Research Article

AI Literacy and Organisational Resilience in AI-Enabled Work: How Psychological Safety Enables Voice and Adaptive Learning — A Grounded Theory Study

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ABSTRACT
The rapid diffusion of artificial intelligence (AI) in organisational settings has heightened the desire to comprehend how employees learn, acquire and apply AI-related skills into sustainable organisational performances. This paper will explore the role of AI literacy of employees in organisational resilience in AI-enabled workplaces and theorise the psychological mechanism through which this relationship can occur. Basing our study on psychological safety theory (Edmondson, 1999, 2018), we use the grounded theory approach and examine 26 in-depth semi-structured interviews with the employees of technology, consulting, education, and healthcare industries in India (2025). Iterative open, axial, and selective coding resulted in three aggregate themes, including (i) AI literacy development as a socially embedded organisational capability; (ii) psychological safety in AI contexts as an enabling mechanism; and (iii) organisational resilience through AI literacy adoption as the most fundamental outcome. The results indicate that AI literacy prepares employees to understand AI outputs, identify system constraints, and critically interact with AI technologies, but these skills can only result in resilient organisational reactions when psychological safety facilitates voice behaviours, namely, speaking up on mistakes, challenging AI-based decisions, and raising ethical issues. The psychological safety therefore acts as the key mediating factor that transforms personal AI competence into the group learning and adaptive response. The article extrapolates the psychological safety model of Edmondson to AI-assisted work and contributes to the organisational resilience literature by defining human and social circumstances, in which AI literacy can be strategically useful.

Keywords: *AI literacy, psychological safety, organisational resilience, grounded theory, voice behaviour, AI adoption, India.*

How To Cite This Article: Vanisri M, Kondapaka P, Sharma H. Ai Literacy And Organisational Resilience In Ai-Enabled Work: How Psychological Safety Enables Voice And Adaptive Learning — A Grounded Theory Study. Int J Drug Deliv Technol. 2026;16(26s):1064-1074. Doi: 10.25258/ijddt.16.26s.114

INTRODUCTION

The rapid diffusion of artificial intelligence (AI) technologies is fundamentally reshaping organisational structures, work processes, and employee experiences across industries (Dwivedi et al., 2021; Tambe et al., 2019). The use of AI streamlines routine operations, streamlines decision-making, and increases operational efficiency, making AI implementation a strategic necessity and not a frivolous innovation (Fountaine et al., 2019; Budhwar et al., 2023). With AI becoming more and more involved in organisational decision-making, be it recruitment and performance management or operational risk assessment, the capacity of the employees to participate in the functioning of AI systems in a meaningful way has become a critical issue in organisational survival (Giri and Sharma, 2025).

At the core of this capability lies AI literacy, which is characterized by cognitive, technical, and interpretive skills, allowing employees and managers to comprehend, judge, and make successful use of AI-based technologies in organisational scenarios (Long and Magerko, 2020; Ng et al., 2021). AI literacy is not technical expertise only, but it also covers the social and interpretive aspects of how AI tools are relied upon, challenged, and incorporated into everyday work routines (Cetindamar et al., 2024). Previous studies make AI literacy a preliminary facilitator of effective AI implementation, especially in environments characterized by a high degree of uncertainty, ethical risk, and complexity of the algorithm (Uren and Edwards, 2023; Pinski, 2024). Notably, AI literacy is starting to be viewed as one of the primary forces of organisational resilience - the ability to foresee, absorb, and adjust to the disruptions caused by

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technological and environmental turbulence (Duchek, 2020; Lengnick-Hall et al., 2011).

However, with scholarship providing the strategic significance of AI literacy, little is known about the psychological processes of how AI-related competencies translate into the resilient organisational outcomes. Employees might have awareness of AI systems, yet they are not ready to doubt AI-based recommendations, report mistakes, or raise ethical issues, especially in a workplace where interpersonal risk is not safe. This gap is the reason why the present study has chosen to explore psychological safety as the intervening factor between AI literacy and organisational resilience.

