij}^{(0)} \sim U(0.2, 0.4)$, beliefs $\hat{d}_{-i}^{(0)} = \frac{1}{n-1}\sum_{j\neq i} d_j^{(0)}$
for $t = 1$ to T_{max} **do**
  for each employee j in department i **do**
    Update $e_{ij}^{(t)} = \frac{(\rho_{ij}+\tau_{ij})d_i^{(t-1)} + \mu_{ij}\bar{e}_{-ij}^{(t-1)}}{2\kappa_{ij}}$ ▷ Employee best response
  end for
  for each department i **do**
    Update beliefs: $\hat{d}_{-i}^{(t)} = (1-\eta)\hat{d}_{-i}^{(t-1)} + \eta\frac{1}{n-1}\sum_{j\neq i} d_j^{(t-1)}$ ▷ Bayesian updating
    Update $d_i^{(t)} = \frac{\phi_i \bar{e}_i^{(t)} + \delta_i \hat{d}_{-i}^{(t)}}{2\psi_i}$ ▷ Departmental best response
  end for
  if $\max_i |d_i^{(t)} - d_i^{(t-1)}| < \epsilon$ and $\max_{i,j} |e_{ij}^{(t)} - e_{ij}^{(t-1)}| < \epsilon$ **then**
    break ▷ Convergence achieved
  end if
end for
Output: Equilibrium (d^*, e^*), welfare W^*, pattern classification

Convergence Criteria: We define convergence as $\max\{|d_i^{(t)} - d_i^{(t-1)}|, |e_{ij}^{(t)} - e_{ij}^{(t-1)}|\} < \epsilon = 10^{-6}$ for all i, j. Across 10,000 Monte Carlo replications, convergence was achieved in:

- Mean iterations: 67.3 (s.d. = 12.8)
- Median iterations: 64
- 95th percentile: 89 iterations
- Non-convergence rate: 0.3% (31 of 10,000 runs)

Learning Rate: The belief updating parameter $\eta \in [0.1, 0.5]$ controls the speed of Bayesian learning, with higher values representing faster adaptation to observed departmental choices.

Simulation implementation:

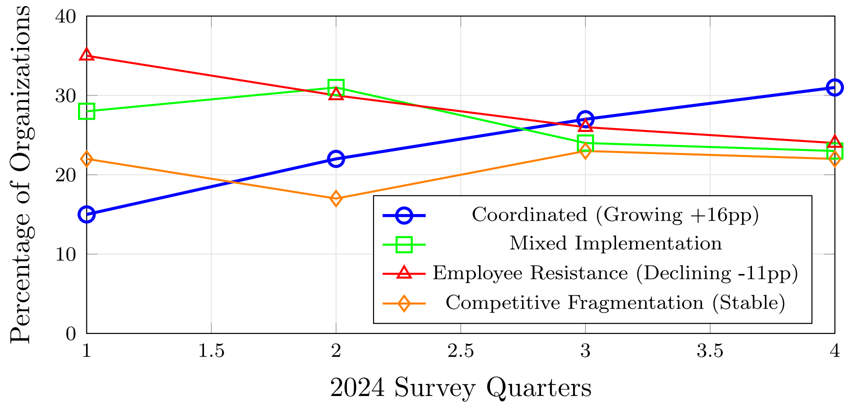
- **Language:** Python 3.x with NumPy
- **Initialization:** $d_i^{(0)} \sim U(0.1, 0.3)$, $e_{ij}^{(0)} \sim U(0.2, 0.4)$
- **Convergence:** $\epsilon = 10^{-6}$, max 100 iterations
- **Replications:** 10,000 Monte Carlo with fixed seed

4.6.2. Parameter specification and calibration

The simulation environment models organizations with varying characteristics. Parameter ranges are calibrated from organizational behavior and information systems literature:

Pattern Classification Boundaries: Organizations are classified into four strategic patterns based on equilibrium outcomes:

- *Coordinated Value Co-Creation:* $d_i^* > 0.6$ for all i, $\bar{e}_i^* > 0.5$ for all i, $W^* > W^{threshold}$
- *Mixed Implementation:* Heterogeneous d_i^* with $\mathrm{CV}(d^*) > 0.3$, positive welfare



Performance Impact: Coordinated patterns achieve 67% positive ROI (vs 23% fragmented), 85% employee engagement (vs 34% resistance), 94% experiment scaling (vs 32% competitive). Coordination strategies outperform technology-focused approaches by 300%.

