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ETHICAL LEADERSHIP, AI CAPABILITY, AND AI TRAINING AS DRIVERS OF EMPLOYEE INNOVATION: THE MEDIATING ROLE OF AI SELF-EFFICACY

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ABSTRACT

The increasing integration of artificial intelligence into organizational work processes has intensified interest in understanding how AI-related conditions influence employee innovation. Drawing on Social Cognitive Theory, this study examines how organizational AI capability, ethical leadership, and AI-related training shape employee innovation through the mediating role of AI self-efficacy. Using a quantitative, cross-sectional design, survey data were collected from employees working in AI-intensive organizational settings. The data were analyzed using SPSS and SmartPLS to assess the measurement and structural models. The findings reveal that organizational AI capability, ethical leadership, and AI-related training positively influence AI self-efficacy, which in turn enhances employee innovation. Mediation analysis confirms that AI self-efficacy serves as a central psychological mechanism linking organizational conditions to innovation outcomes. The study contributes to theory by extending Social Cognitive Theory to AI-enabled workplaces and offers practical insights for fostering innovation through human-centered AI strategies.

Keywords: *Ethical Leadership, AI Capability, AI Training AI Self-Efficacy, Employee Innovation and Social Cognitive Theory*

INTRODUCTION

The rapid diffusion of artificial intelligence across organizational settings has intensified scholarly debate about how digital technologies reshape work, learning, and value creation. Rather than functioning merely as efficiency-enhancing tools, intelligent systems increasingly influence how employees perceive their roles, adapt to change, and contribute creatively within organizations. Recent discussions emphasize that the transformative potential of advanced technologies depends not only on technical deployment but also on human and organizational readiness to engage with them productively (Behera et al., 2025). As workplaces become more algorithmically mediated, attention has shifted toward understanding the psychological and social mechanisms through which individuals interact with intelligent systems and translate technological affordances into meaningful outcomes. Within this discourse, scholars argue that the success of digital transformation is contingent upon employees' confidence, motivation, and perceived ability to work alongside intelligent technologies. Organizations

that fail to address these human-centered dimensions often experience resistance, underutilization of systems, or symbolic adoption without substantive gains. Conversely, environments that foster learning, ethical guidance, and skill development tend to unlock higher levels of engagement and adaptability. This growing body of work reflects a broader shift from technology-centric explanations toward integrative perspectives that recognize human agency as central to digital value creation (Sivathanu et al., 2025; Tanveer, 2025).

Existing literature consistently shows that artificial intelligence alters job design, skill requirements, and performance expectations across sectors. Empirical studies demonstrate that intelligent systems can enhance creativity, task efficiency, and innovative outcomes when employees perceive these technologies as supportive rather than threatening (Wang et al., 2025; Zhang et al., 2025). Research also highlights the role of individual psychological resources, particularly confidence in handling complex technologies, in shaping productive engagement with AI-enabled tasks (Zhao et al., 2025; Zhong et al., 2025). At the organizational level, leadership orientation and institutional support have been shown to influence how employees interpret and respond to digital transformation initiatives. Ethical guidance, transparent decision-making, and continuous learning opportunities are associated with lower resistance and stronger alignment between technological goals and employee behavior (Bian & Wang, 2024; Tanveer, 2025). However, findings remain fragmented, with some studies reporting performance gains and others documenting anxiety, skepticism, and uneven adoption outcomes (Khan et al., 2026; Usman, 2025).

Globally, organizations face mounting pressure to remain innovative amid accelerating technological change and intensifying competition. According to recent industry reports, a significant proportion of AI investments fail to deliver expected returns due to human and organizational barriers rather than technical limitations. Employees frequently report uncertainty about skill relevance, fear of obsolescence, and limited preparedness to work with intelligent systems, particularly in contexts where training and ethical oversight are weak (Cheng et al., 2025; Dadaboyev et al., 2025). In emerging economies and transitional labor markets, these challenges are even more pronounced. Skill mismatches, uneven access to learning opportunities, and limited organizational support exacerbate the risk of technology-driven inequality and disengagement. At the same time, organizations increasingly rely on employee-driven innovation to sustain competitiveness, placing greater importance on psychological readiness and adaptive capability. Without adequate support structures, advanced technologies may suppress rather than stimulate creative contribution. These concerns directly connect broader digital transformation agendas to workplace-level outcomes. The ability of employees to experiment, problem-solve, and innovate in AI-enabled environments has become a critical organizational issue, with implications for productivity, inclusion, and long-term sustainability (Behera et al., 2025; Wang et al., 2025).

