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AI-Driven Leadership and the Innovation Paradox: More Innovation Activity, Lower Innovation Quality

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Abstract

Artificial intelligence is increasingly reshaping leadership practices and organizational decision-making, yet its implications for innovation outcomes remain insufficiently understood. Existing research largely assumes that AI-driven leadership enhances innovation while paying limited attention to its effects on the human capabilities required to sustain innovation quality. This study examines whether AI-driven leadership creates an innovation paradox in which increased innovation activity is accompanied by declining innovation quality. Cross-sectional self-reported data were collected from 2990 employees working in digitally intensive organizational environments. A split-sample EFA–CFA validation procedure was applied, and the proposed framework was tested using structural equation modeling. AI-Driven Leadership was positively associated with Innovation Activity and Human Capital Erosion. Human Capital Erosion was negatively associated with Innovation Quality, while Innovation Activity was also negatively associated with Innovation Quality. Mediation analysis indicated a substantial indirect association between AI-Driven Leadership and Innovation Quality through Human Capital Erosion. Organizational Learning Erosion did not significantly influence Innovation Quality and did not mediate the proposed relationships. The findings suggest an innovation paradox whereby AI-driven leadership is associated with higher innovation activity while simultaneously being associated with greater human capital erosion, potentially reducing innovation quality. Accordingly, preserving human capital may be important for sustaining innovation quality in AI-enabled organizations.

Keywords: AI-driven leadership; innovation paradox; human capital erosion; innovation activity; innovation quality; algorithmic management

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1. Introduction

Artificial intelligence (AI) is rapidly transforming organizational decision-making, operational coordination, and resource management across digitally intensive environments [1–3]. As AI systems become increasingly embedded in managerial processes, organizations are using algorithmic recommendations, predictive analytics, and automated decision-support tools to improve efficiency, responsiveness, and innovation performance [4–6]. Consequently, AI-driven leadership has emerged as an important organizational capability that shapes how firms allocate resources, process information, and respond to complex and dynamic environments [7,8]. Existing research has largely emphasized the positive consequences of AI adoption, including enhanced decision quality, improved operational performance, accelerated innovation processes, and increased organizational agility [9,10]. Within this perspective, AI-enabled leadership is commonly portrayed as a mechanism that strengthens organizational capabilities by improving information processing and supporting more effective strategic and operational decisions [11]. However, this predominantly technology-centric view provides only a partial understanding of how AI-driven leadership influences organizational outcomes [12].

A critical limitation of the existing literature is that it largely assumes that AI-enabled leadership improves innovation by enhancing information-processing capacity, decision speed, and operational efficiency [13–15]. Consequently, innovation outcomes are typically evaluated through indicators such as innovation volume, implementation speed, or organizational performance [16]. However, considerably less attention has been devoted to whether the same mechanisms that stimulate innovation activity may simultaneously undermine the human capabilities required to sustain innovation quality [17]. As a result, the possibility that AI-driven leadership is associated with an innovation paradox—higher innovation activity accompanied by lower innovation quality—remains insufficiently explored [18–20]. This issue is particularly important because innovation activity and innovation quality are not necessarily synonymous [21].

Organizations may generate a growing number of innovations while simultaneously experiencing declines in originality, strategic relevance, long-term value, or problem-solving effectiveness [22,23]. Extensive reliance on AI-supported decision systems may reduce opportunities for employees to develop expertise, exercise judgment, and engage in complex problem-solving, thereby weakening the human capital that underpins high-quality innovation [24]. In the present study, human capital erosion is conceptualized as a gradual decline in employees' capacity to develop, maintain, and apply knowledge, expertise, critical judgment, and problem-solving capabilities in AI-supported work environments. As such, it extends beyond related concepts such as deskilling, automation dependence, or reduced autonomy by capturing the broader deterioration of human capabilities that support sustained innovation quality.

A second limitation concerns the treatment of innovation as a largely homogeneous construct [25]. Previous research has typically focused on innovation generation, innovation adoption, or innovation performance without distinguishing between the quantity of innovation-related activity and the quality of innovation outcomes [26,27]. This distinction is increasingly important in AI-enabled environments, where organizations may be capable of generating innovations at unprecedented speed while simultaneously facing challenges related to knowledge development, expertise retention, and long-term capability building [28–30]. Furthermore, limited attention has been devoted to the mechanisms that connect AI-driven leadership with innovation outcomes. Although human capital and organizational learning are widely recognized as strategic organizational resources [31–33], little is known about whether AI-centered managerial systems influence innovation primarily through changes in employee capabilities, collective learning processes, or both. Consequently, the pathways through which AI-driven leadership shapes innovation quality remain insufficiently understood.

To address these gaps, this study develops and empirically tests a theoretical framework linking AI-Driven Leadership, Human Capital Erosion, Organizational Learning

Erosion, Innovation Activity, and Innovation Quality. Rather than examining whether AI-driven leadership simply increases innovation, the proposed framework explains why higher levels of innovation activity may coexist with lower innovation quality and identifies the organizational mechanisms through which this paradox may emerge. Rather than assuming that AI adoption uniformly improves organizational outcomes [34], the proposed model examines whether the benefits of AI-enabled leadership are accompanied by unintended consequences affecting critical organizational resources. The same leadership practices that accelerate innovation activity through enhanced automation, analytics, and decision support may simultaneously weaken the human expertise, judgment, and capability development required to sustain the long-term effectiveness of innovation outcomes [35,36].

Accordingly, the central research question guiding this study is as follows:

RQ: *Does AI-driven leadership create an innovation paradox in which increased innovation activity is accompanied by declining innovation quality, and to what extent can this relationship be explained by human capital erosion and organizational learning erosion?*

The objective of this study is to examine the mechanisms through which AI-driven leadership influences innovation quality. Specifically, the study investigates whether human capital erosion and organizational learning erosion explain how AI-enabled leadership affects the quality of innovation outcomes. In doing so, the study seeks to provide a more comprehensive understanding of how technological leadership reshapes critical organizational resources in digitally intensive environments.

The study makes three primary contributions. First, it addresses an important gap in the AI leadership and innovation literature by distinguishing between innovation activity and innovation quality, arguing that increased innovation output does not necessarily translate into higher-quality innovation outcomes. In doing so, it develops and empirically tests the concept of an AI-driven innovation paradox, whereby leadership practices associated with AI adoption may simultaneously support innovation activity while being associated with lower innovation quality. Second, it advances the literature by examining human capital erosion as the primary explanatory mechanism linking AI-driven leadership and innovation quality, thereby extending existing technology-centric explanations toward the role of organizational capabilities. Third, it evaluates whether organizational learning erosion represents an additional explanatory pathway, providing a more comprehensive understanding of the mechanisms through which AI-driven leadership shapes innovation outcomes.

2. Literature Review and Hypothesis Development

2.1. AI-Driven Leadership and Innovation Activity

Artificial intelligence is increasingly becoming an integral component of managerial decision-making and organizational coordination [37]. Although leadership has traditionally been examined through competing theoretical approaches that emphasize influence, coordination, authority, motivation, and leader–follower relations [38], AI-enabled environments require this concept to be reconsidered in a new light, such as algorithmic decision support and human–technology coordination. AI-driven leadership refers to leadership practices in which human leaders integrate intelligent systems, predictive analytics, algorithmic recommendations, and automated decision-support mechanisms into managerial decision-making and organizational coordination [39,40]. Accordingly, the concept does not refer to the replacement of managerial judgment by algorithms but rather to the use of AI as a decision-support mechanism that augments human leadership. By enhancing information-processing capacity and reducing decision latency, these AI-enabled decision-support systems enable organizations to identify opportunities more rapidly and respond more effectively to changing environmental conditions [41].