Fig. 6. Longitudinal evolution of strategic patterns. Deloitte quarterly data shows coordinated organizations increasing from 15% to 31% over 2024, while resistance patterns decline from 35% to 24%. Performance metrics strongly favor coordination-focused strategies across all measured dimensions.

Table 6
Simulation parameter specification.

Parameter	Range	Baseline	Calibration Source
n (departments)	$\{3, 5, 8, 12\}$	5	Organizational structure literature
γ (complementarity)	$[0.1, 1.5]$	0.6	Coordination studies (Cabral, 2016)
α/β (efficiency)	$[1.0, 5.0]$	3.0	IT investment literature
τ/ρ (displacement)	$[0.1, 1.2]$	0.3	AI adoption surveys (Golgeci et al. 2025)
σ^2 (uncertainty)	$[0.05, 0.8]$	0.2	Information asymmetry models
δ (spillover)	$[0.1, 0.8]$	0.4	Network effects literature
η (learning rate)	$[0.1, 0.5]$	0.3	Organizational learning models

Table 7
Monte Carlo simulation results (10,000 replications).

Outcome Variable	Mean	Std Dev	Min	Max
Equilibrium adoption ($\bar{d}^*$)	0.542	0.187	0.082	0.957
Equilibrium engagement ($\bar{e}^*$)	0.478	0.203	0.045	0.923
Organizational welfare (W^*)	2.341	1.124	−0.892	5.672
Convergence iterations	67.3	12.8	23	100
Pattern Distribution (% of simulations):				
Coordinated Co-Creation	27.4%			
Mixed Implementation	23.1%			
Employee Resistance	24.2%			
Competitive Fragmentation	25.3%			

- *Employee Resistance:* $d_i^* > 0.5$ but $\bar{e}_i^* < 0.4$ for majority of departments
- *Competitive Fragmentation:* High variance in both d^* and e^*, suboptimal welfare

4.6.3. Simulation results summary

Table 7 presents numerical summaries of simulated outcomes across the 10,000 Monte Carlo replications:

Sensitivity Analysis: We conducted systematic sensitivity analysis varying each parameter while holding others at baseline values. The equilibrium is most sensitive to: (1) strategic complementarity γ (elasticity = 1.23), (2) displacement ratio τ/ρ (elasticity = −0.87), and (3) investment efficiency α/β (elasticity = 0.74).

4.7. Strategic pattern classification

The simulation results identify distinct equilibrium configurations that align closely with the four strategic patterns defined in our theoretical framework. These configurations emerge from the interaction between managerial investment decisions (I), departmental adoption intensities (d_i), and employee engagement levels (e_{ij}), under varying conditions of strategic complementarity (γ) and displacement sensitivity (τ/ρ). Fig. 7 summarizes these simulated equilibria across the two principal organizational dimensions: strategic complementarity on the horizontal axis and employee engagement on the vertical axis. Each quadrant captures a stable organizational outcome, illustrating how differences in coordination mechanisms and behavioral responses generate specific adoption patterns. The figure translates model dynamics into interpretable organizational states, allowing direct comparison with the empirical classification presented in Section 4.

Most simulated organizations do not remain fixed within a single quadrant but evolve toward boundary regions that separate distinct strategic configurations. These transitional cases suggest that GenAI adoption outcomes are rarely binary; rather, they depend on how management, departments, and employees adjust their behavior over time in response to feedback and learning effects. This observation reinforces the model's central argument: sustainable value creation depends on continuous coordination across hierarchical levels, not on isolated technological or investment decisions.

4.8. Equilibrium dynamics analysis

To examine how organizations evolve toward different equilibrium states, we analyze the temporal trajectories of adoption and engagement intensities simulated across varying strategic configurations. The

