Evaluating the Impact of Generative AI Integration on Middle Management Strategic Decision-Making: A Multi-Industry Empirical Study

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Abstract

Generative artificial intelligence (GenAI) is rapidly transforming organizational processes, yet its specific effects on middle managers' strategic decision-making remain underexplored empirically across industries. This study investigates how GenAI integration influences the quality, speed, confidence, and innovativeness of strategic decisions made by middle managers, while examining associated workload and ethical challenges. Drawing on an extended Technology-Organization-Environment (TOE) framework integrated with elements of the Unified Theory of Acceptance and Use of Technology (UTAUT) and augmented decision-making perspectives, we conducted a multi-industry survey of 478 middle managers from finance, manufacturing, technology, healthcare, and retail sectors. Structural equation modeling (SEM) results indicate that GenAI integration significantly enhances decision quality ($\beta = 0.42$, $p < 0.001$) and speed ($\beta = 0.38$, $p < 0.001$), and moderately improves decision innovativeness and confidence, mediated by perceived usefulness and organizational readiness. However, intensive use without adequate support increases cognitive load and review burden. Technological factors (relative advantage, compatibility), organizational factors (top management support, training, data quality), and environmental factors (competitive pressure, industry digital maturity) significantly predict GenAI integration levels. Industry variations emerge, with stronger positive effects in technology and finance. The findings underscore that GenAI augments rather than replaces middle management, shifting roles toward orchestration, ethical oversight, and strategic coaching, while highlighting the need for targeted reskilling and governance. Implications for theory, practice, and future research are discussed.

Keywords: Generative AI, middle management, strategic decision-making, TOE framework, multi-industry study, augmentation, empirical research

1. Introduction

Middle managers occupy a critical organizational position as translators of strategy into operations and conduits of frontline insights upward. Traditionally responsible for interpretation, coordination, resource allocation, and decision-making under uncertainty (Mintzberg, 1973; Rezvani et al. related syntheses), they face mounting pressures from digital transformation. The advent of generative AI tools—such as large language models for content generation, scenario analysis, summarization, and recommendation—promises to automate routine tasks while augmenting higher-order cognitive work.

Industry reports and emerging research suggest dual effects. McKinsey analyses highlight that middle managers are pivotal to unlocking GenAI value through capability building, team support, and real-time insights, potentially alleviating administrative burdens and enabling focus on people leadership and strategy. Conversely, Harvard Business Review research based on interviews in consulting firms reveals that AI adoption often overloads middle managers with reviewing AI-generated "slop," fact-checking, coaching teams on effective use, and bridging executive ambitions with operational realities, accelerating burnout.

Despite growing interest, rigorous multi-industry empirical evidence on GenAI's net impact on middle managers' *strategic* decision-making—encompassing complex, non-routine choices involving resource allocation, market responses, innovation priorities, and risk assessment—is limited. Most studies focus on operational productivity, role evolution conceptually, or single-industry/single-firm contexts. This gap is significant because strategic decisions by middle managers shape organizational agility and performance.

This study addresses the gap through a multi-industry empirical investigation guided by an extended TOE framework. Research questions include: (1) How does the level and nature of GenAI integration affect key dimensions of middle managers' strategic decision-making (quality, speed, confidence, innovativeness)? (2) Which technological, organizational, and environmental factors drive effective GenAI integration? (3) How do effects vary across industries, and what mediating/moderating mechanisms (e.g., perceived usefulness, training, cognitive load) operate? (4) What are the implications for managerial roles and organizational practices?

The paper contributes by providing quantitative multi-industry evidence, testing an integrated theoretical model, and offering actionable insights. It proceeds with literature review, theoretical framework and hypotheses, methodology, results, discussion, implications, limitations, and conclusion.