The dynamic capabilities perspective suggests that organizations capable of sensing opportunities, processing information efficiently, and reallocating resources effectively are more likely to generate innovation-related outcomes [42,43]. AI technologies can strengthen these capabilities by improving the speed and accuracy of managerial decisions, facilitating experimentation, and supporting the implementation of new ideas. Previous studies have similarly argued that AI adoption contributes to organizational agility, innovation generation, and improved strategic responsiveness [44,45].

As organizations increasingly integrate AI into leadership processes, innovation activity is expected to increase due to faster information flows, improved analytical capabilities, and enhanced decision support.

H1. *AI-Driven Leadership positively influences Innovation Activity.*

2.2. AI-Driven Leadership and Human Capital Erosion

While AI technologies offer substantial operational advantages, growing concerns have emerged regarding their long-term effects on employee capabilities [46–48]. Human capital theory emphasizes that organizational competitiveness depends on the accumulation, utilization, and development of employee knowledge, skills, and expertise [49]. Building on human capital theory and prior research on automation, expertise development, and AI-supported decision-making [50–53], the present study conceptualizes Human Capital Erosion as a unidimensional construct representing the gradual deterioration of employees' capacity to develop, maintain, and apply knowledge, expertise, critical judgment, and higher-order problem-solving capabilities in AI-supported work environments. Human Capital Erosion may be reflected in reduced critical thinking, diminished initiative, slower skill development, increased reliance on AI-supported decision-making, and lower confidence in independent judgment. These indicators are conceptualized as manifestations of a single latent construct rather than distinct theoretical dimensions [49–53].

Accordingly, Human Capital Erosion extends beyond related concepts such as deskilling, automation dependence, reduced autonomy, or capability loss by capturing the broader decline in the human capabilities that underpin sustained organizational innovation and organizational adaptability [46,48,49,53]. However, extensive reliance on automated systems may reduce opportunities for employees to engage in complex problem-solving, independent judgment, and experiential learning. Research on automation and algorithmic decision-making suggests that technological systems may substitute for certain cognitive activities traditionally performed by employees, potentially leading to skill degradation and reduced capability development over time [50]. As AI systems assume increasing responsibility for information processing and decision support, employees may become less involved in activities that contribute to expertise formation and knowledge accumulation [51–53]. Consequently, organizations characterized by stronger AI-driven leadership may be more likely to exhibit higher levels of perceived human capital erosion, as employees become increasingly dependent on technological systems.

H2. *AI-Driven Leadership positively influences Human Capital Erosion.*

2.3. Human Capital Erosion and Innovation Quality

Consistent with the conceptualization adopted in this study, Human Capital Erosion reflects a broad decline in the human capabilities that support sustained organizational innovation. Accordingly, innovation quality depends not only on technological resources but also on the availability of employee expertise, creativity, judgment, and problem-solving capabilities [54,55]. Human capital has long been recognized as a fundamental determinant of organizational innovation because it provides the knowledge base required for developing valuable and sustainable innovations [49,56]. When employee capabilities deteriorate, organizations may face difficulties in generating, evaluating, and refining innovations characterized by originality, strategic relevance, and long-term value creation [57–59]. As a result, the erosion of human capital is expected to negatively affect innovation quality.

H3. *Human Capital Erosion negatively influences Innovation Quality.*

2.4. Innovation Activity and Innovation Quality

The innovation literature frequently assumes a positive relationship between innovation effort and innovation outcomes [60,61]. However, increased innovation activity does not necessarily translate into higher innovation quality [62]. Organizations pursuing rapid experimentation and accelerated implementation may prioritize speed and output volume at the expense of refinement, knowledge integration, and strategic coherence. March [63] argued that organizations often face tensions between exploration and exploitation. Excessive emphasis on experimentation and novelty may reduce attention devoted to evaluation, learning, and improvement processes [64,65]. Consequently, high levels of innovation activity may generate numerous initiatives while reducing the attention devoted to evaluation and refinement [66].

AI-enabled environments may further challenge this assumption. By accelerating experimentation, implementation, and decision-making processes, AI-driven organizations may generate larger numbers of innovation initiatives while devoting less attention to reflection, evaluation, capability development, and knowledge integration [67,68]. Under such conditions, innovation quantity and quality may follow different trajectories. Consequently, innovation activity and innovation quality should be viewed as distinct dimensions of innovation performance [69–71]. Innovation activity reflects the quantity, frequency, and pace of innovation efforts, whereas innovation quality captures the strategic value and long-term effectiveness of innovation outcomes.

This distinction provides the theoretical basis for the innovation paradox proposed in this study. AI-enabled organizations may increase the volume and speed of innovation by accelerating information processing, experimentation, and decision-making. However, the same conditions may simultaneously reduce opportunities for critical reflection, expertise development, and knowledge integration, which are essential for generating innovations characterized by originality, strategic relevance, and long-term value. Consequently, AI-driven organizations may produce a greater quantity of innovation while achieving lower levels of perceived innovation quality, thereby giving rise to the innovation paradox examined in this study.

H4. *Innovation Activity negatively influences Innovation Quality.*

2.5. The Mediating Role of Human Capital Erosion

The innovation paradox proposed in this study suggests that the association between AI-driven leadership and innovation quality may be explained by changes in organizational capabilities rather than by technology itself [72]. Human capital represents a particularly important mechanism linking AI-driven leadership and innovation quality [73,74]. If AI-centered leadership contributes to capability erosion, the benefits of increased innovation activity may be offset by declines in innovation quality [75,76]. Consequently, the negative influence of AI-driven leadership on innovation quality is expected to operate indirectly through Human Capital Erosion.

H5. *AI-Driven Leadership negatively influences Innovation Quality through Human Capital Erosion.*

2.6. Organizational Learning Erosion and Sequential Mediation

Organizational learning represents a critical mechanism through which firms acquire, transfer, store, and apply knowledge [77,78]. AI-centered decision environments may reduce opportunities for knowledge exchange, collective reflection, and experiential learning, thereby weakening organizational learning processes [79]. If AI-driven leadership contributes to the erosion of organizational learning, organizations may become less capable of adapting, refining innovations, and maintaining organizational memory [80]. Such deterioration could negatively affect innovation quality by limiting the organization's ability to accumulate and apply knowledge over time.

H6. *AI-Driven Leadership positively influences Organizational Learning Erosion.*

H7. *Organizational Learning Erosion negatively influences Innovation Quality.*

Furthermore, human capital erosion may contribute to broader declines in organizational learning processes [81]. Reduced expertise and lower levels of cognitive engagement may weaken knowledge sharing, collective problem-solving, and organizational memory, ultimately affecting innovation quality [82].

H8. *AI-Driven Leadership negatively influences Innovation Quality through the sequential mediation of Human Capital Erosion and Organizational Learning Erosion.*

Figure 1 presents the conceptual framework and hypothesized relationships examined in this study.