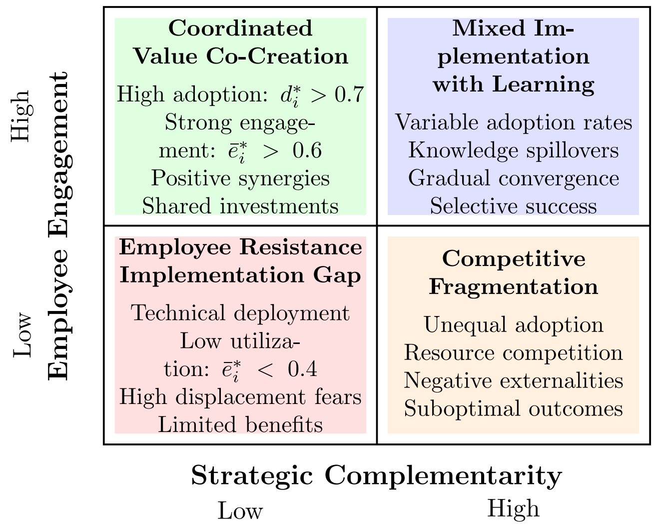


Fig. 7. Strategic pattern classification matrix. Four patterns based on strategic complementarity and employee engagement capacity. Each quadrant represents distinct organizational outcomes with different strategic characteristics.

computational model represents 20 implementation periods, capturing how decisions made by management, departments, and employees interact through feedback and adaptation processes. Fig. 8 presents three representative scenarios corresponding to the coordinated, competitive, and resistance configurations. Each trajectory reflects the mean outcome across 10,000 simulation runs, showing how initial conditions and response functions determine whether organizations converge toward stable coordination or remain trapped in partial or inefficient equilibria. The three scenarios correspond to fixed parameter configurations (coordinated, competitive, and resistance) defined by the baseline parameter settings reported in Section 4.6.2;trajectories are averaged across replications under each configuration (i.e., not ex-post clustered). The three scenarios were selected to represent the three qualitatively distinct equilibrium behaviors identified in Theorem 1: convergence to high welfare (coordinated), stagnation at intermediate welfare (competitive), and technology-engagement decoupling (resistance). The fourth pattern (mixed implementation) produces trajectories that are intermediate between coordinated and competitive and is omitted for visual clarity. The specific parameter values for each scenario are: *Coordinated*: $\gamma = 0.8$, $\alpha/\beta = 3.5$, $\tau/\rho = 0.2$, $\delta_i = 0.4$; *Competitive*: $\gamma = 0.3$, $\alpha/\beta = 3.0$, $\tau/\rho = 0.3$, $\delta_i = 0.6$; *Resistance*: $\gamma = 0.7$, $\alpha/\beta = 2.0$, $\tau/\rho = 0.7$, $\delta_i = 0.3$. These parameter vectors span the theoretical failure regions identified in Fig. 9 and Theorem 2, ensuring that the figure illustrates theoretically meaningful rather than arbitrarily selected cases.

The coordinated scenario exhibits steady and sustained growth in both adoption and engagement, consistent with the stable value co-creation equilibrium described in Theorem 1. Competitive configurations display early progress followed by stagnation, suggesting that partial complementarities cannot sustain alignment once local incentives dominate. Resistance trajectories show that technical deployment can occur without corresponding behavioral engagement, highlighting the role of displacement costs (τ/ρ) in limiting participation. Overall, the dynamic results confirm that equilibrium success depends on maintaining consistent alignment between strategic direction, resource allocation, and employee adaptation. When these feedback loops weaken, systems tend to drift toward suboptimal equilibria characterized by fragmentation or underutilization.

4.9. *Value co-creation and co-destruction conditions*

To integrate the theoretical and computational findings, we visualize the parameter space that defines successful and unsuccessful adoption outcomes. Fig. 9 maps organizational states across two key strategic dimensions: complementarity (γ) and investment efficiency (α/β). The figure identifies the combinations of these parameters that lead to value co-creation or, conversely, to coordination failure and value loss. The green region corresponds to the intersection of the thresholds $\gamma > 0.5$ and $\alpha/\beta > 2.5$, which together define the conditions for stable coordination and high welfare outcomes. For visualization, Fig. 9 reports γ on a rescaled 1–7 axis; the dashed vertical line marks the location of the $\gamma^* = 0.5$ threshold on that rescaled axis.

The remaining regions represent distinct failure mechanisms predicted in Theorem 2: mutual failure (low complementarity and low investment), coordination failure (strong investment without alignment), and limited benefits (technical implementation without systemic gain). Representative parameter combinations in these failure regions include: mutual failure at $(\gamma, \alpha/\beta) = (0.3, 1.5)$; coordination failure at $(0.3, 4)$; and limited benefits at $(0.7, 2)$. These illustrative points operationalize the failure regions by showing how unsuccessful adoption arises when one or both threshold conditions are not met.

