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Artificial Intelligence Leadership and Innovation Efficiency: Evidence of Underutilized Human Capital

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Abstract

This study examines how artificial intelligence (AI) leadership shapes the relationship between technological integration, human capabilities, and innovation activity within organizations, addressing the broader question of whether innovation outcomes are driven by human capital or by AI-enabled efficiency gains. Using a structured survey of 3,079 respondents across industries and regions, the study applies exploratory and confirmatory factor analysis and structural equation modelling to test the proposed relationships. The results indicate that AI leadership has a strong positive effect on innovation activity while simultaneously exerting a significant negative effect on human capabilities, with no statistically significant relationship between human capabilities and innovation activity. The findings do not support a mediation mechanism, suggesting that innovation outcomes can emerge independently of human capability engagement. This pattern indicates a structural misalignment in the innovation production process, where technological inputs are efficiently translated into outputs while human capital remains underutilized. From an economic perspective, the results indicate a shift toward efficiency-driven innovation systems, where productivity gains are achieved primarily through AI-enabled processes. The study contributes to the literature by challenging assumptions of human–AI complementarity and by highlighting the importance of leadership in shaping the allocation and integration of technological and human resources.

Keywords: artificial intelligence leadership; innovation productivity; human capabilities; technological change; efficiency; structural equation modelling; organizational innovation

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1. Introduction

The rapid advancement of artificial intelligence (AI) has fundamentally transformed how organizations approach decision-making, strategy, and innovation (Ozturk, 2024; Ullah et al., 2026). As AI systems become increasingly embedded in organizational processes, leadership practices are evolving toward greater reliance on data-driven insights, predictive analytics, and automated support systems (Mandić et al., 2024; Fontanelli et al., 2025; Pelayo-Díaz et al., 2026). Within this context, Artificial Intelligence Leadership has emerged as a critical mechanism through which organizations seek to enhance innovation performance, improve efficiency, and increase the productivity of innovation outputs relative to organizational inputs (Zhang et al., 2025; Fang et al., 2026; Cheng et al., 2026).

Existing research largely assumes that the integration of AI into leadership practices enhances innovation outcomes by strengthening human capabilities, enabling more effective problem solving, and expanding creative potential (Wang et al., 2024; Lei et al., 2025; Shahzad et al., 2025). At the same time, the literature emphasizes the critical role of human centered capabilities, such as autonomy,

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critical thinking, and creativity, as foundational drivers of innovation (Chen et al., 2024; Otache et al., 2025). Innovation is therefore commonly conceptualized as a socio technical process in which human and technological elements interact synergistically, with leadership aligning these components (Helmi et al., 2024; Yan et al., 2026). From this perspective, AI is viewed as a complementary resource that supports and amplifies human potential (Wang et al., 2024; Meier et al., 2026).

However, this assumption of complementarity remains insufficiently examined from an economic perspective. In particular, it remains unclear how different inputs contribute to innovation outputs and whether observed performance gains reflect the development of human capabilities or efficiency improvements enabled by AI systems (Subash et al., 2024; Drydakis, 2026). As such, the relationship between AI leadership, human capabilities, and innovation requires more precise empirical investigation. Existing studies rarely consider the possibility that AI driven leadership may simultaneously increase innovation activity while weakening human capabilities (Sahoo et al., 2026). They also rarely examine whether innovation outcomes may emerge independently of their development (Haq et al., 2025). Moreover, there is limited empirical evidence on how AI leadership shapes the allocation and utilization of human capital within innovation processes, particularly in terms of innovation productivity and input allocation in AI enabled systems (Ke & Luo, 2026). A key unresolved issue is whether observed productivity gains reflect complementarities between AI and human capabilities or indicate efficiency driven substitution mechanisms (Kong & Xu, 2026).

Understanding this relationship is critical, as organizations increasingly rely on AI systems not only to support but also to shape core innovation processes. If human capabilities are not integrated into AI driven environments, this may lead to forms of misalignment between technological systems and human potential, with important implications for long-term productivity, adaptability, and sustainability (Butlewski, 2026). This raises a central economic issue concerning the relative contribution of human capability development and AI enabled efficiency to innovation outcomes. This issue can be understood through the lens of an innovation production function, where technological inputs and human capital jointly determine innovation outputs and productivity outcomes (Sun & Huang, 2026; Calvino & Fontanelli, 2026).