Despite growing interest in the human side of artificial intelligence, existing research remains limited in several important ways. First, much of the literature examines technological adoption or performance outcomes in isolation, offering fragmented insights into how organizational conditions and individual psychological processes jointly shape innovation-related behavior. While prior studies acknowledge the importance of confidence and learning in AI contexts, these factors are often treated as background variables rather than central explanatory mechanisms (Zhao et al., 2025; Zhong et al., 2025). Second, leadership and organizational practices are frequently discussed at a conceptual level, with insufficient empirical integration into models that explain how employees internalize technological change. Ethical orientation and developmental support are typically examined as direct predictors of outcomes, leaving unanswered questions about how they operate through employee cognition and belief systems (Bian & Wang, 2024; Tanveer, 2025). As a result, the pathways through which organizational environments translate into innovative behavior remain underexplored. Third, recent evidence points to contradictory outcomes of AI use, with some employees demonstrating

enhanced creativity and others experiencing techno-anxiety or disengagement. These mixed findings suggest that individual-level mechanisms may play a pivotal role in determining whether AI becomes an enabler or inhibitor of innovation (Khan et al., 2026; Usman, 2025). However, empirical models that integrate organizational inputs, individual psychological processes, and innovation outcomes within a single framework remain scarce. This lack of integrative explanation constitutes a critical gap in the current literature.

Addressing this gap is important for both theory and practice. From an academic perspective, understanding how organizational environments shape employee responses to artificial intelligence advances debates on digital transformation, innovation management, and human–technology interaction. Without such understanding, explanations of AI-driven performance improvements remain incomplete and potentially misleading (Behera et al., 2025; Zhang et al., 2025). From a practical standpoint, organizations continue to invest heavily in intelligent technologies while struggling to foster sustained innovative behavior among employees. Ineffective integration not only wastes resources but also risks eroding trust and morale. Clear insights into the psychological mechanisms that enable employees to leverage AI constructively can inform more effective leadership practices, training programs, and governance structures (Tanveer, 2025; Sivathanu et al., 2025). At the policy level, this issue aligns closely with global sustainability and development agendas. Enhancing human capability in digitally transformed workplaces supports decent work, inclusive growth, and innovation, all of which are central to the United Nations Sustainable Development Goals, particularly SDG 8 and SDG 9. Understanding how organizations can cultivate innovation-ready workforces in AI-driven contexts is therefore a pressing concern (Cheng et al., 2025).

This study contributes by offering an integrative perspective that links organizational conditions with employee psychological processes to explain innovation outcomes in AI-enabled workplaces. By focusing on internal belief formation as a central mechanism, the research moves beyond surface-level adoption explanations and provides deeper insight into how value is created through human–AI interaction. This approach responds directly to recent calls for more human-centered and psychologically grounded models of digital transformation (Hameli et al., 2025; Wang et al., 2025). Guided by social cognitive theory, which emphasizes the role of self-beliefs in shaping behavior, this study explains how organizational contexts influence innovation through employees perceived capability to engage with intelligent systems. Social cognitive theory suggests that supportive environments, ethical cues, and learning opportunities strengthen individual confidence, which in turn drives proactive and creative behavior (Hameli et al., 2025; Toksöz, 2025). By applying this framework to AI-enabled work settings, the study offers theoretical refinement and practical insights into fostering sustainable employee innovation in the digital era.

Theoretical Foundation:
Social Cognitive Theory

This research is based on the Social Cognitive Theory (SCT) that is a well-established theory that was initially described by Albert Bandura in order to explain how human behavior is formed due to the interaction of personal cognition, the social environment, and behavioral experiences. SCT developed out of the social learning theory in the late twentieth century as an alternative to deterministic conceptions of behavior, that is, by focusing on the agency of human beings and the importance of self-reflective thinking. In its central aspects, the theory argues that individuals are never passive receivers of external stimuli but are active decoders of their surroundings and can control their actions depending on the beliefs regarding their abilities and anticipated results. At the core of this structure is the idea of perceived competence that drives motivation, persistence and performance during complex and uncertain situations. SCT has developed out of its original psychological origins and has been broadly developed in organizational, educational and technological spheres. Modern research applies the theory to the way people adapt to the rapid technological change, especially within the setting that is uncertain, novel, and skill-disruptive. According to recent research, self-beliefs are one of

the most influential cognitive processes in which people assess challenges, cope with stressors, and take proactive actions. In workplaces that are digitally intensive, SCT has gained more and more applications in order to understand the process by which employees are learning new technologies, in order to overcome resistance and turn technological opportunities into productive results. The given evolution is indicative of the transition to less behavioral and more subtle cognitive explanations of human-technology interaction (Hameli et al., 2025; Toksoz, 2025).