Learning, innovation and performance in uncertain organisational practices have been broadly associated with the presence of the feature of psychological safety; a collective conviction that the organisational environment is safe to take interpersonal risk, including speaking-up, challenging decisions, accepting mistakes and experimentation (Edmondson, 1999). The psychological safety within the AI-enabled workplaces, we posit, is particularly consequential: in the absence of it, even the AI-literate employees are likely to develop the voice of criticality further, which strengthens the blind spots in algorithmic structures, limiting the adaptive capacity of the organisation.

This paper fills this gap by exploring, using a grounded theory methodology, the process of AI literacy formation and action by employees, its influence on adaptive responses to AI-mediated change, and the role of psychological safety in facilitating or constraining the conversion of AI literacy into voice, learning, and organisational resilience. The paper adds to the literature on AI adoption by theorising the human and social conditions in which AI capability can be strategically valuable, and provides useful advice on how leaders can develop resilient, AI-enabled organisations.

The research will achieve the following goals: (i) to understand how employees conceptualise and become AI literate in AI-enabled work; (ii) to understand how AI literacy can be enacted in practices that facilitate organisational resilience during uncertainty; and (iii) to theorise how psychological safety facilitates or inhibits the translation of AI literacy to voice, learning, and adaptive response.

Review of Literature

2.1 Theoretical Foundation: Psychological Safety Theory

The psychological safety theory (Edmondson, 1999, 2018) underlines this research as it assumes that the readiness of the employees to assume interpersonal risks (speaking up, admitting mistakes, suggesting new ideas) depends on their collective interpretations of the interpersonal climate in their team or organisation. Psychologically safe environments promote voice behaviour, learning orientation and adaptive response, whereas unsafe environments generate silence, conformity and suppressed learning. Edmondson and Lei (2014) showed that psychological safety is especially essential in the contexts with the features of complexity and quick change, which is exactly what AI-driven change brings about.

We carry this framework into AI-enabled work by placing psychological safety as the mechanism by which AI literacy is an enactment. Employees who are AI-literate can be aware that a given AI-based recommendation is limited, but it is up to them to express such awareness, and do or not do so, depending on whether the interpersonal setting renders such expression a safe action. Psychological safety in this regard transforms personal ability in to organisational resilience, which is made up of collective learning and adaptive capacity.

2.2 AI Literacy and Organisational Resilience

Organisational resilience refers to the capacity of an organisation to cope with disruptions and survive uncertainty and emerge stronger than before due to environmental threats, a meta-capability that includes sensing, absorbing, and reconfiguring responses to these environmental threats (Lengnick-Hall et al., 2011; Duchek, 2020; Williams et al., 2017). Within the framework of an AI-led change, resilience needs not only technological infrastructure but also human capacity: staff that is able to reason AI output, detect system malfunctions, and adjust workflows to the unforeseen AI behaviours.

This human background is offered by AI literacy. According to Long and Magerko (2020), AI literacy refers to a set of skills that help an individual to critically assess AI technologies, work alongside AI systems, and use AI responsibly in a variety of settings. Ng et al. (2021) perceive AI literacy in four dimensions, including knowing and understanding AI, using and applying AI, evaluating and creating AI, and navigating AI ethics. Specifically addressing the issue of employees in digital workplaces, Cetindamar et al. (2024) outline four capability clusters, namely, technology-related, work-related, human-machine-related, and learning-related, highlighting the multi-dimensionality of the workplace AI literacy. It is based on this premise that previous studies in the context of SMEs and technology have indicated that those organisations that are more AI literate can more easily absorb disruption and use AI strategically instead of it causing them to feel fragile (Uren and Edwards, 2023; Borges et al., 2021).

The paper defines AI literacy within the context of employees being capable of: (i) understanding what AI systems cannot or cannot do; (ii) understanding AI outputs in relation to context and uncertainty; (iii) detecting potential error or bias; and (iv) using AI systems responsibly within organisational norms and governance policies.

2.3 Psychological Safety as Mediating Mechanism

While AI literacy supplies the cognitive and interpretive resources for informed AI engagement, the translation of these resources into organisational-level outcomes requires a social infrastructure of trust and openness. Psychological safety provides this infrastructure. Studies by Baer and Frese (2003) and Newman et al. (2017) prove that the connection between the personal abilities and the organisational performance is mediated by the psychological safety, especially in the organisations with the focus on innovations and technologies. Edmondson (2018) goes on to state that learning within complex technological contexts, which is exactly what AI-enabled work places individuals in, can only be maintained within psychologically safe teams.