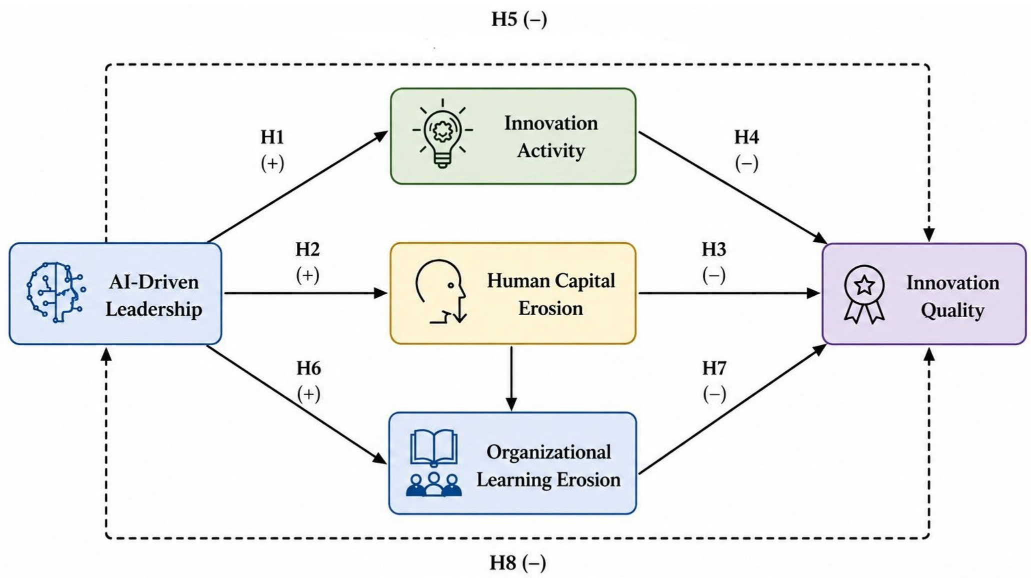

Figure 1. Conceptual framework of the innovation paradox: the effects of AI-driven leadership on innovation quality through innovation activity, human capital erosion, and organizational learning erosion.

3. Materials and Methods

The data were collected between January 2026 and June 2026 using the Prolific academic research platform [83,84]. Prolific was selected because it enables the application of predefined participant screening criteria, provides access to diverse working populations, and incorporates participant identification mechanisms that prevent duplicate participation. Each respondent possesses a unique Prolific identification number, ensuring that individuals can participate only once in the study. Prior to accessing the questionnaire, participants were required to satisfy several screening criteria implemented through Prolific's pre-screening system. First, respondents had to be currently employed in an organization. Second, they were required to use digital systems as part of their work activities. Third, participants had to report exposure to AI-based tools or systems, including automation technologies, recommendation systems, or decision-support applications. Fourth, their job roles had to involve analytical thinking, problem-solving, or decision-making responsibilities. Finally, respondents were required to indicate involvement in developing, improving, or implementing ideas, processes, services, or solutions within their organizations. Only individuals meeting all screening criteria were allowed to participate in the study.

These procedures were implemented to ensure that respondents possessed sufficient exposure to AI-enabled organizational environments and innovation-related activities, thereby increasing the relevance of the collected data to the study objectives. Participants received monetary compensation through the Prolific platform in accordance with Prolific's standard payment policies. The final sample comprised 2990 respondents employed in organizations characterized by varying levels of digitalization and AI integration. A total of 3170 responses were initially collected. Following data screening procedures, 180 responses (5.7%) were excluded because of incomplete questionnaires or failure to satisfy data quality requirements. The final sample comprised 2990 respondents employed in organizations characterized by varying levels of digitalization and AI integration.

The gender structure was relatively balanced, with men representing a slightly larger share of the sample (54.7%) than women (45.3%), reducing the likelihood of substantial gender-related sampling bias. The age distribution indicates that the sample was predominantly composed of economically active and professionally established employees. More than half of all respondents were between 25 and 44 years of age, while fewer than one in ten participants belonged to the oldest age category (55+). This profile is particularly relevant for the present study because employees in these age groups are typically among the most exposed to digital transformation initiatives and AI-supported work processes. The educational profile of the respondents was notably high. More than three-quarters of the sample possessed at least a bachelor's degree, while nearly one in ten respondents held a doctoral degree. Such a distribution suggests that the sample consisted largely of highly educated professionals capable of evaluating organizational leadership practices, technological adoption, and innovation-related processes from informed and experience-based perspectives.

Professional experience was broadly distributed across career stages, although respondents with four to seven years of work experience represented the largest group. At the same time, substantial proportions of participants reported both shorter and longer employment histories, indicating that the sample captured perspectives from employees at different stages of professional development. This diversity strengthens the representativeness of organizational perceptions regarding AI-driven leadership and innovation processes. The sectoral composition was strongly aligned with the objectives of the study. The largest proportion of respondents worked in IT and data-oriented industries, while finance, consulting, marketing, digital services, research and development, and service-sector activities were also well represented. Collectively, these sectors are characterized by intensive use of digital technologies and increasing reliance on AI-enabled systems, making them particularly suitable contexts for examining the organizational consequences of AI-oriented leadership.

A similarly heterogeneous distribution emerged with respect to job functions. Analytical and technical roles constituted the largest category, followed by managerial and strategic positions, while creative and operational functions were also substantially represented. The presence of respondents occupying both decision-making and execution-oriented roles provides a comprehensive view of organizational dynamics associated with digital transformation and innovation. Importantly, the sample demonstrated a high level of exposure to artificial intelligence technologies. Nearly 60% of respondents reported frequent or very frequent use of AI systems in their work activities, while fewer than 10% indicated only rare use. This pattern confirms that the participants possessed sufficient direct experience with AI-enabled environments to provide meaningful assessments of leadership practices, capability development, and innovation outcomes associated with AI adoption. The organizational context was also diverse. Respondents were employed in firms ranging from micro-enterprises to large organizations with more than 1000 employees. Nevertheless, medium-sized organizations constituted the largest segment of the sample. Such variation enhances the external validity of the study by ensuring that the findings are not limited to a particular organizational size category.

The sample reflects a highly educated, professionally experienced, and technologically engaged workforce operating across multiple knowledge-intensive sectors. The substantial prevalence of AI use, combined with the diversity of organizational contexts and professional roles, provides a suitable empirical basis for examining the relationships among AI-driven leadership, human capital erosion, organizational learning erosion, and innovation outcomes.

3.1. Measurement Instrument

The measurement instrument was developed by adapting and extending items from the literature on artificial intelligence, leadership, innovation, human capital, organizational learning, and technology-enabled organizational transformation. All items were measured using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). Item development was informed by prior research on AI-enabled decision-making and digital leadership [44,45], human capital and skill development in technology-intensive environments [49,50], innovation processes and dynamic capabilities [42,43], innovation outcomes and organizational effectiveness [56,63], and organizational learning and knowledge management [77,78].

The initial questionnaire consisted of 35 items designed to capture employee perceptions regarding the role of AI in leadership and decision-making, the effects of AI-supported work environments on employee capabilities, innovation-related activities and outcomes, and organizational learning processes. Accordingly, the Human Capital Erosion construct was operationalized as employees’ perceived deterioration in knowledge, expertise, critical thinking, initiative, confidence, and capability development associated with AI-enabled work environments, rather than as an objective measure of human capital depreciation. Similarly, Innovation Quality was operationalized as employees’ perceptions of the quality, strategic value, effectiveness, and long-term sustainability of innovation outcomes rather than objective organizational innovation performance indicators.