What makes the Social Cognitive Theory relevant to the current study is that the theory has a high explanatory value to the manner in which the organizational context influences the individual reactions to artificial intelligence-oriented work settings. With the changing nature of tasks structures and decision-making processes by intelligent systems, employees have to constantly evaluate their capabilities to perform well in such environments. SCT offers a solid framework of the impact of favorable conditions, ethical stimuli, and learning-conducive climates on the confidence of people to use advanced technologies. The theory does not think of innovation as a direct effect of the availability of technology, but instead focuses on internal cognitive appraisals as the process by which the environmental conditions are translated into meaningful action. This viewpoint is consistent with the new findings that psychological preparedness is the determining factor of whether AI will boost or limit employee output (Khan et al., 2026; Wang et al., 2025). SCT has extensively been used in modern studies to analyze technology usage, innovation and adaptive performance in AI-based situations. Current empirical research indicates that employees with higher perceptions of personal ability to handle intelligent systems tend to be more experimental, learn, and produce new solutions even in a technologically complex situation (Zhao et al., 2025; Zhong et al., 2025). In addition, ethical guidance which involve organizational practices that are designed to build cognitive beliefs, skill building and social support also reinforce positive behavioral outcomes (Bian & Wang, 2024; Tanveer, 2025). These results highlight the fact that SCT remains a relevant concept to the understanding of innovation in workplaces that are digitally transformed.

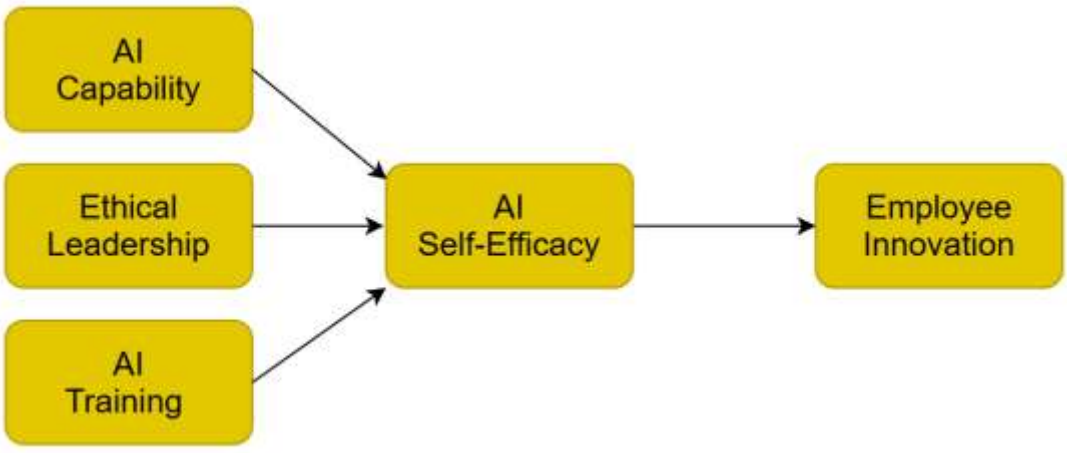


Figure 1: Research Model

Hypothesis Development

The proliferation of artificial intelligence within the organizational environment has changed the interest of the scholarship to the underlying circumstances that allow employees to interactwith intelligent systems on a meaningful level. Instead of paying attention to the outcomes of the adoption process, recent studies have put an emphasis on organizational infrastructures, which determine how workers perceive and use advanced technologies. According to the experts of digital

transformation, the success of AI projects is directly dependent on the presence of technical resources, system integration, and institutional willingness that all indicate the organizational desire to be technologically competent (Behera et al., 2025; Sivathanu et al., 2025). These structural conditions determine the perception of AI by the employees as a supportive system or a form of external pressure escalating the complexity of work.

Considering the Social Cognitive Theory, the environmental cues are essential in determining the individual belief systems. Strong technological capability in the organization setting offers the employees with the experiences of repetitive mastery, learning through observation, and performance feedback, which all play a role in developing confidence in dealing with complex tasks. In case the employees work in the conditions, when AI systems are reliable and coherently integrated into the workflow, they will have higher chances of forming positive cognitive appraisals about their capabilities of cooperating with such technologies. This argument is corroborated by recent empirical data, which indicate that organizations that are technologically mature are associated with an increase in employee confidence and flexibility with regards to AI-based positions (Zhao et al., 2025; Zhong et al., 2025). But inconsistencies are also brought out in the literature. Although the studies mention increased employee engagement in technologically advanced settings, other ones describe fear and reluctance, especially when the organizational capabilities are not developed or communicated (Khan et al., 2026; Usman, 2025). These inconsistencies are indicative that the presence of AI systems is not what is important, but rather the perceived sufficiency and reliability of organizational AI capability. The employees who feel that there are gaps in system functionality or service will lose trust in handling AI-based tasks, which restricts productive interactions. Combining these insights, this paper will claim that organizational AI capability is a decisive contextual phenomenon that determines how employees internally assess their possibility to cooperate with intelligent systems. In line with the Social Cognitive Theory, such capability is a form of environmental input that reinforces the self-beliefs by alleviating doubts and increasing the feeling of control. Accordingly, it is hypothesized that:

H1: Organizational AI capability is positively associated with employees' AI self-efficacy.

