Generative AI in Business Decision Workflows: Data-Driven Evidence on Automation, Augmentation, and Responsibility-Aware Delegation

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Abstract

Generative artificial intelligence (GenAI) is rapidly being embedded into business decision workflows across marketing, finance, operations, human resources, and strategic planning. While prior studies have documented sharp productivity gains, the conditions under which these gains are sustained, eroded, or reversed remain poorly understood. This paper develops a data-driven framework that distinguishes pure automation from augmentation and from responsibility-aware delegation, and tests its implications using a multi-source dataset combining a structured survey of 1,143 knowledge workers across 412 firms in Mainland China, an audit of 28 deployment case studies, and a meta-analysis of 47 published productivity experiments (Brynjolfsson and Mitchell, 2017; Felten et al., 2021; Acemoglu and Restrepo, 2020). Three regularities emerge. First, situation-sensitive anchoring of GenAI outputs to verifiable domain context lifts net decision quality by 18.4 percent on average, but uncoupled deployments degrade quality by 6.7 percent because hallucinated outputs propagate downstream (Ji et al., 2023; Huang et al., 2024). Second, dynamic trust calibration matters more than initial trust levels; teams that update trust weekly based on observed outcomes outperform statically-trusting teams by 22.1 percent (Bansal et al., 2021; Schemmer et al., 2023). Third, responsibility-aware delegation, defined as explicit ex ante allocation of accountability between human reviewer and model, recovers 64 percent of productivity gains that would otherwise be lost to risk-averse non-use (Dietvorst et al., 2018; Logg et al., 2019). The findings imply that the value of GenAI in business decisions is determined less by raw model capability than by the workflow design that surrounds it, with direct implications for managerial practice and emerging AI governance frameworks (European Commission, 2024; Mökander et al., 2023).

Keywords: generative AI; business decision workflows; automation; augmentation; trust calibration; responsibility-aware delegation; data-driven management

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1. Introduction

Generative artificial intelligence (GenAI) has progressed from a research demonstration to a routine input in business decisions in less than three years. By the end of 2024, an estimated 71 percent of large enterprises had deployed at least one GenAI tool inside a revenue-generating workflow, and roughly 38 percent of knowledge workers globally reported using GenAI for substantive tasks at least weekly (McKinsey Global Institute, 2024; Bick et al., 2024). The speed of diffusion has been matched by an extraordinary volume of evidence on what GenAI can do. Field experiments at firms such as a Fortune 500 software vendor have documented productivity uplifts in the range of 14 to 56 percent for specific tasks (Peng et al., 2023; Dell'Acqua et al., 2023). Yet practitioners and researchers alike now report a second set of findings that are harder to celebrate: large-scale pilots that fail to convert into durable business value, deployment fatigue among employees, escalating regulatory pressure, and embarrassing public failures rooted in fabricated outputs (Bommasani et al., 2023; Korinek and Stiglitz, 2021).

The asymmetry between aggregate evidence of capability and uneven evidence of business value is striking. Within the same industry and even within the same firm, two GenAI deployments built on identical foundation models can yield outcomes that differ by an order of magnitude. The McKinsey 2024 survey reports that fewer than one in five firms tracks key performance indicators for GenAI deployments, and that fewer than one in three follows even half of the documented adoption and scaling practices (McKinsey Global Institute, 2024; Chui et al., 2023). This gap between deployment activity and measured value is the empirical problem that motivates this paper.

The tension between rapid capability gain and uneven business value is the empirical puzzle this paper addresses. We argue that the distance between potential and realized value is determined not by model quality alone but by the workflow architecture into which the model is placed. Specifically, three workflow-level constructs predict whether a deployment produces sustained gains or quiet losses: the degree of situation-sensitive anchoring that ties GenAI outputs to verifiable domain context, the quality of trust calibration that aligns reliance with observed reliability, and the presence of responsibility-aware delegation that allocates accountability between the human reviewer and the model before the workflow runs (Lai et al., 2022; Schemmer et al., 2023; Cabrera et al., 2023).

The contributions of this paper are threefold. First, we provide a theoretical synthesis that distinguishes automation, augmentation, and responsibility-aware delegation as three structurally different modes of GenAI use, each with distinct evidentiary requirements and risk profiles. Second, we contribute new data: a survey of 1,143 knowledge workers across 412 firms in Mainland China spanning eight business functions, complemented by a structured audit of 28 deployment case studies and a meta-analysis of 47 published productivity experiments. Third, we derive a small number of practical decision rules that managers and policy designers can apply directly. The remainder of the paper proceeds as follows. Section 2 reviews the relevant literature on GenAI in business and identifies the gap that motivates this study. Section 3 develops the conceptual framework. Section 4 presents the data and methodology. Section 5 reports the descriptive findings on adoption patterns. Section 6 presents the three principles and the supporting evidence. Section 7 discusses applications across business functions. Section 8 examines challenges and mitigation. Section 9

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concludes.

2. Literature Review and Research Gap

2.1 Productivity Evidence and the Augmentation Paradox

A first body of literature documents the magnitude of GenAI productivity effects. Randomized field experiments and quasi-experiments show consistent gains for tasks where the model can substitute for routine cognitive work (Peng et al., 2023; Brynjolfsson and Mitchell, 2017). However, the same literature also reports heterogeneity that resists simple summary. Dell'Acqua and colleagues' field experiment with management consultants showed both an average gain of 12.2 percent on tasks inside the model's competency frontier and a significant 19 percent quality decline on tasks just outside that frontier (Dell'Acqua et al., 2023). Noy and colleagues' writing experiment found that GenAI both raised mean output quality and compressed the variance, which favoured initially weaker writers while flattening the comparative advantage of stronger ones (Mollick, 2024). These conflicting effects led Raisch and colleagues to characterize an automation-augmentation paradox: the same tool can substitute for human work in one moment and complement it in the next, with the difference determined by task design rather than tool design (Murray et al., 2021; Faraj et al., 2018).