Psychologically safe climates in AI-enabled organisations enable AI-literate workers to freely address ethical issues, data privacy threats, system errors, and unintentional AI outcomes, and to facilitate proactive organisational reactions instead of reactive ones. On the other hand, the fearful or pressure-inducing AI adoption contexts drown this voice and AI literacy would be latent and organisational resilience would be an unfulfilled promise. We consequently hypothesise that psychological safety mediates the connection between AI literacy and organisational resilience, acting as the facilitating factor by which the personal AI ability is turned into shared learning and adaptive behavior.

Methodology

This study employs a qualitative research design following grounded theory procedures (Glaser and Strauss, 1968; Gioia et al., 2013). A qualitative methodology is suitable due to the fact that the phenomenon of interest the psychological mechanisms of how AI literacy becomes organisational resilience is multifaceted, situational, and insufficiently known to measure, quantitatively (Eisenhardt and Graebner, 2007). Although the analytical categories were developed inductively through participant data instead of being imposed a priori, theoretically the study was theoretically sensitised using the psychological safety theory (Edmondson, 1999) as a conceptual lens to guide the research.

3.1 Participants and Sampling

In 2025, the participants (N = 26) were recruited in India by snowball sampling. The inclusion criteria required that tparticipants were: (i) actively working; (ii) regularly engaging with AI tools or systems in their daily routine; and (iii) ready to share AI-related experiences freely. The sample included employees working in technology (n = 19), consulting (n = 4), education (n = 2), and healthcare (n = 1) fields, at entry-level to leadership positions in organisations of different sizes (Table 1). The 25th interview was found to be saturated, the 26th was a confirmatory case. Out of the 26 respondents, 19 are men and seven women. The concentration of the technology-sector is indicative of a high level of AI adoption within this sector in India and is recognized to be a limitation of the study.

Table 1: Profile of Interview Participants (N = 26)

Code	Industry	Role	Org. Size	AI Usage (%)
P1, P2	Technology	Managerial	Small–Large	Low (0–40)
P3,P9,P10,P20,P22,P26	Technology, Education, Media	Leadership	Small (<100)	Moderate–High (21–80)
P4–P7,P12–P17,P24,P25	Technology, Consumer, Health	Individual Contributor	Ultra Large (501+)	Low–Moderate (0–60)

P8,P11,P19	Consulting, Technology	Managerial/Leadership	Ultra Large (501+)	High (41–80)
P13,P21	Consulting	Individual Contributor	Small–Ultra Large	Low–Moderate (0–60)
P18	Technology	Entry Level	Large (251–500)	Low (0–20)
P23	Technology	Leadership	Large (251–500)	Low (0–20)

3.2 Data Collection

Semi-structured interviews were conducted in-person between January and June 2025, and led by a protocol that was created based on the study research questions and theoretical framework. The interviews were conducted in 25-35 minutes and were recorded on audio with the consent of the participants. Transcripts were prepared verbatim from all recordings. The corpus was 7,028 words (about 270 words per participant). The participants were provided with the intent of the study, voluntary nature, and withdrawal right as well as data storage procedures. There was no compensation provided. All interviews were informed.

3.3 Data Analysis

Interview transcripts were analysed using grounded theory procedures. The analysis was conducted in three iterative steps, namely: (i) open coding, i.e. line-by-line reading to derive first-order concepts based on the language of participants; (ii) axial and focused coding, i.e. sorting the concepts into higher-order categories by studying patterns, conditions, and consequences across interviews; and (iii) selective coding, i.e. integrating categories into a set of explanatory concepts A coding decision/analytic memo audit trail was kept. The complete coding scheme is incorporated in Table 2, and Table 3 includes the overall thematic scheme.

3.4 Trustworthiness

Trustworthiness was established through four strategies. The credibility was facilitated by the use of iterative peer debriefing of the research team and active negativism case analysis - cases that do not fit into the major patterns were detected and subsequently applied to generalize the categories (Lincoln and Guba, 1985). A complete audit trail of coding and analytic decisions was used to ensure confirmability. Transferability is discussed by describing the sample, industry in detail, and data collection process. Member checking was done by conducting a group of participants and they attested that the emerging themes were a true reflection of their experiences.

