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Adaptive Intelligence as an Emerging Individual Capability: An Exploratory Study in ITES Multinational Enterprises

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Abstract

The rapid diffusion of Industry 4.0 technologies has intensified digital transformation across Information Technology Enabled Services (ITES) multinational enterprises (MNEs). Despite substantial organisational investments in artificial intelligence, automation, and cloud computing, uneven technology adoption driven by persistent employee resistance continues to undermine transformation outcomes. This paradox indicates that successful digital transformation depends not only on technological sophistication but on employees' individual capacity to adapt to continuous technological change. Addressing this gap, the present study conceptualises Adaptive Intelligence, grounded in Sternberg's theory as a distinct individual capability enabling employees to navigate digital disruption effectively. Adaptive intelligence moves beyond conventional cognitive measures to encompass self-adaptation, environmental shaping and selection, practical and creative intelligence, and wisdom-based judgment. An exploratory qualitative research design was employed, drawing on in-depth interviews with ten practitioners in HR, operations, systems, and talent development roles within ITES MNEs, professionals whose direct involvement in technology implementation affords privileged observational access to how employees encounter, resist, and adapt to digital change at the point of deployment. Data were analysed using the Gioia inductive coding methodology. Five interrelated dimensions of adaptive intelligence emerged: adaptive learning and unlearning, techno-emotional regulation, proactive adoption orientation, environmental shaping capability, and collective adaptive wisdom. These dimensions are further related to the Big Five personality traits through Matthews' Cognitive-Adaptive Theory of Personality, deepening the behavioural understanding of adaptive responses to technological change. The study proposes an integrative conceptual framework and six research propositions, extending theory on dynamic capabilities, digital transformation, and technostress, while offering practical guidance for talent recruitment, capability development, and workforce resilience in digitally transforming organisations.

Keywords: Adaptability, Adaptive Intelligence, Technostress, Organizational Adaptation Behavior, Technological Change

1. Introduction

The accelerating pace of technological change has fundamentally transformed the nature of work in knowledge-intensive industries, particularly within Information Technology Enabled Services (ITES) multinational enterprises (MNEs). These organizations exist in a state of perpetual technological turbulence, characterized by the frequent, volatile, and often unpredictable introduction of disruptive digital tools. The integration of advanced computational agents, artificial intelligence (AI), and complex automation systems fundamentally alters the nature of knowledge work, shifting the burden of value creation from routine data processing to complex sense-making and strategic decision-making. While MNEs invest heavily in these technologies to achieve strategic agility and capture global market opportunities, the successful realization of these macroeconomic benefits is frequently derailed by micro-level user resistance. The persistent friction highlights a critical bottleneck in organizational transformation: the successful deployment of disruptive technologies depends less on the objective sophistication of the digital tools themselves and far more on the cognitive, emotional, and behavioral adaptability of the individual employees who use them. Historically, human resource management literature and organizational psychology have emphasized standard cognitive attributes, such as general intelligence or traditional conceptualizations of emotional intelligence, as the primary determinants of individual performance and innovation outcomes.

However, general intelligence tests present well-structured problems with a single correct answer and carry virtually no real-world stakes. Consequently, high general intelligence does not guarantee high adaptive capacity. Traditional psychometric measures of cognitive ability often fail to capture an employee's latent capacity to navigate the ambiguity, acute psychological stress, and shifting role requirements embedded in rapid digital transformations. When confronted with disruptive technological tools that defy established workflows, employees frequently resort to defensive psychological postures, including status quo bias, passive-aggressive avoidance, or deliberate knowledge hiding. To address this profound gap, this research explores the theoretical construct of "Adaptive Intelligence". Originally theorized in the context of broader human adaptation, adaptive intelligence moves deliberately beyond static, culturally bound measures of abstract cognitive capacity to focus on how individuals actively deploy their mental abilities to fit into, proactively shape, or strategically select new environments. When systematically applied in an organizational context, adaptive intelligence is a dynamic, individual-level capability that determines how effectively an employee can align their behaviors with shifting organizational goals, overcome the physiological and psychological impacts of technostress, and drive innovation.

The primary objective of this exhaustive analysis is to explore how adaptive intelligence helps employees successfully navigate technological turbulence, AI adoption, automation, and digital transformation in ITES MNEs. Specifically, the study aims to: (i) Conceptualize Adaptive Intelligence in organizational settings, (ii)Explore how Adaptive Intelligence influences technology adoption, (iii) Examine the relationship between Adaptive Intelligence and the Big Five Personality Traits, (iv) Develop a preliminary conceptual framework.

AI-driven digital transformation is reshaping work at unprecedented speed. Organizations adopt machine learning, automation, and analytics to enhance efficiency, yet the human side of this change remains poorly understood. In many cases, sophisticated AI investments yield slower-than-expected gains. Scholars and executives observe a "productivity paradox" of digital transformation: large investments have not automatically translated into improved performance or sustained competitive advantage. A key reason is the human response:

employees face uncertainty, overload, and identity threats from AI, which existing models (TAM, technostress, etc.) do not sufficiently explain.

This study addresses a central question: Why do we need *adaptive intelligence* as a construct, and how does it differ from existing concepts of adaptation? Why constructs like learning agility, adaptability, cognitive flexibility, resilience, psychological capital, or dynamic capabilities are inadequate proxies. Through an in-depth qualitative study of IT-enabled services (ITES) professionals working with AI, we show that adaptive intelligence integrates cognitive adaptation, emotional regulation, social influence, environmental shaping, and collective wisdom into a unified capability. Our results reveal that adaptation in AI contexts is not just about learning new routines or bouncing back from stress: it involves unlearning past expertise, proactively experimenting with AI, reshaping work processes, and leveraging team knowledge in ways that none of the existing constructs fully capture.

Methodologically, we employ the Gioia inductive coding approach, ensuring rigorous first-order observations and second-order theoretical themes. The result is a nuanced framework (Figure below) that explicates adaptive intelligence as an individual-level meta-capability and micro foundation of organizational dynamic capabilities. The five aggregate dimensions (Adaptive Learning/Unlearning; Emotional Self-Regulation under Technological Turbulence; Proactive Adoption Orientation; Environmental Shaping Capability; and Collective Adaptive Wisdom) emerged from systematic analysis of interview data.

In sum, our contributions are threefold. First, we define and validate Adaptive Intelligence as a higher-order capability (not a mere trait) that integrates cognitive, emotional, behavioral, and wisdom elements. This addresses the "construct proliferation" critique by demonstrating how adaptive intelligence subsumes and extends prior constructs (Matthews 2016; Sternberg, 2021). Second, we link individual adaptation to firm-level dynamic capabilities (sensing, seizing, reconfiguring) by positing adaptive intelligence as their micro foundation (drawing on Teece, 2007; Helfat and Peteraf, 2015). Third, we extend technostress theory (Tarafdar et al., 2007) by identifying not just stressors but adaptive responses that transform stress into developmental opportunities.

The paper proceeds as follows. The next section reviews five streams of literature (Digital Transformation, Technology Adoption, Technostress, Dynamic Capabilities, Adaptability) in a critical synthesis. We then explicitly answer "Why Existing Constructs Are Insufficient", motivating adaptive intelligence. The Theoretical Foundation section integrates Sternberg's adaptive intelligence and related theories into a coherent narrative. After detailing our methodology, we present the findings organized by theme, each linked to evidence and theory. The Discussion interprets these themes, showing how they extend, challenge, and refine theory. We then articulate theoretical contributions, managerial and policy implications, limitations, and future research directions, before concluding.

2. Literature Review

To construct a comprehensive framework of adaptive intelligence in the workplace, it is necessary to integrate and synthesize several distinct streams of psychological and organizational literature, ranging from cognitive adaptability and trait theories to technology acceptance models and dynamic capabilities.

2.1 Theoretical Underpinnings

2.2 Ternberg's Theory of Adaptive Intelligence

In direct contrast to the rigid limitations of general cognitive ability, Robert J. Sternberg's theory of adaptive intelligence provides a highly fluid, ecologically valid framework. Adaptive intelligence is formally defined as the deployment of cognitive abilities and attitudes to serve the ultimate purpose of adaptation to real-world environments, utilizing collective talent in service of a common good. Rather than treating intelligence as a static inventory of cognitive assets, adaptive intelligence is viewed as a foundational capability actively deployed to solve complex, unstructured problems. Broad adaptation encompasses three distinct, interactive dimensions: Self-Adaptation (Changing Self): The process of adjusting one's own behaviors, cognitive skill sets, and psychological attitudes to meet the novel demands of the current environment. Environmental Shaping:

The proactive process of actively altering the existing environment to better align with one's personal capabilities and overarching organizational goals. Environmental Selection: The strategic recognition of when a current environment is irredeemably mismatched with one's abilities, resulting in the decisive action to relocate to a completely new environment. Furthermore, adaptive intelligence heavily incorporates practical intelligence (the application of tacit knowledge to navigate specific sociocultural contexts) and creative intelligence (generating novel solutions to unexpected disruptions). Critically, it is anchored by wisdom-based intelligence. In this framework, wisdom is a highly practical cognitive function involving the deployment of intelligence to achieve a common good, balancing short-term impulses with long-term sustainability, and navigating the intersection of personal and collective interests.

