

Making Sense of Mixed Signals: The Impact of (In)consistent Performance Feedback on Corporate Digital Technology Innovation

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Making Sense of Mixed Signals: The Impact of (In)consistent Performance Feedback on Corporate Digital Technology Innovation

Abstract: Digital technology innovation (DTI) is a vital source of competitive advantage in the digital transformation era. Drawing on the behavioral theory of the firm (BTOF) and the attention-based view (ABV), this study examines how consistent and inconsistent performance feedback influence firms' digital technology innovation and how CEO attentional vigilance moderates these effects. Using data from Chinese A-share listed companies, we distinguish between mitigation and adaptation DTI to capture the heterogeneity of firms' behavioral responses. The results show that when primary performance falls below aspiration, firms increase mitigation digital technology innovation but reduce adaptation digital technology innovation. In contrast, when feedback is inconsistent (primary performance below and secondary performance above aspiration), firms decrease mitigation (and increase adaptation) digital technology innovation. CEO attention quantity weakens (strengthens) the positive (negative) relationship between below-aspiration feedback and mitigation (adaptation) innovation, while CEO attention stability weakens (strengthens) the negative (positive) relationship between inconsistent feedback and mitigation (adaptation) innovation. These findings demonstrate how performance ambiguity and executive attention jointly shape the direction of DTI, advancing understanding of managerial cognition and organizational strategy in the digital context.

Keywords: Consistent and Inconsistent Performance Feedback; Digital Technology Innovation; CEO Attentional Vigilance; Machine Learning

1. Introduction

Corporate digital technology innovation has become a central driver of organizational transformation and competitive renewal in the digital economy. By integrating technologies such as artificial intelligence, blockchain, cloud computing, and big data analytics, firms can reconfigure production and coordination systems and enhance value creation through platform based ecosystems (Helfat & Raubitschek, 2018; Abbate et al., 2022). As a dynamic capability, DTI enables firms to respond to technological disruption and environmental turbulence (Mikalef et al., 2019). However, the process remains highly uncertain and path dependent. Unlike traditional technological upgrading, DTI involves deep changes in organizational routines, coordination logics, and governance structures, requiring firms to balance technological renewal with the inertia of legacy systems. Firms further confront behavioral tensions, such as balancing preventive digital reinforcement with responsive digital renewal (Nambisan & Baron, 2021) and reconciling system stability with adaptive flexibility (Dolata, 2009). These tensions generate managerial ambiguity, making it difficult for decision makers to assess whether digital initiatives are succeeding or require strategic redirection under fluctuating performance conditions (Abebe et al., 2024).

Prior research has identified multiple antecedents of corporate digital technology innovation, including technological capabilities, resource endowments, organizational strategies, and institutional environments (Jiang et al., 2024; Rhee & Leonardi, 2024). While these studies have advanced understanding of how firms adopt and deploy digital technologies, most treat DTI as a homogeneous process (Leiponen & Drejer, 2007). This oversight neglects a dual structure that integrates mitigation and adaptation innovation. Mitigation innovation emphasizes efficiency improvement and the reduction of operational rigidities (Rawley, 2010; Dooley, 2018). In contrast, adaptation innovation focuses on flexibility and strategic adjustment under environmental turbulence (Gemici & Zehir, 2023). This distinction suggests

that digital innovation activities reflect divergent behavioral orientations toward stability or renewal rather than uniform responses to technological opportunities.

This behavioral divergence highlights the importance of understanding how firms interpret and act upon performance signals. Organizations typically evaluate outcomes relative to aspiration levels and adjust search and learning behaviors accordingly (Greve, 2003; Mount & Baer, 2022). However, firms often pursue multiple goals that generate inconsistent feedback signals (Ethiraj & Levinthal, 2009), rather than a single performance reference (Stevens et al., 2015). Such inconsistency creates a fog of feedback characterized by intense interpretive ambiguity (Joseph & Gaba, 2015). Decision makers must reconcile competing assessments of success and failure. This ambiguity represents a fundamental cognitive condition that shapes organizational learning and attention allocation across competing priorities (Levinthal & Rerup, 2021). Despite its relevance, the role of inconsistent performance feedback remains underexplored in digital technology innovation research, limiting understanding of the behavioral heterogeneity underlying digital transformation.

While organizations respond to performance feedback, the specific cognitive mechanisms underlying these responses require further investigation (Kotiloglu et al., 2021). Reactions to performance signals depend critically on managerial attention, particularly how leaders allocate and sustain focus across competing goals (Shi et al., 2023). This study introduces CEO attentional vigilance as a key moderating mechanism linking performance feedback to digital technology innovation. Attentional vigilance captures the breadth and stability of attention to performance signals (Rhee, 2024). CEOs with high attentional vigilance can maintain balanced focus across multiple cues and integrate diverse information without being overly influenced by temporary fluctuations. Conversely, low vigilance may lead to selective attention and overreaction to salient shortfalls (Li & Yang, 2023). The cognitive processes through which firms interpret feedback thus shape the direction of their digital innovation strategies.

This study explains how organizations interpret and respond to consistent and inconsistent performance feedback in the digital era. Moving beyond the traditional focus on single performance goals and uniform behavioral adjustment, the research demonstrates that firms exhibit heterogeneous digital innovation responses that depend on how decision makers cognitively interpret signals across multiple goals. By distinguishing between mitigation and

adaptation digital innovation, it shows that inconsistent feedback is not merely noise but a salient cognitive trigger that shapes whether firms reinforce existing digital trajectories or engage in adaptive renewal. Conceptualizing CEO attentional vigilance as a situational cognitive condition explains how boundedly rational executives allocate and stabilize attention under performance ambiguity, thereby translating feedback into distinct innovation strategies. This approach extends existing views of attention from a passive allocation process to an active mechanism that reconstructs the relationship between feedback and strategy. Methodologically, the study employs a BERT based machine learning approach to identify mitigation and adaptation innovation from patent texts, demonstrating how computational methods can examine cognition driven innovation at scale.

2. Theoretical Framework and Hypothesis

2.1 Behavioral Foundations of Digital Technology Innovation

Digital technology innovation constitutes a central dynamic capability that enables firms to reconfigure resources, restructure coordination mechanisms, and adapt to rapid technological and environmental change (Nassary et al., 2022). Moving beyond traditional typologies such as exploration and exploitation which primarily distinguish knowledge boundaries, this process is inherently heterogeneous and comprises two interrelated orientations tailored to the digital context. Mitigation digital technology innovation emphasizes prospective efficiency and the reduction of operational rigidities, whereas adaptation digital technology innovation focuses on reactive adjustment and organizational resilience. This dual structure reflects the behavioral tension between preventive reinforcement and adaptive renewal and provides a foundation for understanding heterogeneous digital innovation outcomes (Del Giudice et al., 2021). How firms allocate attention and interpret performance outcomes determines the relative emphasis between mitigation and adaptation. Given the high uncertainty inherent in digital transformation (Chen & Tian, 2022), performance feedback serves as a critical cognitive lens through which firms decide whether to reinforce existing technological trajectories or pursue adaptive renewal.

First, recent extensions of the behavioral theory of the firm move beyond single goal assumptions to account for multi goal pursuit with unequal strategic importance (Syrigos et al.,

2023). In technology driven firms, tangible innovation output often serves as the primary strategic goal, while resource commitments such as innovation input function as secondary tracking goals. Performance feedback is consistent when outcomes across these goals uniformly exceed or fall below aspiration levels, and inconsistent when success and failure signals coexist. As Joseph & Gaba (2015) theorize, such inconsistency creates a fog of feedback that introduces severe interpretive ambiguity, requiring decision makers to balance attention between competing cues (Keil et al., 2024). When primary performance falls below aspiration, firms tend to engage in distal search across unfamiliar domains (Berchicci & Tarakci, 2022). However, when secondary goals simultaneously exceed aspirations, self enhancement tendencies suppress this impulse and redirect attention toward familiar search areas. Inconsistent feedback therefore shapes both the intensity and locus of search, influencing whether digital technology innovation prioritizes system stabilization or adaptive transformation.