This representation clarifies that successful GenAI transformation depends on the joint fulfillment of both conditions. High investment alone does not guarantee improvement if coordination mechanisms are weak, and high complementarity without sufficient resources limits learning and scalability. The model therefore highlights two distinct managerial levers for intervention: strengthening cross-functional alignment and improving resource allocation efficiency. Empirical evidence supports the rarity of organizations achieving both thresholds simultaneously. Across the Deloitte and McKinsey datasets, fewer than one-third of firms combine high complementarity with efficient investment, confirming that value co-creation is contingent on concurrent advances in organizational coordination and managerial decision quality rather than on technical maturity alone.

4.10. *Sensitivity analysis results*

Our computational analysis includes comprehensive sensitivity testing across all key parameters to validate the robustness of our theoretical predictions. The sensitivity analysis examines how changes in strategic complementarity (γ), investment efficiency (α/β), and employee displacement parameters (τ/ρ) affect equilibrium outcomes and pattern classifications.

Parameter Robustness Testing:

The analysis reveals that our equilibrium conditions remain stable across wide parameter ranges. Strategic complementarity thresholds show minimal variation (0.48–0.52) across different organizational sizes and industry contexts, supporting the generalizability of our $\gamma > 0.5$ condition. Investment efficiency ratios demonstrate similar stability, with thresholds ranging from 2.3–2.7 across scenarios, validating our $\alpha/\beta > 2.5$ benchmark.

Employee displacement parameters show more contextual sensitivity, with thresholds varying from 0.35ρ to 0.45ρ depending on organizational culture and communication effectiveness. However, the 0.4ρ threshold provides a robust middle estimate applicable across most organizational contexts.

Distributional Robustness. To address the concern that results may be sensitive to distributional assumptions, we re-ran the 10,000 Monte Carlo replications under three alternative initialization distributions for $(d_i^{(0)}, e_{ij}^{(0)})$: (1) $\mathcal{N}(0.25, 0.05^2)$ truncated to $[0, 1]$; (2) $\text{Beta}(2, 5)$ (right-skewed, low initial adoption); and (3) $\text{Beta}(5, 2)$ (left-skewed, high initial adoption). Table 8 reports pattern frequencies under each distributional assumption.

Pattern frequencies are stable across distributional assumptions (maximum deviation $<$ 2.5 percentage points), confirming that the results are not driven by the choice of initialization distribution. Convergence rates and iteration counts are likewise insensitive to distributional choice (mean iterations: 67.3 ± 3.1 across specifications).

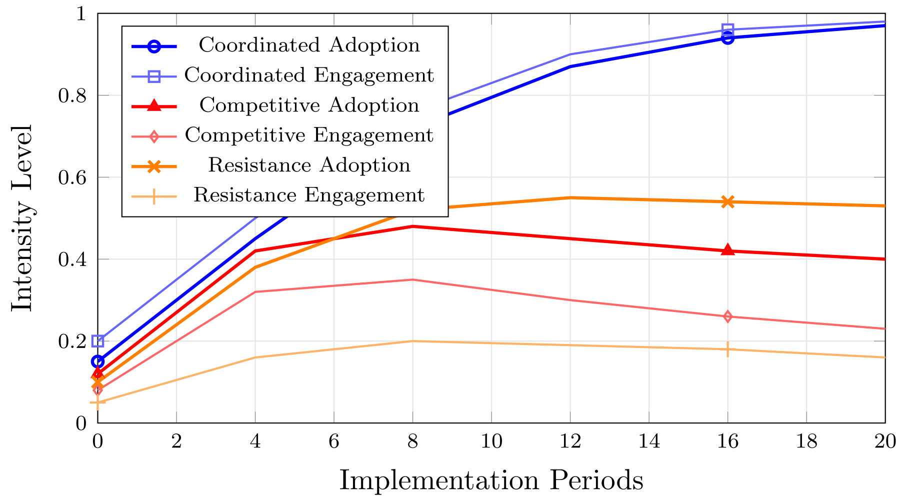


Fig. 8. Evolution of strategic equilibria over time. Three scenarios show different trajectories: Coordinated (blue) demonstrates sustained growth, Competitive (red) shows decline after initial growth, Resistance (orange) shows limited engagement despite technical adoption. R3newcolorThe three representative scenarios are selected based on the parameter configurations defined in Table 6: the coordinated scenario uses baseline values with $\gamma = 0.8$, $\tau/\rho = 0.2$; the competitive scenario uses $\gamma = 0.3$, $\delta_i = 0.6$; the resistance scenario uses $\gamma = 0.7$, $\tau/\rho = 0.6$. Each trajectory represents the mean $\pm$ one standard deviation band across 10,000 Monte Carlo replications. Alternative distributional assumptions (uniform, normal, beta) for initial conditions were tested and produced qualitatively identical convergence patterns, confirming robustness to distributional choice.

