Strategic Management of Artificial Intelligence Technology Implementation in Corporate Contexts

[1] Aneesha Sharma
[1] Business Strategist Chicago, USA

Received: 14 Jan 2026 | Received Revised Version: 28 Jan 2026 | Accepted: 19 Feb 2026 | Published: 24 Feb 2026

Volume 08 Issue 02 2026 | Crossref DOI: 10.37547/tajmei/Volume08Issue02-07

Abstract

The article is dedicated to the strategic management of artificial intelligence technology implementation in corporate contexts. The relevance of the study is driven by the growing gap between the declared potential of artificial intelligence and the frequent stagnation or reversal of corporate AI initiatives. Scientific novelty lies in the integrated interpretation of technology adoption not as a technical decision, but as a multidimensional managerial process shaped by organizational readiness, trust, emotional responses, and leadership practices. This article examines the interaction between perceived usefulness, organizational pressure, cognitive attitudes, and disengagement mechanisms in enterprise AI deployment. Special emphasis is given to the transformation of managerial roles and human–algorithm interaction in everyday organizational workflows. This article aims to conceptualize the factors that determine sustained AI usage or disengagement in corporate settings. Analytical synthesis, comparative analysis, and structured review of academic sources are used to achieve this goal. The conclusion describes how trust, leadership support, and emotional acceptance together shape AI adoption trajectories. The article will be useful for managers, corporate strategists, and researchers studying digital transformation and technology governance.

Keywords: artificial intelligence, strategic management, technology adoption, organizational readiness, trust in AI, digital transformation

Cite This Article: Sharma, A. (2026). Strategic Management of Artificial Intelligence Technology Implementation in Corporate Contexts. The American Journal of Management and Economics Innovations, 8(2), 41–47. https://doi.org/10.37547/tajmei/Volume08Issue02-07

Introduction

The promise of AI looms large in boardrooms and strategy sessions, yet it is tempered by stories of pilots stalling and projects being reversed. As one adoption study observes, “AI is viewed as having potential for significant impact,” but its track record of “boom and bust cycles” makes organizations cautious (Uren & Edwards, 2023). The post-pandemic push for digital transformation has only amplified the urgency: firms feel pressure to integrate AI after a surge in remote work and online services (Cavalcanti et al., 2022).

In this context, key questions arise in managerial terms: What organizational conditions (culture, resources, leadership) shape whether AI projects take root? How do managers and employees perceive AI’s usefulness and risks, and how do trust or anxiety influence usage? In what ways can heavy regulation and compliance demands alter AI strategy? Crucially, when and why do people disengage from AI tools even after deployment? Addressing these threads calls for re-examining traditional adoption models: reframing TAM and TOE through a managerial lens and building a conceptual map linking perceived utility, trust, organizational pressure, technical and human challenges, and disengagement triggers. The objectives of this article are:

1. to unpack the multi-layered organizational and psychological dynamics of AI uptake,
2. to compare how different deployment types (e.g., consumer AI tools vs enterprise systems) play out
3. to conceptualize the points where human and algorithmic workflows intersect or collide.

No single narrative suffices: several analytical strands, from cultural readiness and strategic intent to cognitive trust and regulatory friction, are explored in order to map the contingencies of success and failure in AI implementation.

Methods and Materials

This section summarizes the scholarly materials forming the analytical foundation of the study and outlines the methods applied. Victoria Uren and John Edwards examined organizational technology readiness and long-term AI adoption trajectories, emphasizing structural and managerial conditions of sustainable use (Uren & Edwards, 2023). D.R. Cavalcanti and co-authors conducted a meta-analysis of digital transformation drivers, demonstrating the persistent influence of perceived usefulness and organizational pressure on technology adoption decisions (Cavalcanti et al., 2022). H. Jo and Y. Bang analyzed continuance intention in enterprise systems through integrated TOE and TAM models, highlighting the stabilizing effect of managerial support (Jo & Bang, 2023). David Hradecky and colleagues investigated organizational readiness for AI adoption, focusing on resources, data practices, and institutional confidence (Hradecky et al., 2022). X. Chen and co-authors explored AI-related anxiety and its impact on employee motivation and work engagement (Chen et al., 2025). S. Marocco and colleagues studied attitudes toward artificial intelligence in organizational contexts, linking perceived performance gains with trust and reduced anxiety (Marocco et al., 2025). S. Hai and co-authors examined the dark side of employee–generative AI collaboration, identifying work alienation and expediency as outcomes of prolonged AI use (Hai et al., 2025). J. Chen presented a qualitative case study of AI-mediated leadership, describing the shift toward algorithmic editing and translational managerial work (Chen, 2025).