Second, subsequent research further explains how multi goal feedback mechanisms translate into innovation and investment behaviors. Lucas et al. (2018) find that jointly negative feedback intensifies problem driven search and increases R and D investment, whereas mixed feedback induces selective resource reallocation and strategic caution. Ye et al. (2021) introduce feedback persistence, showing that peer based feedback is more enduring than historical feedback and thus more influential in shaping managerial expectations. Persistent peer underperformance is interpreted as a sustained competitive threat, motivating mitigation or adaptation innovation, whereas transitory historical feedback primarily triggers mitigation responses. These findings indicate that the temporal stability and relational structure of performance feedback influence whether firms engage in preventive digital reinforcement or adaptive digital renewal under conditions of ambiguity.

Third, beyond behavioral interpretations of feedback, executive attentional configuration plays a pivotal moderating role in translating performance signals into innovation outcomes (Zhu et al., 2025). CEO attentional vigilance, defined as the quantity and stability of sustained attention to multiple cues (Rhee, 2024), functions as a cognitive stabilizer under feedback inconsistency. Confronted with a fog of feedback, CEOs with high attentional vigilance maintain balanced attention across competing goals and integrate diverse information without

overreacting to temporary fluctuations. Prior research suggests that such vigilance fosters coherent strategic responses to performance shortfalls and more stable innovation behavior (Eklund et al., 2025). By sustaining attentional continuity and diffusing cognitive stability throughout the organization, vigilant CEOs can transform ambiguous performance feedback into aligned learning trajectories that support sustained engagement in adaptation digital technology innovation.

2.2 Below-Aspiration Performance Feedback and Dual Dimensions of Digital Technology Innovation

Digital technology innovation reflects firms' behavioral responses to performance shortfalls, with mitigation and adaptation depending on how managers interpret outcomes relative to aspiration levels. According to the behavioral theory of the firm, organizations are boundedly rational and adjust their search behavior when performance deviates from aspirations (Greve, 2003). When outcomes fall below aspiration levels, decision makers initiate problem driven search to restore satisfactory performance (Keil et al., 2023). In this context, digital technology innovation constitutes a key strategic response, encompassing mitigation innovation that strengthens system reliability and operational control and adaptation innovation that enables responsive renewal under performance or environmental disturbances.

First, when performance on a primary goal falls below expectations, firms experience performance pressure and prioritize innovations that promise immediate and measurable improvements (Greve, 2008; Deb et al., 2019). This condition stimulates mitigation digital technology innovation, such as process optimization and cost reduction technologies. These responses reflect a behavioral emphasis on preventive reinforcement of existing technological and organizational systems, offering cognitive reassurance under pressure. Prior research indicates that negative feedback intensifies local search and corrective innovation as firms seek to restore performance to aspiration levels (Ben-Oz & Greve, 2015).

Second, the same feedback conditions that activate efficiency initiatives can suppress adaptation digital technology innovation. Adaptation innovation requires resource slack and sustained managerial attention, both of which are often constrained during periods of performance decline (Paeleman & Vanacker, 2015). Under below aspiration conditions, decision makers narrow their attention toward immediate problem resolution rather than

strategic renewal, reducing engagement in distant search. Consistent with prior findings, firms facing performance pressure tend to rely on familiar technological trajectories and existing knowledge bases rather than explore novel domains (Baum et al., 2005; Posen et al., 2018). As a result, firms emphasize mitigation over adaptation, generating an asymmetric innovation response.

Third, this asymmetry suggests that below aspiration performance feedback does not uniformly stimulate innovation but selectively amplifies preventive forms of digital technology innovation. Firms interpret performance shortfalls as a signal to reinforce existing systems and enhance operational control (Chae et al., 2014), thereby encouraging mitigation innovation while discouraging adaptive renewal. This pattern reflects bounded rationality in managerial cognition, whereby attention is directed toward stabilizing existing technological configurations rather than engaging in flexible reconfiguration under uncertainty.

***Hypothesis 1:** Below-aspiration performance feedback on the primary goal is positively associated with mitigation digital technology innovation and negatively associated with adaptation digital technology innovation.*

2.3 Inconsistent Performance Feedback and Divergent Paths of Digital Technology Innovation

Organizations often face the challenge of interpreting conflicting signals from multiple performance goals (Cheng et al., 2007). When the primary goal falls below aspiration while a secondary goal, such as digital investment intensity, exceeds it, decision makers encounter inconsistent performance feedback. Such inconsistency creates cognitive tension because managers receive mixed evaluations of organizational success. As Joseph & Gaba (2015) theorize, these situations heighten interpretive ambiguity by creating a fog of feedback that presents both threat and opportunity cues simultaneously (Selivanovskikh et al., 2025). Managers must then decide whether to treat the shortfall as a problem requiring corrective action or to interpret the success signal as validation of their current strategy. This ambiguity complicates causal attribution and increases the likelihood of selective attention or biased information processing (Audia & Brion, 2007), as managers seek cognitive coherence amid contradictory signals.

First, under these conditions managers are inclined toward self enhancement processes

that emphasize positive aspects of performance while downplaying negative feedback (Lauenstein et al., 2025). When secondary performance is above aspiration, they interpret this as evidence of strategic competence, which reduces perceived urgency to correct shortfalls on the primary goal (Greve, 2002). As a result, organizations experience a decline in problem driven search motivation and shift attention toward familiar and less demanding activities. This psychological reassurance diminishes the likelihood of initiating preventive digital reinforcement within existing systems. Hence, inconsistent feedback is expected to reduce mitigation digital technology innovation, as managers perceive that their broader digital initiatives are already successful enough to justify the status quo.

Second, inconsistent feedback redirects firms' attention from preventive corrective behavior toward adaptive innovation. The coexistence of apparent failure and success provides both cognitive slack and psychological safety (Deng et al., 2019), creating an environment where decision makers can redirect attention toward experimentation and learning. High performance on secondary goals expands resource availability and builds managerial confidence to pursue uncertain projects, while low primary performance fosters awareness of strategic vulnerability that requires renewal. This combination promotes adaptation digital technology innovation which focuses on reactive adjustment and future preparedness. Firms exposed to mixed feedback engage in broader and more distant search, combining diverse knowledge bases and exploring novel technological domains (Billinger et al., 2021). Such behavior represents an adaptive learning process that converts the tension between conflicting feedback signals into an opportunity for strategic exploration.

Third, this behavioral mechanism underscores that inconsistent performance feedback is not mere informational noise but a distinct cognitive condition that reshapes the orientation of digital technology innovation. When managers simultaneously confront a negative primary signal and a positive secondary signal, they experience competing interpretations of organizational performance that prompt a reallocation of attention (Drover et al., 2018). This interaction redirects managerial focus from preventive efficiency reinforcement toward adaptive digital renewal. Firms reinterpret their innovation logic, moving from problem driven mitigation within existing digital trajectories to opportunity driven adaptation in emerging technological domains. Through this reframing process, inconsistent feedback becomes a

catalyst for adaptive renewal rather than mitigative adjustment.

Hypothesis 2: *Inconsistent performance feedback, in which the primary performance is below aspiration and the secondary performance is above aspiration, is negatively associated with mitigation digital technology innovation and positively associated with adaptation digital technology innovation.*

2.4 The Moderating Role of CEO Attention Quantity

Executive attention is a pivotal cognitive resource that conditions how organizations interpret and act upon performance feedback. Although prior work often assumes that more attention is better, emerging evidence indicates that excessive CEO attention quantity can diffuse focus (Yadav & Prabhu & Chandy, 2007; Pan et al., 2025), increase cognitive load, and undermine consistent decision making in complex environments. In digital technology innovation, where managers must process multifaceted signals and allocate resources across mitigation and adaptation agendas, greater attention quantity can paradoxically impair the translation of feedback into aligned strategic responses.