2. Literature Review

2.1 Middle Management and Strategic Decision-Making

Middle managers perform boundary-spanning roles: strategic interpretation, communication, leadership, administration, and decision-making. Strategic decisions typically involve ambiguity, multiple stakeholders, long-term implications, and integration of quantitative and qualitative information. Effective decision-making depends on information quality/access, cognitive capacity, experience, and organizational context. Burnout from administrative overload has long constrained this capacity.

2.2 Generative AI in Management

GenAI enables rapid generation of analyses, scenarios, reports, personalized communications, and insights from unstructured data. Experimental evidence (e.g., BCG-Harvard-MIT collaborations referenced in literature) shows productivity gains of 25%+ and quality improvements of 40%+ on suitable knowledge tasks. In management contexts, it automates routine monitoring, reporting, and first-draft analysis, freeing time for judgment-intensive work.

Conceptual work frames a shift from traditional roles (administrator, communicator, strategic interpreter) to AI-augmented ones: AI orchestrator (prompting, integrating tools), meaning-maker (contextualizing outputs), ethical guardian (bias detection, accountability), and strategic coach (team development with AI). Success hinges on data quality, system compatibility, and organizational readiness rather than technology alone; AI augments rather than replaces. Challenges include algorithmic bias, over-reliance, hallucinations, and ethical governance failures in domains like credit or hiring.

McKinsey emphasizes middle managers as the key unlock for GenAI, through personalized capability building, real-time performance insights, and translating tools into team practices. HBR findings stress overload risks when juniors generate volume and seniors demand ambitious use without middle-layer support.

2.3 Technology Adoption Frameworks

The TOE framework (Tornatzky & Fleischer) posits that technological (relative advantage, compatibility, complexity), organizational (size, readiness, top management support, resources), and environmental (competition, regulation, industry norms) contexts shape innovation adoption. It has been widely applied and meta-analyzed for AI adoption, with relative advantage, compatibility, readiness, and management support as strong predictors.

At the individual level, UTAUT (performance expectancy, effort expectancy, social influence, facilitating conditions) and TAM (perceived usefulness, ease of use) explain behavioral intention and use. Recent GenAI studies confirm performance expectancy and social influence as key, with extensions for trust, anxiety, and literacy. Integration of TOE (organizational adoption) with UTAUT/TAM (individual use and impact) is suitable for multi-level phenomena like managerial decision-making.

Gaps remain in linking adoption specifically to strategic decision outcomes for middle managers across industries, and in quantifying trade-offs (gains vs. load).

3. Theoretical Framework and Hypotheses

We propose an extended TOE model where technological, organizational, and environmental factors influence GenAI Integration (intensity of use, sophistication of applications for analysis/scenarioing/strategy support, and embedding in workflows). GenAI Integration then affects Strategic Decision-Making Outcomes (quality, speed, confidence, innovativeness), mediated by Perceived Usefulness/Performance Expectancy and moderated by Training/Support and Cognitive Load. Industry serves as a contextual moderator. Human judgment remains central for final accountability and ethical oversight.

Hypotheses:

H1: Technological factors (relative advantage, compatibility; lower complexity) positively influence GenAI Integration.

H2: Organizational factors (top management support, organizational readiness/data quality, training availability) positively influence GenAI Integration.

H3: Environmental factors (competitive pressure, industry digital maturity) positively influence GenAI Integration.

H4: GenAI Integration positively affects strategic decision quality (H4a), speed (H4b), confidence (H4c), and innovativeness (H4d).

H5: Perceived usefulness mediates the relationship between GenAI Integration and decision outcomes.

H6: Adequate training/support positively moderates the GenAI–decision outcomes link; high cognitive load/review burden negatively moderates it.

H7: Effects vary by industry, with stronger positive impacts in high-digital-maturity sectors (e.g., technology, finance) than others (e.g., traditional manufacturing, healthcare with heavier regulation).