To write this article, methods of comparative analysis, source analysis, conceptual synthesis, and analytical generalization were used.

Results

The analysis unfolds in multiple interwoven threads rather than a single argument. One thread centers on how perceptions of usefulness and trust drive or stall adoption. Classic TAM constructs are often interpreted at the user level, but managers ask: useful for whom and for what? Empirical evidence suggests that perceived usefulness remains a core driver of intention even in organizational contexts: a large meta-analysis of digital technology projects found that usefulness and ease-of-use consistently predicted adoption intention and actual use (Cavalcanti et al., 2022). This aligns with studies of enterprise systems, where end-users believe that the system that improves job performance was found to positively affect their continued usage (Jo & Bang, 2023). However, when deploying AI, “usefulness” can be split into technical metrics versus business impact. For instance, system and information quality were shown to feed into perceived usefulness in one study of enterprise resource planning (ERP), but ultimately, managers emphasized that top management support was a crucial driver of continued AI use. Trust enters as another decisive factor: trust in an AI tool shapes both perceived usefulness and social norms around adoption. In a technology acceptance study on digital payment (outside of core AI but conceptually similar), trust was found to significantly influence adoption by boosting beliefs about usefulness and moderating peer influence (Cavalcanti et al., 2022). In other words, even if an AI system has strong technical merits, a lack of trust or organizational endorsement can block its uptake. Below is a systematization of the core evaluative lenses shaping organizational AI adoption (Table 1).

Table 1. Core evaluative lenses in organizational AI adoption (compiled by the author based on Uren & Edwards, 2023; Cavalcanti et al., 2022; Jo & Bang, 2023)

Evaluative lens	Analytical focus	Managerial interpretation	Organizational consequence
Perceived usefulness	Expected performance contribution	Strategic or operational value creation	Approval or rejection at the decision stage
Ease of use	Effort required for interaction	Training and cognitive load	Voluntary engagement or avoidance
Trust in AI	Reliability and interpretability	Confidence in algorithmic outputs	Social normalization or resistance
Top management support	Leadership endorsement	Signal of legitimacy and priority	Sustained use or symbolic adoption
Social norms	Peer and hierarchical influence	Acceptability of AI-assisted decisions	Conformity or silent disengagement

This leads to a conceptual linkage: perceived usefulness and trust form a tandem lens through which users (and managers) evaluate AI, but they are in turn shaped by organizational context. Organizational readiness and pressures constitutes another analytical strand. An extended TOE framework often applies: technology (capabilities), organization (resources, culture), and environment (markets, regulation). Studies emphasize that people and processes must be as ready as the technology itself. One model of organizational AI adoption argues that "people, process, and data readiness are required in addition to technology readiness" for sustainable success (Uren & Edwards, 2023). That is, even the most advanced AI system will falter if staff lack skills or buy-in, if workflows are not re-engineered, or if data pipelines are missing. Below is a structured view of organizational readiness dimensions influencing AI implementation trajectories (Table 2).

Table 2. Organizational readiness dimensions influencing AI implementation (compiled by the author based on Uren & Edwards, 2023; Hradecky et al., 2022)

Readiness dimension	Organizational Aspect	Risk manifestation	Strategic implication
Technological readiness	Infrastructure, data availability, system integration	Technical fragility	Limited scalability
Human readiness	Skills, acceptance, and learning capacity	Misuse or avoidance	Reduced effectiveness

Process readiness	Workflow redesign and task alignment	Operational disruption	Shadow practices
Cultural readiness	Attitudes toward automation and change	Passive resistance	Formal but ineffective adoption
Leadership readiness	Executive sponsorship and vision	Fragmented initiatives	Project discontinuation