However, existing research does not explicitly examine whether AI driven leadership leads to a decoupling between human capability development and innovation productivity, particularly in terms of input substitution and efficiency driven outcomes (Wei & Xia, 2026; Loaiza, 2026). Accordingly, the aim of this study is to examine the direct and indirect relationships between Artificial Intelligence Leadership, Human Capabilities, and Innovation Activity. The study addresses the following research question: Does Artificial Intelligence Leadership enhance innovation through human capabilities, or can innovation outcomes emerge independently of them? To address this question, a structural model is developed and empirically tested using data collected from 3,079 respondents across multiple industries and regions.

The findings provide evidence that diverges from dominant expectations. While Artificial Intelligence Leadership significantly increases innovation activity, it also exerts a negative effect on human capabilities, and these capabilities do not exhibit a significant relationship with innovation outcomes. This pattern indicates a potential structural shift in the innovation production process, where output generation becomes less dependent on human capabilities and more driven by AI enabled efficiency. These results suggest that, rather than operating through a complementary mechanism, AI-driven leadership may be associated with a form of misalignment in which human capabilities are not effectively integrated into innovation processes. This study contributes to the literature by challenging prevailing human-centric assumptions about AI-enabled innovation and by providing empirical evidence that AI-driven leadership can influence innovation outcomes independently of human capabilities. In doing so, it reframes the debate from whether AI enhances innovation to how leadership shapes the allocation and interaction of technological and human inputs, thereby opening new avenues for research on human–AI complementarity, productivity, and resource utilization in contemporary organizational settings. In this sense, the study contributes to the literature on technological change and economic growth by examining how leadership shapes

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the relationship between innovation productivity and the utilization of human capital in AI-driven environments.

2. Literature Review and Hypothesis Development

The rapid diffusion of artificial intelligence across organizational contexts has intensified scholarly attention to the role of leadership in shaping innovation processes and outcomes (An et al., 2024). Within this stream, Artificial Intelligence Leadership is typically conceptualized as a mechanism through which organizations align technological capabilities with strategic objectives, thereby enhancing efficiency, decision quality, and innovation performance (Yu & Xu, 2026). Existing research largely adopts an optimistic perspective, suggesting that AI-enabled leadership facilitates knowledge recombination, accelerates problem-solving, and expands the scope of innovation activities (Brynjolfsson & McAfee, 2014; Redaputri et al., 2026). By leveraging data-driven insights and predictive analytics, leaders are increasingly able to identify emerging opportunities and support the development of new products, services, and processes (Calik & Cetinguc, 2026; Mirčetić et al., 2026).

This perspective is consistent with research emphasizing the productivity effects of digital technologies and artificial intelligence in economic systems (Acemoglu & Restrepo, 2020; Ryberg, 2026; Breau & Marchand, 2026). In this sense, AI becomes embedded within the core of organizational innovation systems, positioning leadership as a key driver of technologically enabled innovation outcomes (Dai & Zhang, 2026; Vafaei-Zadeh et al., 2026)). From an economic perspective, this positioning implies that AI-enabled leadership may influence not only the level of innovation output, but also the efficiency with which inputs are transformed into outputs, raising questions about the relative contribution of technological systems and human capital to innovation productivity (Park et al., 2026; Park, 2026).

Based on this perspective, AI leadership can be expected to exert a direct positive effect on innovation activity (Shahzad et al., 2026). The integration of AI into leadership practices enhances the capacity for rapid experimentation, informed decision-making, and systematic opportunity recognition, all of which are essential components of innovation processes (Li et al., 2026; Lin et al., 2026). From an economic perspective, the following hypotheses examine how technological and human inputs jointly shape innovation outputs and efficiency.

H1: Artificial Intelligence Leadership positively influences Innovation Activity by enhancing efficiency in innovation processes.

At the same time, a parallel stream of research emphasizes the importance of human-centered capabilities—such as autonomy, critical thinking, and creativity—as foundational elements of innovation (Nonaka & Takeuchi, 1995; Amabile, 1996). These capabilities enable individuals to generate novel ideas, challenge existing assumptions, and engage in exploratory problem-solving (Alshuaib et al., 2024; Cheng et al., 2026). However, the increasing reliance on AI systems may alter the role of these capabilities within organizational contexts. As decision-making becomes increasingly automated and guided by algorithmic outputs, there is a risk that human agency is reduced, with employees relying more on AI-generated recommendations rather than independent judgment (Gao & Wan, 2026).