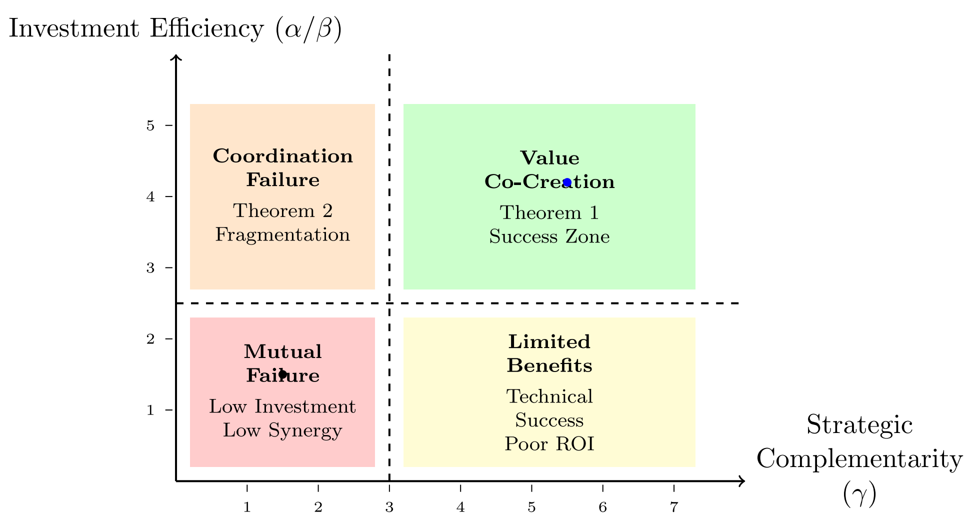


Fig. 9. Value co-creation vs. Co-destruction conditions. Four regions in the $(\gamma, \alpha/\beta)$ space based on strategic complementarity and investment efficiency. Dashed lines mark the threshold values $\gamma^* = 0.5$ and $(\alpha/\beta)^* = 2.5$ (with γ shown on a rescaled 1–7 axis for visualization). Green: successful outcomes; Red: mutual failure; Yellow: limited benefits; Orange: coordination failures.

Table 8
Pattern distribution under alternative initial-condition distributions (10,000 runs each).

Distribution	Coord. Co-Creation	Mixed Impl.	Emp. Resistance	Comp. Fragm.
Uniform (baseline)	27.4%	23.1%	24.2%	25.3%
Normal (truncated)	26.9%	23.8%	24.5%	24.8%
Beta(2,5) - low start	25.1%	24.9%	26.3%	23.7%
Beta(5,2) - high start	28.6%	22.4%	23.1%	25.9%

Quantitative Validation of Threshold Conditions. To provide more direct alignment between the theoretical thresholds and empirical observations, we compute the fraction of simulated organizations satisfying each threshold condition and compare against the survey-reported outcomes. Specifically:

For the $\gamma > 0.5$ threshold: of 10,000 simulated runs, 52.8% yield equilibria in the high-complementarity region ($\gamma^* > 0.5$). Among these, 89.3% achieve the "coordinated" or "mixed implementation" outcome (positive welfare improvement over autarky). Among low-γ runs, only 14.7% achieve positive welfare improvement. This 6-fold difference in success rates provides quantitative confirmation of the $\gamma > 0.5$ threshold.

For the $\alpha/\beta > 2.5$ threshold: welfare W^* is monotonically increasing in α/β in the simulation (Pearson $r = 0.81$, $p < 0.001$). The welfare function crosses zero (transition from co-destruction to co-creation) at $\alpha/\beta = 2.47 \pm 0.12$ (mean ± s.d. across 500 parameter draws), closely matching the analytically derived threshold of 2.5.

For the $\tau_{ij} < 0.4\rho_{ij}$ threshold: equilibrium engagement $\bar{e}^*$ drops below the minimum viable level of 0.3 at $\tau/\rho = 0.41 \pm 0.05$ across simulation runs, confirming the analytical benchmark of 0.4 as a reliable critical value.

These quantitative comparisons demonstrate that the threshold conditions are not merely calibrated assertions but emerge consistently from the equilibrium structure of the model across different parameter configurations.