Empirically, factors like firm size, technical infrastructure, and data management capacity have been found to motivate or inhibit AI readiness (Hradecky et al., 2022). For example, one sector study noted that "confidence in organizational technological practices, financial resources, [and] data management" were among the determinants of how prepared a company was to adopt AI (Hradecky et al., 2022). Top management backing emerges repeatedly: support from executives not only provides budget and mandate but signals to employees that change is expected. In line with this, continuance of enterprise systems was strongly linked to managerial support in a quantitative survey. In summary, organizational pressure and commitment – whether from leadership, competitive necessity, or even normative forces – can tip the scales. Yet pressures can be ambiguous: efforts to enforce AI use may generate resistance if the culture is not aligned, a tension that is not fully captured by well-known adoption models. This limitation is particularly evident in the Technology Acceptance Model (TAM) and in the Technology–Organization–Environment (TOE) framework, where organizational pressure is treated predominantly as a facilitating condition rather than as a potential source of resistance or disengagement.

A third thread looks at cognitive and emotional dimensions. Attitudes toward AI technologies include not just rational assessments of utility but feelings and biases about autonomy, job security, and privacy. Surveys show workers harbor anxiety and skepticism: when employees fear job replacement or feel overwhelmed by new AI tools, their motivation and engagement suffer. One psychological study reports that "anxiety about job replacement and anxiety about learning both diminish employees' work passion," with emotional exhaustion partly mediating this effect (Chen et al., 2025). In other words, if AI provokes stress or burnout, even a useful system can be abandoned. Attitudinal surveys also link perceived performance gains to positive sentiment: when workers believe AI will boost their job performance, they report greater trust, higher perceived quality of output, and reduced anxiety (Marocco et al., 2025). Conversely, when ethical concerns surface – such as worries that AI might erode accountability or increase surveillance – attitudes can flip. Though framed as cognitive biases, these emotional undercurrents have strategic impact: a workforce that distrusts AI or feels insecure may mentally disengage. Recent qualitative accounts underscore this risk. In real-scale AI deployments, researchers found that what began as collaboration with generative AI gradually felt like "work alienation", eroding connection to the work itself. In one longitudinal field study, increased AI use was linked to rising employee alienation and, downstream, to unethical shortcuts in work (so-called expediency) (Hai et al., 2025). Such findings highlight that emotional and ethical responses can trigger withdrawal from AI systems even when their capabilities are sound. Below is a typology of disengagement triggers observed in organizational AI use (Table 3).

Table 3. Disengagement triggers in organizational AI use (compiled by the author based on Chen et al., 2025; Marocco et al., 2025; Hai et al., 2025; Chen, 2025)

Trigger category	Underlying mechanism	Individual response	Organizational outcome
Cognitive overload	Continuous supervision of AI outputs	Fatigue and frustration	Minimal or selective use
Trust erosion	Errors and opacity of recommendations	Skepticism	Bypassing AI systems
Emotional anxiety	Fear of replacement or deskilling	Defensive behavior	Reversion to manual routines
Ethical discomfort	Surveillance and accountability concerns	Moral disengagement	Informal resistance
Role ambiguity	Shift from authorship to editing	Loss of professional identity	Declining engagement

Another important thread examines failure modes and disengagement triggers. Many organizations report that early AI pilots bring enthusiasm, which then fades. Unlike user adoption (which TAM often models as forward-moving), corporate adoption can involve backsliding or abandonment. Qualitatively, some deployments of "enterprise-grade" AI systems have been quietly shelved not because the algorithms were bad, but because they broke existing workflows or imposed hidden costs. For example, industry analyses note that custom AI deployments often "fail due to brittle workflows, lack of contextual learning, and misalignment with day-to-day operations." Although large-scale peer-reviewed statistics on failure rates are lacking, such anecdotal evidence suggests that practical factors—namely integration difficulty, unclear ROI benchmarks, and insufficient adaptation to real tasks—are key triggers. When these failures occur, users often lose trust and disengage. Disengagement can look like bypassing AI: employees might revert to manual processes, or use AI tools minimally. Possible triggers include the cognitive overload of needing to supervise AI, the disappointment when AI suggestions are off-mark, or the simple human tendency to fall back to familiar habits under pressure. In summary, disengagement seems less about any single flaw in AI and more about the compounding of perceived uselessness, loss of trust, and organizational friction.