Findings

Three aggregate themes emerged from the grounded theory analysis: (i) AI literacy development as foundational capability; (ii) psychological safety as enabling mechanism; and (iii) organisational resilience through AI literacy adoption. Tables 2 and 3 present the coding structure and aggregate framework respectively. Figure 1 presents the emergent conceptual model.

Table 2: Coding Structure — Open, Axial, and Aggregate Codes

Theme	Code	Description	Participants
AI Literacy	Structured Training	Formal workshops; institutional AI programs	P2,P3,P12,P15,P19,P26

	Tool-Based Learning	Direct interaction with AI systems	P4,P6,P7,P11,P22
	Self-Directed Learning	Independent exploration; no org. guidance	P8,P13,P16,P23
	Training-Induced Confidence	Reduced anxiety; increased AI comfort	P1,P2,P3,P6,P12,P19,P20,P21,P26
	Hesitation / Limited Training	Uncertainty restraining AI use	P7,P13
	Over-Reliance Risk	Uncritical acceptance of AI outputs	P16
	Active Org. Support	Managerial encouragement; peer learning	P3,P8,P10,P12,P20,P21
	Passive Support	Tools provided without guidance	P11,P22
	No Org. Support	Absence of institutional AI development	P14,P18,P25
Psych. Safety	Safe to Speak Up	Comfort voicing AI concerns	P2,P4,P9,P19,P21,P22
	Conditional Safety	Context-/hierarchy-dependent openness	P1,P3,P5,P12,P24
	Perceived Unsafety	Fear-driven silence; suppressed voice	P7,P8,P18,P26
	Open & Transparent Culture	Communication norms enabling AI dialogue	P2,P4,P8,P19,P21
	Leadership-Driven Safety	Leaders modelling	P10,P11,P21,P26

		curiosity & openness	
	Fear of Job Displacement	AI perceived as threat to employment	P7,P8,P9,P18
	Skill Erosion Concern	Over-reliance reducing human capability	P11,P15,P16
	Privacy & Data Risks	Anxiety over misuse of personal data	P5,P6,P12
	Accuracy & Accountability	Fear of AI hallucinations & errors	P20,P21
	Pressure-Driven Adoption	Timelines reducing psychological safety	P26
	Learning-Oriented Leadership	Framing adoption as a learning journey	P8,P21,P26
Resilience	Open & Adaptive Culture	Curiosity-driven AI adoption readiness	P2,P3,P4,P5,P6,P8,P9,P19,P20,P24,P26
	Gradual Openness	Skepticism transforming to cautious adoption	P7,P9,P11,P12,P21
	Resistant Culture	Minimal support; resistance to adoption	P1,P14,P18,P25
	Enthusiasm & Surprise	AI as transformative & exciting	P3,P5,P8,P20
	Skepticism & Anxiety	Quality, job-threat, misuse concerns	P7,P11,P12,P15,P17

	Collaboration & Innovation	Norms enabling AI experimentation	P3,P8,P10,P19,P24,P26
	Learning-Oriented Climate	Learning culture reducing fear of failure	P2,P6,P12,P20,P26

Table 3: Aggregate Thematic Framework

Aggregate Theme	Core Category	First-Order Codes (Selected)	Key Participants
AI Literacy Development	AI literacy as organisational capability	Structured training; tool-based learning; self-directed learning; training confidence; org. support	P1–P3, P6, P8, P10–P16, P19–P23, P26
Psychological Safety in AI Context	Psychological safety as enabling mechanism	Safe to speak up; conditional safety; perceived unsafety; leadership-driven safety; learning culture	P2–P5, P7–P12, P18–P22, P24, P26
Organisational Resilience through AI Adoption	Resilience as collective adaptive capacity	Open & adaptive culture; collaboration norms; learning climate; enthusiasm vs. skepticism	P2–P9, P11–P12, P19–P21, P24, P26

4.1 AI Literacy Development as Foundational Capability

AI literacy emerged across all participant narratives as the foundational antecedent of resilient AI engagement. Three primary pathways characterised its development in the sample: structured training, tool-based learning, and self-directed learning.