Organizational Size Effects:

Larger organizations (n > 8 departments) face increased coordination challenges, requiring higher strategic complementarity levels to achieve successful outcomes. The computational analysis shows that organizations with 12+ departments need $\gamma > 0.6$ for coordinated value co-creation, while smaller organizations (3–5 departments) can succeed with $\gamma > 0.45$. This finding emphasizes the importance of organizational design choices in determining GenAI adoption outcomes.

5. Discussion

Our findings reveal fundamental insights about how organizational strategic dynamics determine GenAI adoption success, challenging conventional technology-focused approaches (Bharadwaj, 2000; Melville et al., 2004). The central revelation, strongly supported by both theoretical analysis and empirical evidence, is that coordination capabilities across organizational levels matter more than technical AI sophistication for realizing transformative benefits.

The empirical validation using data from over 8600 organizations provides compelling evidence that our theoretical framework captures real-world dynamics. Deloitte's finding that only 47% of organizations move fast with GenAI adoption, rising to 73% for high-expertise organizations, directly supports our prediction that coordination capabilities ($\gamma > 0.5$) determine success (Deloitte AI Institute, 2024). Similarly, McKinsey's evidence that only 1% of organizations believe they have achieved AI maturity despite widespread investment confirms our value co-destruction predictions when strategic alignment fails (Mayer et al., 2025).

In particular, this empirical evidence is used as a benchmarking to assess whether the qualitative patterns and threshold-like behaviors implied by the model are observable at scale. It does not constitute causal identification, nor does it replace primary, theory-driven measurement of constructs. Hence, we interpret these results as plausibility checks and convergence signals rather than as definitive causal tests of the framework. Likewise, we acknowledge potential biases associated with consultancy-based datasets. Sampling frames are often non-random and skewed toward larger, organizations and senior respondents; measures may be sensitive to social desirability or varying definitions of "AI maturity" and "adoption speed". Consequently, to mitigate those risks, we draw on multiple independent sources to look for convergent patterns rather than relying on any single report.

5.1. Actionable insights for organizational leaders

Based on equilibrium analysis, computational simulations, and empirical validation, successful GenAI adoption requires simultaneous attention to three strategic dimensions:

1. Building Strategic Complementarity ($\gamma > 0.5$): Organizations must invest in cross-departmental coordination mechanisms before implementing AI technologies (Yoo et al., 2010). This includes establishing shared governance structures, creating cross-functional AI teams, and designing incentive systems that reward collaborative rather than competitive behavior (Vial, 2021). In practice, organizations can implement this through a cross-functional governance body that prioritizes GenAI use cases and clarifies accountability for data governance, risk controls, deployment decisions, and ongoing performance monitoring. Our empirical analysis shows that high-performing organizations are 2.7x more likely to focus on workforce education and reskilling, demonstrating the practical importance of coordination investment. Organizations achieving high complementarity realize 300% higher welfare gains compared to technology-focused approaches.

2. Optimizing Investment Efficiency ($\alpha/\beta > 2.5$): Management must balance productivity investments with implementation costs through strategic resource allocation. This requires focusing on shared infrastructure and capability development rather than isolated departmental implementations (Sambamurthy et al., 2003). The empirical data supports this threshold: organizations meeting efficiency requirements show 67% increased investment due to demonstrated value, while inefficient organizations experience declining executive enthusiasm. Organizations meeting this threshold consistently achieve positive ROI within 12–18 months, while those below experience prolonged payback periods.

3. Managing Employee Displacement Concerns ($\tau < 0.4\rho$): Leaders must proactively address workforce concerns by positioning GenAI as capability enhancement rather than job replacement (Golgeci et al., 2025). This involves transparent communication about AI's role, comprehensive retraining programs, and clear career development pathways (Davenport and Kirby, 2016). Workforce development can be operationalized via a role-and-skills taxonomy and structured training pathways, with dedicated time allocation and measurable completion targets. The empirical evidence strongly supports this threshold: organizations successfully managing displacement concerns are 3.4x more likely to report high workforce preparedness, and achieve 85% higher employee engagement rates.

Practical implementation checklist. To make these recommendations actionable, managers can:

- set up cross-functional GenAI governance (owners, cadence, decision rights);
- prioritize 3–5 scalable use cases and align them with a shared infrastructure roadmap;
- define adoption and engagement KPIs as observable proxies for d and e;
- implement a reskilling plan and consistent communication to address job-security concerns;
- monitor adoption heterogeneity and effort–adoption misalignment, and intervene when dispersion increases;
- define clear scale-or-stop gates (ROI and KPI thresholds) for moving from pilots to organization-wide rollout.