2.3 Personality Framework: The Big Five Traits

The Five-Factor Model (Big Five) remains the dominant psychometric framework for evaluating human personality, comprising Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (Emotional Stability). Extensive meta-analytical research, such as the seminal work by Barrick and Mount (1991), has consistently demonstrated that traits like Conscientiousness are valid predictors of job performance across virtually all occupational groups. Furthermore, traits like Openness to Experience and Extraversion govern an individual's propensity for innovation, knowledge sharing, and social influence, while Emotional Stability determines stress tolerance. While the Big Five model provides the structural architecture of personality, it requires an active, cognitive processing mechanism to explain how these static traits translate into dynamic workplace adaptation

2.4 Digital Transformation

Digital transformation research underscores that technology adoption often leads to paradoxical outcomes. Firms invest heavily in AI and digitalization, yet many struggle to realize expected benefits. A fundamental tension is between technology and people. On one hand, new AI capabilities promise efficiency and insights (e.g., predictive maintenance in Industry 4.0). On the other hand, the human and organizational changes needed to exploit these tools are substantial. Feliciano-Cestero et al. (2023) note that digital transformation's "soft side" (leadership, culture, human capital) can either enable or threaten success (Jarrahi et al., 2023). This reflects an unresolved debate: should organizations follow a technocentric path ("magic button" approach) or a human-centric one that emphasizes learning and change management?

Another tension is speed versus stability. Advanced AI often requires mature data and processes; rushing implementation can backfire the “Magic Button” syndrome in practitioner sources. Conversely, excessive caution (“analysis paralysis”) delays adaptation. Digital transformation also generates paradoxes at multiple levels: established products vs. New platforms, firm control vs. Ecosystem collaboration, and employees versus tools (Furr et al., 2022). For example, incumbents may struggle between leveraging legacy systems and embracing AI-driven platforms. At the micro level, employees must balance job security concerns with opportunities for upskilling.

Current literature signals a gap: while macro-strategic issues are well-documented, the micro foundational question – how individuals adapt cognitively, emotionally, and socially during such transformation – remains underexplored. This gap motivates an individual-capability perspective. As D. Jarrahi et al. (2023) emphasize, AI’s impact on work can only be understood in context. Our study addresses this by theorizing the individual capability needed to navigate the turbulence of digital transformation.

2.5 Technology Adoption

Traditional technology adoption models, such as TAM and UTAUT, assume that users make rational evaluations of usefulness and ease of use before adopting new systems. These models posit a linear decision process: given enough information about performance benefits, individuals will adopt if it improves their job. However, real-world AI-enabled workplaces challenge these assumptions. For instance, frontline employees may encounter AI not as a planned innovation but as an abrupt mandate, often with opaque decision-making algorithms. They might accept or resist AI for reasons unrelated to perceived ease: fear of job loss, identity threat, or fairness concerns (Jarrahi et al., 2023).

Moreover, TAM/UTAUT presume information completeness and stable attitudes. In reality, AI systems evolve (e.g., self-learning algorithms) and employees may not fully understand how they work. Jarrahi et al. (2023) argue that “current conceptualizations of how intelligent systems support decision-making do not align with emerging AI systems,” which can blur workplace boundaries and exacerbate power imbalances. This suggests technology adoption is as much emotional and political as rational.

Our study moves beyond individual models to consider social and environmental adoption dynamics. Peer influence, collective experimentation, and strategic shaping of technology (beyond passive use) are seldom incorporated in TAM/UTAUT. Our adaptive intelligence framework explicitly includes a proactive adoption orientation and environmental shaping, capturing how employees actively mold technology to fit work (or vice versa). This goes beyond rational utility: it resonates with notions of enactment and sensemaking in organizational studies.

In sum, the technology adoption literature offers insights into the determinants of uptake but often overlooks the complexity of human-AI interaction. The rise of AI characterized by rapid change, autonomy, and ambiguity invalidates many rational-choice assumptions. We argue that adaptation in this context requires integrated cognitive and non-cognitive mechanisms that traditional models do not capture.

2.6 Technostress

The technostress literature documents how ICTs generate stressors such as techno-overload (too much to do), techno-invasion (work invading personal life), techno-complexity (difficulty learning systems), techno-insecurity, and techno-uncertainty (Tarafdar et al., 2007, 2019).

These stressors are linked to strains like burnout, reduced satisfaction, and avoidance behaviors.

Technostress theory is strong on negative outcomes and coping strategies. It shows how technology demands can exceed an individual's resources, invoking the Conservation of Resources (COR) theory: stress occurs when resources are threatened or lost (Sternberg, 2021). However, existing technostress research mainly treats employees as victims of ICTs, focusing on how stressors deplete resources. It rarely addresses how some individuals thrive under the same conditions. For example, why do a few employees appear invigorated by technological turbulence, turning overload into learning opportunities?

Our findings reveal that employees use adaptive strategies not just to reduce stress, but to transform it. For instance, rather than only seeking relief from complexity (as in classic coping), participants described leveraging peer networks and collective learning to master new tools – behaviors akin to job crafting and collective wisdom. This suggests an extension of technostress theory: employees differ not only in exposure but in adaptive intelligence – the ability to see stressors as developmental challenges. The technostress literature thus highlights crucial constructs (overload, invasion, complexity) but does not explain the positive, proactive side of the adaptation we observe.

2.7 Dynamic Capabilities Theory in Individual Capability Development

Dynamic capabilities theory (Teece, Pisano, and Shuen, 1997; Helfat and Peteraf, 2015) posits that in fast-changing environments, firms need the ability to sense opportunities, seize them, and reconfigure resources. This macro-level lens helps explain organizational agility and strategic renewal. However, it says little about how individual employees embody these processes. There is a missing "microfoundation" for dynamic capabilities: the person-level mechanisms by which sensing and seizing actually happen on the ground.

We position adaptive intelligence as precisely this microfoundation. While Teece et al. (2007) describe organizational routines and structures, our study traces how an employee's cognitive flexibility, emotional regulation, and proactive agency realize those routines in practice. For example, a salesperson sensing a shift in customer needs (sensing) must draw on learning and intuition; a team deploying a new AI tool (seizing) depends on the emotional resilience and social influence of members; and a unit reorganizing processes (reconfiguring) leverages employees' creativity and collective wisdom. By anchoring dynamic capabilities at the individual level, we fill a key gap: explaining the who and how behind the what of firm adaptation (Matthews 2016; Sternberg, 2021).

Notably, prior studies of dynamic capabilities often emphasize managerial cognition and system-level processes (macro focus). We bring the focus down: how does an "adaptive intelligence" manifest in everyday work? This includes job crafting behaviors, peer mentoring, and strategic sensemaking all of which are prerequisites for higher-level dynamism but rarely theorized in DC literature.

2.8 Adaptability and Agility Literature

A rich literature examines individual adaptability under various guises. For example, Learning Agility (e.g., De Meuse, 2022) is defined as the willingness and ability to learn from experience and apply it. Resilience (psychological capital: hope, efficacy, optimism) emphasizes the ability to bounce back from setbacks. Adaptability and Cognitive Flexibility refer to the ability to adjust one's thinking and behavior to new situations. Individual Ambidexterity captures switching between exploratory and exploitative tasks.

While each construct highlights important facets, they have limitations. Learning agility focuses on updating skills but ignores emotional and social dimensions. Resilience emphasizes recovery but often assumes restoration of status quo rather than proactive change. Cognitive flexibility covers switching perspectives but not regulating anxiety or shaping contexts. Ambidexterity (Rosing et al., 2011) deals with balancing exploration/exploitation, but usually as a stable trait or ability, without fully accounting for affect or collective factors.

Adaptive intelligence subsumes these by integrating multiple domains. It acknowledges that adaptation is not just cognitive (learning agility), not just affective (resilience) and not just behavioral (job crafting), but a composite process. For instance, an agile learner (cognitive) may still be overwhelmed by fear (emotional) or lack social support. Adaptive intelligence explicitly includes emotional self-regulation and mobilizing peers. Likewise, while psychological capital (Luthans et al., 2007) includes optimism and resilience, it does not encompass the collective dimension of wisdom or deliberate environment shaping.

In sum, the adaptability literature provides building blocks but also conceptual overlap.

2.9 Why Existing Constructs Are Insufficient

Although existing constructs capture isolated slices of employee adaptation, none fully encapsulate the multidimensional complexity revealed by our data. Adaptation within AI-driven contexts demands a synergy of cognitive, emotional, social, environmental, and collective capabilities that prior concepts address only in part. For instance, while learning agility (De Meuse, 2022) accounts for the speed and willingness to acquire new knowledge, it overlooks the equally critical need for deliberate unlearning (legacy detachment) and creative experimentation. Similarly, cognitive flexibility and digital competence capture mental adjustments and technical proficiency, yet they fail to explain why highly skilled individuals frequently struggle without the affective regulation to manage fears of obsolescence or the social judgment to share knowledge. Furthermore, constructs like resilience and psychological capital (Luthans et al., 2007) traditionally frame adaptation as a reactive recovery—simply bouncing back from stress—whereas our findings demonstrate a proactive drive to leverage technological disruption for innovation.

Beyond individual cognition and coping, existing frameworks inadequately address the structural and social demands of digital transformation. Individual ambidexterity (Jansen et al., 2009) describes the paradox of managing routine tasks alongside novel AI exploration, but it assumes a stable capacity, neglecting the peer networks and emotional scaffolding required to sustain it. Likewise, dynamic managerial capabilities restrict the locus of adaptation to strategic leadership, entirely omitting the collective wisdom and environmental shaping enacted by front-line employees. In sum, these fragmented constructs fail to capture the integrated reality of individuals simultaneously engaging in cognitive unlearning, emotional regulation, proactive tool adoption, and collective knowledge leveraging. Adaptive intelligence is therefore not a redundant concept, but a unified, holistic capability necessary to explain the multi-domain endeavor of thriving in AI-enabled workplaces.