First, CEO attention quantity conditions how firms translate below aspiration feedback into preventive innovation responses by influencing the depth and concentration of problem driven search. Performance shortfalls typically activate a threat based learning process in which decision makers seek immediate and reliable outcomes to restore equilibrium (Zhang et al., 2024). This orientation encourages innovative efforts aimed at stabilizing existing operations rather than exploring new opportunities. However, when CEO attention quantity is high, cognitive resources are spread across multiple issues (Haas et al., 2015), reducing the depth of information processing related to any single problem. As attention becomes fragmented, managerial responses to performance shortfalls lose focus, thereby weakening the effectiveness of mitigation innovation as a corrective mechanism.

Second, CEO attention quantity shapes the persistence of adaptive responses to below aspiration feedback by constraining the cognitive resources required for sustained experimentation. Adaptation innovation requires continuous cognitive engagement and a willingness to tolerate uncertainty (Sindakis et al., 2025). When CEOs allocate their attention broadly across many issues, the resulting dispersion reduces cognitive depth and weakens the persistence needed for sustained experimentation (Rhee, 2024). Under performance pressure,

dispersed attention amplifies reactive decision making and discourages commitment to uncertain or risky digital initiatives. This fragmentation of attention narrows the scope of strategic learning and fosters reliance on established technologies (Carayannis & Alexander, 2002). Firms under high attention quantity are less likely to invest in adaptive renewal and more likely to maintain existing digital paths, reinforcing the negative effect of performance shortfalls on adaptation digital technology innovation.

Third, CEO attention quantity moderates the overall integration of performance feedback into aligned innovation strategies by affecting managers' ability to maintain attentional coherence across competing goals. When attention becomes excessively broad, managers struggle to integrate multiple feedback signals into an aligned strategic direction (Eklund & Mannor, 2021). Instead of facilitating the parallel pursuit of mitigation and renewal, dispersed attention weakens follow through and organizational focus. Consequently, mitigation digital technology innovation loses precision and momentum, while renewal projects are further crowded out. This erosion of attentional coherence demonstrates that effective performance adaptation depends not only on recognizing aspiration gaps but also on maintaining a stable attentional structure that supports the coordinated development of diverse innovation activities.

***Hypothesis 3:** CEO attention quantity weakens the positive relationship between below-aspiration performance feedback on the primary goal and mitigation digital technology innovation, and strengthens the negative relationship between below-aspiration performance feedback and adaptation digital technology innovation.*

2.5 The Moderating Role of CEO Attention Stability

Attention stability reflects a CEO's capacity to sustain focus on specific performance signals over time (Rhee, 2024), maintaining cognitive coherence when confronted with complex or conflicting information. Unlike attention quantity which disperses managerial focus across many issues, attention stability functions as a cognitive anchor that enhances the continuity of sensemaking and supports deliberate responses to ambiguity. When firms encounter inconsistent performance feedback where the primary goal underperforms but the secondary goal exceeds aspiration (Ye et al., 2021), stable attention helps executives integrate contradictory information and avoid overreacting to transient success cues.

First, under inconsistent feedback conditions, decision makers often experience cognitive

confusion and emotional ambivalence that lead to self enhancement, thereby reducing the perceived urgency for corrective action and weakening mitigation digital technology innovation (Keil et al., 2024). This mixed feedback creates a fog of feedback that blurs the boundary between success and failure, often encouraging a default reliance on existing routines (Joseph & Gaba, 2015; Edmondson et al., 2001). CEOs with high stable attention provide the necessary cognitive consistency to resist these biases. Because they are less swayed by secondary success cues, their ability to sustain focus on the persistent underperformance of the primary goal ensures that the organization continues to allocate resources toward efficiency improvement. Consequently, CEO stable attention weakens the negative relationship between inconsistent feedback and mitigation digital technology innovation by keeping the primary performance gap at the center of the strategic agenda.

Second, CEO stable attention fosters an integrative mindset that enables executives to interpret conflicting performance signals as complementary rather than contradictory drivers of change. When the primary goal is below aspiration but the secondary goal performs well, CEOs with high stable attention can acknowledge the absolute need for corrective action while simultaneously leveraging the confidence and resources derived from areas of success (Surroca et al., 2016). This cognitive steadiness reduces defensive avoidance and promotes a constructive reinterpretation of inconsistency as a dual opportunity for learning and strategic renewal. Therefore, firms led by CEOs with stable attention are more likely to translate inconsistent signals into a structured pursuit of adaptive digital reconfiguration and capability strengthening. Research suggests that leaders who sustain attention over time exhibit stronger innovation momentum which enhances organizational resilience (McClellan et al., 2019).

Third, CEO stable attention functions as a cognitive moderator that reshapes the behavioral implications of inconsistent performance feedback by stabilizing the firm's learning trajectory. Stable attention reflects a sustained cognitive orientation that enables leaders to maintain strategic coherence amid competing goals (Rhee, 2024). By mitigating defensive reactions such as self enhancement and selective attention, it fosters a more balanced processing of contradictory signals and facilitates the alignment of innovation activities with long term adaptive objectives (Kulkarni et al., 2024). Through this mechanism, CEOs with

high stable attention prevent organizations from being anchored in routine exploitation and instead encourage forward looking digital technology innovation trajectories that support strategic flexibility. This insight advances the behavioral perspective by illuminating how enduring attentional states at the executive level buffer cognitive biases and channel ambiguous performance feedback into more adaptive organizational strategy.

***Hypothesis 4:** CEO attention stability weakens the negative relationship between inconsistent performance feedback and mitigation digital technology innovation, and strengthens the positive relationship between inconsistent performance feedback and adaptation digital technology innovation.*

3. Methodology

3.1 Data and Sample

The sample consists of Chinese A-share listed companies from 2007-2023. The study focuses on firms involved in digital technology innovation to examine how consistent and inconsistent performance feedback, along with CEO attentional vigilance, influence innovation outcomes. Following prior research on organizational strategy and executive behavior (Greve, 2003; Joseph & Ocasio, 2012), we implement a systematic screening process to ensure the validity and robustness of the sample. First, firms designated as Special Treatment (ST) or Particular Transfer (PT) are excluded because financial distress may distort innovation incentives and performance feedback interpretation. Second, companies in the financial industry are removed due to their unique business models and regulatory frameworks, which differ significantly from those of manufacturing and technology-based firms. Third, we eliminate firms with missing or incomplete data necessary for analyzing performance feedback, CEO attention, and digital technology innovation.

Data on DTI activities, including patent applications and innovation-related investments, are obtained from the China Research Data Service Platform (CNRDS). Firm-level financial indicators and governance data are collected from the China Stock Market and Accounting Research (CSMAR) database. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme observations (Xu et al., 2025).

3.2 Variables

3.2.1 Dependent Variable

The dependent variable of this study is digital technology innovation (DTI), which captures how firms adjust their technological behaviors in response to performance feedback. DTI represents a behavioral outcome through which organizations modify their innovation activities when actual performance deviates from aspiration levels (Greve, 2003). Within this framework, DTI consists of two interrelated forms comprising mitigation digital technology innovation and adaptation digital technology innovation. This distinction moves beyond the conventional exploration versus exploitation dichotomy by focusing on the functional intent of digital initiatives within complex technological systems. Mitigation digital technology innovation reflects prospective efforts that strengthen system reliability and operational resilience to avert potential risks. These innovations are forward looking, focusing on optimizing digital processes and improving technological robustness before problems occur. In contrast, adaptation digital technology innovation reflects reactive efforts that help firms detect, diagnose, and respond to immediate challenges, disturbances, or feedback inconsistencies. Such innovations emphasize system adaptability, data traceability, and recovery capability when organizations face environmental or operational shocks.