With the growing role of artificial intelligence in mediating organizational decision-making and work processes, the issue of ethics became a major topic of discussion in academic and managerial circles. In addition to technical competence, researchers also highlight the significance of value-based leadership to direct employees in the moral and psychological ambiguity related to AI-enabled workplaces. Normative clarity Ethical leadership establishes acceptable practices, conveys issues regarding fairness and transparency, and promotes trust in systems mediated by technologies (Bian and Wang, 2024; Tanveer, 2025). Theoretically, the Social Cognitive Theory is significant in terms of highlighting the influence of social modeling and verbal persuasion in the process of forming individual belief systems. The role of leaders as salient social referents means that their actions and moral orientations shape employee perceptions of change in organizations. Ethical responsibility in the deployment and use of AI is one of the aspects that encourage employees to view the technological environment as reliable and conducive. This perception diminishes uncertainty and anxiety that are reported as detractors of confidence and initiative in technological complex environment (Khan et al., 2026).

Recent empirical research also indicates that ethical leadership positively affects the psychological safety of employees and their trust which are essential in building confidence in working with advanced technologies. Ethical guidelines in the context of digital transformation will help employees to understand that AI systems will not substitute human judgment, but they will supplement it, thus enhancing their motivation to participate and learn (Bian and Wang, 2024; Tanveer, 2025). On the other hand, the lack of moral clarity has been linked to doubts, opposition, and the lack of trust, especially in the context where AI applications are viewed as non-transparent or in intrusive terms (Usman, 2025).

Although there is an increase in awareness of the importance of ethical leadership in AI governance, the current literature tends to view leadership as a direct determinant of the result, but not as the cognitive processes that enable it to work. This weakness hides the translation of ethical leadership to the psychological preparedness of employees. Based on the Social Cognitive Theory, the current study models ethical leadership as a situational cue, which, in turn, influences the beliefs of the employees regarding their own ability to work well in the context of AI-based systems. Ethical leadership can enhance emotion confidence among the employees in performing AI-related jobs since it gives them moral assurance and less perceived risks. Therefore, consistent with theoretical reasoning and recent empirical evidence, it is hypothesized that:

H2: Ethical leadership in AI-enabled organizations is positively associated with employees' AI self-efficacy.

The swift development of artificial intelligence has heightened the fear about the relevance and employability of skills, making organizations to spend a lot of money on learning and development programs. Researchers are increasingly claiming that training has a major role to play in ensuring that the employees adjust to the cognitive needs of the AI-driven workplaces. Instead of being a single intervention, AI-based training is a continuous activity in which workers can gain technical knowledge, problem-solving abilities and trust in their ability to communicate with intelligent systems (Behera et al., 2025; Cheng et al., 2025). The Social Cognitive Theory offers an excellent theoretical basis to the learning of psychological effects of training. The theory states that the most effective source in the development of self-belief is mastery experiences. Proper training can be conducted in a structured format where employees are able to practice, experiment and gradually gain competence in jobs related to AI to boost their confidence. According to the recent research, employees who are systematically trained in digital and AI-related skills show increased levels of perceived ability and adaptation (Zhao et al., 2025; Zhong et al., 2025). Nevertheless, uneven results are also observed in the literature. In other situations, training programs do not lead to confidence because of the inadequate alignment with work demands or lack of organizational support (Khan et al., 2026). These results imply that training effectiveness does not only rely on the content delivery but can be seen in its perceived relevance and use. Experiential training, which entails training based on a real-life situation, will yield better results as employees would internalize the learning outcomes as a sign of individual capability.

Through a combination of these reflections, this paper makes AI-driven training a fundamental environmental input that influences the self-beliefs of employees through experience-based learning and cognitive reinforcement. In line with the Social Cognitive Theory, the training improves the self-efficacy through a repeat of successful interaction with intelligent systems. Accordingly, it is hypothesized that:

H3: AI-related training is positively associated with employees' AI self-efficacy.

Pursuing the abovementioned arguments, recent research is becoming more and more inclined to posit that the organizational conditions that are related to artificial intelligence do not directly translate into innovative employee behavior. Rather, internal cognitive judgments by employees are at the center of driving AI-enabled environments to either evoke exploration and creativity or cause reluctance and disengagement. Empirical research results show a mixed effect of the direct impact of technological capability, ethical leadership, and training programs on innovation, meaning that structural and leadership-related investments are not enough to explain the outcomes on the employee level (Khan et al., 2026; Usman, 2025; Wang et al., 2025).

