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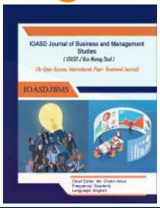

Building an AI-ready workforce: the roles of ethical leadership, knowledge integration, and organizational adaptability

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ABSTRACT

Purpose: This study examines how human capital investment contributes to organizational adaptability through AI workforce readiness and knowledge integration while investigating the moderating role of ethical leadership in entrepreneurial and innovation-oriented organizations. **Design/methodology/approach:** A quantitative survey was conducted among employees working in AI-enabled organizations across Canada. Data were collected from 381 respondents employed in startups, small and medium-sized enterprises, and innovation-focused business units. The proposed model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4. **Findings:** The findings indicate that human capital investment positively influences AI workforce readiness, which subsequently enhances knowledge integration and organizational adaptability. Knowledge integration partially mediates the relationship between AI workforce readiness and organizational adaptability. Ethical leadership strengthens the relationship between AI workforce readiness and knowledge integration, although its moderating effect on the relationship between knowledge integration and organizational adaptability was not significant. The results suggest that organizational adaptability in AI-enabled environments depends on the interaction of workforce capabilities, knowledge-sharing processes, and ethical leadership practices. **Originality/value:** This study extends Human Capital Theory, Organizational Learning Theory, and Ethical Leadership Theory by introducing AI workforce readiness as a distinct organizational capability linking human capital investments to adaptive outcomes. The study also provides new insights into how ethical leadership supports responsible AI adoption and knowledge integration within entrepreneurial and innovation-oriented organizations.

Keywords: Artificial intelligence workforce readiness; Ethical leadership; Knowledge integration; Organizational adaptability; Human capital investment; Entrepreneurial organizations.

1. INTRODUCTION

Artificial intelligence (AI) is transforming how organizations create value, make decisions, and respond to increasingly dynamic business environments. Organizations continue to invest heavily in predictive analytics, intelligent decision-support systems, generative AI applications, and process automation technologies to improve efficiency and competitiveness. However, many organizations still struggle to realize the expected benefits of AI adoption. Research suggests that successful AI implementation depends not only on technological capabilities but also on the human and organizational factors that support effective use (Mowles, 2015). At the same time, concerns regarding transparency, accountability, fairness, and responsible decision-making have increased the importance of ethical considerations in AI-enabled workplaces (Frick *et al.*, 2021).

These challenges are particularly relevant for entrepreneurial and innovation-oriented organizations. Entrepreneurial ventures and SMEs often operate under resource constraints while facing technological uncertainty and intense competition. In such environments, adaptability is essential because survival and growth frequently depend on responding quickly to changing opportunities and market conditions (Mikalef *et al.*, 2023). Although AI technologies offer substantial opportunities, their successful implementation requires employees who possess the knowledge, confidence, and skills needed to work effectively alongside intelligent systems. Consequently, AI workforce readiness has emerged as an increasingly important organizational capability.

Human Capital Theory provides a useful foundation for understanding this challenge. The theory suggests that investments in employee knowledge and skills contribute to organizational performance and competitiveness (Strober, 1990, Sweetland, 1996). Yet, despite growing investments in workforce development and AI-related training, existing studies have focused largely on AI adoption, implementation barriers, and technology acceptance (Uren and Edwards, 2023). As a result, limited attention has been devoted to understanding how workforce de(Mäntymäki *et al*., 2022)velopment contributes to organizational adaptability in AI-enabled environments.

One possible explanation lies in AI workforce readiness and knowledge integration (Acharya *et al*., 2022). Organizations are unlikely to realize substantial benefits from AI unless employees possess the preparedness required to integrate intelligent technologies into their daily work activities. Moreover, AI-generated insights create value only when employees effectively share, combine, and apply knowledge across organizational boundaries. Organizational Learning Theory suggests that knowledge integration is a critical mechanism through which organizations transform individual capabilities into collective outcomes (Grant, 1996, Mäntymäki *et al*., 2022). However, empirical evidence explaining how AI workforce readiness contributes to knowledge integration and organizational adaptability remains limited (Guo *et al*., 2023).

The ethical dimension of AI adoption introduces an additional layer of complexity. Ethical leadership has been associated with positive employee behaviors, knowledge sharing, and organizational learning (Jarrahi, 2018), yet little is known about its role in AI-enabled organizations. This study addresses these gaps by examining how human capital investment contributes to organizational adaptability through AI workforce readiness and knowledge integration while investigating the moderating role of ethical leadership. In doing so, the study integrates Human Capital Theory, Organizational Learning Theory, and Ethical Leadership Theory to provide a more comprehensive explanation of how organizations develop adaptive capabilities in AI-enabled environments.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

As artificial intelligence becomes increasingly integrated into organizational processes, employee preparedness for working alongside intelligent technologies has emerged as a critical organizational concern. While existing research has examined concepts such as digital literacy, technology readiness, and technology acceptance, these constructs do not fully capture the capabilities required in AI-enabled work environments (Misuraca and Viscusi, 2020). Digital literacy reflects an individual's ability to use digital technologies, technology readiness focuses on willingness to adopt new technologies, and AI self-efficacy emphasizes confidence in performing AI-related tasks. However, these concepts do not adequately explain whether employees possess the broader capabilities needed to integrate AI technologies into organizational activities (Chowdhury *et al*., 2023).

