JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

ARTIFICIAL INTELLIGENCE AUGMENTED LEADERSHIP AND ITS INFLUENCE ON EMPLOYEE INNOVATION, TRUST, AND ORGANIZATIONAL ADAPTABILITY

Ansa Shaukat[*1], Waqas Mahmood[2], Saleha Imtiaz[3], Talha[4]

[*1]*University of Okara*
[2]*Assistant Professor, Department of Educational Training, The Islamia University of Bahawalpur, Pakistan. Research Fellow, INTI International University Nilai, Malaysia.*
[2]*ORCID: 0000-0003-4295-4454*
[3]*Independent Researcher*
[4]*University of Makran*

[*1]naseemshaukat43@gmail.com, [2]waqas.mahmood@iub.edu.pk , [3]salyhaimtiaz@gmail.com, [4]talha@uomp.edu.pk

DOI: https://doi.org/10.5281/zenodo.22701412

Keywords
artificial intelligence, augmented leadership, employee innovation, algorithmic trust, organizational adaptability, human capital, strategic agility

Article History
Received: 28 June 2026
Accepted: 15 August 2026
Published: 31 August 2026

Copyright @Author
Corresponding Author: *
Ansa Shaukat

Abstract

The pervasive intrusion of AI into the DNA of an organization has revolutionized management and the ways leaders go about it into a hybrid socio-technical model where human intelligence, coupled with the processing intelligence of smart machines, co-lead. The current paper presents a meta-analysis to systematically summarize evidence from the extant literature on the nexus between AI, leadership, and organizational behavior, the impact of AI-enabled augmented leadership on employee innovation, organizational trust and adaptability, drawing on structural equation modelling results, field experiments, and qualitative case studies from multiple sectors. Results support an evidence-based AI-driven innovation paradox: Augmented leadership boosts the activity level of organizational innovation (= 0.698, p < 0.001), yet triggers a devaluation of human capital (= 0.640, p < 0.001) which results in a lower quality innovation outcome through an indirect-only mediation mechanism. The research finds evidence that the delegation of low transparency procedural tasks through algorithmic mechanisms gives rise to a bias perception, which deteriorates organizational trust through emotional disengagement and the nullification of its effect, and is conditioned by the employee's AI literacy. Dynamic management capabilities act as the necessary fuel for a successful transition from the absorption of AI into strategic agility and technology management fit amplified this process by 123% in case of high fit. Four competencies to become successful in the lead with AI role – curious exploration about future work possibilities, diagnostic and probing questionings as to define problems (Socratic definition), human capability enrichment as in empathizing (empathetic augmentation) and comprehensive knowledge ofAI – are developed. Four practices to deal with these risks related to the dark side of

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

algorithms- namely algorithmic transparency (of the processes), human presence in algorithmic control, failure tolerant approach (safe-to-fail experiments), and flat organisational structures (open team design) are discussed to manage algorithm opacity and promote the creation of a human-AI symbiotic workplace environment. In essence, we find successful adaptation into the AI era necessitates a rebalancing toward integrating human judgment, organizational trust, and human well-being in organizational innovation-not solely the mere machine intelligence optimization.

1. Introduction

The rapid infiltration of artificial intelligence (AI) into our contemporary industrial complex has given rise to a structural transformation in the field of management. More than the automation of processes, AI changes our business by reshaping cognitive, structural and interpersonal dimensions. Current leaders are experiencing a debilitating 'data drowning,' where the simultaneous incoming flood of ambient environmental signals outpaces human cognitive ability (Eppler & Mengis, 2004).

To address this crisis, we are embracing AI-augmented leadership – a socio-technical hybrid that harnesses intelligent technologies as aids to enhance human analysts' cognitive skills while still employing ethical insight, relational competency, and the ability to function as an orchestra conductor (Makarius et al., 2020).

As the literature points out, despite tremendous organizational investments in technology, the road from implementation to revenue generation remains highly unpredictable: 88% of companies experimenting with new AI platforms are not generating any revenue from it (81%), while 72% of corporate officers report being unable to keep up with change, and only one-in-three leaders are confident about their strategy for transitions. A key cause of these failures stems from the underestimation of the role of social capital-psychological safety, trust, and developmental practices- which provide a foundation for sustainable adaptation during times of transition (Edmondson, 1999). This literature review integrates new studies across various fields concerning the interaction of AI, leadership theory, and organizational behavior. Applying quantitative models (SEM) and qualitative case studies and experimental field studies (sector-neutral), this paper explains the double-sidedness of AI-augmented leadership and directly identifies how automation and algorithmic control affect worker innovation, dyadic trust, and adaptive strategy when the market environment is highly ambiguous (Shrestha et al., 2019).

2. Theoretical Foundations of AI-Augmented Leadership

2.1 Integrating Leadership Theory and Machine Agency

AI's rapid integration into our modern industrial landscape has fundamentally altered the structure of leadership. Far from being a mere process automation, artificial intelligence fundamentally reconfigures our businesses' cognitive, structural, and relational architecture. Managers in contemporary work environments struggle with what we call "data drowning," the deluge of signals from our surrounding environments that our human minds simply can't keep up with (Eppler & Mengis, 2004). To theoretically frame an AI-augmented model of leadership, scholars will need to engage in a number of complementary organizational theories. Transformational leadership theory will form the basis for how we explore how managers are going to maintain an organizational vision in light of the deployment of complex, new technology (Glikson & Woolley, 2020).