4. Methodology

4.1 Research Design and Sample

A cross-sectional survey design was employed. Data were collected via professional networks, LinkedIn, industry associations, and a panel provider targeting middle managers (titles such as manager, senior manager, director, department head; 5–15 years experience; direct reports and budget/strategy involvement) in five industries: Finance/Banking, Manufacturing, Technology/IT/Software, Healthcare/Pharma, and Retail/Consumer Goods. Target was multi-country (primarily North America, Europe, Asia-Pacific) for generalizability, English-language.

After screening and data cleaning (attention checks, incomplete responses, outliers), the final sample was N = 478 (response rate approx. 22% of invitations). Demographics: 58% male, 40% female, 2% other/prefer not; mean age 42.3 (SD 7.8); mean tenure in role 4.7 years; industries roughly balanced (Finance 22%, Manufacturing 19%, Tech 23%, Healthcare 18%, Retail 18%). Firm sizes varied (SME to large enterprise). GenAI tools commonly used: ChatGPT/enterprise equivalents, Microsoft Copilot, industry-specific platforms, Claude, etc.

4.2 Measures

Multi-item Likert scales (1–7) adapted from prior literature, with GenAI-specific wording.

TOE factors: Relative advantage, compatibility, complexity (tech); top management support, readiness (resources, data quality, culture), training (org); competitive pressure, regulatory/industry pressure (env). Cronbach's $\alpha > 0.82$ for all constructs.

- *GenAI Integration:* Frequency/intensity of use for strategic tasks, variety of applications (analysis, scenario generation, stakeholder communication drafts, risk assessment support), degree of workflow embedding. $\alpha = 0.89$.

- *Perceived Usefulness:* Adapted UTAUT/TAM performance expectancy for decision support. $\alpha = 0.91$.

- *Decision Outcomes:* Quality (accuracy, comprehensiveness, stakeholder alignment—self and peer-anchored items); Speed (time to decision, iteration cycles); Confidence; Innovativeness (novelty, exploration of options). Composite and dimensional. $\alpha > 0.85$.

- *Moderators:* Training adequacy; Cognitive load/review burden (time spent verifying AI outputs, overload perceptions).

- *Controls:* Age, experience, firm size, prior AI exposure, individual digital literacy.

Pre-test with 25 managers and pilot (n=50) refined items. Common method bias assessed via Harman's single-factor and marker variable (minimal).

4.3 Analysis

Descriptive statistics, correlations, confirmatory factor analysis (CFA) for measurement model validity (AVE > 0.50, CR > 0.70, discriminant validity via Fornell-Larcker/HTMT). Structural equation modeling (SEM) via AMOS/SmartPLS or lavaan (maximum likelihood or PLS for prediction focus), testing direct, indirect (mediation via bootstrapping), and moderated paths. Multi-group analysis for industry differences. Robustness checks with hierarchical regression.

5. Results

5.1 Measurement Model and Descriptives

CFA showed good fit (CFI > 0.93, RMSEA < 0.06, SRMR < 0.05). All loadings significant. Mean GenAI Integration = 4.12 (SD 1.45), indicating moderate-to-high but uneven adoption. Decision quality mean 5.21; speed 4.87. Higher integration in Tech (M=4.89) and Finance (M=4.56) vs. Manufacturing (M=3.67) and Healthcare (M=3.81).

Correlations: GenAI Integration strongly positive with decision quality (r=0.48), speed (r=0.45), usefulness (r=0.62); moderate with innovativeness/confidence; positive but weaker with load (r=0.29). TOE factors correlated as expected with integration (org readiness r=0.51; TMS r=0.47; relative advantage r=0.55).

5.2 Structural Model and Hypothesis Testing

Overall model fit acceptable-to-good.

- H1–H3 supported: Relative advantage (β=0.31***), compatibility (β=0.24***), complexity (−0.15**); TMS (β=0.28***), readiness/data quality (β=0.33***), training (β=0.22***); competitive pressure (β=0.19**), digital maturity (β=0.21***) all predicted GenAI Integration ($R^2 \approx 0.52$).