This study conceptualizes AI workforce readiness as the extent to which employees possess the knowledge, confidence, preparedness, and capability required to work effectively with artificial intelligence technologies in their daily roles. The construct encompasses employees' ability to understand AI systems, utilize AI-generated insights, adapt to AI-enabled work processes, and collaborate effectively in technology-intensive environments. Recent research suggests that successful AI implementation depends heavily on workforce preparedness because organizations frequently face challenges related to employee adaptation, technological uncertainty, and evolving skill requirements (Uren and Edwards, 2023, Mowles, 2015). From a Human Capital Theory perspective, AI workforce readiness represents an organizational capability that helps transform investments in employee development into adaptive organizational outcomes (Strober, 1990).

2.2 Organizational Adaptability in Entrepreneurial and Innovation-Oriented Organizations

Organizational adaptability is particularly important within entrepreneurial and innovation-oriented organizations because these firms often operate in environments characterized by uncertainty, resource constraints, and rapid technological change (Frick *et al*., 2021). Unlike larger organizations that may possess substantial financial and managerial resources, entrepreneurial ventures frequently depend on their ability to respond quickly to market opportunities and emerging technological developments. As artificial intelligence continues to reshape competitive environments, entrepreneurial firms increasingly face pressure to adopt new technologies while simultaneously maintaining operational flexibility and innovation capability (Mikalef *et al*., 2023).

The successful adoption of artificial intelligence within entrepreneurial organizations depends not only on technological investments but also on the workforce capabilities that support effective implementation. Entrepreneurial firms typically rely on smaller and more flexible organizational structures where employees often perform multiple roles and collaborate across functional boundaries. Consequently, workforce readiness, knowledge integration, and ethical leadership may play an especially important role in helping entrepreneurial organizations convert AI investments into adaptive capabilities. Examining these relationships within entrepreneurial and innovation-oriented contexts therefore contributes to a better understanding of how emerging firms can achieve sustainable growth and competitiveness in increasingly AI-enabled environments (Jöhnk *et al*., 2021).

2.3 Human Capital Investment and AI Workforce Readiness

The growing integration of artificial intelligence into organizational processes has increased the importance of workforce preparedness. Although organizations continue to invest heavily in AI technologies, the benefits of these investments often depend on employees' ability to understand, utilize, and collaborate with intelligent systems. Human Capital Theory argues that investments in employee knowledge, skills, and competencies represent valuable organizational resources that contribute to long-term competitiveness and organizational success (Strober, 1990). Consequently, organizations that actively invest in workforce development are more likely to build capabilities that support adaptation to emerging technological environments.

Human capital investment typically includes employee training, professional development programs, knowledge enhancement initiatives, and continuous learning opportunities (Sweetland, 1996, Simpson *et al*., 2002). Such investments can improve employees' AI-related knowledge, confidence, and ability to integrate intelligent technologies into their daily work activities. As organizations increasingly rely on AI-enabled systems, employees who receive greater developmental support are likely to feel better prepared to work with these technologies (Sjödin *et al*., 2021). Therefore, organizations that invest more heavily in workforce development are expected to exhibit higher levels of AI workforce readiness.

H1. Human capital investment positively influences AI workforce readiness.

2.4 AI Workforce Readiness and Knowledge Integration

AI workforce readiness reflects employees' preparedness to work effectively in environments that artificial intelligence technologies support operational and strategic activities. Employees who possess strong AI-related knowledge and confidence are generally better able to interpret technology-generated insights, understand AI-supported processes, and communicate relevant information to colleagues. As AI technologies become increasingly embedded within organizational activities, workforce readiness may play an important role in facilitating collaboration and knowledge exchange across functional boundaries.

According to Organizational Learning Theory, organizational effectiveness depends not only on acquiring knowledge but also on integrating knowledge from different individuals and organizational units (Grant, 1996). Employees who are comfortable working with AI systems are more likely to contribute to knowledge-sharing activities and help combine technology-generated information with existing organizational expertise. This process enables organizations to transform dispersed knowledge into coordinated action and more effective decision-making. Therefore, higher levels of AI workforce readiness are expected to strengthen knowledge integration within organizations.

H2. AI workforce readiness positively influences knowledge integration.

2.5 Knowledge Integration and Organizational Adaptability

Organizational adaptability refers to an organization's ability to respond effectively to environmental changes, technological developments, and evolving market demands (Sousa, 2013, Acharya *et al*., 2022). Adaptable organizations continuously adjust their processes, structures, and strategies to maintain effectiveness under changing conditions. In increasingly dynamic business environments, adaptability has become a critical capability for sustaining organizational performance and competitiveness.