First, the quantitative measurement of DTI follows established research on feedback driven innovation (Joseph & Ocasio, 2012; Keil et al., 2023). We identify indicators that reflect the intensity and scale of firms' digital innovation activities such as R&D expenditure, patent applications, new digital product development, and strategic investment in emerging technologies. These indicators are standardized and aggregated using factor analysis to capture the magnitude of digital technology innovation. This multi dimensional approach ensures that the variable captures both the internal resource commitment and the external output of the innovation process, providing a robust measure of organizational search effort. Mitigation digital technology innovation represents preventive and control oriented innovation behaviors that proactively strengthen system stability, whereas adaptation digital technology innovation reflects responsive and resilience oriented innovation behaviors that enable recovery and adaptive adjustment under disturbances.

Second, to strengthen construct validity and distinguish the specific orientations of these

innovations, we adopt a BERT based semantic classification approach. This method aligns with the emerging text as data literature in strategic management, allowing for a more granular identification of innovation intent than traditional patent class counts. A pretrained Chinese BERT model is fine tuned on a large set of manually labeled innovation sentences derived from corporate disclosures. The fine tuning process involves utilizing contextual embeddings and classification probabilities to distinguish between mitigation and adaptation activities. This supervised learning approach allows the study to capture the nuanced linguistic patterns that differentiate a firm's intent to reinforce existing systems from its intent to engage in adaptive reconfiguration.

Third, the semantic classification is guided by two domain specific lexicons developed from national policy documents, industrial standards, and expert validation, and refined following prior research on digital technology identification (Long & Wang, 2025). The mitigation lexicon focuses on preventive innovations such as intelligent control, predictive maintenance, and process optimization, while the adaptation lexicon emphasizes resilience and risk management such as intelligent inspection, traceability, disaster recovery, and early warning. Both lexicons are expanded using cosine similarity to include semantically related terms and are validated through multifold cross validation. These refined lexicons are subsequently applied to the abstracts of patents filed with the China National Intellectual Property Administration (CNIPA). By combining the frequency of these classified patent texts with the intensity measures derived from factor analysis, we construct a comprehensive index for both mitigation and adaptation digital technology innovation that accounts for both the direction and the strength of the firm's behavioral response.

3.2.2 Independent variable

The independent variable in this study is performance feedback, which captures the discrepancy between a firm's actual performance and its aspiration level. Performance feedback is conceptualized as a key cognitive mechanism that guides organizational responses to performance signals. Consistent with the measurement logic of Keil et al. (2023) and Greve (2003), two types of feedback are distinguished: below-aspiration feedback and inconsistent feedback.

Below-aspiration feedback (FBB) reflects the extent to which a firm's actual performance falls short of its aspiration level. The aspiration level is defined as a weighted average of the firm's historical performance and the industry median in the same period. It is calculated as follows:

$$FB_{i,t}^{\text{below}} = P_{i,t} - (\lambda P_{i,t-1} + (1 - \lambda) \bar{P}_{j,t}) \quad (1)$$

where $P_{i,t}$ represents the actual performance of firm i in year t , measured by return on assets (ROA) or sales growth; $\bar{P}_{j,t}$ denotes the industry mean; and λ is a weighting parameter (Greve, 2003). Negative values of $FB_{i,t}^{\text{below}}$ indicate that firm performance is below the aspiration level, signaling potential performance shortfalls.

Inconsistent feedback (FBI) captures the coexistence of conflicting performance signals when the firm's primary goal is below aspiration but the secondary goal exceeds it. It is calculated as:

$$FB_{i,t}^{\text{incon}} = (P_{i,t}^{\text{primary}} - A_{i,t}^{\text{primary}}) - (P_{i,t}^{\text{secondary}} - A_{i,t}^{\text{secondary}}) \quad (2)$$

where $P_{i,t}^{\text{primary}}$ refers to the firm's performance on its primary goal, measured by digital technology innovation output (e.g., the number of digital technology patents), and $P_{i,t}^{\text{secondary}}$ refers to its performance on the secondary goal, measured by digital technology innovation input (e.g., R&D intensity or digital-related R&D expenditure), and $A_{i,t}$ represents the corresponding aspiration levels. A positive value of $FB_{i,t}^{\text{incon}}$ indicates the presence of inconsistent feedback.

Consistent negative (FBC) feedback occurs when both primary and secondary goals fall below their aspiration levels, representing uniformly poor performance. It is measured as:

$$FB_{i,t}^{\text{consistent-}} = (P_{i,t}^{\text{primary}} - A_{i,t}^{\text{primary}}) + (P_{i,t}^{\text{secondary}} - A_{i,t}^{\text{secondary}}) \quad (3)$$

A negative $FB_{i,t}^{\text{consistent-}}$ indicates simultaneous shortfalls on both goals, signaling consistent negative performance feedback that triggers strong problematic search behavior.

3.2.3 Moderating variables

Following recent attention-based research, particularly Rhee (2024), this study conceptualizes CEO attentional vigilance as a moderating variable influencing firm responses to performance feedback. CEO attentional vigilance is measured through two dimensions: attention quantity (EA) and attention stability (VA).

Attention quantity refers to the extent to which CEOs allocate their attention to innovation, particularly radical innovation. To quantify attention quantity, we calculate the ratio of radical innovation-related keywords to the total innovation-related keywords (including incremental innovation) in CEO communications such as speeches, annual reports, and investor relations activities. The formula for attention quantity (AQ) is:

$$AQ_{i,t} = \frac{\sum_{q=1}^4 \text{Radical Keywords Count}_{i,q}}{\sum_{q=1}^4 (\text{Radical Keywords Count}_{i,q} + \text{Incremental Keywords Count}_{i,q})} \quad (4)$$

Where $\text{Radical Keywords Count}_{i,q}$ is the count of radical innovation keywords in CEO communications in quarter q for firm i . $\text{Incremental Keywords Count}_{i,q}$ is the count of incremental innovation keywords.

Attention stability measures the consistency of the CEO's focus on innovation over time. It is operationalized by calculating the standard deviation of the attention quantity across four quarters, where a lower standard deviation indicates greater stability. Attention stability (AS) is the inverse of this standard deviation, calculated as:

$$AS_{i,t} = \frac{1}{\text{StdDev}(AQ_{i,t})} \quad (5)$$

Where $\text{StdDev}(AQ_{i,t})$ is the standard deviation of attention quantity for firm i in year t .

These two measures capture the dynamic and stable aspects of CEO attention, allowing us to assess how attention quantity and stability influence the relationship between performance feedback and innovation decisions.

3.2.4 Control variables

This study controls for firm characteristics and governance factors that may affect the relationship between performance feedback and digital technology innovation (DTI). Firm size (Size), measured as the logarithm of total assets, captures resource availability, while firm age (ListAge), defined as years since IPO, reflects organizational inertia. Governance characteristics include board size (Board), board independence (Indepa), and CEO duality (Dual). Ownership concentration (Top10) accounts for shareholder influence on innovation risk-taking (Kraiczy et al., 2015). Financial conditions are controlled using leverage (Lev), return on equity (ROE), and asset turnover (ATO), representing financial constraints, internal funding capacity, and operational efficiency, respectively. Inventory intensity (INV) captures capital rigidity. Institutional ownership (INST) reflects the monitoring role of institutional investors. Finally, Tobin's Q (TobinQ) controls for market-based growth opportunities and firms' innovation potential.

3.3 Model specifications

Using firm-level panel data, this study employs a fixed-effects model to examine the impact of performance feedback and CEO attentional vigilance on digital technology innovation (DTI). The fixed-effects model effectively controls for firm-specific, industry-specific, and year-specific effects, thereby mitigating endogeneity concerns. The empirical models for mitigation digital technology innovation (MDTI) and adaptation digital technology innovation (ADTI) are specified as follows:

$$MDTI_{i,t} = \alpha_0 + \alpha_1 FBB_{i,t} + \alpha_2 FBI_{i,t} + \alpha_3 FBC_{i,t} + \alpha_4 EA_{i,t} + \alpha_5 VA_{i,t} + \alpha_k Control_{i,t} + Firm + Industry + Year + \epsilon_{i,t} \quad (6)$$

$$ADTI_{i,t} = \beta_0 + \beta_1 FBB_{i,t} + \beta_2 FBI_{i,t} + \beta_3 FBC_{i,t} + \beta_4 EA_{i,t} + \beta_5 VA_{i,t} + \beta_k Control_{i,t} + Firm + Industry + Year + \epsilon_{i,t} \quad (7)$$

Where FBB represents below-aspiration feedback, FBI represents inconsistent feedback, and FBC represents consistent negative feedback. EA is CEO attention quantity, and VA is CEO attention stability. Control includes firm-level control variables, such as size, leverage, and ROE, as well as industry and year fixed effects.