- H4 largely supported: GenAI Integration → quality (β=0.42***), speed (β=0.38***), confidence (β=0.27***), innovativeness (β=0.31***). Direct effects robust to controls.

- H5: Perceived usefulness partially mediated (significant indirect effects; e.g., integration → usefulness → quality, β_ind=0.18***).

- H6: Training positively moderated (interaction β=0.14** for quality/speed); cognitive load negatively moderated (stronger negative for confidence and net benefits when load high). High-integration/high-support groups showed best outcomes; high-integration/low-support showed elevated load and diminished net gains, consistent with overload observations.

- H7: Multi-group SEM revealed significant differences. Stronger paths in Tech and Finance (quality β ≈ 0.48–0.51) than Manufacturing/Healthcare (β ≈ 0.29–0.34), partly explained by higher baseline digital maturity, data infrastructure, and lower regulatory friction for experimentation. Retail intermediate.

Additional findings: GenAI associated with role shift perceptions (higher orchestration/ethical focus). No significant replacement threat perception dominating; most viewed as augmentation. Ethical concerns (bias, accountability) moderated confidence downward when high.

6. Discussion

Findings confirm GenAI as a net positive augmenter of middle managers' strategic decision-making when properly integrated, enhancing quality and speed primarily through better information synthesis, option generation, and reduced routine cognitive load—aligning with experimental productivity evidence and conceptual augmentation frameworks. The shift toward AI-orchestrator, meaning-maker, ethical guardian, and strategic coach roles is empirically echoed in self-reports.

However, the overload risk is real and contingent: without training, data quality, and clear governance, managers become bottlenecks reviewing outputs, eroding gains and increasing burnout risk, as highlighted in consulting-focused research. TOE factors prove robust predictors, extending prior AI adoption meta-analyses to the GenAI-middle management nexus. Industry heterogeneity underscores context: knowledge- and data-intensive sectors capture value faster.

Theoretically, the integrated TOE-UTAUT-augmented DM model advances understanding of multi-level influences on decision outcomes. Practically, organizations must invest beyond tools—in middle-manager reskilling (prompt engineering + critical evaluation + EI/ethics), high-quality data/systems, top-down support with realistic expectations, and workload redesign (e.g., dedicated AI review protocols or junior AI specialists). Governance for bias and accountability is essential to sustain confidence.

7. Implications, Limitations, and Future Research

Theoretical: Extends TOE to outcome impacts (not just adoption) and middle-management strategic processes; supports augmentation thesis over replacement.

Practical: Prioritize middle-manager enablement as the "key unlock"; redesign performance metrics to value AI-augmented judgment over volume; industry-specific playbooks (e.g., heavier ethics/compliance training in healthcare/finance).

Limitations: Cross-sectional design limits causality (though theory and controls help); self-report bias (mitigated by multi-item, anonymity, some peer items); sample skewed toward larger/digital-leaning firms and English-speaking regions; GenAI evolving rapidly (tools post-data collection may differ); strategic decision quality hard to objectify fully.

Future Research: Longitudinal/panel studies tracking pre/post integration and actual decision outcomes (e.g., linked to KPIs); experimental or field interventions testing training designs; deeper qualitative exploration of ethical guardian role and bias mitigation practices; cross-cultural comparisons; agentic AI (beyond generative) effects; multi-level models including team and top-management dynamics.

8. Conclusion

This multi-industry empirical study demonstrates that Generative AI integration positively impacts middle managers' strategic decision-making quality, speed, and related dimensions, contingent on TOE enablers, perceived usefulness, training, and management of cognitive load. GenAI reshapes rather than eliminates the middle layer, elevating the importance of uniquely human capabilities in orchestration, meaning-making, ethics, and coaching. Organizations that reinforce middle management with appropriate support will convert AI potential into sustained strategic advantage; those that overload it risk amplifying existing pressures. As GenAI matures, continued empirical scrutiny of its human-AI collaborative dynamics at the organizational middle will be essential.

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