Knowledge integration contributes to adaptability by enabling organizations to combine expertise from different sources and apply that knowledge to emerging challenges (Guo *et al*., 2023). Organizational Learning Theory suggests that organizations capable of integrating knowledge effectively are better positioned to identify opportunities, solve problems, and respond to uncertainty (Mäntymäki *et al*., 2022). As AI technologies generate increasing amounts of information, organizations must integrate technology-generated insights with employee expertise to support adaptive decision-making. Consequently, stronger knowledge integration capabilities are expected to enhance organizational adaptability.

H3. Knowledge integration positively influences organizational adaptability.

2.6 AI Workforce Readiness and Organizational Adaptability

Organizations increasingly depend on employees to utilize AI technologies, interpret AI-generated information, and respond to rapidly changing technological requirements. Employees who possess higher levels of AI workforce readiness are generally better equipped to adapt to evolving work processes and contribute to technology-driven organizational initiatives. Their ability to engage effectively with AI systems may support faster responses to environmental and operational changes.

Human Capital Theory suggests that employee capabilities represent strategic resources that enable organizations to achieve superior outcomes (Strober, 1990). AI workforce readiness may therefore contribute directly to organizational adaptability by enhancing employees' ability to support innovation, implement technological change, and respond to new opportunities. As organizations continue to incorporate AI technologies into their operations, workforce readiness is likely to become an increasingly important determinant of adaptive capability. Therefore, organizations with more AI-ready employees are expected to demonstrate greater organizational adaptability.

H4. AI workforce readiness positively influences organizational adaptability.

2.7 The Mediating Role of Knowledge Integration

Although AI workforce readiness may directly contribute to organizational adaptability, the benefits of workforce preparedness are unlikely to be fully realized without organizational mechanisms that enable employees to share and apply knowledge effectively. Employees who possess AI-related knowledge and skills can generate valuable insights and interpret AI-generated information, but these capabilities create greater organizational value when knowledge is exchanged across teams and integrated into organizational decision-making processes. Organizational Learning Theory emphasizes that organizational outcomes often emerge through learning processes that transform individual knowledge into collective capabilities (Grant, 1996).

Knowledge integration may therefore serve as an important mechanism linking AI workforce readiness and organizational adaptability (Guo *et al*., 2023). AI-ready employees are more likely to contribute to knowledge-sharing activities, collaborate across functional boundaries, and apply technology-related insights to organizational challenges. These activities help organizations respond more effectively to environmental uncertainty and technological change. Consequently, the positive influence of AI workforce readiness on organizational adaptability is expected to operate, at least in part, through enhanced knowledge integration (Sousa, 2013).

H5. Knowledge integration mediates the relationship between AI workforce readiness and organizational adaptability.

2.8 The Moderating Role of Ethical Leadership

The growing use of artificial intelligence has created significant ethical challenges for organizations, including concerns regarding transparency, accountability, fairness, privacy, and the responsible use of algorithmic decision-making systems (Mökander *et al*., 2021). These challenges are particularly relevant in entrepreneurial and innovation-oriented organizations where rapid technological adoption may outpace the development of formal governance mechanisms. As employees increasingly interact with AI-enabled systems, uncertainty regarding how AI-generated decisions is produced and utilized may influence trust, collaboration, and knowledge-sharing behaviors. Consequently, leadership practices that promote ethical standards and responsible technology use have become increasingly important in AI-enabled workplaces (Misuraca and Viscusi, 2020).

Ethical leadership is characterized by fairness, integrity, transparency, and accountability in managerial decision-making (Jarrahi, 2018). Ethical leaders create environments where employees feel comfortable sharing knowledge, raising concerns, and engaging with new technologies responsibly. Within AI-enabled organizations, ethical leadership may reduce employee uncertainty, strengthen trust in technology-related initiatives, and encourage greater participation in organizational learning processes (Chowdhury *et al*., 2023). Leaders who promote openness and ethical decision-making can also help employees utilize shared knowledge more effectively when responding to organizational challenges. Therefore, ethical leadership is expected to strengthen both the relationship between AI workforce readiness and knowledge integration and the relationship between knowledge integration and organizational adaptability.

H6. Ethical leadership positively moderates the relationship between AI workforce readiness and knowledge integration, such that the relationship is stronger under higher levels of ethical leadership.

H7. Ethical leadership positively moderates the relationship between knowledge integration and organizational adaptability, such that the relationship is stronger under higher levels of ethical leadership.

Figure 1 illustrates the proposed relationships among human capital investment, AI workforce readiness, knowledge integration, ethical leadership, and organizational adaptability.