These are the agents of change – the curious technician, the flexible structural engineer, who will create an atmosphere of confidence in the AI

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

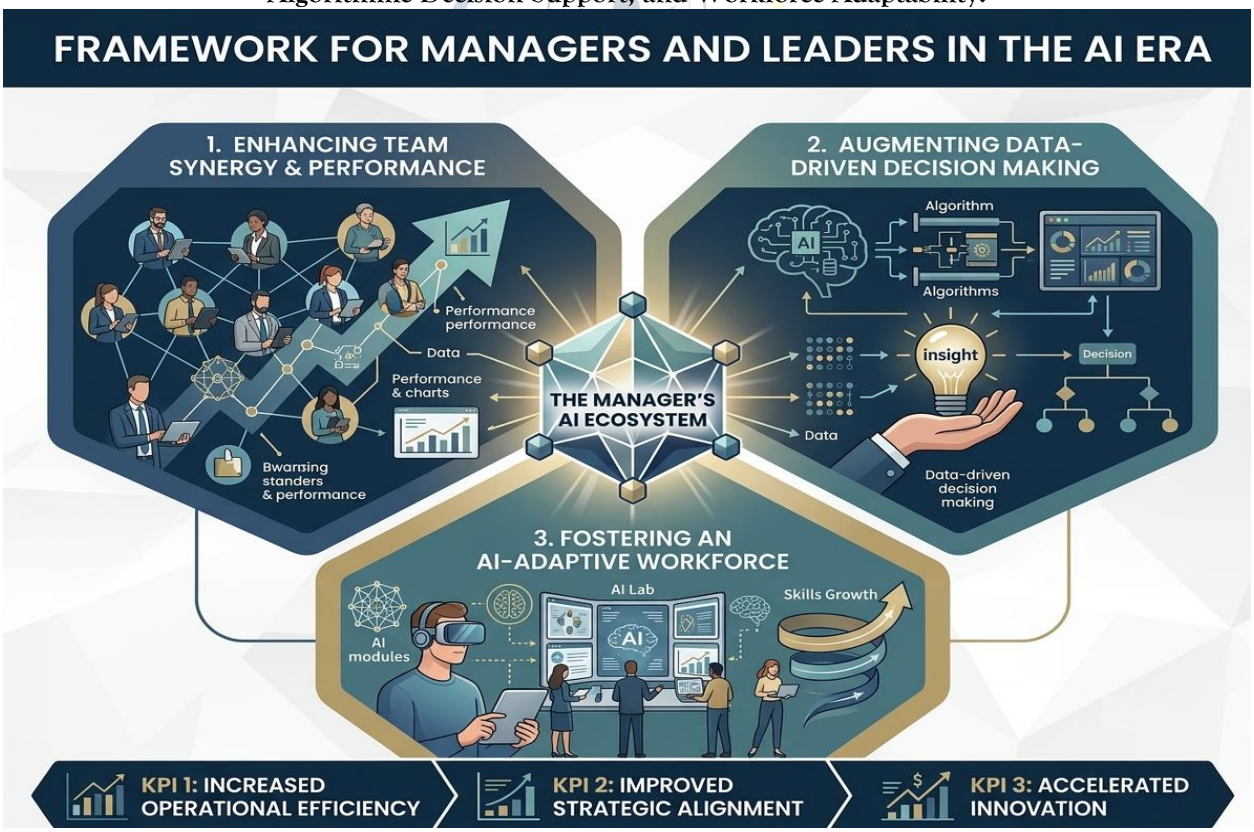
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

era. In an augmented leadership model, leaders would utilize ML and algorithms to bolster a shared vision rather than replace it, providing clearer, rather than more convoluted, information. The transactional leadership theory can be used to examine the role of AI in operational processes, which transactional leaders focus on for the purposes of efficiency, in such functions as the structured monitoring of process events, simple and repeated decision-making processes, and the prescriptive processes for how to deploy resources (Dirks & Ferrin, 2002).

Socio-technical Systems (STS), or STS theory, suggest that social (interpersonal relationships, core values, feelings of community among members) and technical (software algorithms, physical hardware, data infrastructure) subsystems must co-exist and develop together in a healthy organization (Eppler & Mengis, 2004).

According to STS theory, success in organizations depends on an alignment between technical and social subsystems and when this relationship is unbalanced and technical systems dominate the social, the members will feel the strain of the new technology and will fight it. The technology acceptance model (TAM) asserts that technology is adopted based on how easy and useful it is and that leader attitudes towards usage and training may influence perceptions of both technology adoption factors (Carmeli et al., 2010). The collaborative intelligence framework posits that leaders will partner with their machines and the machine will provide as cognitive assist (Accenture, 2024).

Figure 1: The Managerial AI Ecosystem: A Three-Dimensional Framework for Synergistic Performance, Algorithmic Decision Support, and Workforce Adaptability.



JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

2.2 The Taxonomy of Human-AI Interaction and Decision Control

At the heart of the modern management literature will also lie the distinction between algorithmic management and an 'augmented' leadership. While often used in practice in synonymous forms like automated management, algorithmic management utilizes algorithms, data analysis, surveillance technologies, and process optimization to manage human labour input as autonomously as possible (Bughin et al., 2018). Although typically first used with digital labor platforms, algorithmic management practices are increasingly permeating traditional office settings, warehouses, and factory floors. An augmented leader, in contrast, leverages algorithms in an advisory capacity as analytical expert utilizing mathematical and computational methods to uncover patterns, to identify opportunities, and to simulate complex problems, however is able to contextualize these findings within culturally embedded and human-oriented decision making in their organizations (Dellermann et al., 2019).

Table 1: Taxonomy of Decision Authority and Algorithmic Automation Levels

Automation Classification	Core Operational Mechanism	Role of the Human Leader / Manager	Primary Organizational Focus
No Automation	Fully human-driven workflows; information gathering and evaluations rely entirely on subjective experience and manual processes.	Retains complete decision authority, operational execution, and relational control.	Direct relational management, experiential problem-solving, and localized flexibility.
Assistance (Augmentation)	Algorithms serve as a consultative layer, utilizing predictive analytics to generate forecasts, risk profiles, and scenario models.	Exercises strategic oversight, interprets machine outputs, and makes final value-laden judgments.	Combining analytical precision with contextual empathy and ethical responsibility.
Partial-Conditional Automation	Algorithms autonomously make decisions within predefined parameters, alerting human managers only when exceptional or highly complex cases arise.	Acts as a system troubleshooter, handles complex edge cases, and provides periodic structural audits.	Continuous operational scaling, consistent decision metrics, and extreme process efficiency.

3. The Influence of AI-Augmented Leadership on Employee Innovation

3.1 The Algorithmic Innovation Paradox

AI integration in leadership practices reveals an inherent organizational contradiction known as the AI-Driven Innovation Paradox. According to structural equation modeling (SEM) on a validation sample (n = 2,990) in digitally intensive industries, AI-driven leadership may accelerate innovation creativity and quantity at a greater pace but, ironically, it could decrease its outcomes' quality at the end (Mireti et al., 2026). The empirical results support the argument, that AI-driven leadership positively impacts Innovation Activity (=0.698, p<0.001), R2=0.487; by empowering cognitive capacity, exploring complex situations and quick decision-making processes that allow leader teams to quick hypothesize, prototypes and scaling up new idea generation (Brynjolfsson & McAfee, 2017).

AI-driven leadership, however, also positively affects Human Capital Erosion (=0.640, p<0.001,

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

R2=0.410). When algorithms support human decision-making process, recognize talented personnel, or assist problem solving of critical issues, people do not practice their professional judgment very frequently losing the capability of solving complex situations or critical reasoning issues in uncertain contexts (Davenport & Ronanki, 2018). This process of capital erosion has the opposite outcome, the more capital human is eroded, the lower will be the efficiency and quality of innovative products. Therefore, the direct effect of AI-driven leadership over Innovation Quality is statistically non-significant (=-0.006) and occurs through an indirect path with mediators (Raisch & Krakowski, 2021). Put simply, human capital erosion hampers the efficiency of new technology use; and this contradiction grows since Innovation Activity and Innovation Quality are negatively correlated (=-0.189, p<0.001), proving that boosting the number of ideas doesn't mean creating strategic and authentic ideas (Jarrahi, 2018).

Table 2: Structural Path Estimates of the AI-Driven Innovation Paradox

Proposed Structural Path	Standardized Coefficient (β)	Significance Value (p)	Observed Variance Explained (R2)
AI-Driven Leadership → Innovation Activity	0.698	< 0.001	48.7%
AI-Driven Leadership → Human Capital Erosion	0.640	< 0.001	41.0%
Human Capital Erosion → Innovation Quality	−0.619	< 0.001	Direct negative impact
AI-Driven Leadership → Innovation Quality (Indirect Path)	−0.513	< 0.001	Completely mediated
AI-Driven Leadership → Innovation Quality (Direct Path)	−0.006	Non-significant	No direct association
Innovation Activity → Innovation Quality	−0.189	< 0.001	Dilutive quality effect

3.2 Fostering Innovation through Psychological Safety and Identity Alignment

To manage innovation paradox, Organizations should work on the psychological safety of employees and congruency between employee's professional identity and the technology. A significant stream of work across social information processing theory, social cognition, and workplace anxiety has provided evidence that an AI symbolic leadership, i.e., a leadership approach in which managers use symbolic actions to refer to the machine as a supportive coworker, not an impartial judge, leads to greater innovative behaviors among employee. (Deb Biswas et al., 2026).