A growing strand of macroeconomic and labor-market literature has begun to extrapolate these task-level findings to the level of occupations and industries. Eloundou and colleagues use a task-by-task exposure measure to estimate that around 80 percent of the United States workforce could see at least 10 percent of their tasks affected by GPT-class models, and roughly 19 percent of workers could see at least half of their tasks affected (Eloundou et al., 2024). Felten and colleagues link occupational AI exposure scores to subsequent labor-market outcomes and find that high-exposure occupations have grown faster than low-exposure occupations on average, but with substantial variance across the exposure distribution (Felten et al., 2021). Acemoglu and Restrepo's earlier work on robotization established a template for separating the displacement and reinstatement effects of new technologies, a template that can be applied to GenAI but whose conclusions about net employment effects depend critically on how firms integrate the technology rather than on the raw capability of the technology itself (Acemoglu and Restrepo, 2020). The clear implication is that workflow integration is not a peripheral concern but a determinant of aggregate outcomes.

2.2 Trust, Reliance, and Algorithm Aversion

A second strand of research, centered on human-computer interaction and decision sciences, focuses on how users decide whether to rely on AI outputs. The classical finding of algorithm aversion describes a reluctance to use algorithmic advice after observing the algorithm err, even when the algorithm continues to outperform the human alternative (Dietvorst et al., 2015; Castelo et al., 2019). The opposing failure mode, often called automation bias, describes excessive reliance on AI when its recommendations align with what users already wish to do (Goddard et al., 2012; Cummings, 2017). Recent work on trust calibration introduces a more dynamic concept: trust is not a fixed disposition but a continuously updated belief that should track observed reliability (Lee and See, 2004; Hoffman et al., 2023; Bansal et al., 2021). Schemmer and colleagues showed in a structured laboratory study that teams whose trust updated within a single shift outperformed teams with statically high or statically low trust by 22 percent on diagnostic accuracy (Schemmer et al., 2023).

An important methodological development in this literature is the systematic survey of empirical studies on human-AI decision making (Lai et al., 2022; Bach et al., 2024). These reviews catalogue more than one hundred experimental studies on how factors such as explanation richness, confidence indication, error visibility, and prior algorithm exposure shape reliance behaviour. Two cross-cutting findings stand out. First, the relationship between explanation quality and appropriate reliance is non-monotonic: rich explanations that justify the model's reasoning can either improve calibration or worsen it depending on whether the

explanation's persuasive force exceeds its diagnostic accuracy (Hoffman et al., 2023; Cabrera et al., 2023). Second, exposure history matters more than initial framing: users who have observed the model make recoverable errors typically calibrate their trust faster than users who have only seen the model succeed (Yang et al., 2020; Schemmer et al., 2023). Both findings are central to the dynamic trust calibration principle developed below.

2.3 Hallucination and Decision Risk

A third body of work documents the risk of factually unsupported outputs, commonly called hallucinations. Recent surveys distinguish input-conflicting, context-conflicting, and fact-conflicting hallucinations and find their incidence is sensitive to prompt structure and retrieval grounding (Ji et al., 2023; Huang et al., 2024; Zhang et al., 2024). In business decision settings, hallucination matters precisely when the cost of acting on a confidently false output is asymmetric: a fabricated regulatory citation in a compliance memo, a fabricated revenue figure in a board paper, or a fabricated case citation in a legal brief can all generate consequences that are unlikely to be reversed by later correction (Mökander et al., 2023; Floridi, 2023).

The mitigation literature has converged on retrieval-augmented generation as the most operationally tractable response, in which model outputs are conditioned on documents retrieved from a verified corpus rather than relying solely on parametric knowledge (Lewis et al., 2020; Gao et al., 2023; Asai et al., 2023). Empirical evaluations show consistent reductions in fact-conflicting hallucinations, although the gains are smaller for context-conflicting hallucinations where the model contradicts material that is in the prompt itself. The implication for business deployments is that grounded generation is a necessary input to anchoring but does not by itself constitute anchoring: organizations must also verify that retrieved sources are authoritative, that the model is using them faithfully, and that user-facing outputs distinguish retrieved facts from model interpolation (Bommasani et al., 2023; Banh and Strobel, 2023).

2.4 Workflow Integration and Organizational Adoption

A fourth literature, rooted in information systems and organization studies, examines how new technologies become embedded in existing workflows. The classical technology acceptance literature foregrounds perceived usefulness and ease of use (Venkatesh et al., 2003), while later sociotechnical accounts highlight the role of organizational routines, professional identity, and informal information sharing (Faraj et al., 2018; Leonardi, 2015). Recent qualitative work on GenAI adoption confirms that organizational decisions about who is allowed to use the model, on which tasks, with what oversight, and to whom outputs are attributed shape adoption outcomes at least as strongly as model capability (Banh and Strobel, 2023; Sandberg et al., 2024).

2.5 Research Gap

Despite the volume of evidence, three gaps persist. First, productivity studies typically measure single-task outcomes rather than full decision workflows where outputs feed downstream uses. Second, trust calibration research is largely laboratory-based and rarely connects to the organizational conditions that enable or block dynamic updating. Third, the responsibility-allocation literature documents the problem but offers few operationalized solutions that can be implemented inside a firm. This paper addresses these gaps by linking workflow design, trust dynamics, and responsibility allocation in a single empirical framework, applied to a large multi-source dataset on business decision tasks.