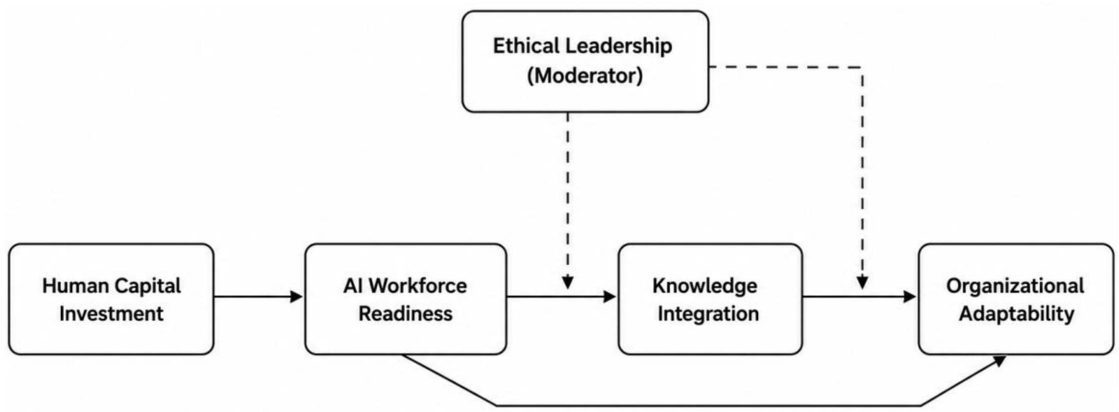

Figure 1. Proposed Research Model

3. METHODOLOGY

3.1 Research Design and Sample

This study employed a quantitative survey design to examine how human capital investment contributes to organizational adaptability through AI workforce readiness and knowledge integration while considering the moderating role of ethical leadership. The study focused on entrepreneurial and innovation-oriented organizations across Canada that actively utilize artificial intelligence technologies to support innovation, growth, and decision-making. Respondents were recruited through entrepreneurship associations, professional networks, innovation hubs, and organizational contacts, with participation limited to employees who had at least six months of experience using AI-supported systems. A total of 612 questionnaires were distributed electronically, resulting in 397 responses, of which 381 usable questionnaires were retained after data screening, representing a response rate of 62.3%. The sample reflected substantial entrepreneurial involvement, with 68.2% of respondents employed in startups and SMEs with fewer than 250 employees. Participating organizations reported varying levels of AI adoption, ranging from pilot projects to organization-wide implementation. Participation was voluntary, responses were anonymous, and no personally identifiable information was collected.

Table 1. Respondent and Organizational Characteristics

Characteristic	Category	Frequency	Percentage
Gender	Male	207	54.3
	Female	174	45.7
Age	Under 30	92	24.1
	30–39	144	37.8
	40–49	86	22.6
	50+	59	15.5
Education	High School	31	8.1
	Diploma	73	19.2
	Bachelor's Degree	178	46.7
	Master's Degree	84	22.0
	Doctorate	15	4.0
Position	Managerial	104	27.3
	Non-managerial	277	72.7
Firm Size	Micro (<10 employees)	43	11.3
	Small (10–49 employees)	108	28.3
	Medium (50–249 employees)	109	28.6
	Large (250+ employees)	121	31.8
Industry	Information Technology	86	22.6
	Manufacturing	69	18.1
	Finance and Insurance	64	16.8
	Logistics and Transportation	55	14.4
	Healthcare	50	13.1
	Professional Services	34	8.9
	Other	23	6.1

The average organizational tenure was 6.4 years (SD = 4.7). Regarding AI usage frequency, 24.1% of respondents reported daily interaction with AI technologies, 38.6% reported weekly interaction, 25.5% reported monthly interaction, and 11.8% reported occasional use.

3.2 Measurement Instruments

All constructs were measured using previously validated scales adapted from established literature. Human capital investment was measured using five items adapted from Sweetland (1996) and Simpson *et al.* (2002). AI workforce readiness was assessed using six items adapted from studies examining digital readiness, AI adoption, and employee preparedness for technology-enabled work environments (Uren and Edwards, 2023, Mäntymäki *et al.*, 2022). Because no universally accepted measure currently exists, the scale was refined through expert review and operationalized through three dimensions: AI knowledge, confidence in working with AI technologies, and perceived capability to integrate AI into daily work activities.

Knowledge integration was measured using five items adapted from Mökander *et al.* (2021). Ethical leadership was assessed using the ten-item scale developed by Lebovitz *et al.* (2022) and adapted to reflect responsible technology use, transparency in AI-related decisions, fairness in AI-supported work processes, and accountability for technology outcomes. Organizational adaptability was measured using six items adapted from Sousa (2013) and Acharya *et al.* (2022). All items were measured on a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). Prior to data collection, the questionnaire was reviewed by three academic experts and five managers involved in AI implementation initiatives, resulting in minor wording revisions to improve clarity and contextual relevance.