The effect was mediated through employee's psychological safety. If employees observe leaders taking a human-machine shared modeling with either an equal or higher priority for human-machine usage, they are less anxious and willing to risk with their creative actions and behaviors. (Fu et al., 2026). On the contrary, if employees have anxiety about technology "AI Anxiety", such as perceived job displacement, lost status, and reduced autonomy due to algorithmic decision-making, their anxiety towards technology acts as a moderator, particularly negatively among those employees working in non-tech industries, who tend to perceive the machine as a threat to professional survival and engage in passive or defensive actions to prevent creative generation. Accordingly, a well-designed, human-centered AI leadership strategy to foster the feeling of security, and self-extension among non-tech employees

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

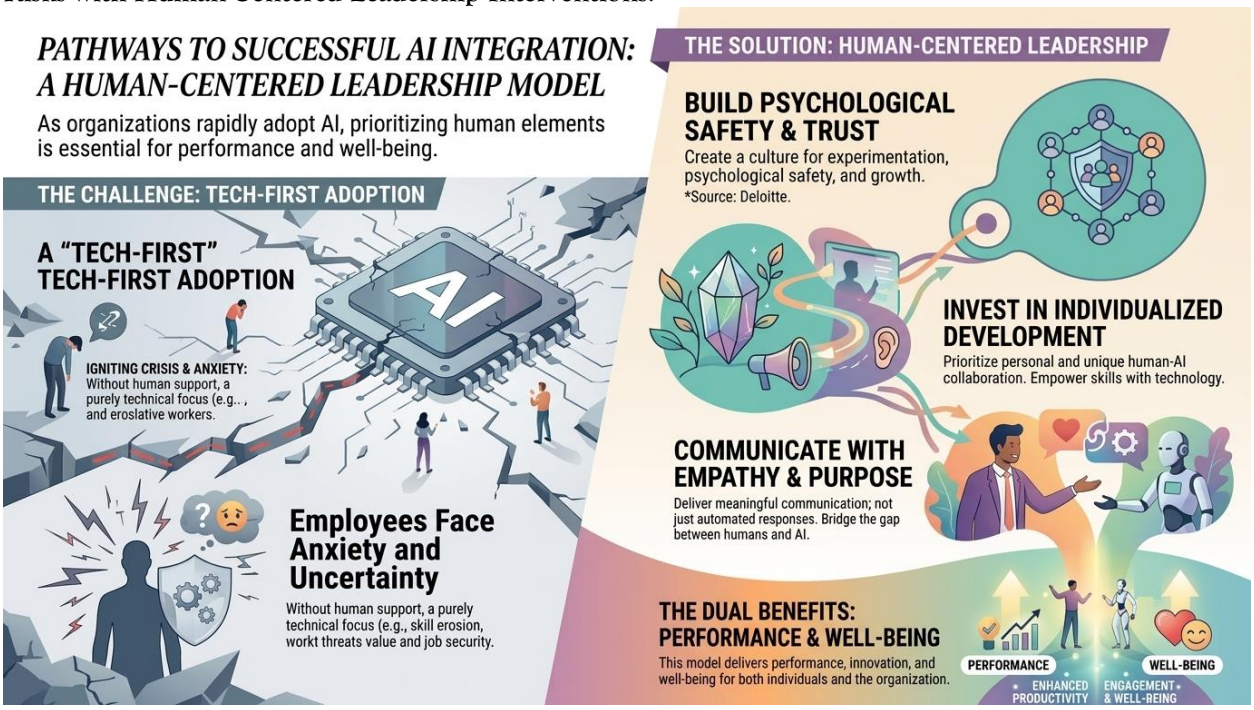
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

helps them re-frame technology as an efficient collaborative partner, enhancing innovative work behaviors through resistance management to engagement (Yu, 2025).

Furthermore, an organization's culture regarding error management positively shapes the psychological capital of employees, thereby improving engagement to IWB. (Arriaza, 2025).

Additionally, the demand for human-oriented leadership also emerges with newer generations in the workforce. Studies conducted on Generation Z professional employees indicate their concern with automation in the leader role and preference for democratic and transformational leadership styles in a digital context due to their high awareness of the role of innovation and their appreciation for humanistic insights. (Zeiser, 2024).

Figure 2: Socio-Technical Pathways to Successful AI Integration: Contrasting Technocentric Displacement Risks with Human-Centered Leadership Interventions.



4. Algorithmic Delegation and the Dynamics of Employee Trust

4.1 Algorithmic Bias Perceptions and Emotional Disengagement

It is when we begin to automate away from the simple use of AI as a basic assistant and move towards having the algorithm delegate managerial responsibilities such as task allocation, promotion and performance reviews away from managers directly to the machines that we are going to see dramatic shifts in our psychological contract with employees. This is identified in the field as Algorithmic Leadership Delegation (ALD) and can have differing effects on employee attitudes and behavior (Kellogg et al., 2020). Indeed, evidence for a two-wave survey study conducted on 241 employees in high-automation work-environments (e.g., Tech, logistics, digital finance etc.) in the UAE suggests that when AI takes over management, it is not automatically met negatively, rather it is significantly mediated by Perceived Algorithmic Bias (PAB) (Jarrahi et al., 2023).