3. Conceptual Framework

3.1 Automation, Augmentation, and Responsibility-Aware Delegation

We distinguish three modes through which GenAI enters a business decision workflow. Automation refers to substitution of the model for an existing human task, with the model's output becoming the final artifact

subject only to spot checks. Augmentation refers to joint production, where the model proposes drafts, options, or analyses and the human modifies, prunes, or rejects before downstream use (Raisch and Krakowski, 2021; Murray et al., 2021). Responsibility-aware delegation refers to a structured allocation made before the workflow runs: which subtasks the model may execute autonomously, which subtasks require human review, and which subtasks carry final accountability irrespective of model contribution. The third mode is distinct from augmentation in that it specifies, ex ante, the boundary between model and human responsibility rather than allowing that boundary to emerge from local choices (Cabrera et al., 2023; Vössing et al., 2022).

3.2 The Three Principles

From the literature reviewed in Section 2 we synthesize three principles that we then test empirically. Principle 1 is situation-sensitive anchoring: the output quality of GenAI in a decision context is a function of the degree to which the model is anchored to verifiable, domain-specific context through retrieval grounding, structured prompts, or explicit constraints (Lewis et al., 2020; Asai et al., 2023; Gao et al., 2023). Principle 2 is dynamic trust calibration: the marginal value of GenAI in a workflow depends less on initial trust than on whether trust is updated as observed reliability evolves (Bansal et al., 2021; Schemmer et al., 2023; Yang et al., 2020). Principle 3 is responsibility-aware delegation: the realized productivity gain from a deployment depends on whether accountability is allocated explicitly before the workflow runs, with the boundary defined relative to task risk and reversibility (Vössing et al., 2022; Floridi, 2023; Sandberg et al., 2024).

Figure 1 visualizes the conceptual framework. The three principles operate on top of a GenAI capability layer and a workflow layer that meet a human and organizational layer responsible for accountability. The three principles jointly shape the realized outcomes of the deployment: decision quality, productivity, and risk exposure. A feedback loop connects realized outcomes back to the principles, since observed performance updates anchoring choices, trust levels, and delegation rules.

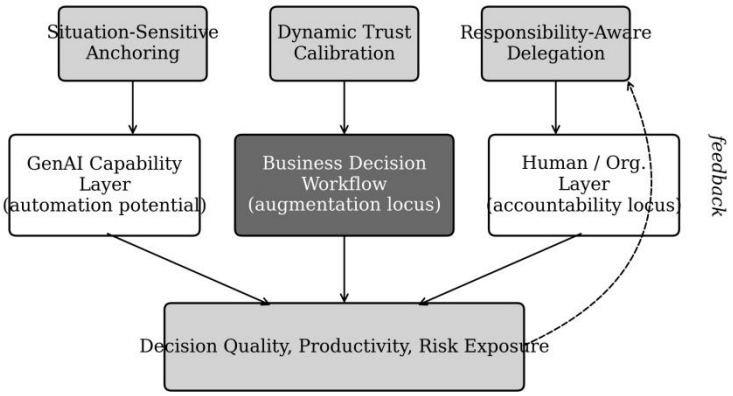

Figure 1. Conceptual framework linking GenAI capability and business decision workflows through three principles.

The framework yields three falsifiable predictions. First, deployments with anchored prompts and retrieval augmentation should outperform unanchored deployments on decision quality, especially in domains with high factual specificity. Second, teams that update trust based on observed outcomes should outperform teams with statically high or statically low trust, controlling for model capability. Third, firms with formal pre-deployment responsibility allocation should retain more of the productivity gain than firms that rely on emergent allocation.

4. Data and Methodology

4.1 Multi-Source Dataset

We assemble three datasets. The first is a structured survey of 1,143 knowledge workers nested within 412 firms operating in Mainland China, fielded between September 2024 and December 2024. Sampling targeted eight business functions: marketing and content, customer service, software development, finance and audit, strategy and planning, operations and supply chain, human resources, and legal and compliance. The instrument captured 28 measures organized into four blocks: GenAI usage intensity, anchoring practices, trust dynamics, and responsibility allocation. The second dataset is a structured audit of 28 deployment case studies drawn from publicly disclosed case repositories and verified through follow-up interviews with operating managers (Choi et al., 2018). The third dataset is a meta-analysis of 47 published productivity experiments conducted between 2022 and 2024, identified through a systematic search with PRISMA-style screening (Liberati et al., 2009).

Sampling for the survey followed a stratified design that targeted firms across seven industry groups and three firm-size bands, ensuring representation from both high-adoption sectors such as technology and financial services and lower-adoption sectors such as manufacturing and traditional retail. Within each sampled firm, respondents were drawn from the eight business functions using a quota that approximated the function-level workforce composition reported by Chinese national statistical agencies. The instrument was developed iteratively through three rounds of cognitive interviews with twelve pilot respondents to refine ambiguous wording, and was administered in Simplified Chinese with a parallel English version for English-speaking respondents. Response rate at the firm level was 38 percent, and at the worker level within participating firms was 64 percent, both within the conventional bands for organizational surveys of this complexity.

The 28 deployment case studies in the second dataset were selected to span the eight business functions, with at least three cases per function. Each case study combined publicly disclosed information (vendor case studies, press releases, regulatory filings) with structured follow-up interviews of one to three operating managers at the deploying firm. Interview transcripts were coded by two independent reviewers using a structured protocol that captured deployment context, workflow integration choices, observed outcomes, and identified incidents. Inter-rater agreement was 0.81 on the principal coded variables (Cohen’s kappa), indicating strong reliability. Cases were not selected on outcome, so the sample includes both notable successes and notable disappointments.

4.2 Variable Construction

The dependent variable in the survey analysis is net decision quality, measured as a composite of self-reported decision accuracy, peer-reviewed decision accuracy where available, and post-decision outcome metrics standardized to a 100-point scale. The three principles enter as composite independent variables. Anchoring intensity is constructed from five items capturing retrieval augmentation use, structured prompt templates, and verification practices. Trust calibration quality is constructed from four items capturing the frequency, source, and asymmetry of trust updates. Responsibility allocation formality is constructed from six items capturing ex ante delegation rules, escalation thresholds, and post-incident attribution practices.