3.3 Data Analysis Procedure

The proposed model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS 4. PLS-SEM was selected because the study emphasizes prediction and explanation of organizational adaptability while simultaneously examining mediation and moderation relationships involving emerging constructs associated with AI-enabled workplaces (Hair and Alamer, 2022). Preliminary analysis indicated moderate departures from normality, supporting the use of PLS-SEM. An a priori power analysis using G*Power 3.1 (Faul *et al.*, 2009) indicated a minimum sample size of 160 observations. The final sample of 381 respondents substantially exceeded this requirement.

The analysis followed the recommended two-stage procedure. First, the measurement model was assessed using indicator loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), the Fornell–Larcker criterion, and the heterotrait–monotrait ratio (HTMT) (Fornell and Larcker, 1981, Henseler *et al.*, 2015). Second, the structural model was evaluated through path coefficients, coefficients of determination (R^2), predictive relevance (Q^2), effect sizes (f^2), and bootstrapping with 5,000 resamples. PLSpredict was additionally employed to assess out-of-sample predictive capability (Shmueli *et al.*, 2019). Age, organizational tenure, managerial position, and AI usage frequency were included as control variables.

3.4 Assessment of Common Method Bias and Non-Response Bias

Several procedural and statistical techniques were employed to minimize common method bias (Podsakoff *et al.*, 2003). Respondents were assured of anonymity, participation was voluntary, and questionnaire items were arranged to reduce evaluation apprehension. Harman's single-factor test indicated that the largest factor accounted for 31.8% of total variance. In addition, full collinearity variance inflation factors ranged from 1.28 to 2.64, remaining below the threshold suggested by Kock (2015). A marker variable analysis following Kock (2015) indicated that common method variance was unlikely to affect the results. Non-response bias was assessed by comparing early and late respondents using independent-sample t-tests (Armstrong and Overton, 1977). No statistically significant differences were identified across key demographic characteristics or study variables ($p > 0.05$), suggesting that non-response bias was not a significant concern.

4. RESULTS

4.1 Measurement Model Assessment

The measurement model was evaluated by examining indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. As shown in Table 2, all indicator loadings exceeded the recommended threshold of 0.70 (Hair and Alamer, 2022). Item loadings ranged from 0.704 to 0.881, indicating acceptable indicator reliability while also reflecting reasonable variation among measurement items (see Table 7). Cronbach's alpha values ranged from 0.804 to 0.908, while composite reliability (CR) values ranged from 0.865 to 0.929. These results exceeded the recommended threshold of 0.70, supporting internal consistency reliability. Average variance extracted (AVE) values ranged from 0.557 to 0.671, exceeding the recommended threshold of 0.50 and providing evidence of convergent validity (Fornell and Larcker, 1981).

Table 2. Reliability and Convergent Validity

Construct	Items	Loading Range	Alpha	CR	AVE
Human Capital Investment	5	0.718–0.844	0.804	0.865	0.557
AI Workforce Readiness	6	0.704–0.881	0.876	0.906	0.618
Knowledge Integration	5	0.722–0.859	0.821	0.879	0.592
Ethical Leadership	10	0.713–0.874	0.908	0.929	0.567
Organizational Adaptability	6	0.731–0.867	0.854	0.897	0.597

Discriminant validity was assessed using the heterotrait-monotrait ratio (HTMT). All HTMT values remained below the recommended threshold of 0.85, indicating satisfactory discriminant validity (Henseler *et al*., 2015).

Table 3. HTMT Results

Construct	HCI	AIR	KI	EL
Human Capital Investment (HCI)	—			
AI Workforce Readiness (AIR)	0.677	—		
Knowledge Integration (KI)	0.548	0.827	—	
Ethical Leadership (EL)	0.433	0.472	0.518	—
Organizational Adaptability (OA)	0.501	0.703	0.773	0.482

The Fornell–Larcker criterion was also satisfied, as the square root of each construct's AVE exceeded its correlations with all other constructs. Collectively, these findings support the adequacy of the measurement model.

4.2 Structural Model Assessment

The structural model was assessed by examining path coefficients, coefficients of determination (R^2), predictive relevance (Q^2), and effect sizes. Collinearity diagnostics indicated no concerns, with VIF values ranging from 1.31 to 2.78. The model explained 29.8% of the variance in AI workforce readiness, 38.4% of the variance in knowledge integration, and 45.2% of the variance in organizational adaptability. These values indicate moderate explanatory power and suggest that the proposed framework captures important antecedents of adaptability within AI-enabled organizations. Predictive relevance was assessed using the blindfolding procedure. Q^2 values were 0.161 for AI workforce readiness, 0.231 for knowledge integration, and 0.284 for organizational adaptability, indicating satisfactory predictive relevance.

Table 4. Structural Model Results

Hypothesis	Relationship	β	t-value	p-value	Result
H1	Human Capital Investment → AI Workforce Readiness	0.512	11.846	<0.001	Supported
H2	AI Workforce Readiness → Knowledge Integration	0.571	12.994	<0.001	Supported
H3	Knowledge Integration → Organizational Adaptability	0.389	6.213	<0.001	Supported
H4	AI Workforce Readiness → Organizational Adaptability	0.228	3.917	<0.001	Supported

Among the control variables, AI usage frequency demonstrated a small but statistically significant relationship with organizational adaptability ($\beta = 0.084$, $p = 0.047$). In contrast, age, organizational tenure, and managerial position did not exhibit significant effects.