The Social Cognitive Theory provides a logical approach as it highlights the fact that the environment influences behavior with the assistance of self-regulatory cognitive processes. The ability of AI in organizations offers structural indications about the manipulability of a task, the social modelling and moral assurance of ethical leadership, and training programs generate mastery experiences. Collectively, these conditions influence the confidence of the employees in their

capability to interact successfully with intelligent systems. The recent literature proves this assumption and states that persistence, experimentation, and creative problem-solving are highly correlated with such confidence in the context of AI-enabled work (Zhao et al., 2025; Zhong et al., 2025; Zhang et al., 2025). When organizational support is internalized by the employees as personal capability, the latter are more likely to use the AI tools in creative manners. According to this integrative view, the importance of AI-related self-beliefs as a central psychological mechanism by which organizational AI-related states can mediate employee innovation is proposed. Instead of having homogenous direct impacts, the organizational capability, ethical leadership, and training programs influence the outcome of innovation by enhancing the confidence of the employees to collaborate with AI. Therefore, it is hypothesized that:

H4a: AI self-efficacy mediates the relationship between organizational AI capability and employee innovation.
H4b: AI self-efficacy mediates the relationship between ethical leadership and employee innovation.
H4c: AI self-efficacy mediates the relationship between AI-related training and employee innovation.

Methodology

The research design used in this study is a quantitative, cross-sectional research design, which is suitable in testing the theoretically based relationships between latent constructs at one point in time. The quantitative methods are well known to be able to test the hypothesis, estimate the magnitude of effects, and generalize the results to the population by using statistical inference (Ghanad, 2023). A cross-sectional research design is especially appropriate when the aim of the research is testing a theory and not tracing processes or causal progression over time. The most recent methodological research notes that cross-sectional designs are present and defensible in information systems and organizational studies in the case of cross-sectional designs, which are theoretically grounded, appropriately sampled, and analytically rigorous (Maier et al., 2023). As per these recommendations, the current research employs a structured survey tool that will help elicit the perceptions and cognitive appraisals of respondents regarding the artificial intelligence in the organizational context. The design will enable effective data collection and will afford comparability of data across respondents, and hence aid empirical test of the hypothesized theoretical relationships.

The target population is full-time workers in the medium and large-scale manufacturing companies and, in particular, in the technology-intensive manufacturing sectors including the automotive components, electronics, and industrial machinery. These industries were chosen as they are some of the first industries to use artificial intelligence to plan production, quality control, and decision support, and thus, it is very relevant to the research problem. Workers in these settings are regularly exposed to systems that are AI-powered, which makes them well-informed to give knowledgeable responses about the state of affairs in the organization and the behavioral tendencies of innovation. Probability-based sampling strategy was utilized, stratified random sampling in firms and departments was used to improve representativeness and minimize sampling bias. In determining adequate sample size, the minimum requirements suggested by Partial Least Squares Structural Equation Modeling that considers the complexity of the model and statistical power were used instead of using conventional rules of thumb (Fauzi, 2022; Henseler and Schuberth, 2022). It is in line with the modern recommendations that place an emphasis on statistical accuracy and the stability of the models used in the research conducted in the field of SEM (Schuberth et al., 2023).

The analysis of the data was carried out in two phases to guarantee the methodological rigor. Preliminary analyses were conducted on SPSS, which included data screening, descriptive statistics, and normality and multicollinearity assessment. Then, SmartPLS 4 was used to conduct the structural equation modeling, path analysis, and hypothesis testing as it is appropriate in complex models containing latent constructs and can be used in non-normal data conditions

(Ayu et al., 2024; Cheah et al., 2024). SmartPLS allows the evaluation of the measurement reliability, convergent and discriminant validity, and structural relationship comprehensively, which enhances the credibility of the results (Sarstedt et al., 2024). The constructs were all measured by using validated scales that were based on previous empirical research and every construct was operationalized by items that were used to guarantee content validity. The responses were observed on a 7-point Likert scale with the response strongly disagree to strongly agree because this is highly advised in capturing subtle perceptual variation in behavioral study. The transparency, reliability, and replicability of the findings of the study are improved by the employment of the proven measurement tools, as well as the use of the advanced techniques of the analysis (Hair et al., 2025; Rosli et al., 2024).