3. Methodology

3.1 Research Design and Rationale

This study adopts an exploratory, qualitative research design grounded in the constructivist epistemology of Gioia et al., (2013), with the objective of inductively building theory regarding adaptive intelligence as a critical individual-level capability. The rapid proliferation of AI-driven technological turbulence is predominantly driven by industry actors, academic conceptualizations frequently lag behind contemporary organizational practices. Consequently, exploring experiential, expert knowledge is methodologically necessary to capture constructs that do not yet exist in established scales or frameworks. A qualitative methodology is uniquely suited for this objective, as it facilitates the capture of natural-language data necessary for uncovering complex cognitive and behavioral phenomena and translating them into robust theoretical constructs. In-depth, semi-structured interviews were therefore employed, providing the requisite flexibility to elicit deep insights into individual experts' experiences with talent development and technology transformation, while ensuring systematic topical coverage and uniform depth across all respondents.

The Gioia methodology was selected over alternatives on three grounds. First, the study's primary objective is the construction of mid-range theory, that is, propositional constructs that are abstract enough to travel across organizational contexts yet specific enough to be empirically tested, which the Gioia methodology is explicitly architected to produce (Gioia et al., 2013; Cornelissen, 2017). Classical grounded theory (Glaser & Strauss, 1967; Strauss & Corbin, 1998), while also inductive, is oriented toward generating substantive theory from scratch through constant comparison and theoretical sampling across iterative data collection cycles; this study, by contrast, begins with an existing theoretical anchor in Sternberg's (2021) framework and seeks to extend and operationalize it in a specific organizational domain, a goal more consistent with Gioia's theory-elaboration logic than with grounded theory's theory-generation imperative.

Second, reflexive thematic analysis (RTA) (Braun & Clarke, 2019, 2021), while appropriate for rich interpretive inquiry, is not designed to produce the propositional theoretical structures, the data structure diagram, the second-order theme abstraction, and the formally stated research propositions. RTA's constructivist stance resists the movement from themes to generalized theoretical claims that the present paper explicitly undertakes. Third, the Gioia methodology's emphasis on preserving informant-centric language in first-order coding while enabling researcher-driven abstraction at the second-order and aggregate-dimension levels is particularly well-matched to practitioner-facing domains such as ITES management, where the construct of interest (adaptive intelligence) is enacted and described by practitioners in ways that existing academic vocabulary does not yet fully capture.

Consistent with the Gioia methodology's theory-building orientation, semi-structured interviews generate first-order informant-centric concepts, which are progressively abstracted into second-order theoretical themes and aggregate dimensions through iterative analytical cycles. The resulting data structure forms the foundation for the conceptual framework and research propositions presented in the findings and discussion section, with constructs that can be used as inputs for subsequent large-sample quantitative validation.

3.2 Context of the Study

India has emerged as a premier global hub for knowledge-intensive multinational enterprises (MNEs), particularly within the IT-enabled services (ITES) sector, making it an ideal context for exploring adaptive intelligence. The Indian ITES industry is characterized by a massive, highly skilled workforce and an escalating pace of technological turbulence, necessitating continuous digital transformation and innovation. Our study focused on this dynamic demographic, where organizations make substantial investments in training and development to maintain global competitiveness. However, despite these structural investments, firms operating within this region persistently encounter systemic resistance and highly uneven adoption rates regarding emerging technologies. This operational friction might be attributed to employees' limited adaptability rather than deficits in technical infrastructure.

The study engaged ten practitioners drawn from consulting and ITES MNEs operating within the Indian ecosystem, occupying roles that span HR operations, systems administration, talent acquisition, digital strategy, employee experience, and change enablement. Consistent with the Gioia methodology's emphasis on knowledgeable informants (Gioia et al., 2013), participants were selected not because of hierarchical seniority but based on epistemic proximity.

Their sustained, direct engagement with the dynamics of technology implementation and the observable adaptive responses of the employees they work alongside. Practitioners in these interface roles occupy a uniquely productive vantage point: they are neither so distant from day-to-day operations as to rely exclusively on aggregated performance metrics, nor so embedded in individual contributor tasks as to lack comparative perspective across teams and implementation cycles. They witness, document, manage, and in many cases design the organizational conditions under which employee adaptability either succeeds or fails. This positioning makes them precisely the kind of informants from whom inductively built theory about adaptive intelligence can be credibly derived. By focusing on this specific cohort, the research captures a broad spectrum of practitioner insights to conceptualize adaptive intelligence as a critical individual capability aligned with organizational goals in a highly volatile technological landscape.

3.3 Sample and data collection

To access rich, experiential knowledge of technological transformation, employee resistance, and uneven technology adoption, the study engaged ten practitioners from consulting and knowledge-intensive ITES MNEs. Participants were purposively selected based on a criterion of epistemic proximity to the phenomenon rather than organizational rank: each respondent occupied a role that placed them in sustained, first-hand contact with the processes by which employees encounter and adapt to new technology. This included professionals in HR operations, systems integration, talent acquisition, digital strategy, employee experience management, and change enablement, roles that sit at the organizational interface between strategic technology decisions and their on-the-ground behavioral consequences. Practitioners in these positions accumulate distinctive observational knowledge that senior executives or purely technical staff rarely possess: they observe adaptation and resistance as it unfolds, manage the interpersonal and structural conditions that shape it, and frequently design the interventions intended to address it. Their accounts therefore constitute a form of practitioner expertise that is particularly well-suited to the inductive construction of theory about individual-level adaptive capability.

A combination of purposive and snowball sampling was employed to ensure variation across both consulting and ITES organizational contexts, strengthening the transferability of the emergent constructs (Gioia et al., 2013). A cohort of ten was engaged, at which point theoretical saturation was reached: no substantively new first-order concepts regarding employee adaptability emerged after the eighth interview, with the ninth and tenth interviews serving a confirmatory function. Respondent profiles are provided in Table 1.

Table 1: Respondent profiles (n=10)

Respondent	Role	Experience	Industry Segment
R1	IT Project Manager	8 years	ITES / Cloud Infrastructure
R2	HR Operations Lead	6 years	ITES / Global Talent Management
R3	Systems Administration Manager	9 years	Enterprise Software Solutions

Respondent	Role	Experience	Industry Segment
R4	Systems Integration Lead	5 years	Systems Integration
R5	Digital Strategy Analyst	6 years	ITES / Digital Ecosystems
R6	Talent Acquisition Team Lead	7 years	Human Resources
R7	HR Business Partner	6 years	ITES / Employee Experience
R8	Workplace Experience Manager	7 years	Strategic Operations
R9	HR Manager	10 years	Talent Management
R10	Employee Training Coordinator	5 years	Change Enablement

Source: Authors' creation

3.3.1 Theoretical Saturation

Theoretical saturation was operationalized using the criterion of information redundancy following Guest et al., (2006): data collection continued until no substantively new first-order concepts relating to adaptive capability emerged from successive interviews. The saturation process unfolded as follows. The first four interviews (R1–R4) were highly generative, collectively producing 25 distinct first-order concepts. Interviews R5, R6 and R7 each contributed a new concept, signaling a progressive approach to saturation as the conceptual space narrowed. Interview R8 introduced no new concepts and confirmed all 29 concepts already in the repository, marking the point of information redundancy and the achievement of theoretical saturation. Interviews R9 and R10 were completed as confirmatory interviews, serving to strengthen confidence in the stability of the emergent structure rather than to generate further conceptual variation. The concept-accumulation trajectory across all ten interviews is documented in Table 2. A full saturation audit table recording concept-level detail is available from the corresponding author upon request.

Table 2: Theoretical saturation audit table showing emergence of concept from interview

Interview	New 1st-order concepts introduced	Cumulative concept count	Concepts confirmed (present in prior interviews)	Status
R1	9	9	0	Generative
R2	7	16	2	Generative
R3	5	21	4	Generative
R4	4	25	5	Generative
R5	2	27	7	Approaching saturation
R6	1	28	9	Approaching saturation
R7	1	29	10	Approaching saturation
R8	0	29	12	Saturated
R9	0	29	13	Confirmatory

Interview	New 1st-order concepts introduced	Cumulative concept count	Concepts confirmed (present in prior interviews)	Status
R10	0	29	14	Confirmatory

Source: Authors Creation.
Note: Concept counts reflect distinct first-order codes. "Confirmed" counts indicate concepts that appeared in the focal interview and had already appeared in at least one prior interview. The saturation criterion of Guest et al. (2006) was met after R8.

3.4 Setting and procedure

The interviews were conducted over an eight-week period, from September 2025 to November 2025, primarily via secure video-conferencing platforms (such as Microsoft Teams and Zoom) and in-person visits to corporate offices, to accommodate participants' professional schedules in the ITES sector. Before the interview, participants were explicitly informed that the research aimed to capture their practical experiences and that there were no right or wrong answers, thereby reducing the likelihood of idealized or socially desirable responses. All participants provided informed consent and were assured strict confidentiality regarding their identities and the specific multinational enterprises (MNEs) they represented. Additionally, the interviews were recorded, with verbal and written consent obtained beforehand. This study received approval from the Institute's Ethical Clearance Committee.