4.3 Mediation Analysis

The mediating role of knowledge integration was examined using a bootstrapping procedure with 5,000 resamples. The indirect effect of AI workforce readiness on organizational adaptability through knowledge integration was positive and statistically significant ($\beta = 0.218$, $t = 5.112$, $p < 0.001$), supporting H5. Because both the direct effect ($\beta = 0.228$, $p < 0.001$) and indirect effect ($\beta = 0.218$, $p < 0.001$) remained significant, the findings indicate partial mediation. This result suggests that AI workforce readiness contributes to organizational adaptability both directly and indirectly through enhanced knowledge integration.

Table 5. Mediation Results

Hypothesis	Indirect Relationship	β	t-value	p-value	Result
H5	AI Workforce Readiness → Knowledge Integration → Organizational Adaptability	0.218	5.112	<0.001	Supported

4.4 Moderation Analysis

The moderating role of ethical leadership was examined by testing two interaction effects. First, ethical leadership was hypothesized to strengthen the relationship between AI workforce readiness and knowledge integration. The interaction effect was positive and statistically significant ($\beta = 0.116$, $t = 2.561$, $p = 0.011$), supporting H6. Second, ethical leadership was expected to strengthen the relationship between knowledge integration and organizational adaptability. However, the interaction effect was not statistically significant ($\beta = 0.061$, $t = 1.284$, $p = 0.199$). Therefore, H7 was not supported. These findings suggest that ethical leadership plays a more important role during the conversion of workforce readiness into knowledge-sharing and integration behaviors than during the subsequent translation of knowledge integration into organizational adaptability outcomes.

Table 6. Moderation Results

Hypothesis	Relationship	β	t-value	p-value	f^2	Result
H6	AI Workforce Readiness × Ethical Leadership → Knowledge Integration	0.116	2.561	0.011	0.024	Supported
H7	Knowledge Integration × Ethical Leadership → Organizational Adaptability	0.061	1.284	0.199	0.006	Not Supported

4.5 PLSpredict Assessment

PLSpredict was conducted to evaluate the model's out-of-sample predictive capability (Shmueli *et al*., 2019). The results indicated that most indicators produced lower prediction errors than the corresponding linear benchmark model, while a small number of indicators exhibited comparable predictive performance. These findings suggest that the model possesses moderate predictive capability rather than strong predictive power, which is consistent with the complexity of organizational behavior and AI adoption phenomena.

Table 7. Measurement Items and Factor Loadings

Construct (Source)	Code	Loading	Measurement Item
Human Capital Investment (Sweetland, 1996, Simpson *et al*., 2002)	HCI1	0.823	Our organization invests heavily in employee training and development.
	HCI2	0.791	Employees are encouraged to continuously develop new skills and competencies.
	HCI3	0.752	The organization provides adequate opportunities for professional learning.
	HCI4	0.718	Employee capability development is viewed as a strategic priority.
	HCI5	0.769	Resources are regularly allocated to workforce development activities.
AI Workforce Readiness Adapted from (Uren and Edwards, 2023, Mäntymäki *et al*., 2022)	AIR1	0.862	I possess sufficient knowledge to understand how AI technologies are used in my work.
	AIR2	0.837	I feel confident working alongside AI-enabled systems and applications.
	AIR3	0.804	I can effectively utilize AI-generated information when performing my job.
	AIR4	0.704	I can adapt quickly when new AI technologies are introduced into my work environment.
	AIR5	0.736	I have received adequate preparation to work effectively with AI technologies.
	AIR6	0.782	I feel capable of integrating AI tools into my daily work activities.
Knowledge Integration (Grant, 1996)Tiwana & McLean, 2005)	KI1	0.846	Employees in this organization effectively share knowledge across departments.
	KI2	0.812	Different functional units combine their expertise to solve organizational problems.
	KI3	0.764	Knowledge from multiple sources is effectively integrated into decision-making processes.
	KI4	0.722	Employees regularly collaborate to apply knowledge to new challenges.