Because the underlying dimensional structure of these relationships has received limited empirical attention in the context of AI-driven organizational environments, the instrument was subjected to exploratory factor analysis to identify the latent structure emerging from the data. Items were retained if they demonstrated factor loadings of at least 0.50, exhibited no substantial cross-loadings, and were conceptually consistent with the emerging factor structure. Based on these criteria, nine items were removed during the EFA stage. The resulting factor structure, consisting of 26 retained items, was subsequently validated through confirmatory factor analysis and incorporated into the structural model. The final measurement model was therefore established through a sequential EFA–CFA procedure, ensuring construct validity and reliability prior to hypothesis testing. The complete list of initial measurement items, item codes, and their retention status following exploratory factor analysis is presented in Appendix A (Table A1).

3.2. Data Analysis

To enhance the robustness of the measurement validation process and reduce the risk of sample-specific results, the full sample (N = 2990) was randomly divided into two equal subsamples. The first subsample (n = 1495) was used for exploratory factor analysis (EFA), while the second subsample (n = 1495) was reserved for confirmatory factor analysis (CFA) and structural equation modeling (SEM). This split-sample validation procedure reduces the likelihood of sample-specific results and strengthens the robustness and generalizability of the measurement and structural models.

The EFA was conducted using Maximum Likelihood extraction with Oblimin rotation and Kaiser normalization. Prior to factor extraction, the suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. Factor retention decisions were based on eigenvalues greater than 1.0, factor loadings of at least 0.50, the absence of substantial cross-loadings, and conceptual consistency with the emerging factor structure. Items failing to satisfy these criteria were removed before proceeding to the confirmatory stage.

To assess the potential influence of common method bias, both Harman's single-factor test and a Common Latent Factor (CLF) analysis were performed. To assess the potential influence of non-response bias, a late-response bias analysis was conducted by comparing the first 25% and last 25% of valid respondents. Independent-samples t-tests revealed no statistically significant differences across the focal constructs (all $p > 0.05$), suggesting that non-response bias is unlikely to affect the findings. Harman's single-factor test examined whether a single latent factor accounted for the majority of covariance among the observed variables. Following the commonly accepted criterion, common method bias is considered unlikely if the first unrotated factor explains less than 50% of the total variance [85]. The CLF analysis provided an additional assessment by estimating a common latent factor loading on all observed indicators.

The measurement model identified through EFA was subsequently validated using CFA on the independent validation subsample. Model fit was evaluated using multiple goodness-of-fit indices, including the chi-square to degrees-of-freedom ratio (χ^2/df), the Comparative Fit Index (CFI), the Tucker–Lewis Index (TLI), the Incremental Fit Index (IFI), and the Root Mean Square Error of Approximation (RMSEA). The reliability and validity of the measurement model were assessed through composite reliability (CR), average variance extracted (AVE), the heterotrait–monotrait ratio (HTMT), and the Fornell–Larcker criterion.

Following validation of the measurement model, the proposed hypotheses were tested using structural equation modeling (SEM). Direct relationships among the latent constructs were estimated using maximum likelihood estimation. In addition, mediation effects were examined using bootstrap procedures with 5000 resamples and bias-corrected confidence intervals to evaluate the indirect effects proposed in the conceptual framework. The explanatory power of the model was assessed using the coefficient of determination (R^2) for all endogenous constructs. All statistical analyses were conducted using IBM SPSS Statistics version 28.0 and IBM SPSS AMOS version 28.0 (IBM Corp., Armonk, NY, USA).

4. Results

Prior to factor extraction, the adequacy of the EFA subsample (n = 1495) was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was 0.963, indicating a high level of sampling adequacy, while Bartlett's test was statistically significant (χ^2 = 20,645.458; df = 595; $p < 0.001$). These results confirmed the suitability of the data for exploratory factor analysis.

The exploratory factor analysis conducted on the EFA subsample (n = 1495) supported a five-factor solution, as shown in Table 1. Five factors exhibited eigenvalues greater than 1 and were therefore retained for further interpretation. Collectively, these factors accounted for 53.983% of the total variance. The first factor explained the largest proportion of variance (29.597%), while the remaining four factors contributed an additional 24.386% of explained variance. Following Maximum Likelihood extraction, the retained factors accounted for 46.319% of the common variance, indicating that the factor structure captured a substantial proportion of the shared variance among the observed variables. The results therefore provided empirical support for proceeding with the interpretation of the five-factor solution and the subsequent examination of item loadings.

Table 1. Total variance explained (EFA subsample, n = 1495).

Factor	Eigenvalue	% of Variance	Cumulative %
1	10.359	29.597	29.597
2	3.397	9.707	39.304
3	2.268	6.480	45.784
4	1.720	4.914	50.697
5	1.150	3.286	53.983

Extraction method: Maximum Likelihood.

The pattern matrix presented in Table 2 supported a clear five-factor structure. All retained items loaded strongly on their intended factors, with standardized loadings ranging from 0.593 to 0.690. No substantial cross-loadings were observed, indicating satisfactory factor distinctiveness and supporting the convergent and discriminant validity of the extracted dimensions. The resulting factor structure was consistent with the proposed conceptual framework and was therefore retained for subsequent confirmatory factor analysis.

Table 2. Pattern matrix of the retained five-factor solution (EFA subsample, n = 1495).

Item	AI-Driven Leadership	Organizational Learning Erosion	Innovation Quality	Innovation Activity	Human Capital Erosion
AI Guidance	0.649	−0.026	−0.019	−0.033	0.005
AI Validation	0.648	−0.039	0.013	−0.016	0.040
AI Priority	0.671	−0.016	−0.022	−0.043	−0.016
AI Centrality	0.641	0.022	−0.015	−0.027	0.038
Reduced Autonomy	0.679	0.002	−0.011	−0.052	−0.034
Thinking Decline	0.007	−0.002	−0.018	−0.052	0.632
Lower Initiative	0.067	0.013	0.014	0.050	0.652
Learning Slowdown	−0.065	−0.023	−0.009	−0.061	0.638
AI Dependency	0.011	−0.069	−0.046	−0.009	0.593
Expertise Reduction	0.010	−0.010	−0.007	−0.010	0.645
Confidence Loss	0.004	−0.019	0.010	−0.030	0.664
Idea Frequency	0.044	0.016	−0.041	−0.647	−0.015

Table 2. *Cont.*

Item	AI-Driven Leadership	Organizational Learning Erosion	Innovation Quality	Innovation Activity	Human Capital Erosion
AI Acceleration	0.049	−0.026	−0.003	−0.662	−0.014
Experiment Support	0.042	−0.029	0.037	−0.690	−0.031
Active Development	−0.018	−0.012	−0.020	−0.679	0.024
Speed Increase	0.062	0.033	0.004	−0.626	0.024
Impact Value	−0.017	−0.016	0.631	0.027	−0.037
Long-Term Value	0.000	0.057	0.671	0.021	0.058
Quality Improvement	0.036	−0.045	0.634	0.034	−0.081
Problem Effectiveness	−0.013	0.015	0.667	−0.010	0.039
Sustainable Quality	−0.033	0.029	0.649	−0.038	−0.033
Experience Loss	0.003	−0.676	−0.003	−0.030	−0.042
AI Preference	−0.031	−0.660	−0.055	−0.024	−0.003
Training Weakness	−0.046	−0.659	−0.028	0.004	0.045
Collective Weakness	0.026	−0.641	0.047	0.002	0.022
Knowledge Transfer	−0.012	−0.613	0.025	0.010	0.090

Extraction method: Maximum Likelihood; Oblimin rotation with Kaiser normalization. Only primary loadings are presented.