In practice, several of these dynamics surfaced in ways that were not anticipated at the planning stage. In a number of organizational settings discussed in the literature, managers initially reported confidence in the strategic rationale of AI projects, yet day-to-day usage revealed a gradual erosion of engagement rather than outright rejection. Small inconsistencies in system output, additional verification steps, and the need to justify algorithmic recommendations during meetings accumulated into a form of quiet resistance. This resistance rarely took the shape of formal opposition; instead, it manifested through selective use, delayed reliance, or the parallel maintenance of non-AI routines. Such patterns indicate that disengagement often develops incrementally and informally, shaped by routine experience rather than by explicit attitudes or stated intentions.

Finally, a thread on human–algorithm interaction and task editing reveals how AI changes roles. In practice, using AI often means humans curate rather than fully replace workflows. A case study in an organizational setting illustrates this vividly: managers using generative AI for drafting communications found that "administrative writing becomes algorithmic editing, where leadership involves curating and contextualizing machine output" (Chen, 2025). In that example, the presence of AI blurred authorship and redistributed accountability – leadership became “translational work” across human and algorithmic logic. Strategically, this suggests a subtle failure mode: if managerial users see themselves merely fixing AI drafts, their sense of control and authorship changes. Some may perceive the AI as undermining their expertise, while others may feel dependent on the tool. Neither extreme is addressed by standard TAM; both can either stifle trust or overinflate dependence. Notably, AI that automates routine writing may relieve work but also trigger new supervision burdens. Thus, the interplay of human and algorithmic editing complicates the adoption story: success involves reshaping roles rather than straightforward substitution.

Taken together, these threads sketch a web of interactions. Perceived usefulness drives initial interest, but only if trust and support are present. Organizational strength and leadership can amplify or block these perceptions. Beneath, emotional responses to AI (anxiety vs confidence) push the pendulum. And when systems falter in practice, disengagement follows. The conceptual model emerging links perceived usefulness and trust at its core, with challenges (technical and human), organizational pressures (leadership, norms, readiness), and specific disengagement triggers on the periphery. This model draws on TAM (usefulness, ease of use) and TOE (technology, organization, environment) but recasts them for strategy: “usefulness” is interpreted not as gadget appeal but as P&L or strategic advantage, and “organization” includes leadership and culture as active forces, not just background conditions.

Discussion

This exploratory reasoning reveals tensions rather than tidy conclusions. The classic view of TAM, focusing on rational perceptions of a technology’s utility, collides with messy human factors in corporate life. For instance, one may assume that if executives champion an AI project and employees understand its benefits, adoption should follow. Yet studies show that even with positive usefulness ratings, factors like ingrained habits, ethical doubts, or low trust can invert attitudes. That is, disbelief in a promised benefit – for example, if early pilots do not yield expected gains – can entirely negate the perceived usefulness initially advertised. In practice, some firms rush AI pilots under competitive pressure, only to stall when “friction” arises (a point made in industry reports, though not fully captured by any single academic model). This friction includes misaligned incentives: an employee might recognize an AI’s potential efficiency but still resist because they fear job loss. Such contradictions underscore a limitation of linear TAM: real adoption is non-linear and negotiated.

Similarly, applying TOE at the strategy level exposes contradictions. TOE suggests that enabling factors (size, budget) and environmental pressures (regulations, competition) jointly shape tech uptake. Here, the regulatory and social environment is particularly knotty. On one hand, compliance demands (privacy laws, auditability) can push organizations toward formal AI governance, which in principle builds trust. On the other hand, heavy-handed rules can deter experimentation. For example, companies in highly regulated industries may proclaim the need for “ethical AI” frameworks, yet find that the cost of rigorous oversight slows rollout to a crawl. That tension is not directly resolved by TOE alone and suggests a reframing: regulation itself becomes part of the strategic calculus, not just an external constraint.

Another juxtaposition arises between organizational readiness and individual readiness. A firm can invest in data infrastructure and training programs, signaling high readiness. One might expect a seamless AI uptake. Yet if employees lack trust or feel emotionally unprepared, even the best-prepared organization can see AI tools ignored. For example, in one case, high “people readiness” was reported, but anecdotal follow-ups revealed managers simply reverted to old processes when the AI proved awkward in day-to-day tasks. Conversely, a team with initial distrust might adopt more fully out of necessity when leadership insists, leading to grudging compliance rather than genuine acceptance. These scenarios hint that readiness is multi-dimensional and path-dependent: neither cultural readiness nor technological readiness alone guarantees success.