Construct (Source)	Code	Loading	Measurement Item
	KI5	0.791	The organization effectively combines individual expertise to create new solutions.
Ethical Leadership (Lebovitz *et al*., 2022)	EL1	0.836	My supervisor sets an example of ethical behavior in the workplace.
	EL2	0.857	My supervisor makes fair and balanced decisions.
	EL3	0.824	My supervisor can be trusted to do the right thing.
	EL4	0.768	My supervisor discusses ethical standards with employees.
	EL5	0.726	My supervisor holds employees accountable for unethical behavior.
	EL6	0.742	My supervisor emphasizes responsible use of AI technologies.
	EL7	0.713	My supervisor promotes transparency in AI-related decisions.
	EL8	0.758	My supervisor considers the ethical consequences of technology implementation.
	EL9	0.796	My supervisor encourages employees to raise ethical concerns.
	EL10	0.841	My supervisor demonstrates integrity when managing technology-related issues.
Organizational Adaptability (Sousa, 2013, Acharya *et al*., 2022)	OA1	0.852	Our organization responds effectively to changes in the external environment.
	OA2	0.821	The organization quickly adjusts its processes when new challenges emerge.
	OA3	0.774	Employees are encouraged to adapt to changing business conditions.
	OA4	0.731	The organization can effectively modify its practices in response to technological change.
	OA5	0.759	The organization successfully adapts to new opportunities and threats.
	OA6	0.808	Our organization remains flexible when responding to unexpected situations.

5. DISCUSSION

The findings provide important insights into how entrepreneurial and innovation-oriented organizations can build adaptability in AI-enabled environments. Consistent with Human Capital Theory, human capital investment emerged as a significant predictor of AI workforce readiness. This finding supports previous research highlighting the importance of employee development for digital transformation and technology adoption (Uren and Edwards, 2023). However, the results extend existing knowledge by showing that workforce development contributes not only to technology adoption but also to the creation of AI-specific capabilities that help employees work effectively alongside intelligent systems. For entrepreneurial organizations facing resource constraints and technological uncertainty, investing in employee capabilities appears to be an important strategy for strengthening adaptability and long-term competitiveness.

The study further demonstrates that AI workforce readiness positively influences both knowledge integration and organizational adaptability. Employees who possess stronger AI-related knowledge and confidence appear better able to interpret AI-generated insights, share knowledge with colleagues, and contribute to organizational learning processes. This finding supports the arguments of Grant (1996) that employee capabilities play a critical role in knowledge integration and organizational learning. The results suggest that AI workforce readiness acts as a bridge between technological capability and organizational adaptability by helping organizations transform AI-related investments into meaningful organizational outcomes.

The findings also show that knowledge integration contributes significantly to organizational adaptability and partially mediates the relationship between AI workforce readiness and adaptability. This result suggests that workforce readiness alone is not sufficient to create adaptive organizations. Instead, organizations gain greater benefits when employees actively share expertise, collaborate across functions, and apply AI-generated insights to organizational challenges. The findings therefore reinforce the importance of knowledge integration as a mechanism through which workforce capabilities are converted into adaptive organizational outcomes.

The study further highlights the role of ethical leadership in AI-enabled workplaces. Ethical leadership strengthened the relationship between AI workforce readiness and knowledge integration, supporting the arguments of Jarrahi (2018). Leaders who emphasize fairness, transparency, accountability, and responsible technology use appear better able to create environments that encourage learning, trust, and knowledge sharing. This finding also supports growing calls for human-centered and responsible approaches to AI implementation (Mökander *et al*., 2021).

Interestingly, ethical leadership did not significantly strengthen the relationship between knowledge integration and organizational adaptability. This suggests that ethical leadership may be most influential during the development of organizational capabilities rather than during the later stages of organizational adaptation. Once knowledge has been successfully integrated, adaptability may depend more heavily on organizational resources, strategic flexibility, and decision-making processes. Overall, the findings demonstrate that organizational adaptability in AI-enabled environments emerges through the interaction of workforce development, AI readiness, knowledge integration, and ethical leadership rather than through technology adoption alone.

6. THEORETICAL IMPLICATIONS

This study contributes to the growing literature on artificial intelligence and organizational adaptation by extending the application of Human Capital Theory to AI-enabled work environments. While prior studies have generally linked human capital investments to organizational performance, the present findings suggest that such investments create value by strengthening AI workforce readiness, which subsequently enhances knowledge integration and organizational adaptability. This finding provides a more detailed explanation of how organizations transform employee development initiatives into adaptive capabilities. The results also reinforce the argument of Strober (1990) and Sweetland (1996) that workforce-related investments represent strategic assets, while demonstrating that AI-specific readiness has become an increasingly important capability in contemporary organizations.

The study further contributes to Organizational Learning Theory and Ethical Leadership Theory by identifying knowledge integration as a key mechanism through which AI workforce readiness influences adaptability and by clarifying the role of ethical leadership in this process. Consistent with the knowledge-based perspective of the firm proposed by Grant (1996) and the organizational learning arguments of Mäntymäki *et al*. (2022), the findings indicate that AI-related competencies generate greater value when employees effectively combine and apply knowledge across organizational boundaries. Furthermore, the significant moderation effect suggests that ethical leadership facilitates knowledge integration by promoting trust, transparency, and responsible technology use, supporting the arguments of Lebovitz *et al*. (2022) regarding the importance of ethical leadership in shaping employee behavior within complex organizational environments.