Harman's single-factor test and a Common Latent Factor (CLF) analysis were conducted as additional assessments of common method bias. In the Harman single-factor assessment, the first unrotated factor explained 27.328% of the total variance. Furthermore, the inclusion of the CLF produced only minimal changes in the standardized factor loadings, with differences ranging from −0.10 to 0.08, well below the recommended threshold of 0.20. Accordingly, the results of both assessments suggest that common method bias is unlikely to pose a substantial threat to the validity of the study findings. As shown in Table 3, all constructs demonstrated satisfactory composite reliability, with CR values ranging from 0.784 to 0.833, exceeding the recommended threshold of 0.70. The AVE values ranged from 0.421 to 0.489. Although several AVE values were slightly below the conventional benchmark of 0.50, all constructs exhibited adequate composite reliability, suggesting acceptable convergent validity according to the criterion proposed by Fornell and Larcker. Overall, the measurement model demonstrated satisfactory internal consistency and acceptable convergent validity.

Table 3. Composite reliability (CR) and average variance extracted (AVE).

Construct	CR	AVE
AI-Driven Leadership	0.812	0.464
Organizational Learning Erosion	0.784	0.421
Innovation Quality	0.820	0.477
Innovation Activity	0.827	0.489
Human Capital Erosion	0.833	0.455

As shown in Table 4, all HTMT values ranged from 0.300 to 0.700 and remained below the recommended threshold of 0.85, providing evidence of satisfactory discriminant validity among the five constructs.

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Table 4. HTMT ratios.

Construct	AI-Driven Leadership	Organizational Learning Erosion	Innovation Quality	Innovation Activity	Human Capital Erosion
AI-Driven Leadership	–	0.420	0.520	0.700	0.650
Organizational Learning Erosion	0.420	–	0.430	0.300	0.650
Innovation Quality	0.520	0.430	–	0.450	0.680
Innovation Activity	0.700	0.300	0.450	–	0.420
Human Capital Erosion	0.650	0.650	0.680	0.420	–

The Fornell–Larcker assessment produced mixed results (Table 5). Although the square root of AVE exceeded most inter-construct correlations, several correlations were marginally higher than the corresponding AVE square roots. However, all HTMT values remained below the recommended threshold of 0.85, providing additional evidence of satisfactory discriminant validity.

Table 5. Fornell–Larcker criterion.

Construct	AI-Driven Leadership	Organizational Learning Erosion	Innovation Quality	Innovation Activity	Human Capital Erosion
AI-Driven Leadership	0.681	0.420	0.520	0.700	0.650
Organizational Learning Erosion	0.420	0.649	−0.430	0.300	0.650
Innovation Quality	0.520	−0.430	0.691	−0.450	−0.680
Innovation Activity	0.700	0.300	−0.450	0.699	0.420
Human Capital Erosion	0.650	0.650	−0.680	0.420	0.675

Diagonal elements represent the square root of AVE.

Confirmatory factor analysis was conducted using the validation subsample (n = 1495) obtained through the split-sample procedure. The results indicated a satisfactory fit of the measurement model to the observed data (χ^2/df = 1.32; RMSEA = 0.018; CFI = 0.992; TLI = 0.991; IFI = 0.992). The RMSEA value was below the recommended threshold of 0.08, while the incremental fit indices exceeded the commonly accepted criterion of 0.90. These findings support the adequacy of the proposed measurement structure and provide evidence for the validity of the retained factor solution.

Figure 2 presents the estimated structural relationships among the latent constructs. Overall, the results indicate that AI-Driven Leadership increased Innovation Activity and Human Capital Erosion, while Human Capital Erosion was associated with lower Innovation Quality.

The structural model results are presented in Table 6. AI-Driven Leadership demonstrated a significant positive effect on Innovation Activity ($\beta = 0.698$, $p < 0.001$), supporting H1. A significant positive relationship was also observed between AI-Driven Leadership and Human Capital Erosion ($\beta = 0.640$, $p < 0.001$), providing support for H2. Human Capital Erosion exhibited a significant negative effect on Innovation Quality ($\beta = -0.619$, $p < 0.001$), supporting H3. In addition, Innovation Activity was negatively associated with Innovation Quality ($\beta = -0.189$, $p < 0.001$), providing support for H4. In contrast, the relationship between AI-Driven Leadership and Organizational Learning Erosion was not statistically significant ($\beta = 0.003$, $p = 0.942$); therefore, H6 was not supported. Similarly, Organizational Learning Erosion did not significantly influence Innovation Quality ($\beta = 0.036$,

$p = 0.354$), leading to the rejection of H7. Furthermore, although not formally hypothesized, Human Capital Erosion exhibited a significant positive effect on Organizational Learning Erosion ($\beta = 0.650$, $p < 0.001$), indicating that declines in employee capabilities were associated with deterioration in organizational learning processes.