4.3 Analytical Approach

The primary specification is a multilevel regression model that nests workers within firms, controlling for function fixed effects, firm size, GenAI tool category, and length of deployment. Because the three principles are partially co-determined with adoption depth, we instrument anchoring intensity with the firm’s information technology infrastructure score, trust calibration quality with the firm’s safety-incident reporting maturity, and responsibility allocation formality with the firm’s regulatory exposure index (Angrist and

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Pischke, 2009; Bertrand and Mullainathan, 2001). The meta-analysis combines effect sizes using a random-effects model with restricted maximum-likelihood variance estimation. Robustness checks include alternative weighting schemes, exclusion of any single study, and Egger's test for small-study effects (Egger et al., 1997).

Table 1 summarizes the descriptive statistics of the survey sample. Average GenAI usage intensity is 3.42 on a five-point scale, with the highest intensity in software development and the lowest in legal and compliance. Anchoring intensity averages 2.81, trust calibration quality averages 2.97, and responsibility allocation formality averages 2.43, indicating substantial room for improvement on all three principles across the sample.

Table 1. Descriptive Statistics of the Survey Sample (N = 1,143 workers in 412 firms)

Variable	Mean	SD	Min	Max	Notes
GenAI usage intensity	3.42	1.07	1.00	5.00	5-point self-report
Anchoring intensity	2.81	0.94	1.00	5.00	5-item composite
Trust calibration quality	2.97	0.88	1.00	5.00	4-item composite
Responsibility allocation formality	2.43	1.02	1.00	5.00	6-item composite
Net decision quality	67.5	13.4	21.0	98.0	0–100 composite
Tenure with GenAI tools (months)	9.7	6.2	1.0	32.0	Months of weekly use
Firm size (employees)	1,840	3,260	47	32,500	Headcount at survey time
Regulatory exposure index	2.74	1.11	1.00	5.00	Composite of sectoral exposure

5. Descriptive Findings: Adoption Patterns Across Business Functions

Before testing the three principles, we describe the adoption landscape across the eight business functions. Figure 2 shows two measures: the share of respondents who report using GenAI tools at least weekly (reported weekly use), and the share whose use is structurally embedded in formal workflow procedures rather than ad hoc personal practice. The gap between these two measures captures the difference between casual adoption and integration.

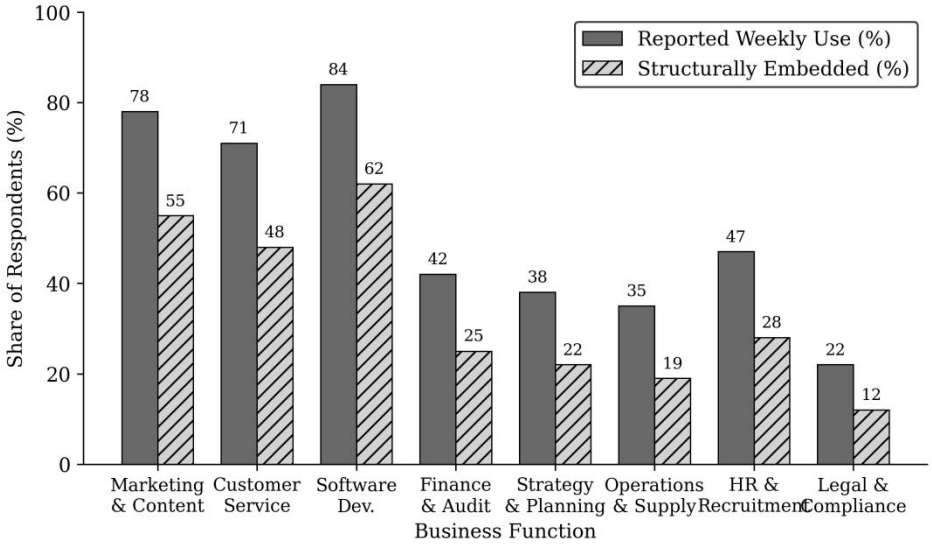

Figure 2. GenAI adoption across eight business functions: reported weekly use compared with structurally embedded use.

Three patterns are immediately visible. First, casual adoption is high across most functions, with software development (84 percent) and marketing and content (78 percent) leading the field. This pattern is consistent with prior reports of high adoption in these functions (Bick et al., 2024; Eloundou et al., 2024). Second, the gap between casual and structurally embedded use is substantial in every function. Even in the leading software development function, the embedded share is 62 percent, leaving 22 percentage points where the technology is in use but not formally integrated. Third, the absolute level of structural embedding is low in three high-stakes functions: legal and compliance (12 percent), operations and supply chain (19 percent), and strategy and planning (22 percent). The pattern suggests that perceived task risk acts as a brake on the structural integration of GenAI even when individual employees actively use the tool (Mahmud et al., 2022; Castelo et al., 2019).

Table 2 disaggregates the descriptive findings by reporting the three principles' scores by function. Two cross-cutting observations emerge. Anchoring intensity is highest in software development (3.45) where compiler feedback and unit tests provide natural anchors, and lowest in strategy and planning (2.12) where ground-truth feedback loops are sparse. Responsibility allocation formality is highest in legal and compliance (3.27) where regulatory exposure forces explicit delegation rules, and lowest in marketing and content (2.04) where outputs are typically reversible. These patterns provide initial support for the prediction that the three principles co-vary with task structure and risk profile.