Those respondents who had access to formal training (P2, P3, P12, P15, P19, P26) identified formal workshops and institutional AI programs as granting both technical competence and organisational legitimacy. P3 found: formal training helped me realize that we were not supposed to operate the AI blindly, but rather question it: it was part of doing a good job. This was also linked to reduced anxiety and increased experimentation, which agrees with training-related confidence found in nine participants (P1, P2, P3, P6, P12, P19, P20, P21, P26).

Practical ease of use was facilitated by tool-based learning (P4, P6, P7, P11, P22), although it was not always associated with fostering the confidence to discuss mistakes and challenge AI outputs. The pathway resulted in operational use of AI without critical engagement and, therefore, restricted the resilience-enabling potential of literacy in areas where psychological safety was less strong. The self-directed learning (P8, P13, P16, P23) also contributed to the personal adaptability, but decreased the shared sense-making opportunities: when I was learning alone, I had expertise, but I wasn't sure whether what I was doing was correct or not - since there was no one to consult (P8).

A paradox was also noted between the subjects in organisations with passive or no formal support (P11, P14, P18, P22, P25): accessing the tools without organisational support generated operational compliance with no adaptive capacity. Respondents limited AI to low stakes and low-critical activities, hesitant to display uncertainty in an environment that had already indicated AI uptake as a performance pressure, but not a learning one. One of the participants of a big technology company (P18) mentioned: the system was there another day, no training, no explanation. I did not want to misuse it and get condemned because of it. This dynamic (the presence of tools but no psychological scaffolding) is a severe weakness in the organisational AI adoption strategies.

4.2 Psychological Safety as Enabling Mechanism

Psychological safety emerged as the critical mediating condition determining whether AI literacy translated into voice behaviour, collective learning, and ultimately organisational resilience. The data yielded three distinct safety configurations: safe environments, conditional safety, and perceived unsafety.

Participants in safe environments (P2, P4, P9, P19, P21, P22) described cultures where open communication and leader modelling made it possible to question AI outputs without fear. P21 described this vividly: when my manager said 'I don't trust this number either, let's dig into it together,' it became normal for all of us to push back on AI results. In these contexts, AI literacy was actively mobilised: concerns were surfaced, errors were reported, and AI recommendations were evaluated rather than accepted. This constituted the pathway from AI competence to organisational resilience.

Respondents in conditional safety designs (P1, P3, P5, P12, P24) indicated that their readiness to speak up regarding AI issues was contingent on audience, hierarchy, or subject. Critical on AI outputs was fine in peer discussion but not in leadership appraisal (P12). This part parsimony limited the communal quality of learning - personal interests did not turn into organisational knowledge.

Individuals who perceived unsafety or silence (P7, P8, P18, P26) characterized a scenario in which the use of AI was a performance requirement, and doubting AI implied an implicit risk of being labeled as resistant or incompetent. P26 was straight forward: there is a culture of just use it and deliver. None of us would like to be the one that slows down with the argument that the AI made an error. In such settings, AI literacy was hidden. Even the technically competent subjects did not raise concerns, which led to the undisputed AI-driven decisions, the opposite of the resilience.

There were a few specific fears that influenced the perception of safety in the sample, such as the fear of job loss (P7, P8, P9, P18), worry about losing skills due to over-dependence on AI (P11, P15, P16), and concerns about data privacy and AI responsibility (P5, P6, P12, P20, P21). Group participants concurred that psychologically safe settings enabled these issues to be brought to the fore and solved by governance and dialogue in unsafe settings, the same fears turned into resistance or silent obedience of the rules -both of which diminished resilience.

The only contextual factor with the most influence on psychological safety was leadership. Leaders who exemplified curiosity and embracing uncertainty and non-punitive response to mistakes, learning-oriented leadership (P8, P21, P26) was the only type that yielded better safety perceptions and active AI literacy enactment. The opposite was the case with pressure-based leadership typified by aggressive schedules and performance requirements (P26).

4.3 Organisational Resilience Through AI Literacy Adoption

The third overall theme summarises the realisation of AI literacy mediated through psychological safety as organisational resilience among the participating organisations. Resilience was also found to be on a continuum between adaptive and rigid which is closely related to the above safety and literacy conditions.