Recent studies in the economics of automation suggest that advanced technologies can substitute for certain cognitive and analytical functions traditionally performed by humans (Acemoglu & Restrepo, 2020; Ryberg, 2026; Breau & Marchand, 2026). In leadership contexts, this substitution effect may manifest through the prioritization of data-driven decision-making over human intuition and creativity (Hao et al., 2026). As a result, AI-driven leadership may inadvertently diminish human capabilities, particularly when organizational practices emphasize efficiency and standardization over autonomy and critical reflection (Le et al., 2025). In such contexts, the increasing reliance on AI may shift the balance from human-centered capability development toward efficiency-oriented decision-making, potentially altering the role of human capital within innovation processes.

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H2: Artificial Intelligence Leadership negatively influences Human Capabilities by reducing the effective utilization of human capital in innovation processes.

Despite these concerns, the dominant view in the innovation literature maintains that human capabilities remain central to innovation processes (Yang & Wang, 2026). Creativity, domain expertise, and critical evaluation are widely regarded as key drivers of both incremental and radical innovation (Amabile, 1996). Human actors play a crucial role in interpreting information, generating original ideas, and integrating diverse knowledge sources (Tang et al., 2026). Even in technologically advanced environments (Karabašević et al., 2026), innovation is often conceptualized as a socio-technical process in which human and technological elements interact synergistically (Rauner & Stummer, 2025). Accordingly, higher levels of human capabilities are expected to contribute positively to innovation activity. From an economic standpoint, innovation is closely linked to productivity growth and long-term economic development (Aghion et al., 2014), making it essential to understand how AI-driven leadership influences not only the volume but also the efficiency of innovation outputs. Individuals who possess greater autonomy, creativity, and critical thinking skills are more likely to engage in idea generation, experimentation, and collaborative exploration (Giotopoulos et al., 2026). This assumption reflects the enduring importance of human agency in shaping innovation outcomes (Vuong et al., 2026).

H3: Human Capabilities positively influence Innovation Activity through their contribution to knowledge creation and problem-solving.

Building on these relationships, prior research frequently assumes that the impact of leadership on innovation is mediated by human capabilities (Mustafa et al., 2026). Leadership practices are expected to influence how individuals think, act, and engage with innovation processes, thereby indirectly shaping innovation outcomes through their effects on human potential. Within this framework, AI leadership would enhance or constrain innovation depending on its ability to support or undermine human capabilities (Gazi et al., 2025). However, the coexistence of AI-driven leadership and human-centered capabilities raises the possibility of misalignment.

While AI leadership may enhance innovation through efficiency and data-driven decision-making, it may simultaneously weaken the human capabilities that are traditionally considered essential for innovation. This creates a potential indirect pathway in which the negative effect of AI leadership on human capabilities translates into reduced innovation activity (Tran et al., 2025). This potential divergence suggests that innovation systems may operate under conditions of misalignment, where technological inputs drive observable outputs, while human capabilities are not fully utilized as productive resources within the innovation process (Wadho & Chaudhry, 2024).

H4: Artificial Intelligence Leadership has a negative indirect effect on Innovation Activity through Human Capabilities, reflecting potential misalignment between technological inputs and human capital.

3. Methodology

The empirical data were collected through an online survey administered via the Prolific platform over a twelve-month period, from March 2025 to March 2026. This platform was selected due to its established reliability in providing high-quality, diverse, and pre-screened respondent pools suitable for behavioral and organizational research. The study adopts a cross-sectional, explanatory research design aimed at examining causal relationships between artificial intelligence leadership, human capabilities, and innovation activity. To ensure the validity and relevance of the sample, a multi-stage screening procedure was implemented prior to questionnaire completion. Participation was restricted to respondents employed in organizations where artificial intelligence tools or systems are actively used in daily business operations, thereby ensuring that all participants had direct exposure to AI-enabled work environments. Additionally, only individuals currently employed, either full-time or part-time, were included in the final sample to maintain consistency in organizational experience.