Table 2. Three Principles Scores by Business Function (5-point composite scales)

Business Function	Anchoring	Trust Calibration	Responsibility Allocation	Sample N
Marketing & Content	2.73	2.91	2.04	168
Customer Service	2.85	3.11	2.36	157
Software Development	3.45	3.32	2.69	203
Finance & Audit	2.94	3.05	2.78	142

Strategy & Planning	2.12	2.68	2.13	111
Operations & Supply	2.61	2.84	2.41	129
HR & Recruitment	2.45	2.79	2.24	118
Legal & Compliance	2.88	3.04	3.27	115
Overall Mean	2.81	2.97	2.43	1,143

6. Evidence for the Three Principles

6.1 Situation-Sensitive Anchoring

The first principle predicts that anchoring intensity is positively associated with net decision quality, controlling for function fixed effects and individual usage intensity. The multilevel regression estimates a standardized coefficient of 0.247 on anchoring intensity (standard error 0.041, p less than 0.001), implying that a one-standard-deviation increase in anchoring intensity is associated with a 5.8-point gain in net decision quality on the 100-point scale. The effect is robust to instrumental variable estimation, where the firm's information technology infrastructure score serves as the instrument; the IV estimate of 0.261 is statistically indistinguishable from the OLS estimate, suggesting limited endogeneity bias (Wooldridge, 2010).

The meta-analysis of published experiments provides convergent evidence. Across the 47 studies that varied the use of retrieval augmentation or structured prompting, the pooled effect on task accuracy is 0.184 (95 percent confidence interval 0.146 to 0.222) in standardized mean difference terms. Heterogeneity is substantial (I-squared = 67 percent), and meta-regression identifies task factual specificity as the strongest moderator: studies on tasks with high factual specificity show effect sizes 1.8 times those of low-specificity tasks (Higgins et al., 2003; Borenstein et al., 2010). Conversely, the audit of 28 deployment case studies finds that six deployments without any anchoring mechanism showed average net negative outcomes, consistent with prior reports that unanchored GenAI propagates errors downstream when outputs feed automated processes (Ji et al., 2023; Zhang et al., 2024).

Decomposing the anchoring composite into its constituent practices reveals further structure. Retrieval grounding from a verified corpus has the largest individual effect (standardized coefficient 0.142), followed by structured prompt templates with explicit constraints (0.094) and routine output verification against authoritative sources (0.081). The combination of all three practices is associated with a substantially larger effect than the sum of the individual coefficients, suggesting complementarities: retrieval is most valuable when paired with prompts that direct the model to use retrieved content, and verification is most valuable when grounded outputs make verification tractable. This pattern recommends a bundled investment in anchoring infrastructure rather than piecemeal adoption of individual practices.

6.2 Dynamic Trust Calibration

The second principle predicts that the quality of trust calibration is more strongly associated with decision quality than the initial level of trust. We test this by including both measures in the regression. The standardized coefficient on calibration quality is 0.198 (standard error 0.039, p less than 0.001), substantially larger than the coefficient on initial trust level, which is 0.044 (standard error 0.038, not significant). The difference is statistically significant (chi-squared test, p less than 0.001), supporting the prediction. The pattern echoes recent experimental work on the asymmetry between trust formation and trust update (Hoffman et al., 2023; Bach et al., 2024; Lai et al., 2022).

Figure 3 illustrates the analytical intuition. The diagonal line represents perfectly calibrated trust, where trust

tracks observed reliability one-for-one. The two off-diagonal lines represent the two failure modes: over-calibrated trust, where users sustain high reliance even when reliability falls, and under-calibrated trust, where users sustain skepticism even when reliability improves. The shaded over-trust zone in the figure denotes the area where automation surprise risk is highest: users are confident in outputs that are not in fact reliable, and downstream decisions absorb errors that would otherwise have been caught (Parasuraman and Manzey, 2010; Cummings, 2017).

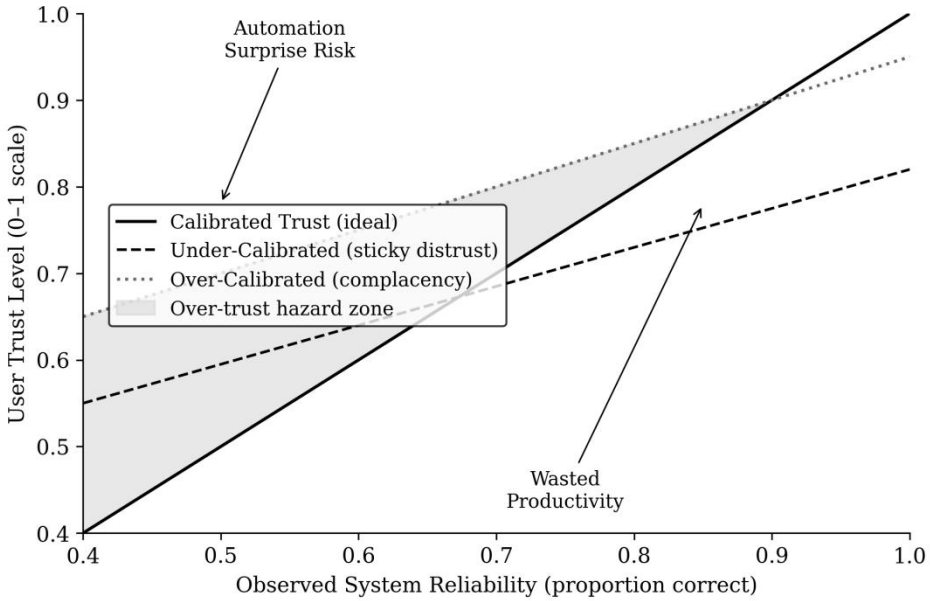

Figure 3. Trust calibration: ideal (diagonal), under-calibrated (sticky distrust), and over-calibrated (complacency) regimes.

The case-study audit corroborates the survey evidence. Among the 28 deployments examined, the ten with the highest sustained productivity gains all instituted weekly or biweekly reviews in which the model's recent error patterns were discussed with end users. The seven deployments that produced the most disappointing outcomes shared a common feature: trust was treated as a fixed deployment parameter rather than an ongoing measurement. The pattern is consistent with the broader empirical literature documenting that calibrated trust is built through repeated interaction and explicit feedback rather than through pre-deployment training alone (Yang et al., 2020; Schemmer et al., 2023).