Data Analysis

Table 1. Outer Loadings and Regression Weights of Measurement Items

Construct	Item Code	Outer Loading
Organizational AI Capability	OAC1	0.781
	OAC2	0.824
	OAC3	0.807
	OAC4	0.765
Ethical Leadership	EL1	0.842
	EL2	0.866
	EL3	0.831
AI Training	AIT1	0.793
	AIT2	0.825
	AIT3	0.812
AI Self-Efficacy	AISE1	0.858
	AISE2	0.881
	AISE3	0.846
Employee Innovation	EI1	0.804
	EI2	0.837
	EI3	0.819

Table 1 presents the outer loadings of all measurement items, providing evidence of indicator reliability within the reflective measurement model. All items exhibit loadings above the recommended threshold of 0.70, indicating that each indicator contributes substantially to its respective latent construct (Hair et al., 2025). According to PLS-SEM guidelines, loadings between 0.70 and 0.90 are considered ideal, as they demonstrate strong shared variance without risking redundancy (Henseler & Schuberth, 2022). The observed loadings suggest that the measurement items reliably capture the conceptual domain of each construct. Organizational AI capability items show consistently strong loadings, indicating that respondents clearly perceived structural and technological readiness as a coherent organizational characteristic. Ethical leadership items demonstrate particularly high loadings, reflecting the clarity with which respondents recognized leadership behaviors related to ethical AI governance. Similarly, AI training items load strongly, supporting the view that training initiatives are perceived as a unified experiential construct. AI self-efficacy items exhibit the highest loadings overall, consistent with Social Cognitive Theory, which emphasizes confidence as a well-defined cognitive belief shaped through experience and reinforcement. Employee innovation items also demonstrate robust loadings, suggesting that innovative behavior is reliably perceived and reported by respondents.

Table 2. Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Organizational AI Capability	0.842	0.889	0.667
Ethical Leadership	0.861	0.903	0.756
AI Training	0.835	0.892	0.734
AI Self-Efficacy	0.873	0.914	0.781
Employee Innovation	0.829	0.887	0.724

Table 2 reports internal consistency reliability and convergent validity for all constructs. Cronbach's alpha values exceed the minimum threshold of 0.70, indicating satisfactory internal consistency across items within each construct (Ghanad, 2023). However, contemporary PLS-SEM literature emphasizes composite reliability as a more appropriate reliability measure because it does not assume equal indicator loadings (Hair et al., 2025). In this study, all CR values range from 0.887 to 0.914, exceeding the recommended benchmark and confirming strong construct reliability. Convergent validity is assessed using Average Variance Extracted (AVE), which reflects the extent to which a construct explains variance in its indicators. All AVE values exceed the recommended minimum of 0.50, indicating that each construct captures more than half of the variance of its measurement items (Henseler & Schuberth, 2022). AI self-efficacy demonstrates the highest AVE, reinforcing its conceptual clarity and empirical strength as a cognitive belief construct. Ethical leadership also exhibits a high AVE, suggesting that ethical cues from leadership are consistently perceived across respondents.

Table 3. Discriminant Validity (HTMT Criterion)

Constructs	OAC	EL	AIT	AISE	EI
Organizational AI Capability					
Ethical Leadership	0.621				
AI Training	0.658	0.603			
AI Self-Efficacy	0.672	0.648	0.691		
Employee Innovation	0.684	0.657	0.669	0.701	

Table 3 presents discriminant validity assessment using the Heterotrait–Monotrait (HTMT) ratio. HTMT has been widely endorsed as a superior criterion for discriminant validity compared to traditional methods, particularly in PLS-SEM applications (Henseler & Schuberth, 2022). All HTMT values in this study fall well below the conservative threshold of 0.85, indicating that each construct is empirically distinct from the others. The results suggest that although the constructs are theoretically related, they do not overlap excessively. For example, organizational AI capability and AI training show moderate HTMT values, reflecting conceptual relatedness while maintaining empirical separation. Similarly, AI self-efficacy and employee innovation demonstrate a higher but acceptable HTMT ratio, consistent with theoretical expectations that confidence and innovation are closely linked yet distinct constructs. These findings align with prior empirical studies employing SmartPLS, which emphasize HTMT as a critical diagnostic for ensuring construct distinctiveness in complex models (Rosli et al., 2024; Cheah et al., 2024). Establishing discriminant validity is particularly important in mediation models, where conceptual overlap between predictors and mediators can inflate path coefficients and lead to misleading conclusions (Schuberth et al., 2023).