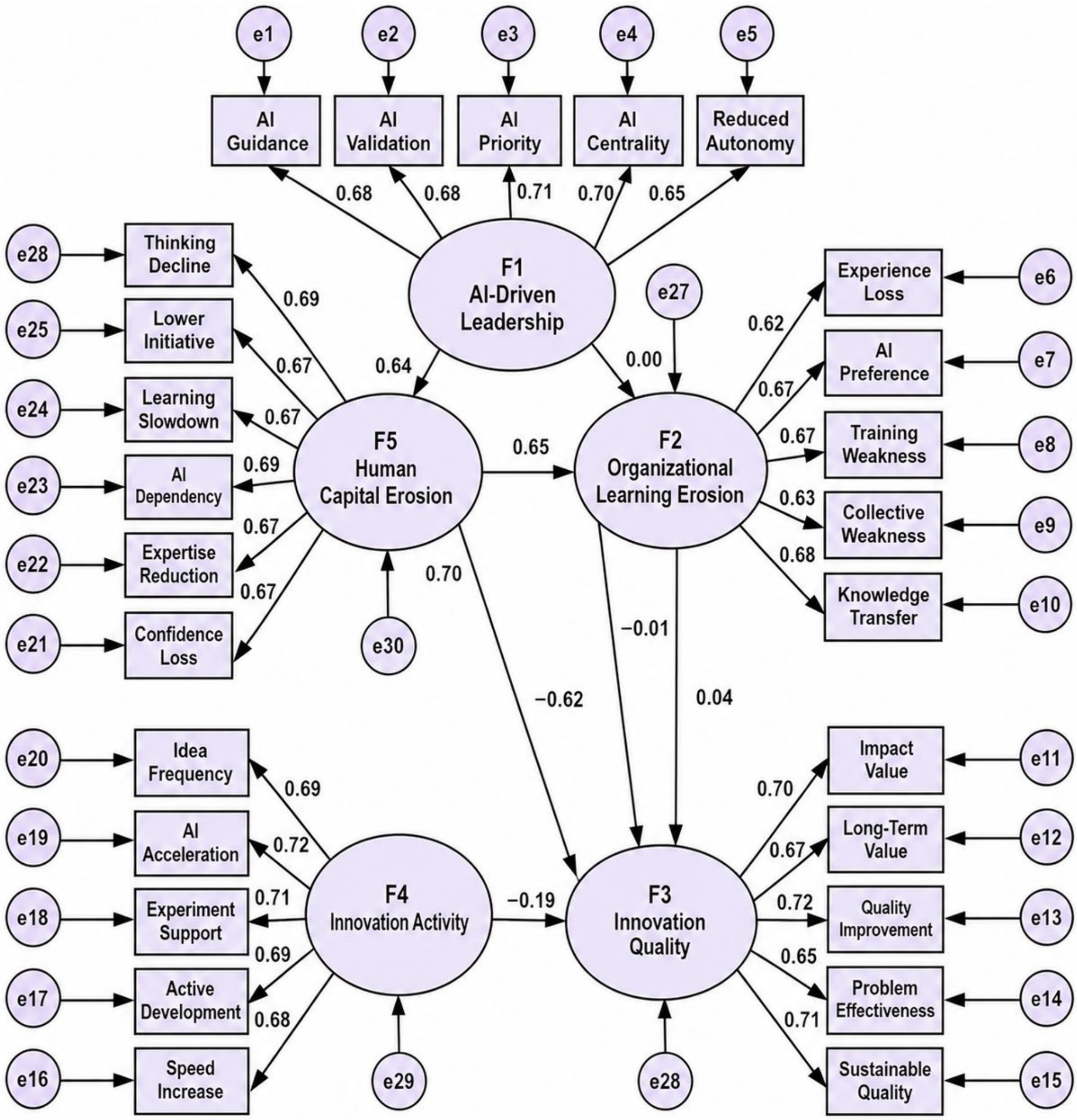

Figure 2. Structural equation modeling (SEM). Source: own elaboration.

Table 6. Structural model results.

Hypothesis	Path	β (Standardized)	SE	C.R.	*p*-Value	Result
H1	AI-Driven Leadership → Innovation Activity	0.698	0.035	18.284	<0.001	Supported
H2	AI-Driven Leadership → Human Capital Erosion	0.640	0.038	17.153	<0.001	Supported

Table 6. *Cont.*

Hypothesis	Path	β (Standardized)	SE	C.R.	*p*-Value	Result
H3	Human Capital Erosion → Innovation Quality	−0.619	0.058	−11.403	<0.001	Supported
H4	Innovation Activity → Innovation Quality	−0.189	0.049	−4.554	<0.001	Supported
H6	AI-Driven Leadership → Organizational Learning Erosion	0.003	0.034	0.073	0.942	Not Supported
H7	Organizational Learning Erosion → Innovation Quality	0.036	0.049	0.927	0.354	Not Supported

The mediation analysis results are presented in Table 7. The indirect effect of AI-Driven Leadership on Innovation Quality through Human Capital Erosion was statistically significant (β = −0.513), with the 95% confidence interval ranging from −0.565 to −0.470, thereby supporting H5. The direct effect of AI-Driven Leadership on Innovation Quality was negligible (β = −0.006), indicating an indirect-only mediation pattern. In contrast, the proposed sequential mediation pathway involving Human Capital Erosion and Organizational Learning Erosion was not supported. The indirect effect associated with this pathway was not statistically significant, and the corresponding confidence interval included zero. Therefore, H8 was not supported.

Table 7. Mediation effects (standardized).

Hypothesis	Path	Direct Effect	Indirect Effect	95% CI Lower	95% CI Upper	Mediation Type	Result
H5	AI-Driven Leadership → Human Capital Erosion → Innovation Quality	−0.006	−0.513	−0.565	−0.470	Indirect-only mediation	Supported
H8	AI-Driven Leadership → Human Capital Erosion → Organizational Learning Erosion → Innovation Quality	−0.006	n.s.	Includes 0	Includes 0	No mediation	Not Supported

Table 8 presents the explained variance (R^2) values for the endogenous constructs included in the structural model. AI-Driven Leadership accounted for 41.0% of the variance in Human Capital Erosion and 48.7% of the variance in Innovation Activity. Together, AI-Driven Leadership and Human Capital Erosion explained 42.1% of the variance in Organizational Learning Erosion. The highest level of explained variance was observed for Innovation Quality (R^2 = 0.560), indicating that Human Capital Erosion, Innovation Activity, Organizational Learning Erosion, and AI-Driven Leadership jointly accounted for 56.0% of its variance.

Table 8. Explained variance (R^2).

Endogenous Construct	R^2	Interpretation
Human Capital Erosion	0.410	Moderate explanatory power
Innovation Activity	0.487	Moderate explanatory power
Organizational Learning Erosion	0.421	Moderate explanatory power
Innovation Quality	0.560	Substantial explanatory power

5. Discussion

The findings suggest an innovation paradox associated with AI-driven leadership. While AI-oriented leadership practices were associated with higher levels of innovation activity, they were also associated with higher levels of perceived human capital erosion, which may reduce the human capabilities required to sustain innovation quality. This pattern of associations suggests that the organizational implications of AI-driven leadership may extend beyond operational efficiency and involve a potential tension between technological acceleration and capability preservation. Although AI-oriented management systems are often presented as mechanisms that simultaneously improve efficiency, innovation, and organizational performance, the present findings suggest that their organizational implications may extend beyond operational gains and be associated with changes in fundamental organizational capabilities.

5.1. The Innovation Paradox of AI-Driven Leadership

The findings suggest that the innovation paradox identified in this study is primarily associated with differences in human capital rather than direct technological effects. Although AI-oriented leadership was associated with increased innovation activity, its strongest indirect association with innovation quality was observed through perceived human capital erosion. This finding is consistent with the central premise of human capital theory, which posits that organizational performance ultimately depends on the knowledge, skills, expertise, and cognitive capabilities embedded within employees [49]. While intelligent systems can improve efficiency, automate routine decision processes, and accelerate information processing, they cannot replace the forms of judgment, creativity, contextual understanding, and critical reflection that underpin high-quality innovation. The findings therefore suggest that technological sophistication alone may be insufficient to sustain innovation quality when employees perceive declines in their knowledge, expertise, and cognitive capabilities.

The results are also consistent with broader concerns regarding the unintended consequences of automation and algorithmic decision-making. Previous research has suggested that extensive reliance on automated systems can reduce opportunities for learning-by-doing, weaken individual expertise, and diminish active engagement in complex cognitive tasks [50]. These arguments from the existing literature are consistent with the pattern observed in the present study, whereby higher innovation activity was associated with higher perceived human capital erosion and lower perceived innovation quality.

An equally important finding is that innovation activity and innovation quality appear to represent distinct organizational outcomes rather than different manifestations of the same phenomenon. This distinction may help explain why AI-enabled organizations may simultaneously demonstrate higher levels of innovation output while experiencing declines in the originality, strategic relevance, or long-term value of those innovations. Consequently, evaluating innovation exclusively through activity-based indicators may provide an incomplete picture of organizational innovation performance.