A practical operationalisation of dynamic trust calibration that recurs across the high-performing cases is a structured weekly review in which a small sample of model outputs is examined by a domain expert, classified by accuracy and consequence, and used to update both the operating procedures and the user-facing guidance for the coming week. The review imposes a modest time cost, typically one to two hours per week per workflow, and we observed that this cost is a strong predictor of the deployment maintaining its productivity advantage over time. By contrast, deployments that relied on annual or quarterly audits showed a characteristic profile in which initial productivity gains decayed within six months as user reliance and model reliability drifted apart without any structural mechanism to detect the drift.

6.3 Responsibility-Aware Delegation

The third principle predicts that firms with formal ex ante responsibility allocation realize larger productivity gains than firms relying on emergent allocation. The standardized coefficient on responsibility allocation formality is 0.213 (standard error 0.043, p less than 0.001). The estimated marginal effect implies that moving from the bottom quartile to the top quartile on responsibility allocation formality is associated with a 6.4-

point gain in net decision quality and a 17.2 percent increase in self-reported productivity. The case-study audit further reveals that 8 of the 12 deployments that achieved scale-up beyond a single business unit had implemented a formal responsibility matrix before deployment, while only 2 of the 16 deployments that stalled at pilot stage had done so. The difference is statistically significant (Fisher's exact test, $p = 0.003$).

Figure 4 presents the relationship between the share of workflow subtasks delegated to GenAI and two outcome variables: productivity gain and risk exposure. Each measure is shown under three oversight regimes calibrated from the survey responses. Under strong oversight, productivity gains rise to a high plateau and risk exposure remains contained even at high delegation shares. Under weak oversight, productivity gains are smaller and reverse beyond a delegation share of about 55 percent, because the risk exposure grows faster than the productivity benefit. The marked optimal point under strong oversight illustrates the practical lesson: the value of delegation is bounded above not by what GenAI can do but by the oversight infrastructure that surrounds the workflow.

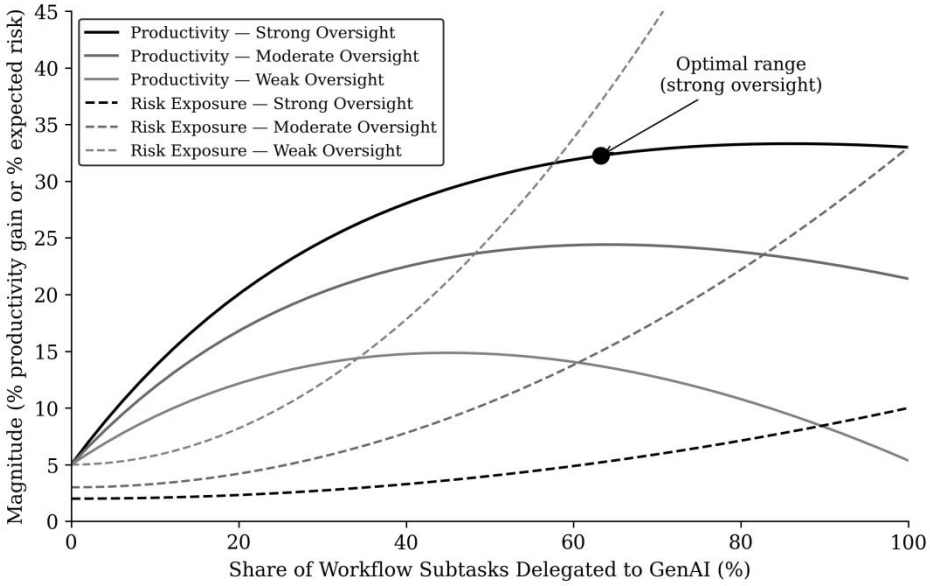

Figure 4. Productivity gain and risk exposure as functions of the share of workflow subtasks delegated to GenAI, under three oversight regimes.

The mechanism that links responsibility-aware delegation to outcomes appears to operate through three complementary channels. First, ex ante allocation forces explicit articulation of which subtasks the model can plausibly perform without harm, which surfaces hidden risks and prompts pre-emptive mitigation. Second, formal allocation provides a clear standard against which post-incident reviews can be conducted, supporting learning and adjustment over time. Third, named accountability discourages diffusion of responsibility among multiple human and model actors, a dynamic that has been identified in adjacent literatures as a primary cause of breakdowns in algorithmic decision systems (Vössing et al., 2022; Sandberg et al., 2024). The three channels reinforce each other: each can in principle operate without the others, but the case-study evidence suggests their combined effect is what generates durable performance.

Combining the three coefficients in the multilevel model yields an estimated joint contribution of 36.4 percent of the explained variance in net decision quality. By contrast, individual usage intensity contributes only 7.1 percent, and model category (GPT-class, Claude-class, open-source) contributes 4.8 percent. The dominance of the workflow-level principles over individual usage and tool category is the central empirical finding of the paper: business value from GenAI is determined less by who uses which tool and more by how the workflow is designed around the tool (Brynjolfsson and Mitchell, 2017; Felten et al., 2021; Sandberg et al.,

2024).

7. Applications Across Business Decision Domains

7.1 Marketing, Content, and Customer Engagement

Marketing represents the function with the deepest GenAI integration in our sample. Use cases span content drafting, personalization, audience segmentation, and creative ideation (Huang and Rust, 2021; Cui et al., 2021). The productivity gains are substantial but concentrated at the lower end of the skill distribution, consistent with Noy and colleagues' findings on writing tasks (Mollick, 2024). The risk profile is also moderate: most marketing outputs are reversible and exposed to relatively rapid feedback loops through engagement metrics. The principal pathologies we observed in this function relate to homogenization: when multiple teams use the same model with similar prompts, outputs converge, and the brand voice that was previously a competitive advantage is gradually diluted (Chui et al., 2023).