The semi-structured conversational format provided the necessary flexibility to explore the complex cognitive and behavioral phenomena surrounding technology adoption, allowing key themes regarding individual-level capabilities to emerge naturally. In qualitative research, follow-up questions, also known as "probes", are systematic methodological tools used to encourage participants to elaborate on concepts they have introduced organically. We utilized probes to clarify vague terminology or to deeply explore a specific thought process without introducing researcher bias. For instance, when a respondent stated, "We noticed significant pushback from middle management when we rolled out the new AI-integrated CRM system." Here, we probed: "When that pushback occurred, how did the employees specifically express their resistance, and what coping mechanisms did they use?" The respondent then elaborated:

> "*Many simply reverted to using legacy spreadsheets to bypass the new system. It wasn't that they couldn't learn the software; they were overwhelmed by the pressure to unlearn their established workflows while still meeting strict daily output metrics.*"

This approach allows the study to clearly ascertain the specific adaptability challenges without leading the respondent toward a predetermined conclusion.

In contrast, a leading question uses biased phrasing to steer the participant toward a predetermined conclusion, potentially distorting the data with the interviewer's own theoretical assumptions. In this study, we strictly avoided leading questions to ensure the authenticity of the data collected on adaptability-driven competencies. We only asked follow-up questions to elicit granular details about the experts' strategic management of technological turbulence. To ensure all respondents shared a baseline understanding of the study's context, the research included a brief introductory briefing outlining the scope of "technological turbulence," using recent examples such as generative AI and advanced automation in knowledge-intensive firms. The interviews were conducted in English, the primary business language of the Indian ITES and consulting ecosystem, ensuring that complex organizational and technical nuances were accurately captured and directly transcribed for analysis.

3.5 Analysis Method

Data coding and analysis followed the Gioia methodology (Gioia et al., 2013), a structured inductive approach for building grounded theoretical constructs from practitioner data. The analytical protocol proceeded in three inductive phases followed by one post-inductive theoretical elaboration step, as illustrated in Figure 1. To ensure coding transparency and credibility, all three inductive phases were conducted by two independent researchers referred to herein as Coder A and Coder B, working from the verbatim transcripts without access to each other's codes until the reconciliation stage of each round.

3.5.1 Inter-Researcher Agreement.

Because the Gioia methodology operates within a constructivist rather than positivist epistemology, the study does not report Cohen's Kappa, a statistic developed for and appropriate to nominally defined, pre-specified category systems. Instead, inter-researcher agreement was assessed qualitatively at each coding round through systematic comparison of independent code lists, followed by structured discrepancy resolution discussions (see Table 3). This approach is consistent with the epistemological commitments of inductive qualitative research, in which the goal is not pre-established category reliability but the iterative construction of a defensible conceptual structure (Gioia et al., 2013; Saldaña, 2021).

3.5.2 Phase 1: Informant-Centric Coding

Both coders independently applied open coding to all ten verbatim transcripts, with the primary commitment being fidelity to informants' own language and conceptual categories. Codes were generated to reflect the terms, metaphors, and distinctions that participants themselves used, without imposing prior theoretical categories. Coder A generated an initial set of 29 codes; Coder B generated 26. Following independent coding, the two code lists were compared systematically. Three discrepancies relating to the boundary between "algorithmic replacement panic" and "identity threat from AI" were resolved through a structured discussion session in which both coders returned to the relevant transcript passages and re-examined informant intent, ultimately consolidating the two into a single concept ("techno-existential threat") with clearer definitional boundaries. The final first-order repository comprised 29 distinct concepts.

3.5.3 Phase 2: Second-Order Analysis

Both coders independently grouped the 29 first-order concepts into theoretically coherent second-order themes by applying conceptual questions internal to the data: What underlying capability does this concept reflect? How do these concepts relate within the context of sustained technological adaptation? Coder A produced 18 themes; Coder B produced 17. A single theme-boundary discrepancy whether "Exploratory Learning" and "Adoption Velocity" constituted one or two themes was resolved by returning to the first-order quotes underpinning each and re-examining whether the informant accounts pointed to a single capability or two functionally distinct ones. Transcript evidence supported maintaining them as distinct themes. The final second-order structure comprised 18 themes.

3.5.4 Phase 3: Aggregate Dimensions.

Both coders independently synthesized the 18 second-order themes into aggregate dimensions. Full consensus was reached without discrepancy, yielding five aggregate dimensions: (1) Adaptive Learning and Unlearning, (2) Techno-Emotional Regulation, (3) Proactive Adoption Orientation, (4) Environmental Shaping Capability, and (5) Collective Adaptive Wisdom. This deductive mapping facilitated the aggregation of themes into overarching theoretical dimensions, linking the emergent construct of adaptive intelligence with established personality taxonomies to enable future scale development.

3.5.5 Analytical Illustration and Validity

The first-order analysis captured verbatim concepts such as "resistance to give up old methods" and "rapid upskilling." Applying the conceptual lenses of adaptability and capability formation, these initial concepts were abstracted into the second-order themes of Cognitive Flexibility and Learning Agility. Ultimately, examining these themes through the Big Five framework enabled their categorization into the aggregate dimensions of Openness to Experience and Conscientiousness.

To ensure methodological rigor and trustworthiness, the study integrated several validation mechanisms. The interview protocol underwent initial expert validation by multiple scholars specializing in strategic management, organizational behavior, and qualitative methods, who provided critical inputs into the instrument's construction. Furthermore, data source triangulation was achieved by recruiting participants from diverse segments within both the consulting and ITES domains. Finally, independent peer debriefing and collaborative review of the coding structure by multiple researchers were conducted to mitigate subjective bias and ensure the robustness of the conceptual framework for subsequent empirical operationalization. The entire method has been summarized in Figure 1.

3.6 Post-Inductive Theoretical Elaboration: Big Five Personality Mapping.

Following the completion of the three inductive phases, a distinct and explicitly deductive interpretive step was undertaken: the five aggregate dimensions were mapped onto the Big Five personality traits (McCrae & Costa, 1999) using Matthews' Cognitive-Adaptive Theory of Personality (Matthews, 2018) as the theoretical bridge. This step is not a fourth phase of the Gioia coding process and is not presented as an inductive outcome of the data. It is a post-hoc theoretical elaboration, deductive in character and performed after the construct architecture had been fully established, aimed at facilitating future psychometric operationalization.

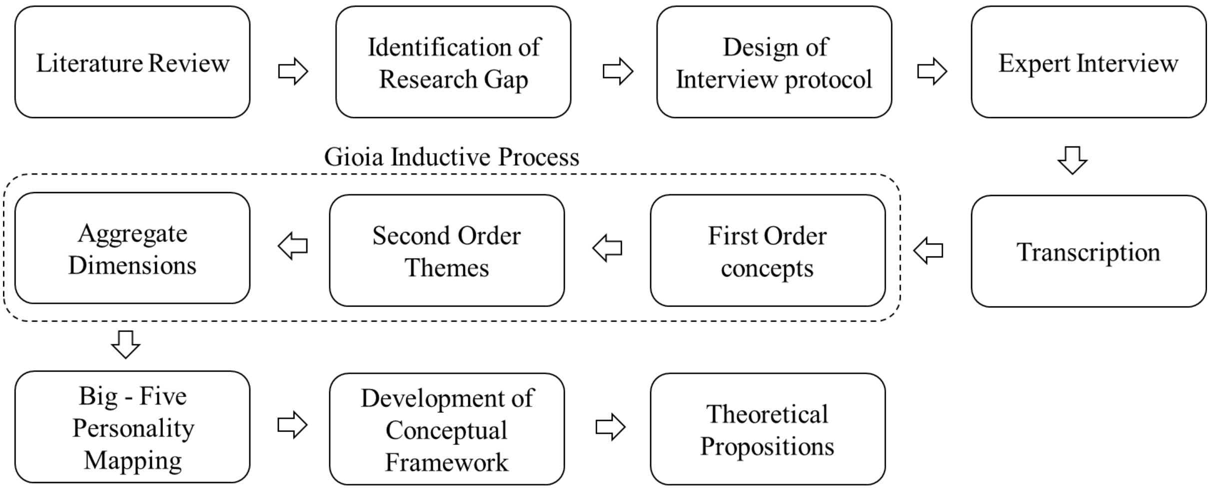

Figure 1: Methodological Flow

Source: Authors' creation

3.7 Credibility, Transferability, and Coding Transparency

Consistent with the quality criteria appropriate for Gioia-based inductive research (Gioia et al., 2013), this study establishes methodological rigor through three criteria - credibility, transferability, and coding transparency. Each criterion is addressed below through specific, verifiable mechanisms.

3.7.1 Credibility

Credibility was established through four mechanisms. First, instrument validation: the semi-structured interview protocol was reviewed prior to data collection by three scholars specializing in strategic management, organizational behavior, and qualitative methods, who assessed its capacity to elicit relevant practitioner knowledge without introducing researcher bias. Second, inter-researcher coding: as detailed in Section 3.5 and Table 3, all three inductive coding phases were conducted independently by two researchers with distinct disciplinary backgrounds, and all discrepancies were resolved through structured consensus discussions before proceeding. Third, member-checking: following the completion of second-order analysis, the emergent theme structure was shared with two participants (R3 and R9), who were asked to assess whether the researcher-level constructs accurately reflected the experiences and intentions underlying their accounts. Both confirmed the face validity of the themes; no substantive modifications were required because of this check. Fourth, negative case engagement: three instances of adaptive regression, where participants described employees becoming less adaptive following technology exposure, were identified during first-order coding and retained in the analysis, sharpening the definitional boundaries of the construct dimensions rather than being absorbed into confirming categories.