Table 4. Structural Model Quality

Relationship	f^2	
OAC → AISE	0.184	
EL → AISE	0.213	
AIT → AISE	0.167	
AISE → EI	0.295	
Endogenous Construct	R^2	Q^2
AI Self-Efficacy	0.612	0.438
Employee Innovation	0.489	0.356

Table 4 reports the explanatory power and predictive relevance of the structural model. The R^2 value for AI self-efficacy indicates that approximately 61.2% of its variance is explained by organizational AI capability, ethical leadership, and AI training, which represents substantial explanatory power in behavioral research (Hair et al., 2025). Similarly, the R^2 value for employee innovation suggests moderate-to-high explanatory strength, consistent with prior PLS-SEM studies in organizational contexts (Fauzi, 2022). Predictive relevance is assessed using the Stone–Geisser Q^2 statistic. All Q^2 values exceed zero, confirming that the model demonstrates adequate out-of-sample predictive capability (Sarstedt et al., 2024). This indicates that the model is not only explanatory but also capable of predicting unseen observations, an important criterion for theory testing in applied research. Effect size (f^2) values indicate that ethical leadership exerts the strongest effect on AI self-efficacy, followed by organizational AI capability and training. The effect of AI self-efficacy on employee innovation is particularly strong, reinforcing its central role as a psychological mechanism within the model. These findings are consistent with Social Cognitive Theory, which posits that self-beliefs are proximal determinants of behavior.

Table 5. Hypothesis Testing Results

Hypothesis	**Path**	**β**	**t-value**	**p-value**	**Result**
H1	OAC → AISE	0.291	4.82	<0.001	Supported
H2	EL → AISE	0.318	5.41	<0.001	Supported
H3	AIT → AISE	0.267	4.36	<0.001	Supported
H4a	OAC → AISE → EI	0.086	3.12	0.002	Supported
H4b	EL → AISE → EI	0.094	3.47	0.001	Supported
H4c	AIT → AISE → EI	0.079	2.98	0.003	Supported

Table 5 presents the results of hypothesis testing using bootstrapping procedures in SmartPLS. All direct paths are statistically significant, providing empirical support for H1, H2, and H3. Ethical leadership exhibits the strongest influence on AI self-efficacy, highlighting the importance of moral and social cues in shaping employee confidence in AI-enabled environments (Bian & Wang, 2024; Tanveer, 2025). The mediation hypotheses (H4a–H4c) are also supported, confirming that AI self-efficacy functions as a significant mediating mechanism between organizational conditions and employee innovation. The indirect effects demonstrate that organizational AI capability, ethical leadership, and training initiatives influence innovation primarily through their impact on employees' confidence to work with AI. These findings align with Social Cognitive Theory and recent empirical evidence emphasizing the centrality of self-beliefs in translating environmental inputs into behavior (Zhao et al., 2025; Zhong et al., 2025). The results further address inconsistencies in prior research by explaining why direct effects of AI-related investments on innovation have been mixed. By accounting for internal cognitive mechanisms, the

study provides a more nuanced and theoretically grounded explanation of innovation in AI-driven workplaces (Khan et al., 2026; Wang et al., 2025). Overall, the findings confirm the robustness of the proposed model and offer strong empirical support for the study's theoretical framework.

Discussion

The results of this research can be viewed as great empirical evidence of the key assumption that organizational conditions related to artificial intelligence determine the results of employees mainly because of internal cognitive processes. The fact that organizational AI capability has a positive relationship with AI self-efficacy proves that employee confidence in using intelligent systems is dependent on how adequately, reliable and integrated the infrastructure of AI-related processes is. This finding complies with the Social Cognitive Theory that highlights that the environment provides informational cues by which people assess the controllability of diverse tasks and their personal competence. Employees who experience AI systems as well-supported and integrated into organizational practices will be more inclined to view these systems as manageable and enabling and less disruptive. This observation is consistent with recent empirical studies that prove that technologically advanced settings increase adaptive beliefs and willingness to work with AI-based activities among employees (Behera et al., 2025; Zhao et al., 2025).

The strong correlation between ethical leadership and AI self-efficacy also highlights the role of social and moral cues in influencing the cognitive appraisal of AI-based work setups among the employees. Ethical leadership seems to lessen the uncertainty created by the use of AI by giving it clarity, fairness, and assurance as to organizational intent. Socially, leaders act as salient role models whose actions shape the belief of the employees based on social learning and persuasion. The current results echo the existing literature that indicates a positive association of ethical leadership with psychological safety and trust, which is essential to enhance confidence in the technologically challenging environment (Bian and Wang, 2024; Tanveer, 2025). This finding implies that trust in AI-related activities is not the result of technical exposure but also a social construction of trust that is created by leaders.