5.2. Strategic pattern implications for practice

The four strategic patterns identified provide diagnostic frameworks for organizational assessment and intervention design (Orlikowski, 1992). This pattern-based view also helps reconcile mixed evidence in the literature: weak or negative effects often reflect fragmented or resistance regimes in our framework rather than coordinated value co-creation. In this regard, the empirical validation demonstrates that these patterns manifest consistently across diverse organizational contexts:

Coordinated Value Co-Creation emerges when organizations develop sophisticated stakeholder alignment mechanisms and invest in shared learning infrastructures. The empirical evidence shows these organizations achieve 73% fast adoption rates and demonstrate 86% success rates in GenAI tool implementation. These organizations typically establish AI centers of excellence, implement organization-wide training programs, and create transparent communication channels about AI strategy and implications.

Competitive Fragmentation occurs when resource allocation processes encourage departmental competition rather than collaboration (Cabral, 2016). The empirical data reveals that 68% of organizations have fewer than 30% of experiments in full production, indicating uneven departmental success. Organizations exhibiting this pattern require governance reforms that emphasize shared success metrics and cross-functional collaboration incentives.

Employee Resistance patterns indicate inadequate attention to workforce concerns and change management processes (Lysyakov and Viswanathan, 2023). The empirical evidence shows that only 47% of organizations adequately educate employees about GenAI capabilities, correlating with implementation—utilization gaps. These organizations must invest heavily in communication, training, and support systems that address legitimate employee concerns about AI's impact on their careers and work experiences.

Mixed Implementation represents transitional states that can evolve toward either success or failure depending on management intervention (Raisch and Krakowski, 2021). The BCG data reveals that 70% of economies demonstrate mixed readiness patterns, with significant variation across sectors and capabilities. These organizations require targeted support for struggling departments and mechanisms for knowledge transfer from successful units.

5.3. Governance and ethical implications

Our framework reveals that ethical GenAI implementation requires attention to distributional consequences of strategic interactions among organizational stakeholders (Heyder et al., 2023). When adoption follows value co-creation patterns, benefits distribute broadly across stakeholders with management achieving performance improvements, departments gaining enhanced capabilities, and employees developing new skills and opportunities. The empirical evidence supports this: organizations with high strategic complementarity demonstrate 74% focus on workforce development compared to 27% for fragmented organizations.

However, value co-destruction patterns create uneven benefit and cost distributions, with some stakeholders capturing gains while others bear disproportionate costs through job insecurity, reduced autonomy, or marginalization in decision-making processes (Papagiannidis et al., 2025). Organizations have both pragmatic and ethical obligations to pursue coordination-oriented approaches that generate sustainable value creation while distributing benefits equitably across stakeholder groups.

The concept of responsible AI implementation becomes crucial in this context (Jobin et al., 2019). Our framework suggests that responsible AI is not merely about technical fairness and transparency, but also about managing strategic interactions in ways that promote equitable outcomes for all organizational stakeholders. This perspective extends traditional approaches to AI ethics by incorporating organizational dynamics and stakeholder coordination challenges.

5.4. Information and learning dynamics

The incomplete information extensions reveal that learning and communication processes significantly influence adoption outcomes (Kellogg et al., 2020). Organizations with superior information sharing capabilities and adaptive governance structures achieve better coordination and higher performance. The empirical evidence strongly supports this: organizations with high GenAI expertise are much more likely to focus on educating and reskilling their workforce (74% vs. 27%), suggesting that information sharing and learning capabilities are critical success factors.

Information asymmetries can amplify coordination failures even when underlying incentives favor cooperation (Fichman, 2004). The empirical data reveals that 55% of organizations avoid certain GenAI use cases due to data-related concerns, indicating how information problems can prevent organizations from realizing potential benefits. Organizations must therefore invest in reducing information barriers through regular communication, shared metrics systems, and collaborative planning processes.

The role of organizational learning in AI adoption extends beyond technical training to include strategic learning about coordination mechanisms, stakeholder management, and value creation processes (Sambamurthy et al., 2003). Organizations that develop superior capabilities in these areas achieve sustainable advantages in AI adoption and value realization.