3.7.2 Transferability

Transferability was strengthened through deliberate variation in participant roles and organizational segments. The ten informants span HR operations, systems administration, talent acquisition, digital strategy, employee experience, and change enablement within both consulting and ITES MNEs (Table 1). This cross-segment, cross-function variation ensures that the aggregate dimensions were not derived from a single organizational subculture or role perspective, supporting the applicability of the framework across a range of ITES contexts. Readers and researchers can assess transferability directly by comparing the sample characteristics in Table 1 with the contexts to which they seek to apply or extend the framework. The saturation audit in Table 2 further supports transferability by demonstrating that the conceptual structure was stable across the full range of participants, not dependent on the contributions of any single respondent.

3.7.3 Coding Transparency.

Coding transparency established through three artifacts embedded in this paper. First, Table 2 (Saturation Audit) documents the concept-emergence trajectory across all ten interviews, allowing readers to evaluate the evidentiary basis of the saturation claim independently. Second, Table 3 (Inter-Researcher Agreement) records initial agreement rates and resolution methods for each coding round, making the credibility of the coding process verifiable. Third, the data structure table (Table 4, presented in Section 4) provides representative first-order quotations alongside the second-order themes and aggregate dimensions to which they were coded, enabling readers to evaluate the inferential logic connecting raw practitioner language to theoretical constructs. The full saturation audit and complete code list are available from the corresponding author upon request.

4. Findings and Discussion

The analysis generated 29 distinct initial codes, which were subsequently grouped into 18 robust axial categories. These categories were then synthesized into five major themes that define adaptive intelligence in the ITES context. Table 2 provides a sample of the coding process, demonstrating the transition from raw participant quotations to initial theoretical codes, while Table 2 outlines the theme development.

Table 3: Codes, categories, and themes

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
"The people who adapted best didn't hold on too tightly to how things were done before; they focused on discarding old processes and treating past experience as useful, but not something that dictates the future."	***Discarding old processes***	***Legacy Discarding***	***Theme 1: Adaptive Learning and Unlearning***	***Openness to Experience***	*R5, Digital Strategy Analyst*
"The biggest challenge wasn't just learning the new tool; it was accepting skill obsolescence and letting go of a process they had spent years perfecting."	***Accepting skill obsolescence***	***Legacy Discarding***	*Theme 1: Adaptive Learning and Unlearning*	*Openness to Experience*	*R2, HR Operations Lead*
"The employees who succeeded weren't always the smartest technically; they succeeded by calmly navigating software ambiguity without getting frustrated when the new interface was confusing."	***Navigating software ambiguity***	***Exploratory Learning***	*Theme 1: Adaptive Learning and Unlearning*	*Openness to Experience*	*R3, Systems Administration Manager*
"The fastest learners relied on trial and error, jumping in and figuring things out as they went instead of waiting for detailed, step-by-step instructions."	***Trial and error***	*Exploratory Learning*	*Theme 1: Adaptive Learning and Unlearning*	*Openness to Experience*	*R10, Employee Training Coordinator*
"They chose curiosity over fear, keeping at it and asking basic questions until the new system finally made sense, because their	***Curiosity over fear***	*Exploratory Learning*	*Theme 1: Adaptive Learning and Unlearning*	*Openness to Experience*	*R6, Talent Acquisition Team Lead*

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
curiosity was stronger than looking inexperienced."					
"The quickest adapters engaged in continuous daily learning, making it a habit rather than treating the software training as a one-time event."	***Continuous daily learning***	***Autonomous Skill Acquisition***	*Theme 1: Adaptive Learning and Unlearning*	***Conscientiousness***	*R10, Employee Training Coordinator*
"The best learners didn't sit around waiting for the next training session; they relied on independent self-training and started exploring the technology on their own."	***Independent self-training***	*Autonomous Skill Acquisition*	*Theme 1: Adaptive Learning and Unlearning*	*Conscientiousness*	*R10, Employee Training Coordinator*
"Small groups would naturally form for ad-hoc micro-learning, helping each other figure things out long before formal IT support arrived."	***Ad-hoc micro-learning***	*Autonomous Skill Acquisition*	*Theme 1: Adaptive Learning and Unlearning*	*Conscientiousness*	*R1, IT Project Manager*
"For some employees, the first reaction was job replacement panic, immediately wondering whether the new technology was going to replace them."	***Algorithmic replacement panic***	***Threat Perception***	***Theme 2: Techno-emotional Regulation***	***Emotional Stability (Inverse of Neuroticism)***	*R4, Systems Integration Lead*
"With such a strong self-preservation focus, people became too worried about losing their role, making it very difficult to concentrate on learning something new."	***Self-preservation focus***	*Threat Perception*	*Theme 2: Techno-emotional Regulation*	*Emotional Stability (Inverse of Neuroticism)*	*R7, HR Business Partner*
"Once anxiety takes over, they slip into a fight-or-flight	***Fight-or-flight mindset***	*Threat Perception*	*Theme 2: Techno-*	*Emotional Stability (Inverse of Neuroticism)*	*R7, HR Business Partner*

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
mindset where they become afraid of making mistakes, which completely slows down the learning process."			*emotional Regulation*		
"While highly capable employees often became overwhelmed when things didn't work, the adaptable ones stood out for their system crash calmness."	***System crash calmness***	***Resilience Mechanisms***	*Theme 2: Techno-emotional Regulation*	*Emotional Stability (Inverse of Neuroticism)*	*R3, Systems Administration Manager*
"The adaptable employees don't see a system failure as a disaster; they are great at pivoting after failure and viewing it as a natural part of the learning process."	***Pivoting after failure***	*Resilience Mechanisms*	*Theme 2: Techno-emotional Regulation*	*Emotional Stability (Inverse of Neuroticism)*	*R1, IT Project Manager*
"They excel at preserving self-worth, understanding that struggling with a confusing new tool doesn't mean they are technically incapable."	***Preserving self-worth***	*Resilience Mechanisms*	*Theme 2: Techno-emotional Regulation*	*Emotional Stability (Inverse of Neuroticism)*	*R2, HR Operations Lead*
"The adaptable employees don't necessarily love the change immediately, but by dropping resistance quickly, they adjust much faster than everyone else."	***Dropping resistance quickly***	***Adoption Velocity***	***Theme 3: Proactive Adoption Orientation***	***Extraversion and Openness (Social Influence)***	*R9, HR Manager*
"They understand the learning curve is temporary, prioritizing long-term gains because the time-saving benefits are worth the initial effort."	***Prioritizing long-term gains***	*Adoption Velocity*	*Theme 3: Proactive Adoption Orientation*	*Extraversion and Openness (Social Influence)*	*R5, Digital Strategy Analyst*

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
"Seeing a colleague successfully adopt the technology was the turning point that eased departmental resistance and encouraged wider acceptance."	***Shattering departmental resistance***	***Peer Advocacy and Resistance Mitigation***	*Theme 3: Proactive Adoption Orientation*	*Extraversion and Openness (Social Influence)*	*R8, Workplace Experience Manager*
"Every team seems to have one or two people who step up as the informal tech champion, becoming the go-to person whenever someone gets stuck."	***Informal tech champion***	*Peer Advocacy and Resistance Mitigation*	*Theme 3: Proactive Adoption Orientation*	*Extraversion and Openness (Social Influence)*	*R8, Workplace Experience Manager*
"They help peers through practical tech translation, showing everyone exactly how the technology fits into everyday work, not just theory."	***Practical tech translation***	*Peer Advocacy and Resistance Mitigation*	*Theme 3: Proactive Adoption Orientation*	*Extraversion and Openness (Social Influence)*	*R1, IT Project Manager*
"The most adaptable employees rarely use the system exactly as introduced, opting instead for an instant workflow redesign to fit their specific needs."	***Instant workflow redesign***	***Digital Customization***	***Theme 4: Environmental Shaping Capability***	***Extraversion***	*R5, Digital Strategy Analyst*
"If something doesn't work well, they find a workaround by building custom macros instead of waiting for someone else to fix it."	***Building custom macros***	*Digital Customization*	*Theme 4: Environmental Shaping Capability*	*Extraversion*	*R3, Systems Administration Manager*
"What impressed me most was how some employees were effectively redefining job descriptions and completely rethinking their role	***Redefining job descriptions***	***Proactive Job Crafting***	*Theme 4: Environmental Shaping Capability*	*Extraversion*	*R6, Talent Acquisition Team Lead*