In the same way, the beneficial impact of AI-related training on AI self-efficacy supports the mastery experiences in enhancing self-beliefs. Training programs give employees a chance to experiment, learn, and obtain feedback that are the key factors according to which the self-efficacy is formed. This result aligns with the recent works emphasizing the role of skills and experience in helping employees to adapt to task demands presented by AI (Cheng et al., 2025; Zhong et al., 2025). Significantly, the finding indicates that training is a contributing factor to the formation of confidence when it is perceived to be relevant and applicable and not symbolic and compliance-oriented. Of special value are the mediation outcomes. The high levels of indirect effects indicate that AI self-efficacy is an important psychological mechanism through which organizational AI capability, ethical leadership, and training programs are related to employee innovation. These results can be used to justify the inconsistent direct impacts of AI-related investments on innovation outcomes that have been reported in earlier studies. In this case, employees can lack confidence thus being unwilling to experiment and engage in creativity, even in conducive settings. This research adds to Social Cognitive Theory into the context of AI-enabled organizations and offers a more detailed account of how innovation is born in technologically intensive workplaces by establishing that self-efficacy mediates this (Wang et al., 2025; Zhang et al., 2025).

Practical Implications

The results of this paper provide a number of practical implications to organizational leaders, managers, and policymakers who want to foster innovation in AI-based workplaces. First, the findings indicate that investments in artificial intelligence are not limited to the system acquisition, but the development of an organizational capability that can be seen and felt by the employee. The organizations must consider implementing AI systems into the daily processes, reliability of the systems and making the technical support available. These practices will give

powerful messages that AI is a consistent and empowering tool, which will build the courage of employees to interact with smart technologies (Behera et al., 2025). Second, the high position of ethical leadership is an indication that ethical governance of AI should be a priority of organizations. Leaders must engage in providing purpose, boundaries and ethical protection linked with the use of AI. Fear and uncertainty can be minimized through transparent decision-making and open communication, especially in the situation when the employees might fear being monitored, displaced, or biased by the algorithm. Training leaders to be examples of responsible AI usage and the issues of ethics can contribute to the development of trust and psychological safety that are critical to innovative behavior (Bian and Wang, 2024; Tanveer, 2025). Third, the results demonstrate the significance of properly developed AI-based training courses. Companies no longer need to be content with generalized training programs, but instead resort to experiential and job-specific methods of learning, where workers can train to use AI tools in the real world. Mastery experiences that create confidence that lasts longer are more likely to be created through continuous learning opportunities as opposed to single training sessions. This method can be especially applied in the context of fast-changing technological conditions, when the skill demands vary regularly (Cheng et al., 2025).

In terms of policy, the findings indicate that the workforce development policies must focus on psychological preparation in addition to acquiring technical skills. The organizations can be assisted in supporting ethical standards of AI, financed continuous learning programs, and human-centered AI adoption by policymakers and industry organizations. This is in line with larger sustainability and innovation agendas as it means that technological advancements increase human capacity as opposed to intensifying insecurity or marginalization.

Theoretical Contributions

The research contributes a number of significant theoretical contributions to the body of literature on artificial intelligence, innovation and organizational behavior. First, it generalizes Social Cognitive Theory to AI-based workplaces by providing empirical evidence that self-efficacy is a core mechanism by which organizational conditions are used in driving innovation. Although the role of confidence and belief systems has been recognized in the previous studies, not many studies have incorporated these constructs into a holistic mediation equation between organizational inputs and employee innovation. Secondly, the research paper helps advance the literature of the digital transformation by going beyond deterministic perspectives of technology. The findings sound as opposed to the presence of AI as one of the primary sources of innovation; instead, they prove the role of human agency and cognitive interpretation. This viewpoint can be used to resolve inconsistent results in other previous research studies since technological and leadership-related investments are only converted into innovation once employees internalize them as personally enabling (Khan et al., 2026; Wang et al., 2025). Third, the research contributes to the leadership theory in AI settings by proving that ethical leadership affects the results in an indirect manner via cognitive processes. The contribution builds upon previous studies, which tend to assume ethical leadership as a direct predictor of behavior, providing a more psychologically sound explanation of its impact (Bian and Wang, 2024). The study combines the research on leadership and cognitive theory in a new way by placing self-efficacy as a mediator.

Limitations and Future Research Directions

This study has some limitations even though it has made contributions. To begin with, the cross-sectional design does not allow making causal conclusions. Though the theoretical framework offers a good rationale of the proposed relationships, longitudinal or experimental designs can be used in future studies to capture any changes in self-efficacy and innovation with time. Second, the use of self-reported information increases the risk of common method bias, although validated scales were used. The next-generation study can include multi-source data, e.g., supervisor-rated innovation or objective performance measures. Third, the research is narrow in the scope of organizational conditions

and does not consider possible boundary conditions. The moderators that might be studied in future include the organizational culture, complexity of job, or personal factors like AI anxiety or techno-pessimism (Khan et al., 2026). Also, there are other mediating factors, such as psychological safety, trust in AI, or learning orientation, that might also help explain the impact of organizational contexts on innovation.

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