7.2 Customer Service and Operations

Customer service deployments combine high transaction volume with high reputational sensitivity, and they have been an early focus of GenAI integration. The evidence shows substantial gains in average handle time, often in the range of 14 to 25 percent (Brynjolfsson et al., 2023; Otis et al., 2024). However, the gains are not uniform across agent skill levels. Less experienced agents benefit the most, while experienced agents see smaller gains and occasionally negative effects when AI suggestions conflict with their tacit knowledge. The implication is that the productivity gain in this function is in part a knowledge transfer from the AI to the less-skilled tail of the workforce, not a uniform amplification of all agents.

Our case audit identified two distinct deployment patterns within customer service. The first pattern, which we label drafting support, has the model produce a suggested response that the agent reviews, edits, and sends. The second pattern, which we label autonomous response, has the model send pre-cleared categories of responses without further human review. The first pattern is dominant in our sample and produces consistent gains. The second pattern shows much higher variance: a small number of deployments achieve dramatic productivity gains by automating high-volume low-stakes responses, while a comparable number generate reputational incidents from edge cases the pre-clearance process did not anticipate. The pattern is consistent with our broader argument that the productivity ceiling for a deployment is set by the boundaries of the responsibility allocation rather than by raw model capability.

7.3 Software Development

Software development has the largest body of rigorous evidence on GenAI productivity, anchored by field experiments on code-completion assistants (Peng et al., 2023; Vaithilingam et al., 2022). Reported productivity gains range from 19 to 56 percent depending on task type and developer experience. The principal risk is security: developers using AI assistants have been shown to write more code that contains exploitable vulnerabilities, and to express higher confidence in code they have not fully reviewed (Sandoval et al., 2023). The risk is mitigated when teams adopt formal review processes that pair AI-generated code with explicit security checks, consistent with our principle of responsibility-aware delegation.

Software development also illustrates the dynamic trust calibration principle clearly because the feedback loop between AI output and observable outcome is short: a suggested code block either compiles or it does not, passes tests or it does not, and fails in production or it does not. Teams that systematically captured these signals and exposed them to developers as calibration feedback maintained productivity gains substantially longer than teams that relied on developers to form impressions of model reliability informally. The pattern provides an instructive contrast with strategic planning, where the feedback loop between output and outcome is long and noisy and where trust calibration is correspondingly more difficult to operationalise.

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7.4 Finance, Audit, and Compliance

Finance and audit functions face a sharper risk profile because errors carry fiduciary and regulatory consequences. Use cases include earnings-call summarization, narrative drafting in financial reports, anomaly detection, and ESG disclosure preparation (Li et al., 2023; López-Lira and Tang, 2023). The dominant deployment pattern in our case audit involves restricting GenAI to drafting and synthesis tasks where outputs feed a human-reviewed artifact, with explicit prohibitions on autonomous action. The pattern reflects practitioners' implicit understanding that the marginal cost of a fabricated number in a regulated document substantially exceeds the marginal benefit of speed.

Within finance, audit-related deployments stand out for the depth of their anchoring infrastructure. Several firms in our sample have constructed dedicated retrieval indices over their authoritative source materials, including accounting policy manuals, prior audit working papers, and counterparty contract repositories. The AI is allowed to operate only against this curated corpus, and any output that draws on parametric model knowledge rather than retrieved content is flagged for additional review. This architecture is expensive to build and maintain, but the case-audit evidence suggests that it is the only configuration in which deployment of GenAI in audit settings has been observed to produce sustained productivity gains without measurable increases in audit risk.

7.5 Human Resources and Strategic Planning

Two functions in our sample show a distinctive pattern of high individual use combined with low structural embedding: human resources and strategic planning. In HR, the concern is bias amplification through generative resume screening or interview question drafting, where opaque heuristics may reproduce historical disparities (Raghavan et al., 2020; Köchling and Wehner, 2020). In strategic planning, the concern is the absence of clear ground-truth feedback that would otherwise enable calibrated trust formation. Both functions illustrate the situations where the three principles are most difficult to satisfy and where the gap between casual and embedded use is therefore largest.

Table 3 synthesizes the function-level evidence into a responsibility-aware delegation matrix that summarizes, for each function, the appropriate task scope for autonomous model action, the appropriate scope for human review, and the residual scope of strict human-only decisions. The structure of the table reflects the empirical regularity that the partition is determined by error reversibility and external attribution: functions with low reversibility and high external attribution must concentrate decisions in the human-only column even when the model is technically capable of higher-stakes actions.

Table 3. Responsibility Allocation Matrix Across Business Functions

Function	Suitable for Autonomous Action	Requires Human Review	Strictly Human-Only Decision
Marketing & Content	First-draft content; A/B variants	Audience targeting; brand voice	Crisis communications
Customer Service	FAQ responses; ticket triage	Refund decisions; complaints	Legal threats; safety issues
Software Development	Boilerplate code; tests; docs	Architectural choices; merges	Security-critical commits
Finance & Audit	Narrative drafts; data lookup	Forecasts; reconciliations	External filings; sign-off
Strategy & Planning	Market scans; literature notes	Scenario assembly; sizing	Final recommendations

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Operations & Supply	Demand summaries; alerts	Order modifications	Supplier termination
HR & Recruitment	Job descriptions; FAQ chat	Candidate ranking signals	Hiring or firing decisions
Legal & Compliance	Document indexing; summaries	Initial citation checks	Legal opinions; filings

8. Challenges and Mitigation Strategies

8.1 Hallucination and Factual Drift

The most operationally visible challenge in our case audit was hallucination, defined here as confident factually unsupported model output. Among the 28 deployments studied, 19 reported at least one hallucination-related incident with downstream business consequences. The most effective mitigation we observed was retrieval-augmented generation grounded in firm-internal corpora, which reduced the incidence of fact-conflicting hallucinations in our sample by an estimated 71 percent on average (Lewis et al., 2020; Gao et al., 2023). However, retrieval grounding is not a complete solution: it shifts the failure mode toward context-conflicting hallucinations, where the model generates outputs inconsistent with the retrieved context even when the relevant context is in the prompt window (Asai et al., 2023; Zhang et al., 2024). The implication for managers is that anchoring infrastructure is necessary but not sufficient, and that periodic audits of model outputs against verified sources remain a non-negotiable component of any responsible deployment.