If the entirety of our career path depends on an

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

unknowable, decontextualized computation then we may come to assume there is an inherent bias against treating everyone in an equal manner. As we already discussed with the Three Pillars of Trust (ability, benevolence, integrity) when an employee perceives the organization's capability (ability), benevolence and integrity to be lacking they begin to develop trust issues with the firm (Lee, 2018). Perceiving bias within the algorithm means that the algorithm and leaders who are implementing the use of it lack either the quality of ability, benevolence or integrity respectively. This negative inference about the absence of the qualities of integrity and benevolence is what then can cause Emotional Disengagement - a withholding of effort, motivation, and commitment to one's work and the overall organization (Saks, 2006). While this relationship from perceived algorithmic bias from leadership delegation to emotional disengagement exists, a worker's Algorithmic Literacy (AL) can buffer it. When an employee possesses high digital skills and an understanding of how algorithms make their decisions, they can discriminate between real systemic bias and normal algorithmic limits. From the lens of the Theory of Planned Behavior, AL provides the necessary cognitive skills to support self-efficacy and promote employee control enabling them to reject the algorithm and remain less disengaged (Dogruel et al., 2022). These findings reveal what happens when organizations start moving towards what Pasquale calls the "Black Box Society", essentially a situation where managerial control is consolidated at the highest level by hiding algorithms and decision processes from workers who need access to that information and would likely to organize to resist it. Even at the most digitalized level we are finding that workers are finding innovative digital means of resistance and adaptations for themselves in order to survive and thrive in the face of algorithmic surveillance by companies in which it is likely that turning managers into algorithms could in itself sow the seeds for systemic employee disengagement (Pasquale, 2015).

4.2 Building Trust through Procedural and Outcome Transparency

This is overcome through high levels of transparency at the process and outcomes level should Leaders seek to build trust within an organisation. High levels of automation require transparency as the outcomes of a wide-reaching survey on the views of job-seekers and employed workers demonstrated. Employees were more receptive to the use of AI to complete the routine and lower-risk tasks that are associated with tasks such as scheduling and skills assessment but demonstrated a high degree of distrust and concern in the use of AI within recruitment and selection processes. This was particularly amplified where the use of automated recruitment and selection was in relation to biometric methods, such as facial recognition and voice-tracing, perceived to be most invasive and exclusive to the diverse talent pool (Colquitt et al., 2001).

High levels of automated decisions were demonstrated to result in steep increases in mistrust for the candidate with the absence of transparent processes, however this trust was again established where the use of an active human review was available, the process for the application of selection criteria was transparent and candidates were given the opportunity to appeal. (Ajzen, 1991).

Table 3: Trust and Fairness Appraisals in Algorithmic Evaluation Systems

Survey Parameter / Statement	Strongly Disagree / Disagree	Neutral	Agree / Strongly Agree

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

Concerns on Group Bias: AI evaluations can produce biased outcomes for candidates from underrepresented social groups.	10.8%	8.5%	80.8%
Skepticism of Historical Data: Training algorithms on historical hiring data simply reinforces existing inequalities.	12.5%	9.8%	77.7%
Anxiety on Non-Performance Metrics: Automated systems evaluate factors that are not directly related to job performance.	14.3%	10.7%	75.0%
The Retaliatory Loss of Trust: Trust in an employer drops sharply when undisclosed AI tools are discovered in evaluations.	12.1%	9.8%	78.2%
Mitigating Role of Human Oversight: Automated decisions are more trustworthy when reviewed by a human before implementation.	11.2%	9.4%	79.4%
The Right of Appeal: Candidates must have a clear right to challenge decisions made about them by AI recruitment models.	9.0%	7.6%	83.5%

Adding weight to the argument for transparency, one longitudinal study, following 316 employees for a 18-month period, found that for each one unit increase in opacity of the algorithmic management of career choices, employee career self-efficacy decreases by 0.21 standard deviations. That this negative impact occurred even when employees received positive performance appraisals highlights the psychic cost of working with an opacity (Mayer et al., 1995).

Directly, transparency and career self-efficacy are directly correlated (=0.29, p<0.001) and high transparency supports employee job crafting through building organisational trust (=0.42, 95% Confidence Interval [0.31, 0.54]) that puts career development in employee hands (Ajmal et al., 2025).

Table 4: Corporate AI Transparency Index by Industry Sector

Industry Sector	Reported Organizational Disclosure Level	Regulatory and Cultural Pressures
Technology	47% of employees reporting adequate disclosure.	Driven by high digital literacy and strong developer advocacy.
Financial Services	39% of employees reporting adequate disclosure.	Shaped by strict compliance rules and operational risk metrics.
Healthcare	23% of employees reporting adequate disclosure.	Limited by complex data privacy and fragmented patient workflows.
Retail	19% of employees reporting adequate disclosure.	Constrained by a heavy focus on short-term efficiency and transactional data.
Manufacturing	17% of employees reporting adequate disclosure.	Dominated by legacy processes and a focus on physical automation over transparency.

In the case of financial institutions such as banking firms, the tension can also arise. It is known that in the consumer-focused branch the introduction ofautomated creditanalysisandscoringmodels have improved decision speed by as much as 40 per cent and

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

increased profitability by 25 per cent versus standard processes (Mettler, 2024). However, the adoption of equivalent levels of internal monitoring automation, involving the capture of keystrokes, tone analysis, and other daily activity measures, has shown an increase in stress among human resource employees and a decrease in trust (Boyd & Andalibi, 2023).

5. Organizational Adaptability, Strategic Agility, and Dynamic Capabilities

5.1 Dynamic Managerial Capabilities in Saturated Environments

From a Dynamic Managerial Capabilities perspective, AI-augmented leadership is not just an administrative tool; it acts as an executive capacity that helps organizations sense, seize, and reconfigure resources in response to volatile market conditions (Kohli, 2025).