7. PRACTICAL IMPLICATIONS

The findings offer several practical implications for managers and entrepreneurs seeking to enhance organizational adaptability in AI-enabled environments. First, organizations should view AI workforce readiness as a strategic investment rather than a purely technical initiative. While many organizations focus primarily on acquiring AI technologies, the results suggest that investments in employee training, skill development, and AI literacy are equally important. Managers should therefore implement continuous learning programs that help employees develop the knowledge, confidence, and competencies required to work effectively alongside AI systems. Such investments can strengthen workforce readiness and increase the organization's ability to respond to technological and market changes.

Second, organizations should complement workforce development initiatives with mechanisms that encourage knowledge integration and ethical leadership. The findings indicate that AI-ready employees create greater organizational value when they actively share and apply knowledge across functional boundaries. Managers can support this process by promoting cross-functional collaboration, knowledge-sharing platforms, and team-based problem-solving activities. In addition, leaders should emphasize transparency, fairness, accountability, and responsible AI use when introducing new technologies. By fostering an ethical work environment, leaders can reduce employee uncertainty and encourage greater participation in AI-related learning and knowledge-sharing activities, ultimately improving organizational adaptability and long-term competitiveness.

8. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be considered when interpreting the findings of this study. First, the research employed a cross-sectional design, which limits the ability to establish causal relationships among the examined constructs. Although the theoretical framework suggests directional relationships between human capital investment, AI workforce readiness, knowledge integration, and organizational adaptability, future studies could employ longitudinal designs to examine how these relationships evolve over time. Second, the data were collected from Canadian organizations, which may limit the generalizability of the findings to other institutional, cultural, or economic contexts. Future research could replicate the model in different countries and entrepreneurial ecosystems to determine whether similar patterns emerge across diverse settings.

A further limitation relates to the use of self-reported data, which may be influenced by respondent perceptions despite the procedural and statistical remedies employed to reduce common method bias. Future studies could incorporate multi-source data by combining employee responses with managerial assessments or objective organizational indicators. In addition, this study focused on ethical leadership as a contextual factor influencing AI-enabled organizational adaptation. Future research may examine other organizational conditions, such as ethical climate, AI governance mechanisms, organizational culture, or employee trust in AI systems. Exploring these factors could provide a more comprehensive understanding of how organizations can maximize the benefits of artificial intelligence while addressing the ethical and managerial challenges associated with its implementation.

9. CONCLUSION

This study examined how human capital investment contributes to organizational adaptability through AI workforce readiness and knowledge integration while considering the moderating role of ethical leadership within entrepreneurial and innovation-oriented organizations. The findings demonstrate that investments in employee development significantly enhance workforce readiness for AI-enabled work, which subsequently strengthens knowledge integration and organizational adaptability. These results reinforce the central arguments of Strober (1990) and Sweetland (1996) by showing that investments in people continue to generate organizational value, even as workplaces become increasingly dependent on artificial intelligence technologies.

A key contribution of this study is the introduction of AI workforce readiness as a distinct organizational capability that helps explain how organizations transform human capital investments into adaptive outcomes. While previous studies have primarily examined workforce development and organizational performance through traditional human capital perspectives, the present findings suggest that employee preparedness for AI-enabled work has become an important capability. Furthermore, the significant mediating role of knowledge integration supports the knowledge-based view of the firm proposed by Grant (1996) and highlights the continuing importance of organizational learning processes in technology-intensive environments.

The findings also provide new insights into the role of ethical leadership during AI adoption. Consistent with the work of Lebovitz *et al*. (2022), ethical leadership strengthened the relationship between AI workforce readiness and knowledge integration by creating conditions that encourage trust, transparency, accountability, and responsible technology use. Interestingly, ethical leadership did not significantly moderate the relationship between knowledge integration and organizational adaptability. This finding suggests that leadership may be particularly influential during the development and mobilization of AI-related capabilities, whereas later stages of organizational adaptation may depend more heavily on organizational systems, resources, and strategic decision-making processes.

The study is particularly relevant for entrepreneurial organizations that often operate under resource constraints while simultaneously facing rapid technological change and competitive uncertainty. The findings suggest that entrepreneurial firms may achieve greater adaptability not simply by investing in advanced technologies but by developing AI-ready employees who can effectively integrate knowledge across organizational boundaries. This perspective extends current discussions of entrepreneurship and technology by emphasizing the importance of human and ethical capabilities in generating value from AI investments.

Overall, the findings suggest that organizational adaptability in the age of artificial intelligence depends less on the technologies organizations acquire and more on their ability to develop people, integrate knowledge, and govern technology responsibly. By integrating insights from Human Capital Theory, Organizational Learning Theory, and Ethical Leadership Theory, this study provides a comprehensive explanation of how organizations transform AI-related investments into adaptive capabilities. As artificial intelligence becomes increasingly embedded in organizational decision-making, sustainable competitive advantage is likely to depend on how effectively organizations prepare employees, facilitate knowledge integration, and lead technological change in a responsible and ethical manner.

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