Organizations operating under AI-driven leadership may generate a larger number of innovation initiatives, experiments, and implementation efforts, yet these increases in innovation output do not necessarily translate into superior innovation outcomes. The negative association between innovation activity and innovation quality suggests that accelerated innovation cycles may be associated with greater emphasis on speed, responsiveness, and experimentation at the expense of refinement, reflection, and knowledge integration. This observation is consistent with March's [63] distinction between exploration and exploitation, which emphasizes that the pursuit of rapid innovation generation may reduce organizational attention devoted to evaluation, learning, and capability development processes that contribute to the quality and sustainability of innovation outcomes. However, this relationship is unlikely to be universal. Organizations characterized by mature AI governance, participative leadership, high levels of employee expertise, and advanced digital capabilities may be better positioned to combine rapid innovation with sustained innovation quality. Conversely, organizations that emphasize automation without adequate investment in human capability development may be more vulnerable to the innovation paradox identified in the present study.

Taken together, these findings suggest that the principal challenge associated with AI-driven leadership may lie not in the technology itself but in the way organizations balance technological capabilities with the preservation of human expertise. Innovation quality appears to be more closely associated with the organization's ability to preserve, develop, and effectively utilize human capital than with the volume of AI-supported activity. In this respect, human capital therefore emerges as a key explanatory mechanism associated with the relationship between AI-driven leadership and innovation quality.

5.2. The Limited Role of Organizational Learning Erosion

Contrary to expectations, Organizational Learning Erosion did not emerge as a significant component of the proposed framework. Neither the relationship between AI-driven leadership and Organizational Learning Erosion nor the relationship between Organizational Learning Erosion and Innovation Quality reached statistical significance. These findings suggest that organizational learning erosion may play a less central role in explaining innovation quality than initially assumed.

One possible explanation is that organizational learning extends beyond individual cognition and is embedded within routines, structures, repositories, and collective knowledge systems [78]. Contemporary organizations increasingly rely on formalized knowledge management systems, digital repositories, collaborative platforms, and AI-supported information-sharing mechanisms that preserve organizational knowledge independently of individual employees. Consequently, reductions in individual cognitive engagement may not necessarily translate into the deterioration of collective learning processes.

The findings suggest that AI-driven leadership was more strongly associated with individual capability-related perceptions than with organizational learning perceptions. This distinction is consistent with organizational learning theory, which views learning as a multilevel phenomenon involving individuals, groups, and organizational systems [77]. While AI-centered managerial practices may influence employee expertise, judgment, and capability development, they do not necessarily disrupt the mechanisms through which organizations acquire, store, transfer, and institutionalize knowledge.

The absence of a significant sequential mediation effect further reinforces this interpretation. The results do not support the proposed sequential association involving organizational learning erosion as an explanatory pathway linking AI-driven leadership and innovation quality. Instead, the evidence indicates that the consequences of AI-centered leadership are concentrated primarily within the domain of human capital. Collectively, the findings suggest that perceived human capital erosion may represent a more important explanatory mechanism than organizational learning erosion within the proposed framework.

5.3. Theoretical Implications

This study contributes to the growing literature on AI-enabled leadership by addressing an important gap in prior research, which has largely treated innovation as a homogeneous outcome while paying limited attention to the distinction between innovation activity and innovation quality. The findings suggest that these dimensions represent distinct organizational outcomes that may evolve in opposite directions under conditions of intensive AI integration. This distinction extends existing AI leadership research by demonstrating that increased innovation activity should not be assumed to indicate higher innovation quality, thereby providing a more nuanced understanding of organizational innovation in AI-enabled environments.

Rather than proposing a new measurement model or construct-validation study, the primary contribution of this research lies in empirically testing a theoretically grounded explanation of the AI-driven innovation paradox. Specifically, the study examines how AI-driven leadership may simultaneously be associated with higher innovation activity and lower innovation quality, with perceived human capital erosion emerging as the principal explanatory mechanism. In doing so, it integrates insights from human capital theory with emerging perspectives on algorithmic management and digital transformation. The present findings indicate that AI-driven leadership is associated with both technological capabilities and human resource systems. By identifying human capital erosion as a key explanatory mechanism, the study extends current theoretical discussions beyond technology-centric perspectives and highlights the importance of examining how AI reshapes the development, utilization, and preservation of organizational expertise.

The findings further suggest that AI-related transformation may affect organizational resources asymmetrically. While individual capabilities appear sensitive to increasing technological dependence, collective organizational mechanisms demonstrate greater stability. This observation contributes to a more differentiated understanding of technological transformation and indicates that individual-level and organizational-level resources should not be assumed to respond uniformly to AI adoption. Future theoretical frameworks may therefore benefit from explicitly distinguishing between the effects of AI on human capital, organizational learning, and other strategic organizational resources.

5.4. Practical Implications

The findings indicate that the success of AI implementation should not be evaluated exclusively through indicators of efficiency, automation, or innovation output, as increases in innovation activity do not necessarily translate into higher innovation quality. Organizations should complement technology-oriented performance metrics with indicators that capture employee capability development, expertise retention, knowledge utilization, and critical thinking capacity. Such measures may provide early signals regarding the long-term sustainability of AI-supported innovation systems. Organizations that increasingly delegate analytical and decision-support functions to AI technologies should ensure that employees remain actively involved in cognitively demanding activities. Opportunities for problem-solving, reflection, experimentation, and capability development remain essential for maintaining the human resources upon which high-quality innovation depends. Organizations may also benefit from maintaining human-in-the-loop decision-making for complex or strategically important tasks, thereby preserving employee autonomy, professional judgment, and opportunities for continuous learning alongside AI-supported decision systems.

Leadership development programs should increasingly incorporate competencies related to AI governance, capability stewardship, and human–technology collaboration. Effective AI leadership therefore requires balancing technological efficiency with the preservation of employee capabilities and learning opportunities. AI-driven leadership should not be understood solely as the deployment of intelligent technologies but also as the capacity to create organizational environments in which technological capabilities and human expertise evolve simultaneously. Organizations that preserve this balance may be better positioned to achieve sustainable innovation outcomes over the long term.

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5.5. Limitations and Future Research

The findings should be interpreted in light of several limitations. The cross-sectional design limits the ability to establish causal relationships among the investigated constructs. Although the proposed model is theoretically grounded, longitudinal studies would provide stronger evidence regarding the cumulative effects of AI-driven leadership on human capital and innovation outcomes over time. Moreover, the cross-sectional design does not allow alternative causal explanations to be ruled out, including the possibility that employees working in environments characterized by lower perceived innovation quality may evaluate AI-driven leadership more negatively.

The study relies on self-reported perceptions, which may be influenced by subjective evaluations of organizational practices and technological environments. In addition, because all focal constructs were measured using the same questionnaire and collected from the same respondents at a single point in time, the potential influence of common method variance cannot be entirely ruled out. Although both Harman's single-factor test and a Common Latent Factor (CLF) analysis suggested that common method bias was unlikely to represent a substantial threat, the use of a cross-sectional self-report design means that method-related variance cannot be completely ruled out. Accordingly, the reported associations should be interpreted with appropriate caution. Future research may benefit from combining survey data with objective organizational indicators, managerial assessments, archival performance measures, multi-source data, and additional procedural or statistical approaches to further reduce the potential influence of common method bias.

In addition, several measurement properties warrant cautious interpretation. Although all constructs demonstrated satisfactory composite reliability and acceptable discriminant validity according to the HTMT criterion, several AVE values remained slightly below the recommended threshold of 0.50, and the Fornell–Larcker criterion produced partially inconsistent results. These findings suggest that the convergent and discriminant validity of some constructs should be interpreted with appropriate caution. Nevertheless, the overall measurement model was considered acceptable because all constructs demonstrated satisfactory composite reliability and acceptable discriminant validity according to the HTMT criterion, despite the more conservative results obtained using the AVE and Fornell–Larcker criterion. Future research should further refine the measurement scales and re-examine the proposed framework using alternative samples and additional validation procedures.