- **Sensing Opportunities and Threats**: In highly volatile environments, AI engines can scan massive datasets to help leaders identify emerging trends, generate risk profiles, and recognize early warning signals that human analysis might miss.
- **Seizing Strategic Directions**: AI-powered decision-support dashboards compress complex strategic scenario evaluations from weeks to seconds. This speed allows leaders to make fast, data-backed commitments under conditions of high market uncertainty.
- **Reconfiguring Resources and Processes**: Dynamic adaptability requires the flexible alignment of an organization's structures, systems, and assets. AI supports this by optimizing supply chains, predicting shifting workforce needs, and coordinating cross-functional collaborations (Hakimpour, 2026).

The positive role of the technical and strategic fit is proven by empirical studies. The results from PLS-SEM on 385 SMEs shows that the adoption of AI positively impacts on strategic innovation performance, on market competitiveness, driven by dynamic capabilities, and it explains 41% of the total variance on innovation performance (Baran, 2025). The work by [21] provided evidence on the importance of AI strategic capabilities as the strongest predictor for strategic agility in SMEs (=0.42, p<0.001), whereby the total effect is mostly driven by digital dynamic capabilities (67%) (Chen, 2026).

However, this research found an important contingency where the relationship between technology and strategic agility is moderated by a fit between the technology and management. In these high technology-management fit conditions the relationship between AI adoption and agility would be 123% stronger than in low fit conditions (=0.58 vs =0.26) (Ajmal et al., 2025). Further studies Using a machine learning technique found a nonlinear relation between AI and the number of hours invested, where an increasing and later on decreasing return to AI adoption appears after the 75th percentile, indicating that a higher level of automation will create new stiffities and the organization is vulnerable to this risk when not able to leverage their adaptive human capacities in specific non-routine tasks (Makarius et al., 2020).

Table 5: Structural Dynamic Capabilities Model for Strategic Agility

Structural Predictor Variable	Agility Path Impact (β)	Significance Value (p)	Observed Systemic Effect
AI Strategic Capabilities	0.42	< 0.001	Mediated 67% by digital dynamic capabilities.
High Technology-Management Fit	0.58	< 0.001	Amplifies operational agility by 123%.
Low Technology-Management Fit	0.26	< 0.05	Represents a major performance drop.

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

Transformational Leadership (Direct)	0.28	< 0.001	Drives strategic alignment and team cohesion.
Transformational Leadership (Interaction)	0.21	< 0.01	Moderates and secures the AI-agility path.
Policy Uncertainty Buffering	0.12	< 0.05	Helps turn institutional constraints into manageable variables.

5.2 Industry Applications and Boundary Conditions of AI Integration

The various applications of AI-enhanced leadership functions range between diverse across different industry. For instance, the aviation industry is using a transformational leadership style to allow for wide spread use of AI in order to facilitate maintenance operations and in reducing carbon footprint. AI coupled with insight drawn from data and the strong strategic leadership prevalent within this industry allows them to not only obtain major cost savings but to sustain their operations long term (Eppler & Mengis, 2004).

Alternatively, within certain industries such as the healthcare industry, although there are immense benefits to implementing operative AI tools there are also limitations. Leaders within healthcare system has adopted AI into command centers that control hospitals in real time, the operations management of patient flow, among other things. For example, if an algorithm would determine priority for a normal case scenario, then an operative AI could work very well. But for patients who has atypial issues then the health professionals should consider adjusting the automatically prioritize decisions in order to maintain trust and provide a safe healthcare to their patients (Edmondson, 1999).

Oupu Building Materials, traditionally a very hierarchical organisation based in Tangerang, Indonesia managed to shift from intuitive decision based on experience into data driven decision after the implementation of AI and successfully increased their operational cycles speed, while this necessitated an shift in leadership approach to a more participative style and focused on developing a more adaptive workforce as well as digital literacy skills on their employees part (Shrestha et al., 2019).

All the previous examples showed that even if AI can assist in numerous decisions on the analytical part, it is still with help of human being interpretation of these analyses combined with good corporate governance can deliver substantial strategic and business value. (Accenture, 2024).

6. Building the Collaborative Human-AI Leadership Ecosystem

6.1 Leadership Profiling, Succession, and the AI Success Profile

However, to capitalize on hybrid management, proactive leadership development programs for the leaders of tomorrow must be established. Leadership profiling with a higher degree of objectivity compared to traditional assessment centers where subjective performance evaluation often combined with traditional static self-report inventories were utilized in the past. Future-ready leadership development, with increased emphasis on leveraging AI as part of AI-augmented leadership profiling (Raisch & Krakowski, 2021).

Specifically, advanced supervised learning algorithms (such as, Random Forest, Gradient Boosting and Transformer-based models) have successfully been utilized with training multimodal data (such as communication logs, decision-making logs and authenticated psychometric scales), to accurately and reliable assess both transformational and ethical leadership (Dellermann et al., 2019).

As a result, evaluator bias can be mitigated, non-obvious behavior patterns discovered and a more scalable approach to leadership assessment, identification and succession planning can be attained (Mireti et al., 2026).