These models focus on the main effects of performance feedback on DTI, with CEO attentional vigilance (EA and VA) as the key moderating variables. To further explore the interaction between performance feedback and CEO attentional vigilance, we extend the baseline models to incorporate interaction terms. The extended models are specified as follows:

$$\begin{aligned} MDTI_{i,t} = & \beta_0 + \beta_1 FBB_{i,t} + \beta_2 FBI_{i,t} + \beta_3 FBC_{i,t} + \beta_4 EA_{i,t} + \beta_5 VA_{i,t} \\ & + \beta_6 (FBB_{i,t} \times EA_{i,t}) + \beta_7 (FBI_{i,t} \times VA_{i,t}) \\ & + \beta_k Control_{i,t} + Firm + Industry + Year + \epsilon_{i,t} \end{aligned} \quad (8)$$

$$\begin{aligned} ADTI_{i,t} = & \gamma_0 + \gamma_1 FBB_{i,t} + \gamma_2 FBI_{i,t} + \gamma_3 FBC_{i,t} + \gamma_4 EA_{i,t} + \gamma_5 VA_{i,t} \\ & + \gamma_6 (FBB_{i,t} \times VA_{i,t}) + \gamma_7 (FBI_{i,t} \times EA_{i,t}) \\ & + \gamma_k Control_{i,t} + Firm + Industry + Year + \epsilon_{i,t} \end{aligned} \quad (9)$$

In these models, the interaction terms such as $(FBB \times EA)$ and $(FBI \times VA)$ capture the moderating effects of CEO attention quantity and stability on the relationship between different types of performance feedback and innovation outcomes. The coefficients for the interaction terms (e.g., β_6, β_7) indicate how the effect of performance feedback on DTI changes based on variations in CEO attention dimensions. The focus of the analysis is on understanding how CEO attentional vigilance moderates the relationship between below-aspiration, inconsistent, and consistent negative feedback and the firm's innovation response.

4. Results and Analysis

4.1 Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables used in the analysis. The average value of MDTI and ADTI is 0.129, indicating that firms generally engage in low levels of both mitigation and adaptation innovation, with moderate variation ($SD = 0.446$ and 0.500 , respectively). FBB has a mean of 0.317, reflecting moderate below-aspiration performance

feedback, while FBI and FBC show considerable variability with means of 0.172 and 0.604, respectively. EA has a mean of 0.477, suggesting moderate CEO attention to innovation, with a standard deviation of 0.091, indicating low variation. VA shows a mean of 0.053, suggesting stable attention patterns across firms. The control variables exhibit trends consistent with prior studies, with firm size (Size) having a mean of 22.069 and ROE reflecting moderate profitability (mean = 0.068). The remaining control variables show trends that align with previous studies.

Table 1 Descriptive statistics

Variable	Observations	Mean	SD	Min	Median	Max
MDTI	37680	0.129	0.446	0.000	0.000	2.944
ADTI	37680	0.129	0.500	0.000	0.000	3.434
FBB	37680	0.317	0.460	0.000	0.108	1.983
FBI	37680	0.172	0.739	0.000	0.000	6.439
FBC	37680	0.604	1.649	0.000	0.000	10.037
EA	37680	0.477	0.091	0.258	0.475	0.708
VA	37680	0.053	0.047	0.000	0.044	0.212
Size	37680	22.069	1.260	19.406	21.880	26.430
ListAge	37680	1.976	0.952	0.000	2.197	3.401
Board	37680	2.128	0.200	1.609	2.197	2.708
Indepa	37680	0.374	0.053	0.250	0.333	0.600
Dual	37680	0.284	0.451	0.000	0.000	1.000
Top10	37680	0.589	0.154	0.208	0.599	0.910
Lev	37680	0.412	0.203	0.027	0.405	0.925
ROE	37680	0.068	0.132	-0.962	0.077	0.446
ATO	37680	0.680	0.444	0.055	0.580	3.106
INV	37680	0.131	0.106	0.000	0.110	0.778
INST	37680	0.443	0.248	0.001	0.458	0.940
TobinQ	37680	2.036	1.324	0.802	1.623	16.647

4.2 Hypothesis Testing Results

Table 2 reports the baseline regression results for the relationship between performance feedback and digital technology innovation (DTI), with all control variables included. The results show that below aspiration feedback (FBB) is positively and significantly associated with mitigation digital technology innovation (MDTI) ($\beta = 0.012$, $p < 0.01$), indicating that performance shortfalls encourage preventive digital innovation responses. In contrast, inconsistent feedback (FBI) is negatively related to MDTI ($\beta = -0.003$, $p < 0.01$), while

consistent negative feedback (FBC) exhibits a positive effect ($\beta = 0.003$, $p < 0.01$), suggesting that sustained underperformance reinforces corrective digital innovation.

For adaptation digital technology innovation (ADTI), below aspiration feedback has a negative and significant effect ($\beta = -0.052$, $p < 0.01$), whereas inconsistent feedback shows a positive association ($\beta = 0.002$, $p < 0.05$). Consistent negative feedback is negatively related to ADTI ($\beta = -0.009$, $p < 0.01$), indicating that persistent performance pressure constrains adaptive innovation. Overall, these findings support Hypotheses 1 and 2 and demonstrate that different forms of performance feedback systematically shape firms' orientations toward mitigation versus adaptation in digital technology innovation.

Table 2 Baseline regression results

	(1) MDTI	(2) MDTI	(3) MDTI	(4) ADTI	(5) ADTI	(6) ADTI
FBB	0.012*** (2.603)			-0.052*** (-9.171)		
FBI		-0.003*** (-3.012)			0.002** (2.397)	
FBC			0.003*** (2.929)			-0.009*** (-6.218)
Size	0.021*** (3.666)	0.021*** (3.614)	0.021*** (3.650)	0.019*** (2.967)	0.020*** (3.149)	0.019*** (3.046)
FirmAge	0.024 (0.859)	0.022 (0.810)	0.023 (0.855)	0.014 (0.383)	0.017 (0.474)	0.015 (0.415)
Board	0.020 (0.907)	0.019 (0.900)	0.019 (0.881)	0.022 (0.788)	0.023 (0.805)	0.024 (0.854)
Indepa	0.124* (1.762)	0.123* (1.750)	0.123* (1.747)	0.069 (0.811)	0.071 (0.835)	0.073 (0.855)
Dual	-0.005 (-0.817)	-0.005 (-0.782)	-0.005 (-0.804)	-0.002 (-0.217)	-0.002 (-0.334)	-0.002 (-0.280)
Top10	-0.034 (-1.345)	-0.032 (-1.281)	-0.032 (-1.271)	-0.055 (-1.630)	-0.059* (-1.739)	-0.062* (-1.822)
Lev	0.016 (0.842)	0.016 (0.853)	0.016 (0.853)	0.028 (1.316)	0.025 (1.157)	0.026 (1.239)
ROE	0.045*** (2.700)	0.044*** (2.644)	0.045*** (2.671)	0.076*** (3.919)	0.077*** (3.951)	0.078*** (3.994)
ATO	-0.019**	-0.019**	-0.020**	-0.008	-0.008	-0.007

	(-2.116)	(-2.147)	(-2.167)	(-0.762)	(-0.752)	(-0.626)
INV	-0.019	-0.020	-0.020	-0.004	0.001	-0.000
	(-0.651)	(-0.707)	(-0.681)	(-0.108)	(0.017)	(-0.008)
FIXED	-0.002	-0.004	-0.003	0.038	0.045*	0.043*
	(-0.107)	(-0.179)	(-0.152)	(1.515)	(1.777)	(1.713)
Growth	-0.011**	-0.011**	-0.011**	-0.008	-0.008*	-0.008
	(-2.386)	(-2.367)	(-2.397)	(-1.526)	(-1.680)	(-1.539)
_cons	-0.523***	-0.512***	-0.519***	-0.470**	-0.510***	-0.494***
	(-3.492)	(-3.415)	(-3.456)	(-2.565)	(-2.769)	(-2.688)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37649	37649	37649	37649	37649	37649
Adj. R ²	0.026	0.026	0.026	0.031	0.030	0.031

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; *t*-values are shown in parentheses.