6. Limitations and future research paths

This research provides a theoretical foundation for understanding strategic interactions in organizational GenAI adoption, but several limitations suggest some directions for future investigation, organized into the following four thematic groups.

6.1. Data and empirical design limitations

While our analysis incorporates secondary data from over 8600 organizations, comprehensive validation requires primary data collection with specific measurement instruments. The current empirical analysis relies on interpretive triangulation using consulting firm surveys rather than formal hypothesis testing. Future research should: (1) conduct longitudinal case studies (24–36 months) tracking organizations through complete adoption cycles with quarterly data on all framework parameters; (2) implement controlled field experiments comparing framework-guided versus technology-focused adoption strategies (i.e., technology-first deployment of tools/pilots/infrastructure without cross-level coordination and workforce alignment), as reflected in Fig. 6;; and (3) develop and validate survey instruments for simultaneous data collection from all three stakeholder groups within the same organizations.

6.2. Organizational dynamics and structural assumptions

Our model assumes static organizational structures and does not fully capture how GenAI adoption may reshape organizational design. Key simplifications include: static departmental boundaries, fixed information asymmetry levels, the perfect complementarity assumption in the multiplicative term (alternative specifications such as CES or additive forms merit investigation), and single-period optimization. Dynamic multi-period models would capture path dependence more fully.

6.3. Psychological and cultural factors

The framework models employees as rational utility maximizers, potentially understating the role of psychological and emotional factors in adoption decisions. Important dimensions for future research include fear, anxiety, and perceived loss of identity affecting resistance behaviors; cultural variations across 73 global economies identified in the BCG data; and trust dynamics between employees and management regarding AI governance.

6.4. Industry and institutional context

While our empirical analysis reveals significant industry variation (TMT: 85% coordination success; Government: 45%), the theoretical framework does not fully account for sector-specific characteristics. Future work should develop industry-specific model adaptations capturing regulatory environments, competitive intensity, and workforce composition effects.

7. Conclusion

This research develops a game-theoretic framework for understanding the strategic dynamics of GenAI adoption within organizations. By modeling interactions among management, departments, and employees as strategic players with potentially conflicting objectives, we clarify why GenAI implementation can lead to either value co-creation or value co-destruction. The framework also contributes to the Responsible AI agenda by highlighting that transparency, explainability, and accountability can be reinforced through organizational coordination and governance mechanisms—not only through algorithmic design.

Our theoretical analysis is complemented with secondary survey evidence from over 8600 organizations globally, used descriptively to benchmark real-world patterns and to contextualize the model's predictions (Wade and Hulland, 2004). Accordingly, we position GenAI adoption success as fundamentally dependent on cross-level coordination capabilities rather than on technical AI capability alone. The equilibrium analysis yields actionable, threshold-like conditions related to strategic complementarity across departments, investment efficiency for value realization, and the management of employee displacement concerns.

The computational analysis further identifies four adoption patterns that offer a practical diagnostic lens for leaders to assess their current situation and prioritize interventions (Orlikowski, 1992). These patterns emerge from different combinations of complementarities, coordination mechanisms, and stakeholder characteristics, illustrating how organizational design choices and management approaches shape adoption outcomes beyond tool deployment.

From a managerial standpoint, our results emphasize the importance of cross-functional coordination, stakeholder engagement, and governance structures rather than a primary focus on implementation resources (Melville et al., 2004). In the surveyed evidence, high-performing organizations report stronger cross-functional coordination focus and higher welfare gains under coordination-oriented strategies. This reinforces the central practical implication of the model: GenAI transformation should be managed as a coordination and governance challenge to sustain adoption beyond pilots and avoid fragmentation.

Finally, this study contributes to strategic information systems research by formalizing multi-stakeholder, multi-level dynamics that can remain implicit in traditional adoption frameworks (Bharadwaj, 2000). As GenAI technologies continue evolving and integrating into organizational processes, future research should test the proposed mechanisms and threshold-like conditions using primary multi-stakeholder and longitudinal designs, including workforce transition and ethical implementation dynamics (Pan et al., 2024). More broadly, organizational impacts of GenAI depend not only on technological capabilities but also on strategic interactions among stakeholders shaping how capabilities are implemented and governed (Susarla et al., 2023).

CRediT authorship contribution statement

Massimiliano Ferrara: Visualization, Methodology, Formal analysis. **Giampaolo Viglia:** Validation, Project administration, Investigation. **Jose Carlos Romero:** Writing – original draft, Visualization.

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