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
to leverage the new technology.”					
“The successful employees treated the new tech as an AI personal assistant that could help them work better rather than something that threatened their job.”	***AI personal assistant***	*Proactive Job Crafting*	*Theme 4: Environmental Shaping Capability*	*Extraversion*	*R4, Systems Integration Lead*
“Instead of adapting themselves entirely to the technology, they took charge by commanding the software and finding ways to make it work for them.”	***Commanding the software***	*Proactive Job Crafting*	*Theme 4: Environmental Shaping Capability*	*Extraversion*	*R3, Systems Administration Manager*
“The people who adapted best were very open, constantly sharing prompt tricks instead of keeping useful tips to themselves.”	***Sharing prompt tricks***	***Knowledge Distribution***	***Theme 5: Collective Adaptive Wisdom***	***Agreeableness***	*R4, Systems Integration Lead*
“Even when they were incredibly busy, they offered selfless peer assistance and took time to help someone struggling with the system.”	***Selfless peer assistance***	*Knowledge Distribution*	*Theme 5: Collective Adaptive Wisdom*	*Agreeableness*	*R8, Workplace Experience Manager*
“The best mentors excelled at recognizing legacy protection, understanding that resistance often comes from fear rather than stubbornness.”	***Recognizing legacy protection***	***Prosocial Adaptation***	*Theme 5: Collective Adaptive Wisdom*	*Agreeableness*	*R9, HR Manager*
“During difficult digital transitions, they naturally became a stabilizing peer-	***Stabilizing peer-mentor***	*Prosocial Adaptation*	*Theme 5: Collective Adaptive Wisdom*	*Agreeableness*	*R7, HR Business Partner*

Representative Quote	***Core First-Order Concepts***	***Second-Order Themes***	***Aggregate Dimension***	***Big Five Personality Mapping***	***Respondent***
mentor and a source of reassurance for others in the team."					
"They understood that if the team failed to adapt, individual wins wouldn't matter, so they were always prioritizing collective success."	***Prioritizing collective success***	*Prosocial Adaptation*	*Theme 5: Collective Adaptive Wisdom*	*Agreeableness*	*R9, HR Manager*
"A lot of their effort went into tech fear mentoring, helping colleagues become more comfortable with AI and less worried about their future."	***Tech fear mentoring***	*Prosocial Adaptation*	*Theme 5: Collective Adaptive Wisdom*	*Agreeableness*	*R4, Systems Integration Lead*

4.1 Adaptive Learning and Unlearning

One of the core cognitive mechanisms for successfully navigating technological disruption is the capacity to intentionally unlearn obsolete practices termed "Legacy Discarding" to facilitate "Autonomous Skill Acquisition" (Helfat and Peteraf, 2015). Employees facing rapid digital transitions often find that deep historical competence acts as a significant cognitive barrier rather than an asset. R5, Digital Strategy Analyst says this tension: "*The people who adapted best didn't hold on too tightly to how things were done before; they focused on discarding old processes and treating past experience as useful, but not something that dictates the future."* The decision to consciously abandon a previously mastered skill set reflects the profound cognitive flexibility required for what Sternberg defines as Self-Adaptation (Changing Self).

The findings suggest a sequential cognitive process akin to an internal resource-allocation assessment. First, employees must evaluate the diminishing utility of their existing knowledge base against the novel demands of the incoming technology. Operating at the Symbolic Level of Matthews' Cognitive-Adaptive Theory (2008, 2018), they must decide how to deploy their computational software and finite working memory. When employees cling to past expertise, they expend heavy cognitive resources defending obsolete routines, leaving little capacity for new learning. Conversely, highly adaptable individuals recognize this cognitive mismatch and actively "detach." Facilitated by the Big Five trait of Openness to Experience, they perceive technological ambiguity not as a threat, but as an exploratory challenge, favoring "curiosity over fear."

Because these individuals possess the flexibility to discard their legacy status without overwhelming emotional or mental resistance, the cognitive "sacrifices" required to learn the new system remain low. This frees up working memory, which they immediately redirect toward proactive learning behaviors. Rather than waiting for formal instruction, they engage in "purposeful system-breaking" and "independent self-training." Cognitive adaptation is fundamentally driven by this rapid reallocation of mental resources; individuals who "didn't hold on too tightly to how things were done before" effectively minimize their internal latency, allowing them to sense and seize new technological assets with high efficiency (Helfat and Peteraf, 2015). It is this decisive cognitive detachment and calculated reallocation of effort that ultimately transforms into rapid, autonomous skill acquisition.

Proposition 1: Employees possessing stronger adaptive learning capabilities, especially the ability to discard obsolete knowledge and routines, will transition more quickly to autonomous technology use during periods of technological disruption.

4.2 Techno-Emotional Regulation

Technological transitions frequently trigger acute anxiety, encapsulated by the Threat Perception category. The data revealed that initial reactions often involved an "algorithmic replacement panic," where employees slipped into a "fight-or-flight mindset" focused on self-preservation.

This visceral reaction is perfectly explained by the intersection of Technostress (Tarafdar et al., 2007, 2019) and Conservation of Resources (COR) theory (Hobfoll, 1989). When techno-complexity and techno-invasion threaten to render an employee's established tacit knowledge obsolete, they perceive a critical loss of their core occupational resources, triggering defensive, self-preservation behaviors. According to Matthews' Cognitive-Adaptive Theory, this failure occurs at the Semantic Level (assigning a terminal threat appraisal to the new software) and the Biological Level (unregulated limbic arousal).

However, individuals with high adaptive intelligence bypassed this panic through robust Resilience Mechanisms. Anchored by the Big Five trait of Emotional Stability (low Neuroticism), they rapidly neutralized tech-induced stress. They exhibited a notable "calmness in the face of system crashes" and excelled at preserving their self-worth. As R1, IT Project Manager highlights, "*The adaptable employees don't see a system failure as a disaster; they are great at pivoting after failure and viewing it as a natural part of the learning process.*" We find that while stressors exist, adaptive individuals not only recover but use stress as fuel (echoing *post-traumatic growth* ideas in organizational crises). This refines resilience research by adding an emotional intelligence dimension specific to technological change. Emotional self-regulation is crucial; without it, cognitive learning stalls. By managing fear of AI (e.g. job loss), adaptive employees stay engaged and open to experimentation. This theme underscores that adaptive intelligence is not just about cognitive flexibility, but also about *affective stability* in the face of rapid change.

Proposition 2: Techno-emotional regulation mediates the relationship between technological disruption and technology adoption, such that employees who effectively regulate emotional responses to technological change will perceive lower levels of threat and adopt new technologies more rapidly.

4.3 Proactive Adoption Orientation

The third theme addresses the momentum and interpersonal influence surrounding new system integration, comprising Adoption Velocity, Peer Advocacy and Resistance Mitigation.

Traditional adoption models, such as the Technology Acceptance Model (TAM) and UTAUT, assume compliance rather than proactivity. While they emphasize cognitive evaluations of a tool's usefulness, our study reveals that rapid adoption is driven by an inherent, dynamic psychological capability rather than by the tool's features alone. Learning agility implies a willingness to learn when told, but our theme shows that people sometimes lead the learning. In our study, the motivation is integrally tied to AI enthusiasm and adaptability. We extend adaptability research by showing that some employees push technology on others, converting personal readiness into organizational momentum. Highly adaptable employees were observed “skipping the denial phase” and “prioritizing long-term gains” over short-term discomfort. These adaptive individuals act as “early adopters” or even “change agents,” leveraging social networks (Rogers, 2003).

Beyond personal adoption, these individuals catalyzed broader organizational change through Sternberg’s concept of Practical Intelligence, which is the application of tacit knowledge to navigate specific sociocultural contexts. By stepping up as an “informal tech champion” and engaging in practical tech translation, they utilized the Big Five trait of Extraversion to exert social influence. R8, Workplace Experience Manager, summarized this cascading effect: *“Seeing a colleague successfully adopt the technology was the turning point that eased departmental resistance and encouraged wider acceptance.”*

Proposition 3: Individuals possessing high Practical Intelligence paired with the Big Five trait of Extraversion will function as central nodes in informal organizational networks, significantly amplifying the adoption rates of their immediate peer groups through practical tech translation.

4.4 Environmental Shaping Capability

Rather than passively conforming to new software constraints, adaptive employees exhibited a strong propensity for Digital Customization and Proactive Job Crafting.

This theme is the direct operationalization of Sternberg’s Environmental Shaping dimension, a proactive process of altering the existing environment to better align with one’s personal capabilities. Some scholars on flexible work have noted resourceful behaviors (e.g., digital tinkering), but it’s rarely conceptualized as a distinct dimension of adaptability. We fill that gap: shaping one’s job is as important as shaping one’s mind. It demonstrates that adaptive intelligence encompasses structural action alongside mental agility. Driven by the Big Five trait of Conscientiousness (a universal predictor of performance; Barrick and Mount, 1991), participants detailed behaviors such as “building custom macros,” “creating custom APIs,” and initiating an “instant workflow redesign” to force the technology to serve their specific needs.

This mirrors job crafting (Wrzesniewski and Dutton, 2001), wherein employees proactively redesign their task boundaries to make work more engaging. The most adaptable workers completely re-envisioned their utility. As R3, Systems Administration Manager powerfully illustrates,

> “*Instead of adapting themselves entirely to the technology, they took charge by commanding the software and finding ways to make it work for them.*”

In doing so, they neutralized potential technostress by manipulating their digital environment to maximize utility.

Proposition 4: Employees with higher levels of conscientiousness are more likely to engage in environmental shaping through digital customization and proactive job crafting to overcome technological constraints.