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal
ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

Building a strong talent pipeline requires a shift toward what Korn Ferry defines as the "Success Profile of the AI-Augmented Leader". This modern leadership profile focuses on four core competencies:

- **Future-Focused Curiosity**: A driving interest in learning and technological evolution, encouraging teams to cultivate an AI-first mindset.
- **Socratic Problem Definition**: Moving away from providing direct answers and instead focusing on asking precise questions to guide hybrid teams as they prototype solutions.
- **Empathetic Augmentation**: A focus on using AI to elevate and expand human capabilities, rather than simply automating roles to reduce headcount.
- **Deep AI Literacy**: A strong foundational understanding of how to quickly integrate emerging technologies into diverse, hybrid team workflows (Fu et al., 2026).

6.2 Collaborative Dyads and Practical Hybrid Governance Structures

Leadership At the team level, leadership dynamics can experience a bit of a shakeup once AI has been incorporated into work processes. In classical Leader-Member Exchange (LMX) theory, leaders individually build differing degrees of relationship with members of their teams. There are three stages of relationship building between leaders and their team members as theorized in LMX: Role-taking (new employees are evaluated for competence), Role-making (leader and follower's resource exchange creates mutual expectations and splits the team into the "in-group" and the "out-group"), and Routinization (a steady and continued interaction between leader and follower) (Jarrahi, 2018).

In highly automated contexts, this is a relationship that can be quickly disrupted: "If a leader relies on an algorithm to assign work and measure performance, it's easier to lose visibility of an individual's needs, and thus, the process can easily leave the out-group exposed to digital alienation, a reduction of a sense of work autonomy, and the erosion of the social relationship between leaders and teams" (Davenport & Ronanki, 2018).

In relation to impact on the team, research has shown that "instrumental AI use" can overcome drawbacks from managers who do not foster balanced or well-developed relationships with their teams. Instrumental use of AI as a nonjudgmental objective work support for teams can help members of a team utilize "the instrument AI affords to seek assistance and guidance regardless of leader and team members' specific role or skills, leveling some of the unevenness of leader-member exchange and buffering against negative outcomes" (Boyd & Andalibi, 2023). Leveraging an instrumental perspective helps members access uniform data that can "enhance their perceptions of team psychological empowerment" and protect their productivity outcomes. This is also facilitated by the presence of Governance; "Socratic interrogation by leaders would allow the leader, along with members, to probe for assumptions that may inform the design of an AI tool, its potential biases, and its intended application. In fact, organizations may well require "shadow auditing," or manual examination of the outputs of the decision-making of AI algorithms" (Colquitt, 2001).

"Amnesty programs where members feel safe to experiment with systems and report failures without punishment, along with "safe-to-fail sandboxes where risks can be tested" may also increase visibility and diminish possible pitfalls (Pasquale, 2015).

Conclusion

Based on the evidence from this systematic review, AI-augmented leadership represents a process of organizational change and development, which when conceived to ensure the collaborative and interplay between machine analytics and human intuition, provides possibilities of enhanced speed of strategic decision making, a wider array of potential innovation opportunities, and improved dynamic capabilities in conditions of uncertainty.

JOURNAL FOR SOCIAL SCIENCE STUDIES
An International Peer-Reviewed Open Access Journal

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

Yet the findings from this systematic review also demonstrate that critical fault-lines do exist, firstly a paradox in innovation, where although AI-augmented leadership accounts for a substantial proportion of variation in innovation activity (48.7%), the value of such is annihilated by the negative contribution to innovation quality of human capital depreciation (-0.619, $p < 0.001$) (very limited evidence for a positive direct effect of AI-Augmented leadership on quality of innovation); Secondly that the process of algorithmically delegated decision making without transparency diminishes all three key dimensions of the organisation's trustability - beneficence - integrity due to a perceived algorithmic bias; and thirdly, the significance of technology – management fit as a moderator to enhance the effects of AI-agilty by 123% with high level of match and diminishes to insignificant when utilization goes over the 75% utilization percentile. In conclusion, achieving sustainable organizational performance within an era of artificial intelligence requires, not merely utilizing AI-based technology but also pro-actively developing robust human-AI systems which embrace adequate attention to all of the five crucial core competences of AI-augmented leaders (future-orientated curiosity, Socratic inquiry, empathy and augmented intelligence, general literacy across different forms ofAIand cross-disiciplinary learning) built upon the bedrock of dignity and psychological safety of all members (trustability, integrity, beneficence) accompanied by rigorous processes of human oversight, procedural justice, and safe-to-fail operational environments. Organisations which successfully find the equilibrium between these opposing tensions will find they can continue to thrive, organisations who pursue merely technological optimisation will eventually find systems become brittle.

References

Ajmal, M., Sareet, Z., & Islam, A. (2025). Unleashing innovation through employee voice behavior in the hotel industry: the impact of ambidextrous leadership on innovative work behavior. *Journal of Hospitality and Tourism Insights*, *8*(2), 448-471.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Arriaza, J. (2025). *Navigating the New Normal: A Grounded Theory Study of Lessons Learned About Leadership Practices Since the Pandemic in Multimodal Workplace Settings and the Future of Work* (Doctoral dissertation, Pepperdine University).

Baran, M. (2025). AI-augmented leadership: Redefining leaders' style and competencies. In *AI and Humanistic Management* (pp. 147-169). Routledge.