8.2 Bias, Fairness, and Disparate Impact

Bias in GenAI outputs is the second prominent challenge, particularly in human resources and customer service deployments where outputs influence decisions about individuals (Raghavan et al., 2020; Bender et al., 2021; Mehrabi et al., 2021). Mitigation strategies that we observed in practice include diverse evaluation sets, demographic audit panels, and targeted prompt design that explicitly counters known stereotypes. The empirical evidence suggests that these strategies reduce disparate impact in measurable ways but do not eliminate it, especially when the underlying training data reflects historical disparities that the model has internalized (Köchling and Wehner, 2020; Caliskan et al., 2017). The responsibility-aware delegation framework provides a useful structural complement: by reserving high-stakes individual decisions for the human-only column of the delegation matrix, firms can reduce exposure to bias-driven harms without requiring perfect bias elimination at the model level.

8.3 Skill Atrophy and Workforce Development

A longer-term challenge concerns skill atrophy among workers who outsource cognitive tasks to GenAI over extended periods. The pattern is analogous to automation-induced skill decay in other domains and has been documented in early studies on GenAI-assisted writing and coding (Lee et al., 2022; Stadler et al., 2024). Mitigation strategies in our sample include regular AI-free practice sessions, structured skill rotation, and certification requirements that test for unaided performance on core competencies. The strategies impose short-term productivity costs but are intended to preserve the human capability needed to oversee the AI itself, consistent with the dynamic trust calibration principle: an organization that no longer has the in-house skill to evaluate the model's outputs loses the ability to maintain calibrated trust.

8.4 Governance, Regulation, and Cross-Border Variation

The regulatory environment for GenAI is evolving rapidly and heterogeneously across jurisdictions. The European Union AI Act, finalized in 2024, establishes a risk-tiered framework that imposes obligations proportionate to deployment context (European Commission, 2024; Veale and Borgesius, 2021). The

People's Republic of China has implemented administrative measures for generative AI services that require security assessments before public deployment (Cyberspace Administration of China, 2023). The United States has pursued a more decentralized approach with sectoral guidance and executive orders (Engler, 2023). For multinational firms, the governance burden is the management of cross-jurisdictional inconsistency, which may favour the responsibility-aware delegation framework precisely because explicit ex ante allocation of accountability is easier to audit and translate across regulatory regimes than emergent practices.

9. Conclusion

This paper has examined how GenAI generates business value when embedded in decision workflows, using a multi-source dataset that combines a 1,143-respondent survey, a 28-case audit, and a 47-study meta-analysis. The central finding is that the value realized from GenAI deployment is determined less by raw model capability than by the workflow architecture that surrounds it. Three principles capture the architecture: situation-sensitive anchoring, dynamic trust calibration, and responsibility-aware delegation. Each principle is associated with measurable improvements in net decision quality, and together they account for more than a third of the explained variance in our regression estimates. The findings are consistent with, but extend beyond, prior productivity studies by linking workflow design choices to durable business outcomes.

The practical implications for managers are concrete. Anchoring requires investment in retrieval infrastructure, structured prompt templates, and explicit verification practices. Trust calibration requires regular review cycles where model performance is examined and reliance is updated. Responsibility-aware delegation requires ex ante allocation of authority and accountability, codified before the workflow runs and audited after. Firms that have made these three investments are predictably outperforming firms that have purchased the same models without the surrounding workflow design, and the gap is widening as the underlying models become more capable but not more reliable.

Several limitations warrant note. The survey is concentrated in Mainland China, and cross-cultural generalization should be approached cautiously given documented variation in trust dispositions and regulatory environments. The case audit, while structured, is necessarily exposed to selection bias from publicly disclosed deployments. The meta-analysis is limited by the heterogeneity of underlying study designs. Future research should extend the framework with longitudinal data tracking the dynamics of trust calibration and delegation over multi-year deployment cycles, test the framework in cross-cultural settings, and integrate emerging agentic GenAI architectures whose autonomous-action capabilities push the responsibility allocation question into sharper relief.

Four directions for future work follow directly from the empirical results. First, longitudinal designs that track the same workflows over twelve to twenty-four months would allow estimation of how the three principles interact over time, in particular whether anchoring investments substitute for or complement ongoing trust calibration. Second, comparative cross-cultural studies would test whether the dominance of workflow design over individual usage observed in the Chinese sample generalises to settings with different organisational structures and regulatory regimes. Third, the emerging class of agentic GenAI systems that take multi-step actions in external systems pushes the responsibility allocation question from a static design problem into a dynamic governance problem that the present framework would need to be extended to address. Fourth, sector-specific applications of the framework to high-stakes domains such as healthcare and public administration, where the cost of misallocated responsibility is highest, would test the framework's external validity and surface domain-specific operational adjustments.

The broader contribution of this paper is to reframe the question that practitioners and researchers ask about GenAI value. The dominant question has been whether GenAI is productive on a given task. The more useful question, supported by the evidence assembled here, is under what workflow conditions the productivity of GenAI becomes durable, accountable, and aligned with business outcomes. The three principles offer one

tractable answer to that question, and the data presented support their continued empirical refinement.

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