4.3 Moderating Effects Analysis

Table 3 reports the regression results examining the moderating role of CEO attentional vigilance in the relationship between performance feedback and digital technology innovation. Columns (1) to (3) show that below aspiration feedback (FBB) is positively associated with mitigation digital technology innovation (MDTI), whereas the interaction between FBB and vigilance is negative and significant. This indicates that greater CEO attentional stability weakens the tendency for firms to respond to performance shortfalls through preventive digital innovation, supporting Hypothesis 4.

Columns (4) and (5) further reveal that attentional stability positively moderates the relationship between inconsistent feedback (FBI) and adaptation digital technology innovation (ADTI), while weakening the effect of consistent negative feedback (FBC) on ADTI. These findings suggest that stable CEO attention enables firms to respond more effectively to ambiguous feedback signals while dampening adaptive responses to uniformly negative feedback, providing additional support for Hypothesis 4.

With respect to attention quantity, the interaction terms indicate a significant moderating effect. Higher levels of executive attention quantity weaken the positive relationship between below aspiration feedback and MDTI, while strengthening the effect of inconsistent feedback on ADTI. These results support Hypothesis 3 and suggest that excessive dispersion of executive

attention constrains preventive responses to performance shortfalls while amplifying adaptive innovation under feedback inconsistency.

Table 3 Moderating effect results

	(1) MDTI	(2) MDTI	(3) MDTI	(4) ADTI	(5) ADTI	(6) ADTI
FBB	0.012** (2.574)			-0.051*** (-9.035)		
VA	-0.062 (-1.241)	-0.048 (-0.963)	-0.063 (-1.233)			
FBB×VA	-0.142** (-2.149)					
FBI		-0.004*** (-3.241)			0.001 (1.004)	
FBI×VA		0.065*** (2.792)				
FBC			0.002** (2.371)			-0.009*** (-6.352)
FBC×VA			-0.067*** (-5.256)			
EA				0.009 (0.237)	0.018 (0.456)	0.011 (0.260)
FBB×EA				-0.147*** (-2.718)		
FBI×EA					0.042*** (2.907)	
FBC×EA						-0.047*** (-3.425)
Size	0.021*** (3.677)	0.021*** (3.624)	0.021*** (3.665)	0.019*** (2.971)	0.020*** (3.128)	0.020*** (3.092)
FirmAge	0.025 (0.899)	0.023 (0.856)	0.026 (0.928)	0.014 (0.395)	0.017 (0.469)	0.015 (0.404)
Board	0.019 (0.879)	0.019 (0.895)	0.018 (0.860)	0.022 (0.792)	0.023 (0.804)	0.024 (0.846)
Indepa	0.123* (1.749)	0.124* (1.755)	0.124* (1.756)	0.068 (0.802)	0.071 (0.839)	0.071 (0.839)
Dual	-0.005 (-0.816)	-0.005 (-0.789)	-0.005 (-0.778)	-0.002 (-0.230)	-0.002 (-0.328)	-0.002 (-0.303)
Top10	-0.034 (-1.342)	-0.033 (-1.314)	-0.032 (-1.274)	-0.055 (-1.618)	-0.059* (-1.733)	-0.061* (-1.806)
Lev	0.015 (0.833)	0.016 (0.873)	0.016 (0.850)	0.028 (1.323)	0.025 (1.166)	0.026 (1.241)

ROE	0.045*** (2.675)	0.044*** (2.629)	0.045*** (2.662)	0.076*** (3.933)	0.076*** (3.924)	0.078*** (3.993)
ATO	-0.020** (-2.163)	-0.020** (-2.167)	-0.020** (-2.214)	-0.009 (-0.821)	-0.008 (-0.760)	-0.007 (-0.639)
INV	-0.019 (-0.671)	-0.020 (-0.706)	-0.020 (-0.702)	-0.004 (-0.094)	0.001 (0.027)	0.001 (0.032)
FIXED	-0.002 (-0.093)	-0.004 (-0.160)	-0.003 (-0.122)	0.038 (1.500)	0.045* (1.796)	0.043* (1.714)
Growth	-0.011** (-2.330)	-0.011** (-2.323)	-0.011** (-2.299)	-0.008 (-1.530)	-0.008* (-1.691)	-0.008 (-1.535)
_cons	-0.520*** (-3.468)	-0.514*** (-3.426)	-0.523*** (-3.484)	-0.490*** (-2.659)	-0.508*** (-2.751)	-0.506*** (-2.742)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37649	37649	37649	37649	37649	37649
Adj. R ²	0.026	0.026	0.026	0.031	0.030	0.031

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; *t*-values are shown in parentheses.

4.4 Robustness Checks and Additional Analyses

To further validate the robustness of our findings. First, we use digital technology innovation at T+1 (denoted as FMDTI and FADTI) as the outcome variables. The results, presented in Columns (1)–(6) of Table 4, show that the coefficients for FBB, FBI, and FBC remain statistically significant across all models. Specifically, the coefficient for FBB remains positive and significant in FMDTI models ($\beta = 0.011$, $p < 0.01$) and negative in FADTI models ($\beta = -0.020$, $p < 0.01$), reinforcing the negative relationship between FBB and adaptive innovation. Similarly, FBI exhibits a significant negative effect on FMDTI ($\beta = -0.004$, $p < 0.01$) and a positive effect on FADTI ($\beta = 0.005$, $p < 0.01$), confirming the influence of feedback-based behaviors on digital innovation outcomes. These robustness checks with the lagged dependent variable validate the stability of our initial findings, reinforcing the observed relationships between feedback behaviors and digital technology innovation.