4.5 Collective Adaptive Wisdom

The final theme transcends individual technical mastery, focusing on the collective and ethical dimensions of adaptation. It is characterized by Knowledge Distribution and Prosocial Adaptation. In stark contrast to the rigid limitations of general cognitive ability, this theme is anchored by Sternberg’s Wisdom-Based Intelligence. Adaptable employees prioritized "systemic team improvement," utilizing collective talent in service of a common good. Rather than engaging in resource protection or knowledge hiding, these individuals, motivated by the Big Five trait of Agreeableness, frequently offered "selfless peer assistance" and engaged in continuous sharing of "prompt tricks" and "custom macros. We observed frequent knowledge-sharing networks R4, Systems Integration Lead noted:

> "*The people who adapted best were very open, constantly sharing prompt tricks instead of keeping useful tips to themselves.*"

Furthermore, they demonstrated profound situational awareness by "recognizing legacy protection" in their peers, understanding that resistance often stems from fear rather than stubbornness at the Semantic Level of appraisal. Consequently, they naturally emerged as "stabilizing peer mentors," dedicating significant effort to "tech fear mentoring" to ensure collective resilience and balance short-term disruptions with long-term organizational sustainability.

This dimension vividly brings to life Sternberg's premise that adaptive intelligence is fundamentally a collective endeavor, directly echoing the wisdom-based elements of his original model. When viewed through the lens of organizational theory, this dynamic naturally intersects with established concepts such as Knowledge Sharing and Social Learning. Crucially, adaptive intelligence pushes beyond the boundaries of the isolated expert to harness the "wisdom of crowds," effectively mobilizing the tacit knowledge embedded within groups. Furthermore, while this collective capability shares the prosocial DNA of Organizational Citizenship Behavior (OCB), it is distinct in its focus. Rather than representing general workplace helpfulness, it is a targeted form of prosocial action that is explicitly calibrated to drive and sustain collective adaptation.

Proposition 5: Collective adaptive wisdom positively moderates the relationship between individual technological mastery and team resilience, such that higher levels of collective adaptive wisdom strengthen team resilience by reducing the adverse effects of resource-protective behaviors during digital transformation.

Proposition 6: Adaptive Intelligence, as a higher-order construct encompassing self-adaptation, environmental shaping, and wisdom-based capability, demonstrates greater explanatory power for digital innovation performance than traditional measures of cognitive ability.

4.6 Conceptual Framework

The conceptual framework illustrates a dynamic process in which external environmental pressures trigger specific individual capabilities, which then scale up to produce critical organizational outcomes. The entire flow progresses from inputs (external factors) on the far left, through a central core process (individual adaptation), to final outputs (behavioral and collective performance) on the right.

The framework's narrative begins on the left, detailing the external environmental stressors facing contemporary workplaces. This is characterized by technological turbulence, encompassing rapid advances in AI, automation, and broader digital transformation. As illustrated by the connecting arrows, this turbulence acts as a potent stressor, leading directly to the acute disruption of established routines, increased levels of technostress among employees, and a perceived threat to an individual's occupational resources and skill value. This environmental pressure acts as a catalyst, triggering the model's central core.

In response to this disruption, the central component of the framework, labeled Individual Capability Integration," activates. This is defined as "Adaptive Intelligence," depicted not as a single skill but as a dynamic hub integrating five distinct capability "nodes," each moderated by specific personality traits (The Big Five Personality Traits). These dimensions are: Learning Agility (driven by the curiosity and discipline associated with Openness and Conscientiousness); Emotional Resilience (logically moderated by Low Neuroticism, providing the emotional stability to manage technostress); Cognitive Flexibility (using creative and analytical meta components to handle multiple shifting concepts simultaneously); Environmental Shaping (proactively altering one's own job role and environment through Extraversion and Job Crafting); and Wisdom-Based Action (ensuring decisions are ethical and prosocial, driven by Agreeableness). Adaptive intelligence, therefore, represents the complex integration of cognitive, emotional, and social resources to successfully meet environmental challenges.

The successful operation of this internal core mechanism then drives the individual's outward behavioral response, found on the right side of the diagram. The primary individual outcome is technology adoption and overcoming status quo bias, depicted metaphorically by a rocket launching away from a static, stagnant platform labeled "Status Quo." Adaptive intelligence equips individuals with the toolkit to overcome natural inertia and successfully embrace and use new technologies. Finally, this individual-level behavioral change scales up to create group-wide impact. Aggregated across the organization, these adaptive behaviors result in key Organizational Outcomes, specifically innovation performance and sustained organizational adaptability, visually represented by interlocking gears and a rising growth chart, thus ensuring the company's long-term resilience in a volatile landscape.

5. Theoretical Contributions

5.1 Contribution to the Adaptive Intelligence Theory

Our findings paint a richer picture of adaptation than any single existing construct provides, with each emergent dimension simultaneously extending and challenging prior theory. At the cognitive level, we found that adaptation often requires unlearning identity-defining expertise. Rather than merely accumulating new skills, employees must actively let go of obsolete knowledge. This extends the learning agility literature by emphasizing identity reconstruction and challenges traditional learning models that assume knowledge accumulation is universally positive, pointing to a critical need for theories of "strategic forgetting" in organizational learning. Concurrently, at the affective level, the role of emotional regulation in technology adoption remains fundamentally underappreciated. Our results demonstrate that fear and anxiety management are just as critical as technical skill development. This insight challenges purely cognitive-focused adoption models and extends technostress literature by illustrating how highly adaptive individuals transform stressors into motivators. Consequently, this refines established resilience theory; rather than simply "bouncing back" to a baseline state, these individuals channel stress into focused, proactive action a nuanced behavioral response not captured in traditional resilience scales.

Moving beyond internal cognitive and affective states, the data reveal that adaptation is also a highly proactive, strategic, and collective endeavor. Employees do not merely adapt in isolation; they actively drive group behavior. This challenges traditional technology acceptance frameworks, such as UTAUT-like models, by positioning social influence as an outcome— where adaptable individuals emerge as peer influencers rather than merely an input condition. Furthermore, this dynamic extends individual ambidexterity theory, suggesting that effective ambidexterity during turbulent periods operates as a team-level property fueled by these adaptive individuals. Perhaps the most novel behavioral insight is the capacity for environmental shaping, wherein employees actively redefine their work environments as an integral part of their adaptation. This introduces a significant layer to adaptation theories that traditionally treat the work context as a static, given constraint. By demonstrating that adaptation cannot be fully understood without accounting for how individuals actively modify their surroundings, this finding explicitly links micro-level job crafting behaviors to macro-level organizational design.

Ultimately, adaptation manifests as a profoundly social process rooted in collective wisdom. These finding challenges purely individualistic perspectives, such as those relying solely on psychological capital, and strongly supports network-based models of organizational learning. Theoretically, it implies that adaptive intelligence is both firmly grounded in individual capabilities and synergistically emergent from social interaction. This dual nature refines the overarching theory of adaptive intelligence by delineating its specific, interdependent dimensions. Practically, it challenges educators and organizational leaders to radically reconceptualize training interventions. Fostering adaptive intelligence requires moving beyond siloed technical instruction to cultivate holistic capabilities, demanding interventions that simultaneously target individual resilience, cognitive flexibility, and the structural development of peer learning networks and communities of practice.

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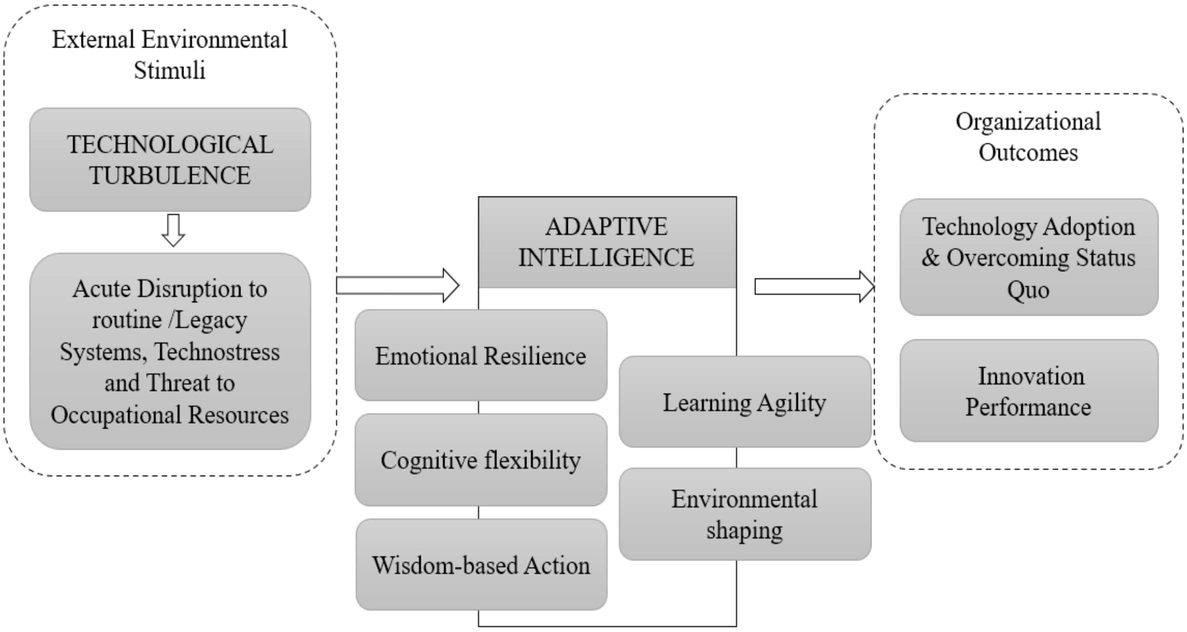

Figure 2: Conceptual Framework

Source: Authors' creation

5.2 The Micro foundation of Dynamic Capabilities

Second, building on Teece (2007) and Helfat and Peteraf (2015), we establish adaptive intelligence as the critical employee-level micro foundation enabling organizational dynamic capabilities. Whereas dynamic capabilities theory traditionally treats sensing, seizing, and reconfiguring as macro-level firm routines, we demonstrate that these routines cannot materialize without employees who can individually sense subtly shifting conditions, emotionally engage with innovation, and proactively craft new processes. In effect, adaptive intelligence embodies the human architecture of dynamic capabilities: individual sensemaking aggregates into firm-level sensing, and collective wisdom enhances organizational reconfiguration. This bridges organizational theory and psychology by identifying exactly *who* executes the dynamic work, thereby significantly refining the explanatory power of dynamic capabilities theory.