Boston Consulting Group. (2024). *AI radar: From experimentation to value*. https://www.bcg.com

Boyd, K. L., & Andalibi, N. (2023). Automated emotion recognition in the workplace: How proposed technologies reveal potential futures of work. *Proceedings of the ACM on human-computer interaction*, *7*(CSCW1), 1-37.

Brynjolfsson, E., & McAfee, A. (2017). *The business of artificial intelligence. Harvard Business Review*. https://hbr.org/2017/07/the-business-of-artificial-intelligence

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics, 13*(1), 333–372. https://doi.org/10.1257/mac.20180386

Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., Henke, N., & Trench, M. (2018). *Notes from the AI*

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

frontier: Modeling the impact of AI on the world economy. McKinsey Global Institute.

Carmeli, A., Brueller, D., & Dutton, J. E. (2010). Learning behaviours in the workplace: The role of high-quality interpersonal relationships and psychological safety. *Systems Research and Behavioral Science, 26*(1), 81–98. https://doi.org/10.1002/sres.932

Chen, X. (2026). *AI-Augmented Adaptive Leadership: Novel Theoretical Frameworks to Address Technological Challenges* (Doctoral dissertation, Golden Gate University).

Colquitt, J. A., Conlon, D. E., Wesson, M. J., Porter, C. O., & Ng, K. Y. (2001). Justice at the millennium: A meta-analytic review of 25 years of organizational justice research. *Journal of Applied Psychology, 86*(3), 425–445. https://doi.org/10.1037/0021-9010.86.3.425

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Deb Biswas, D., & Sengupta, R. (2026). Reimagining leadership for the AI era: a grounded theory of adaptive, ethical and contextually situated practices in workplaces. *Leadership & Organization Development Journal*, *47*(2), 395-416.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering, 61*(5), 637–643. https://doi.org/10.1007/s12599-019-00595-2

Dirks, K. T., & Ferrin, D. L. (2002). Trust in leadership: Meta-analytic findings and implications for research and practice. *Journal of Applied Psychology, 87*(4), 611–628. https://doi.org/10.1037/0021-9010.87.4.611

Dogruel, L., Frischlich, L., Boberg, S., & Schatto-Eckrodt, T. (2022). Development and validation of an algorithm literacy scale. *Computers in Human Behavior, 129*, 107173. https://doi.org/10.1016/j.chb.2021.107173

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly, 44*(2), 350–383. https://doi.org/10.2307/2666999

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of literature. *The Information Society, 20*(5), 325–344. https://doi.org/10.1080/01972240490507974

Fu, J., Liu, H., Sindakis, S., & Biginas, K. (2026). Navigating the dark side of digital transformation: Addressing discrimination and toxicity in tech-driven organizations. *Journal of Organizational Change Management*, *39*(2), 298-327.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals, 14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Hakimpour, H. (2026). The AI-Augmented Strategic Management Process. In *Strategic Thinking with AI: Foresight, Tools, and Leadership for the Digital Age* (pp. 63-102). Cham: Springer Nature Switzerland.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jarrahi, M. H., Newlands, G., Lee, M. K., Wolf, C. T., Kinder, E., & Sutherland, W. (2023). Algorithmic management in a work context. *Big Data & Society, 10*(1). https://doi.org/10.1177/20539517231177660

ISSN (Online): 3006-2071 | ISSN (Print): 3006-2063
Volume 4 • Issue 4 • August 2026

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. *Academy of Management Annals, 14*(1), 366–410. https://doi.org/10.5465/annals.2018.0174

Kohli, R. (2025). AI-Augmented Program Leadership as Dynamic Capability: A Resource-Based View of Competitive Advantage.

Lee, M. K. (2018). Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. *Big Data & Society, 5*(1), 1–16. https://doi.org/10.1177/2053951718756684

Makarius, E. E., Mukherjee, D., Fox, J. D., & Fox, A. K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research, 120*, 262–273. https://doi.org/10.1016/j.jbusres.2020.07.045

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review, 20*(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

Mettler, T. (2024). The connected workplace: Characteristics and social consequences of work surveillance in the age of datification, sensorization, and artificial intelligence. *Journal of Information Technology*, *39*(3), 547-567.

Mirčetić, V., Pavlović, Z., Ignjatović Pertini, A., Vujko, A., & Kovačević, I. (2026). AI-Driven Leadership and the Innovation Paradox: More Innovation Activity, Lower Innovation Quality. *World*, *7*(7), 120.

Pasquale, F. (2015). *The Black Box Society: The Secret Algorithms That Control Money and Information*. Harvard University Press.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review, 46*(1), 192–210. https://doi.org/10.5465/amr.2018.0072

Saks, A. M. (2006). Antecedents and consequences of employee engagement. *Journal of Managerial Psychology, 21*(7), 600–619. https://doi.org/10.1108/02683940610690169

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California Management Review, 61*(4), 66–83. https://doi.org/10.1177/0008125619862257

Yu, S. (2025). Paradoxical Leadership and Innovation Performance in AI-Enabled Teams: The Serial Mediation Role of Algorithmic Trust and Psychological Safety. *Journal of Business and Economic Research*, *1*(9).

Zeiser, M. R. (2024). *Understanding the Experiences of Women Leaders in Technology Organizations* (Doctoral dissertation, Fielding Graduate University).