Table 4 Robustness Test with Effects on FMDTI and FADTI in T+1 Period

	(1)	(2)	(3)	(4)	(5)	(6)
	FMDTI	FMDTI	FMDTI	FADTI	FADTI	FADTI

FBB	0.011*** (3.112)			-0.020*** (-3.514)		
FBI		-0.004*** (-2.968)			0.005*** (3.672)	
FBC			0.003*** (4.061)			-0.006*** (-4.979)
Size	0.019*** (3.113)	0.019*** (3.075)	0.019*** (3.108)	0.022*** (2.876)	0.022*** (2.926)	0.022*** (2.884)
FirmAge	0.000 (0.016)	-0.001 (-0.034)	0.001 (0.018)	0.003 (0.082)	0.005 (0.138)	0.003 (0.080)
Board	0.007 (0.287)	0.007 (0.284)	0.006 (0.271)	-0.001 (-0.035)	-0.001 (-0.033)	-0.001 (-0.017)
Indepa	0.009 (0.119)	0.008 (0.101)	0.008 (0.102)	0.014 (0.153)	0.016 (0.174)	0.017 (0.177)
Dual	0.002 (0.223)	0.002 (0.246)	0.002 (0.224)	0.001 (0.077)	0.000 (0.038)	0.001 (0.076)
Top10	-0.049* (-1.670)	-0.048 (-1.631)	-0.047 (-1.607)	-0.053 (-1.323)	-0.054 (-1.358)	-0.056 (-1.397)
Lev	0.016 (0.792)	0.016 (0.799)	0.016 (0.793)	0.003 (0.133)	0.003 (0.111)	0.003 (0.130)
ROE	0.036* (1.786)	0.035* (1.752)	0.035* (1.758)	0.040 (1.541)	0.041 (1.570)	0.041 (1.576)
ATO	0.008 (0.728)	0.007 (0.692)	0.007 (0.677)	0.008 (0.682)	0.008 (0.723)	0.009 (0.760)
INV	-0.019 (-0.601)	-0.020 (-0.638)	-0.020 (-0.620)	0.038 (0.945)	0.040 (0.987)	0.040 (0.972)
FIXED	0.001 (0.063)	0.000 (0.004)	0.001 (0.042)	0.041 (1.522)	0.043 (1.603)	0.042 (1.553)
Growth	-0.001 (-0.222)	-0.001 (-0.195)	-0.001 (-0.237)	-0.002 (-0.301)	-0.002 (-0.351)	-0.001 (-0.279)
_cons	-0.374** (-2.396)	-0.363** (-2.329)	-0.371** (-2.379)	-0.420** (-2.033)	-0.438** (-2.116)	-0.426** (-2.058)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	30419	30419	30419	30419	30419	30419
Adj. R ²	0.023	0.023	0.023	0.027	0.027	0.027

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; *t*-values are shown in parentheses.

Second, we conduct an analysis excluding the years 2008 and 2015, which are characterized by significant financial volatility. The results, presented in Columns (1)–(6) of

Table 5, show that the key coefficients largely remain consistent with the previous analysis. Specifically, FBB remains positively significant for MDTI and negatively significant for ADTI, reinforcing the relationship between feedback-based behaviors and innovation outcomes. FBI also maintains its statistically significant effect, with a negative impact on MDTI ($\beta = -0.003$, $p < 0.05$) and a positive effect on ADTI ($\beta = 0.003$, $p < 0.05$), confirming the stability of the observed effects.

The exclusion of the financial crises years 2008 and 2015, ensures that the results are not unduly influenced by these periods of significant economic volatility. This approach strengthens the validity of our findings by confirming that the effects of feedback behaviors on digital technology innovation are not driven by extreme market conditions, thereby increasing the generalizability of the results.

Table 5 Robustness Test with Excluding Financial Crises

	(1) MDTI	(2) MDTI	(3) MDTI	(4) ADTI	(5) ADTI	(6) ADTI
FBB	0.010** (2.247)			-0.053*** (-9.232)		
FBI		-0.003** (-2.306)			0.003** (2.566)	
FBC			0.002** (2.145)			-0.008*** (-6.136)
Size	0.021*** (3.725)	0.021*** (3.682)	0.021*** (3.706)	0.015** (2.331)	0.016** (2.522)	0.016** (2.416)
FirmAge	0.008 (0.315)	0.008 (0.281)	0.008 (0.313)	0.005 (0.124)	0.007 (0.188)	0.005 (0.138)
Board	0.023 (1.013)	0.022 (1.003)	0.022 (0.992)	0.036 (1.245)	0.038 (1.287)	0.039 (1.324)
Indepa	0.141* (1.842)	0.141* (1.839)	0.140* (1.835)	0.119 (1.323)	0.120 (1.332)	0.122 (1.353)
Dual	-0.008 (-1.204)	-0.008 (-1.182)	-0.008 (-1.191)	-0.004 (-0.537)	-0.005 (-0.622)	-0.005 (-0.594)
Top10	-0.047* (-1.792)	-0.046* (-1.734)	-0.046* (-1.739)	-0.038 (-1.088)	-0.043 (-1.211)	-0.045 (-1.276)
Lev	0.015 (0.787)	0.016 (0.794)	0.016 (0.803)	0.036 (1.630)	0.032 (1.471)	0.034 (1.535)
ROE	0.048***	0.047***	0.048***	0.079***	0.080***	0.080***

	(2.844)	(2.798)	(2.829)	(3.777)	(3.802)	(3.825)
ATO	-0.023**	-0.023**	-0.023**	-0.010	-0.010	-0.008
	(-2.405)	(-2.428)	(-2.438)	(-0.892)	(-0.874)	(-0.770)
INV	-0.013	-0.014	-0.013	0.006	0.011	0.010
	(-0.397)	(-0.440)	(-0.422)	(0.142)	(0.257)	(0.243)
FIXED	-0.014	-0.016	-0.015	0.043	0.050*	0.049*
	(-0.591)	(-0.651)	(-0.631)	(1.634)	(1.906)	(1.847)
Growth	-0.009*	-0.009*	-0.009*	-0.006	-0.007	-0.006
	(-1.796)	(-1.783)	(-1.798)	(-1.076)	(-1.210)	(-1.099)
_cons	-0.463***	-0.455***	-0.460***	-0.419**	-0.458**	-0.442**
	(-3.206)	(-3.146)	(-3.176)	(-2.276)	(-2.483)	(-2.400)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	33940	33940	33940	33940	33940	33940
Adj. R ²	0.027	0.027	0.027	0.032	0.031	0.031

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; *t*-values are shown in parentheses.

Third robustness test, the models were estimated using Driscoll-Kraay (D-K) standard errors, which correct for heteroskedasticity, serial correlation, and cross-sectional dependence in panel data. As shown in Table 6, the results remain consistent with the baseline estimations. FBB continues to show a positive effect on MDTI and a negative effect on ADTI, confirming that below-aspiration feedback drives preventive innovation responses while constraining adaptive renewal. Likewise, FBI and FBC maintain their expected signs and levels of significance, indicating stable behavioral patterns across feedback types. The coefficients of key control variables such as Size and ROE remain robust in both direction and significance. Overall, the D-K estimation reinforces that the observed relationships between performance feedback and digital innovation strategies are not sensitive to alternative specifications.

Table 6 Robustness Test with Driscoll–Kraay standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
	MDTI	MDTI	MDTI	ADTI	ADTI	ADTI
FBB	0.011**			-0.050***		
	(2.297)			(-5.687)		
FBI		-0.004***			0.004***	
		(-3.510)			(3.160)	

FBC			0.003**			-0.008***
			(2.337)			(-5.228)
Size	0.019***	0.019***	0.019***	0.016***	0.017***	0.017***
	(3.182)	(3.159)	(3.232)	(3.420)	(3.644)	(3.583)
FirmAge	0.028	0.027	0.028	0.012	0.015	0.013
	(1.376)	(1.311)	(1.385)	(0.481)	(0.588)	(0.498)
Board	0.018	0.018	0.018	0.023	0.023	0.024
	(1.629)	(1.622)	(1.609)	(1.024)	(0.997)	(1.060)
Indepa	0.120***	0.120***	0.120***	0.088	0.090	0.091
	(4.040)	(3.971)	(3.976)	(1.262)	(1.306)	(1.328)
Dual	-0.005	-0.005	-0.005	-0.001	-0.002	-0.002
	(-1.092)	(-1.055)	(-1.079)	(-0.275)	(-0.485)	(-0.405)
Top10	-0.032	-0.030	-0.030	-0.052**	-0.056***	-0.058***
	(-1.665)	(-1.586)	(-1.588)	(-2.788)	(-2.972)	(-3.125)
Lev	0.018*	0.018*	0.018*	0.038**	0.035**	0.036**
	(1.835)	(1.826)	(1.849)	(2.375)	(2.230)	(2.368)
ROE	0.047**	0.046**	0.047**	0.079***	0.080***	0.080***
	(2.882)	(2.809)	(2.866)	(4.869)	(5.032)	(4.954)
ATO	-0.015	-0.015	-0.015*	-0.008	-0.008	-0.007
	(-1.700)	(-1.728)	(-1.783)	(-1.308)	(-1.177)	(-1.055)
INV	-0.018	-0.020*	-0.019	0.003	0.008	0.007
	(-1.623)	(-1.758)	(-1.691)	(0.102)	(0.253)	(0.222)
FIXED	-0.004	-0.006	-0.005	0.040***	0.047***	0.045***
	(-0.162)	(-0.218)	(-0.191)	(3.030)	(3.406)	(3.278)
Growth	-0.010***	-0.010***	-0.010***	-0.007	-0.007	-0.007
	(-3.333)	(-3.336)	(-3.449)	(-1.459)	(-1.571)	(-1.481)
_cons	-0.494***	-0.485***	-0.493***	-0.425***	-0.460***	-0.444***
	(-3.521)	(-3.457)	(-3.553)	(-3.992)	(-4.105)	(-4.054)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	37174	37174	37174	37174	37174	37174
Within R ²	0.026	0.026	0.026	0.031	0.030	0.031

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; *t*-values are shown in parentheses.