5.3 Advancing Technostress, COR, and Technology Adoption Literatures

Third, this research significantly extends existing paradigms of technostress and technology adoption. Traditional technostress models focus primarily on how technology creates uniform strain. We shift this narrative toward a resource-based view of "technostress transformation," illustrating how employees vary in their ability to turn technological strain into developmental growth. Adaptive intelligence explains why two workers facing equal techno-overload diverge: individuals drawing on a reservoir of self-regulation and social resources convert threats into challenges, while others succumb to stress and fatigue.

Concurrently, this study refines the intersection of technostress and Conservation of Resources (COR) theory. While traditional COR posits that employees will defensively hoard knowledge under the threat of technological obsolescence, this study reveals that Wisdom-Based Capability (driven by Agreeableness) actively suppresses this defensive behavior. By prioritizing prosocial adaptation and peer tech mentoring, adaptively intelligent employees create decentralized support networks that mitigate collective technostress. Finally, the study moves beyond traditional rational-evaluation models (such as TAM and UTAUT) by demonstrating that adoption velocity is driven less by cognitive evaluations of a tool's utility, and far more by the employee's innate psychological capacity for Environmental Shaping.

6. Implications, Limitations, and Conclusion

6.1 Managerial Implications

The persistent and costly failure of enterprise technology rollouts is frequently rooted in a fundamental misallocation of organizational resources: MNEs heavily over-index on raw technical upskilling while largely ignoring the cognitive-adaptive profile and psychological readiness of their workforce. To radically enhance organizational resilience, HR leaders, talent managers, and practitioners responsible for capability development at every level of the organization, must systematically integrate the dimensions of adaptive intelligence into their overarching talent management strategies. This includes not only CHROs and digital transformation leads setting strategic direction, but also the HR business partners, training coordinators, and operations managers who design and deliver the conditions under which adaptation occurs. Building adaptive intelligence requires holistic interventions that address both individual capabilities and the broader organizational culture.

First, during recruitment and selection, organizations must move beyond traditional technical assessments, evaluations of experience, or general intelligence (g) metrics. Talent acquisition systems should incorporate validated psychometric instruments to assess the Big Five traits, specifically targeting candidates who exhibit high Openness, high Conscientiousness, and low Neuroticism, which serve as superior baseline indicators of adaptation. Furthermore, new assessment protocols should simulate ambiguous technological scenarios to evaluate candidates' real-time cognitive and emotional response patterns.

Second, corporate training and development paradigms require radical redesign. Rather than solely teaching the mechanical, point-and-click operation of new software platforms, training must cultivate the attitudinal and cognitive components of adaptive intelligence, specifically, learning how to learn, strategically unlearn, and regulate emotions. Employees should be routinely placed in unstructured simulation scenarios to practice formulating novel strategies, managing induced techno-uncertainty, and engaging in collaborative problem-solving. To build collective wisdom, organizations should implement formal mentorship programs in which tech-savvy employees coach peers, alongside emotional resilience workshops to help employees cope with AI-related anxiety.

Third, managers must proactively engineer supportive contexts that facilitate adaptation. Recognizing that even highly motivated employees face legacy constraints, leadership must decentralize decision-making and provide the autonomy necessary for active job crafting and the customization of digital interfaces. Offering flexible job designs, such as dedicated time for experimentation, and providing adequate resources (e.g., time, tools, and psychological support) align with COR theory to effectively buffer initial technological stressors. Furthermore, leadership training should emphasize the automation–augmentation paradox (Raisch and Krakowski, 2021), urging managers to resist full automation and to balance human–AI roles. Finally, internal communication strategies must pivot to highlight developmental narratives and peer success stories rather than technological threats, transforming defensive resistance into proactive innovation by positively shifting employee threat appraisals.

7. Policy Implications

At a policy level, our results suggest that workforce development initiatives should include adaptive capacities. Educational curricula might integrate digital literacy with "learning to learn" skills, emotional intelligence training, and collaboration exercises. Governments and industry consortia can fund cross-sector communities of practice for AI (echoing the concept of collective wisdom) to disseminate best practices.

Labor policies could encourage job crafting freedoms, acknowledging that employees often know best how to adjust roles. Regulations around AI deployment should consider human-centric factors: for example, mandates for transparent AI to reduce fear (addressing techno-uncertainty) or funding for reskilling programs that explicitly target adaptive capabilities. In sum, public policy should not only subsidize technical reskilling but also psychosocial training, preparing citizens for rapid tech changes.

8. Limitations and Directions for Future Research

While this exploratory qualitative study establishes a robust conceptual foundation for Adaptive Intelligence within the ITES context, it possesses inherent limitations that present critical avenues for future empirical research.

First, although our sample of 10 industry experts is sufficient for achieving theoretical saturation in inductive theory building, it restricts the generalizability of the findings to MNEs within the ITES sector. The behavioral manifestations of adaptive intelligence may differ significantly in other industries, such as manufacturing or healthcare. Consequently, extensive cross-cultural validation is required. Future research must specifically investigate how the "wisdom" component, which necessitates balancing individual self-preservation with collective interests, manifests across divergent sociocultural contexts, such as highly individualistic Western cultures versus collectivistic Eastern cultures, to ensure the construct's global ecological validity.

Second, while our qualitative approach effectively identifies the structural dimensions of adaptive intelligence, it inherently lacks the statistical power required for broad predictive validation. To meet the rigorous demands of empirical science, future researchers must prioritize developing a standardized, psychometrically sound quantitative measurement tool: the Corporate Adaptive Intelligence Scale (CAIS). Utilizing the dimensions and theoretical mapping derived from this study, scholars should execute rigorous Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to establish strict construct validity and reliability. Once a validated scale is established, large-sample quantitative studies utilizing Structural Equation Modeling (SEM) should be deployed. Such studies can empirically test the exact predictive relationships and mediating roles of adaptive intelligence between environmental technological turbulence, technostress levels, and objective firm-level innovation metrics, carefully controlling for general cognitive ability.

Third, our cross-sectional design captures adaptation retrospectively. To fully understand the dynamic nature of this meta-capability, researchers are strongly directed to conduct longitudinal studies utilizing latent change score analysis. Tracking cohorts across multi-year technology implementation phases will reveal how an individual's adaptive intelligence fluctuates in real time under continuous digital disruption. Crucially, longitudinal designs will clarify the extent to which adaptive intelligence operates as a static psychological baseline governed by the Big Five traits, versus a malleable behavioral capability that can be systematically trained and expanded through targeted organizational interventions.

Finally, while this study integrates several foundational paradigms, the conceptual framework could be further enriched by applying alternative theoretical lenses. For instance, incorporating Self-Determination Theory could elucidate the motivational drivers behind autonomous skill acquisition, while Actor-Network Theory could more deeply map the socio-technical networks formed during peer advocacy. Moreover, future scholars should rigorously investigate the construct's boundary conditions. Research must examine whether high adaptive intelligence universally yields positive outcomes, or if potential “dark sides” and maladaptation exist, such as excessive environmental shaping or workflow “tinkering” that inadvertently disrupts overarching organizational alignment.

9. Conclusion

As extreme, AI-driven technological turbulence becomes the permanent operating condition for global enterprises, traditional paradigms relying on general cognitive ability and raw technical proficiency are fundamentally insufficient to predict or manage workforce success. Today, the ultimate limiting factor for organizational survival is no longer the objective sophistication of the digital ecosystem, but the adaptive capacity of the human workforce. This study establishes Adaptive Intelligence as a paramount, multidimensional meta-capability that transcends fragmented existing constructs by seamlessly integrating cognitive learning and unlearning, emotional regulation, proactive environmental shaping, and prosocial wisdom.

Theoretically, this research positions Adaptive Intelligence as the critical micro foundation of organizational dynamic capabilities at the individual level. By intertwining Sternberg’s structural intelligence framework with Matthews’ Cognitive-Adaptive Trait Theory, the study elucidates how the Big Five personality traits provide the latent psychological architecture necessary for employees to collectively sense, seize, and reconfigure in the face of AI-induced change. Furthermore, this integration significantly extends existing technostress and technology adoption theories by demonstrating how adaptively intelligent individuals actively convert technological threats and stressors into proactive developmental opportunities.

Ultimately, for modern multinational enterprises, the mandate is abundantly clear. Recognizing, hiring for, and systematically cultivating this dynamic capability is not merely an HR optimization metric; it is an absolute strategic imperative. Organizations that successfully foster adaptive intelligence will be uniquely positioned to dismantle defensive employee resistance, mitigate the paralyzing effects of technostress, and harness the full disruptive power of emerging technologies to sustain long-term innovation and competitive advantage in the digital age.

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