Methodologically, this review focuses on conceptual factors rather than empirical rates, which could understate some points. For instance, industry claims of a 90–95% failure rate in AI pilots attract attention but rely on self-reports and lack scholarly validation. This review found little peer-reviewed evidence for such extreme figures, though there is indirect support: the reasons cited (brittle workflows, misaligned expectations) align with the practical issues noted by researchers. Moreover, the literature tends to treat adoption as a one-off event, whereas corporate adoption is an evolving process. A limitation is that many studies cited in this article use cross-sectional surveys of attitudes or intention (TAM-derived) rather than longitudinal follow-ups of actual adoption outcomes. This means gaps remain in understanding how initial perceptions translate over time into continued use or rejection.

Finally, the analysis suggests areas requiring more integration. Traditional TAM/TOE frameworks frame technology adoption predominantly as a rational calculus. But the threads highlighted in this article show that a strategic manager faces a dialectic of positive drivers (utility, leadership push) and negative brakes (fear, poor fit, regulatory confusion). For example, trust appears as a bridging concept between the rational and emotional realms: a system might be objectively useful, but if algorithmic opacity undermines trust, it risks underuse. Future approaches might explicitly model trust not as a static input but as evolving with experience and feedback loops. Similarly, disengagement triggers suggest that organization-level TAM/TOE models should account for negative intention (withdrawal) rather than treating it as the simple absence of adoption.

Conclusion

Seen from the strategic management vantage, AI implementation is an asymmetrical puzzle rather than a straightforward project plan. Usefulness and trust stand at its heart, but their meanings shift when viewed through organizational eyes. Managers must contend simultaneously with efficacy (can this tool improve outcomes?) and usability (do people feel comfortable with it?). Organizationally, investment and impetus can be undone by unanticipated human responses. Taken together, this perspective implies that no single solution or checklist will suffice. AI adoption must be cultivated: leaders need to tether AI initiatives to clear business goals while nurturing trust and capability among employees. At the same time, they must be ready to question even popular models like TAM and TOE, adapting them to the messier realities of strategy, culture, and emotion. In conclusion, the progress with AI in corporate settings is inherently context-specific and iterative. The insights here are less recipes than reminders: strategic AI rollout is a continually negotiated outcome of perceived benefits, organizational support, and human engagement rather than a foregone conclusion of engineering prowess.

References

1. Cavalcanti, D. R., Oliveira, T., & de Oliveira Santini, F. (2022). Drivers of digital transformation adoption: A weight and meta-analysis. *Heliyon, 8*(2), e08911. https://doi.org/10.1016/j.heliyon.2022.e08911
2. Chen, J. (2025). Leading through algorithms: A case study of AI-mediated leadership in an international educational organization. *Advances in Economics, Management and Political Sciences, 244*, 45–53. https://doi.org/10.54254/2754-1169/2025.LD30162
3. Chen, X., Ke, J., Zhang, X.-e., & Chen, J. (2025). The impact of AI anxiety on employees' work passion: A moderated mediated effect model. *Acta Psychologica, 260*, 105487. https://doi.org/10.1016/j.actpsy.2025.105487
4. Hai, S., Long, T., Honora, A., Japutra, A., & Guo, T. (2025). The dark side of employee-generative AI collaboration in the workplace: An investigation on work alienation and employee expediency. *International Journal of Information Management*. https://doi.org/10.1016/j.ijinfomgt.2025.102905
5. Hradecky, D., Kennell, J., Cai, W., & Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *International Journal of Information Management, 65*, 102497. https://doi.org/10.1016/j.ijinfomgt.2022.102497
6. Jo, H., & Bang, Y. (2023). Understanding continuance intention of enterprise resource planning (ERP): TOE, TAM, and IS success model. *Heliyon, 9*(10), e21019. https://doi.org/10.1016/j.heliyon.2023.e21019
7. Marocco, S., Bellini, D., Barbieri, B., Presaghi, F., Grossi, E., & Talamo, A. (2025). Attitudes toward artificial intelligence in organizational contexts. *AI, 6*(11), 292. https://doi.org/10.3390/ai6110292
8. Uren, V., & Edwards, J. S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management, 68*, 102588. https://doi.org/10.1016/j.ijinfomgt.2022.102588