5. Conclusion and Implications

5.1 Conclusion

Using data from Chinese A-share listed firms, this study examines how multi-goal performance feedback and CEO attentional vigilance influence digital technology innovation. The results show that firms react asymmetrically to below-aspiration performance. When primary performance falls short of expectations, firms increase mitigation DTI characterized

by preventive digital reinforcement and reduce adaptation DTI characterized by reactive digital reconfiguration in response to feedback signals. Inconsistent feedback, where primary performance is low and secondary performance is high, changes this pattern by decreasing preventive digital reinforcement while encouraging adaptive digital renewal. CEO attentional vigilance further moderates these effects. CEO attention quantity weakens the positive (negative) effect of below-aspiration feedback on mitigation (adaptation) innovation, whereas CEO attention stability strengthens the negative (positive) effect of inconsistent feedback on mitigation (adaptation) innovation. Overall, the findings highlight that DTI outcomes depend not only on resources or technology but also on how managers interpret and respond to complex performance signals through their attentional patterns.

5.2 Theoretical Contributions

This study advances the understanding of organizational behavior under digital transformation by integrating the behavioral theory of the firm with the attention based view to explain how firms interpret and act upon consistent and inconsistent performance feedback. Existing research has predominantly conceptualized feedback as a single directional trigger of search intensity (Zhang et al., 2024; Gao et al., 2023), often overlooking the cognitive complexity that arises when firms pursue multiple goals simultaneously. By reinterpreting feedback ambiguity as a critical behavioral condition rather than mere informational noise, this study develops an integrated framework that links feedback consistency, innovation heterogeneity, and managerial cognition.

First, our study contributes to research grounded in the behavioral theory of the firm by advancing the understanding of how organizations respond to performance feedback across multiple goals. While recent extensions suggest that firms rarely pursue a single aspiration but operate within constellations of goals that can generate conflicting signals (Gaba & Greve, 2019; Kostopoulos et al., 2023), it has remained less clear how organizations interpret and prioritize among competing demands when feedback is inconsistent. Building on the notion of the fog of feedback (Joseph & Gaba, 2015), we introduce an ambiguity centered view that highlights the interpretive nature of feedback responses. This perspective suggests that feedback ambiguity constitutes a distinct cognitive condition that shapes how adaptation is conceived and enacted. By distinguishing between mitigation and adaptation in digital

technology innovation, we broaden the behavioral logic to show that these orientations are not mere relabeling of traditional exploration and exploitation, but represent functionally distinct responses to systemic digital demands. Our study shifts the focus from feedback as a mechanical behavioral trigger to feedback as a cognitive lens through which organizations define and navigate the complexity of multiple performance requirements. Furthermore, while prior studies on digital technology innovation mainly focus on technological capability accumulation (Li et al., 2022), this study highlights the behavioral and cognitive processes through which firms respond to the ambiguity inherent in mixed signals.

Second, this study advances the attention based view by highlighting how CEO attentional vigilance moderates the behavioral consequences of feedback ambiguity. While traditional research has primarily focused on the structural determinants of attention (Ocasio et al., 2018), often conceptualizing attention as a static allocation process (Plotnikova et al., 2024), this study reconceptualizes attention as a dynamic mechanism. It demonstrates that CEO attentional vigilance, comprising both attention quantity and attention stability, determines how executives interpret and respond to complex, inconsistent feedback. Specifically, we reveal that while attention quantity reflects the breadth of cues monitored, it can paradoxically diffuse focus under pressure, whereas attention stability captures the persistence and coherence of focus required to resolve ambiguity over time. By distinguishing these two dimensions, the study reveals that variations in attentional dynamics systematically affect the ability of decision makers to navigate conflicting performance signals. By integrating these micro level processes into the behavioral theory of the firm, the study enriches the theory by demonstrating that the effects of performance feedback are not mechanically determined but are reconstructed through the vigilance of boundedly rational executives who play a pivotal role in shaping innovation trajectories.

Third, this study contributes methodologically by combining BERT based semantic text analysis with econometric modeling to operationalize the heterogeneity of digital technology innovation. This approach goes beyond traditional keyword or classification based methods by capturing contextual meanings embedded in patent texts (Venugopalan & Rai, 2015), enabling a behaviorally grounded distinction between mitigation and adaptation innovation. By employing machine learning as a cognitive measurement tool, the study bridges abstract

theoretical constructs such as search direction and feedback interpretation with observable data, enhancing construct validity and empirical precision. This methodological innovation aligns with the emerging paradigm of computational behavioral strategy (Cristofaro et al., 2024), demonstrating how natural language processing techniques can illuminate the cognitive foundations of organizational strategy and innovation behavior in the digital era.

5.3 Practical Contributions

This study offers practical implications for firms seeking to enhance digital technology innovation under performance ambiguity. Managers should recognize that performance feedback is interpretive rather than purely evaluative. When performance falls below expectations, structured routines such as cross functional review sessions or digital learning platforms can facilitate collective sensemaking. These practices help firms balance preventive digital reinforcement with adaptive reconfiguration, allowing feedback to support learning rather than reactive decision making.

CEOs should treat attention as a strategic resource that requires deliberate structuring and monitoring. In dynamic technological environments, excessive dispersion of attention may weaken aligned innovation efforts. Establishing structured attention mechanisms, including periodic focus reviews, strategic reflection meetings, and digital dashboards, can help align executive attention with evolving innovation priorities and maintain cognitive coherence when feedback is inconsistent.

Firms should also develop governance systems that transform feedback ambiguity into opportunities for renewal. Linking digital innovation metrics to both preventive and adaptive objectives can reduce overreaction to temporary fluctuations. Incorporating learning oriented evaluation criteria into incentive systems further encourages experimentation while supporting sustained digital transformation under uncertainty.

5.4 Limitations and Future Research

This study has several limitations that suggest avenues for future research. First, the current design does not fully capture the dynamic evolution of the feedback innovation relationship over time. The effects of below aspiration and inconsistent feedback may vary across different stages of digital transformation, ranging from initial adoption to technological

renewal. Early-stage firms may respond more sensitively to performance gaps, whereas more mature firms may develop routines that buffer or reinterpret feedback. Future research could employ longitudinal or panel-based designs to examine how changing feedback patterns shape innovation trajectories over time and across different phases of digital transformation.

Second, the focus on Chinese A share listed firms may limit the generalizability of the findings. Institutional and cultural features, including formalized CEO communication and conservative disclosure practices, may constrain attention allocation and feedback interpretation relative to firms operating in other contexts. Comparative studies across countries or institutional environments would help assess whether the identified attention based mechanisms are context specific or more broadly applicable, thereby extending the external validity of the findings.

Third, although this study emphasizes CEO attentional vigilance as the primary moderating mechanism, additional boundary conditions warrant exploration. Individual characteristics such as CEO tenure, education, or cognitive orientation, as well as organizational features such as board oversight and ownership structure, may interact with feedback interpretation in shaping innovation outcomes. A configurational approach could further illuminate how combinations of personal, structural, and environmental factors jointly influence digital technology innovation under performance ambiguity.

Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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Ethics Declarations

Competing Interests

The authors declare no competing interests.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.

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