The model focuses on Human Capital Erosion and Organizational Learning Erosion as explanatory mechanisms. The non-significant role of Organizational Learning Erosion suggests that alternative mechanisms may better explain the associations between AI-driven leadership and innovation outcomes. Additional pathways may also influence the relationship between AI-driven leadership and innovation outcomes. Constructs such as employee autonomy, technological dependence, psychological empowerment, trust in AI systems, knowledge-sharing behavior, and digital resilience may provide valuable directions for future investigation.

Although the sample was large and intentionally recruited from digitally intensive work environments through Prolific, the findings should not be interpreted as representative of the broader workforce or all organizational contexts. The screening criteria intentionally targeted employees with direct experience of AI-enabled work environments, resulting in a sample concentrated in knowledge-intensive and digitally oriented occupations. Consequently, the generalizability of the findings is primarily limited to comparable organizational settings. In addition, as with other online research platforms, Prolific-based samples may be subject to platform-specific selection biases despite offering diverse participant pools and high-quality data collection procedures. Future research should examine the proposed framework across different countries, industries, occupational groups, and organizational contexts to further assess the external validity of the findings.

The findings further suggest that contextual conditions deserve greater attention. Factors such as organizational culture, digital maturity, AI governance practices, leadership style, and employee technological competence may strengthen or weaken the associations identified in this study. Examining these boundary conditions would contribute to a more comprehensive understanding of when AI-driven leadership enhances innovation and when it contributes to the innovation paradox identified in the present study. Future research may also extend the present model by applying multi-criteria decision-making approaches to prioritize HRM interventions aimed at preventing human capital erosion [86] or by testing the proposed model under crisis-induced uncertainty, where responsible leadership, organizational resilience, and human capability preservation become increasingly salient [87].

6. Conclusions

Artificial intelligence is increasingly becoming an integral component of contemporary leadership practices, yet its long-term implications for organizational innovation remain insufficiently understood. By distinguishing between innovation activity and innovation quality and examining the relationships among AI-driven leadership, human capital erosion, organizational learning erosion, and innovation outcomes, this study offers a theoretically grounded perspective on the AI-driven innovation paradox. The findings suggest that the organizational implications of AI-driven leadership cannot be evaluated solely through indicators of technological efficiency or innovation output. Overall, the relationships observed in this study indicate that AI-driven leadership and innovation outcomes are more complex than commonly assumed and involve important interactions between technological systems and human organizational resources. In particular, the study highlights the importance of employee capabilities as a key factor associated with sustainable innovation outcomes in AI-enabled organizational contexts.

The findings suggest that technological advancement may not automatically translate into the preservation and development of organizational capabilities. Organizations may successfully expand their technological capabilities while simultaneously facing challenges related to the preservation of expertise, judgment, and knowledge-based competencies. As AI technologies continue to become embedded within managerial and decision-making processes, understanding this balance will become increasingly important for both researchers and practitioners. The study underscores that sustaining innovation in AI-enabled organizations is likely to be associated not only with the sophistication of technological systems but also with organizations' ability to preserve and develop the human capabilities associated with meaningful and sustainable innovation.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Singidunum University (protocol code 267, 30 December 2025) for studies involving humans.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The dataset used in this study was collected via the Prolific platform and is not publicly available due to privacy, data protection considerations, and third-party restrictions. The data are stored by the authors in an Excel file containing anonymized responses and can be made available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Initial measurement items and EFA retention results.

Code	Measurement Item	Final Factor	Status
AI Guidance	Decision-making in my organization is increasingly guided by AI-based recommendations.	AI-Driven Leadership	Retained
AI Reliance	Leaders rely on AI systems to evaluate performance and guide actions.	—	Removed
AI Validation	Strategic decisions are frequently supported or validated by AI outputs.	AI-Driven Leadership	Retained
AI Priority	Managers prioritize AI-generated insights over human judgment.	AI-Driven Leadership	Retained
AI Centrality	AI tools are central to planning and operational control.	AI-Driven Leadership	Retained
AI Encouragement	Leadership encourages the use of AI for problem-solving and decision-making.	—	Removed
Reduced Autonomy	Human discretion in decision-making is reduced due to AI reliance.	AI-Driven Leadership	Retained
Skill Decline	Employees rely less on their own expertise due to AI assistance.	—	Removed
Thinking Decline	Critical thinking skills are declining as AI tools take over cognitive tasks.	Human Capital Erosion	Retained
Lower Initiative	Employees show reduced initiative in problem-solving.	Human Capital Erosion	Retained
Learning Slowdown	Skill development is slowing because tasks are automated.	Human Capital Erosion	Retained
AI Dependency	Over time, employees become dependent on AI systems.	Human Capital Erosion	Retained
Expertise Reduction	The need for deep expertise is decreasing in my organization.	Human Capital Erosion	Retained
Confidence Loss	Employees are less confident in making independent decisions.	Human Capital Erosion	Retained
Idea Frequency	The organization frequently introduces new ideas or solutions.	Innovation Activity	Retained
Innovation Growth	The number of innovations has increased in recent years.	—	Removed
AI Acceleration	AI tools accelerate the generation of new concepts.	Innovation Activity	Retained
Process Speed	Innovation processes are faster and more frequent.	—	Removed

Table A1. *Cont.*

Code	Measurement Item	Final Factor	Status
Experiment Support	Employees are encouraged to experiment with new ideas.	Innovation Activity	Retained
Active Development	The organization actively develops new products, services, or processes.	Innovation Activity	Retained
Speed Increase	AI contributes to increased speed in innovation activities.	Innovation Activity	Retained
Impact Value	Innovations in the organization are meaningful and impactful.	Innovation Quality	Retained
Long-Term Value	New solutions demonstrate long-term value.	Innovation Quality	Retained
Outcome Efficiency	Innovation outcomes are efficient and well-implemented.	—	Removed
Quality Improvement	The quality of innovations has improved over time.	Innovation Quality	Retained
Problem Effectiveness	Innovations solve complex problems effectively.	Innovation Quality	Retained
Sustainable Quality	The organization produces sustainable and high-quality innovations.	Innovation Quality	Retained
Strategic Alignment	Innovation results meet strategic and long-term goals.	—	Removed
Knowledge Decline	Knowledge sharing among employees is declining.	—	Removed
Experience Loss	Learning from experience is becoming less important.	Organizational Learning Erosion	Retained
AI Preference	Employees rely more on AI than on organizational knowledge.	Organizational Learning Erosion	Retained
Learning Loss	The organization is losing its ability to learn from past actions.	—	Removed
Training Weakness	Training and skill development are becoming less effective.	Organizational Learning Erosion	Retained
Collective Weakness	Collective problem-solving is weakening.	Organizational Learning Erosion	Retained
Knowledge Transfer	Organizational knowledge is not being effectively retained or transferred.	Organizational Learning Erosion	Retained

Note: The initial instrument contained 35 items. Following exploratory factor analysis, items that did not satisfy the predefined retention criteria (factor loading $\geq$ 0.50, absence of substantial cross-loadings, and conceptual consistency with the emerging factor structure) were removed prior to confirmatory factor analysis. The final measurement model consisted of 26 retained items across five latent constructs.

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