In open, adaptive cultures (P2, P3, P4, P5, P6, P8, P9, P19, P20, P24, P26), AI literacy and psychological safety used in conjunction to generate visible markers of resilience: teams

changed decision routines based on AI error; workflows were adjusted when AI advice was not suitable in that context; and shared learning about AI-related As P9 wrote: we made all the AI errors into a learning loop - what did the system get wrong, why, and what will we do differently? And now it was our way.

Resilience was described as gradual and effortful by participants in organisations with gradual or conditional openness (P7, P9, P11, P12, P21): initial skepticism was replaced by wary adoption or adoption as the employees learned both technical knowledge and confidence in the fact that speaking up would not be met with punishment. These paths indicate that resilience is not an organisational attribute but a dynamic ability, which emerges as AI literacy and psychological safety co-evolve.

Conversely, organisations that were resistant or had weak AI support (P1, P14, P18, P25) were fragile: employees were reluctant to engage with AI, only used it in routine decisions that were not critical, and were more anxious when AI was involved in consequential decision-making. The lack of AI literacy increased fear and inflexibility, which is exactly what the resilience theory defines as vulnerability indicators (Lengnick-Hall et al., 2011).

The resilience-enhancing impact of AI literacy was also always stronger with collaboration and innovation norms (P3, P8, P10, P19, P24, P26) and learning-oriented organisational climates (P2, P6, P12, P20, P26) in place, which supports the notion that the social and cultural circumstances of AI adoption are consequences of technological infrastructure as much as

4.4 Conceptual Framework

Figure 1 presents the conceptual framework emerging from the grounded theory analysis. AI literacy functions as the foundational capability enabling critical, informed AI engagement. Psychological safety mediates the conversion of this individual capability into collective voice, learning, and adaptive response. Organisational resilience — specifically the learning and adaptation-oriented dimension of resilience — is the outcome of this mediated pathway. The framework also acknowledges a partial direct relationship between AI literacy and resilience, which is substantially attenuated in the absence of psychological safety.

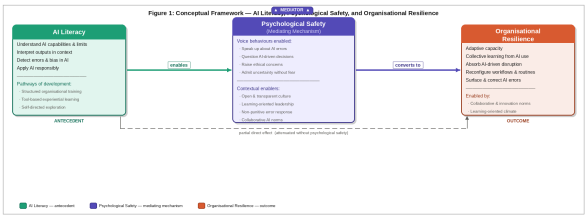

Figure 1: Conceptual Framework — AI Literacy, Psychological Safety, and Organisational Resilience

Discussion

This study set out to examine how AI literacy contributes to organisational resilience and to uncover the psychological mechanisms mediating this relationship. Grounded in psychological safety theory (Edmondson, 1999, 2018), the findings advance theoretical understanding and offer actionable insights across three domains.

First, the results prove that AI literacy is a key enabler of organisational resilience. The participants regularly highlighted that to implement AI systems in a meaningful way, one needs the ability to understand, interpret, and critically evaluate them. This builds on the previous research that places AI literacy as a technical or operational skill (Long and Magerko, 2020; Ng et al., 2021; Cetindamar et al., 2024) by showing that it is strategic to be adaptive capacity. Organisations with a more AI-literate environment were in a better position to assimilate uncertainty, re-invent work processes and use AI as a strategic asset instead of it becoming a disruptive element. On the contrary, low AI literacy hindered learning and adaptability, which strengthened rigid practices and increased anxiety, which aligns with the resilience theory that considers sensemaking and flexibility as key resilience skills (Duchek, 2020; Williams et al., 2017).

Second, and most importantly, the research shows that psychological safety is a key mediating variable in AI literacy to organisational resilience. Although the AI literacy can provide employees with the required knowledge and skills, such capabilities do not necessarily result in resilient outcomes. Psychological safety defines how AI-related knowledge would be expressed, shared, and implemented in organisational settings. The result is an extension of the framework by Edmondson (1999, 2018) to the field of AI-enabled work, as it addresses the recent calls to conduct research beyond the surface-level outcomes of adoption to understand the underlying psychological mechanics that influence the impact of AI on organisations (Budhwar et al., 2023; Uren and Edwards, 2023). It aligns with previous studies on innovation and high-reliability organisations that proved that psychological safety is an essential social scaffolding of learning and change (Baer and Frese, 2003; Newman et al., 2017).

Third, the research highlights a critical paradox of AI adoption practice, which is that the presence of AI tools and even formal AI training does not ensure resilience-enabling results in the absence of psychological safety. The passive support and pressure-driven cases of adoption, where AI was implemented without safety infrastructure, yielded exactly the opposite of resilience: silence, avoidance, and strict adherence. The discovery presents organisations with the challenge of treating the adoption of AI as a technological change initiative, as well as a social and psychological change initiative that demands an active development of interpersonal safety.

Combined, these results put the AI literacy-psychological safety-organisational resilience pathway as a theoretically sound and practically implicative model of AI-driven organisational change.

Managerial Implications

The findings carry several actionable implications for organisational leaders and HR practitioners managing AI adoption.First, managers must consider AI literacy as a strategic organisational ability and not necessarily as a technical one. By investing in role-specific and ongoing AI literacy programs, rather than introducing tools once, employees can develop a critical, reflective and responsible engagement with AI. Such programs must actively normalise the questioning of AI output, reporting mistakes, and ethical concerns, and indicate that critical AI involvement is anticipated and appreciated.

Second, the investments in AI literacy should be supported by the intentional development of psychological safety. Leaders are the key units of safety climates: they should act as role models, admit uncertainty, and react to AI-related issues and mistakes in a non-punitive way. Companies implementing AI when under performance stress without the safety infrastructure to back it up are likely to squash the very voice behaviours that cause AI adoption to be resilience-enhancing instead of resilience-destroying.

Third, psychological safety must be a design requirement in AI governance structures. The training programs, change management initiatives, and AI oversight mechanisms must be equipped with structured means of allowing employees to be able to raise issues, detect mistakes, and oppose AI suggestions without the fear of being penalized. It is not just a people management problem, but a risk management necessity, as silence of voice will be unchallenged AI errors.

Lastly, organisations will need to track the quality of AI adoption climates and adoption metrics. The willingness of the employees to raise issues about AI and the rate of reporting AI errors and the existence of learning-focused versus performance-focused AI cultures are leading indicators of how much AI literacy is being translated into organisational resilience..

Limitations

The study is subject to several limitations. First, the sample of 26 participants, while appropriate for grounded theory, is weighted toward the technology sector (n = 19), limiting transferability to other industry contexts. Future research should replicate and extend this framework in healthcare, education, manufacturing, and public sector environments, where AI adoption trajectories and organisational cultures differ substantially. Second, the sample was specifically selected in India, and cultural variables, such as hierarchy, respect to authority, and individualism versus collectivism, could have influenced the perception of psychological safety among participants in a way that cannot be generalisable to the national context. Third, being a cross-sectional qualitative study, the study only reflects the perception of participants at one time and is unable to determine any cause and effect relationships among the three constructs. To support and expand the conceptual framework that was formulated in this paper, longitudinal research and mixed-method designs that include quantitative measurement of AI literacy, psychological safety, and resilience are required.

Conclusion

This study contributes an empirically grounded theoretical framework explaining how AI literacy translates into organisational resilience through the mediating mechanism of psychological safety. Three core findings emerge. First, AI literacy is a multi-dimensional, socially embedded ability of employees to interpret, evaluate, and responsibly use AI and is in turn influenced by the quality of organisational learning support. Second, the enabling mechanism that has to be critical is psychological safety: unless it is there, even technically competent employees do not voice their concerns, do not raise objections, and do not challenge AI decisions, which creates rigidity, but not resilience. Third, AI-enabled work organisational resilience is not a natural consequence of AI adoption but a socially constructed ability that not only needs personal AI competence but also joint psychological safety to become a reality.

To academics, the paper generalises the psychological safety framework proposed by Edmondson (1999, 2018) to AI-enabled work settings and offers a theoretically informed and empirically developed framework that contributes to the AI adoption and organisational resilience literatures. To practitioners, it presents a very straightforward guidance: invest in AI literacy and the psychological safety infrastructure in which the literacy becomes actionable. Organisations that do both both enabled by AI will be significantly in a better place to absorb disruption and learn through failure, as well as emerge stronger due to the AI-driven transformation.

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