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Further screening criteria were applied to ensure an adequate level of familiarity with AI usage within the organization. Respondents were required to demonstrate at least a moderate understanding of how AI systems are integrated into work processes, thereby reducing the risk of uninformed or speculative responses. In addition, the sample was limited to individuals who are at least occasionally involved in decision-making, problem-solving, or innovation-related tasks, ensuring that responses reflect meaningful engagement with organizational processes relevant to the study. This screening strategy allowed for the exclusion of low-quality or non-relevant responses and ensured that the final dataset reflects informed perceptions of AI-supported organizational environments and their implications for innovation-related outcomes.

The empirical analysis is based on a large and structurally diverse sample of 3,079 respondents, providing a robust foundation for examining the relationships between AI leadership, human capabilities, and innovation outcomes. The gender distribution is relatively balanced, with 51.9% male and 48.1% female participants, reducing the likelihood of gender-based bias and enhancing the generalizability of the findings. In terms of age, the sample is dominated by economically active cohorts, with the largest proportion of respondents aged 31–40 years (28.2%), followed by 18–30 years (22.5%) and 41–50 years (20.5%). This distribution indicates a concentration of participants in mid-career stages, which is particularly relevant for studying leadership dynamics and innovation processes. However, a minor irregularity is observed in the age variable, where 5.0% of responses fall into an undefined category (“6”), suggesting a minor coding inconsistency that does not affect the overall distribution or subsequent analysis; this does not substantially affect the overall distribution but should be acknowledged for transparency.

The educational structure of the sample is notably high, with 40.3% of respondents holding a master’s degree and 19.2% a doctoral degree, while 32.2% have completed a bachelor’s degree. This indicates that over 90% of participants possess tertiary education, supporting the assumption that respondents are capable of engaging with complex organizational and technological constructs such as AI-driven leadership and innovation systems. The employment structure further reinforces this interpretation, as the majority of participants occupy knowledge-intensive roles, including specialists or professionals (40.3%) and middle management (23.3%), while entry-level employees account for 24.5% and senior management for 11.9%. This distribution ensures that the sample captures both operational and strategic perspectives within organizations.

Sectoral representation is heterogeneous, with the largest share coming from IT and software (23.5%), followed by manufacturing (13.4%), finance and banking (13.9%), marketing and media (12.9%), consulting (10.4%), and tourism and hospitality (10.5%), alongside 15.3% from other industries. Such diversity enhances the external validity of the study by encompassing multiple innovation contexts, from technology-intensive environments to service-oriented sectors. Similarly, firm size distribution is balanced across small, medium, and large enterprises, with 32.2% of respondents working in firms employing 50–249 employees, 29.4% in firms with 10–49 employees, 19.5% in large organizations (250+), and 18.9% in micro-enterprises (<10). This spread allows for the examination of AI leadership across different organizational scales.

Geographically, the sample demonstrates strong international coverage, including respondents from Western Europe (11.5%), Eastern Europe and the Balkans (9.5%), North America (10.8%), Latin America (9.1%), the United Kingdom and Ireland (7.5%), Nordic countries (10.1%), Southern Europe (10.1%), the Middle East and North Africa (10.4%), South and Southeast Asia (10.0%), and Australia and New Zealand (11.0%). The relatively even distribution across regions reduces geographic bias and supports the cross-contextual relevance of the findings, particularly important for a phenomenon such as AI leadership, which operates within globally interconnected innovation systems. Work experience is well distributed, with the largest group having 5–10 years of experience (26.3%), followed by 1–3 years (23.4%), more than 10 years (20.4%), and 3–5 years (20.1%), while only 9.9% report less than one year of experience. This indicates that the majority of respondents possess sufficient professional exposure to evaluate leadership practices and innovation processes. Finally, the frequency of AI tool usage confirms the relevance of the sample for the research context: 35.2% of respondents report daily use of AI, 30.6% weekly use, and 24.7% occasional use, while only 9.5% report never using AI. This distribution suggests that the sample is strongly embedded in AI-enabled work environments, making it appropriate for investigating the dynamics of AI leadership and its potential misalignment with human capabilities.

The sample structure reflects a highly educated, professionally active, and globally distributed population with substantial exposure to artificial intelligence in organizational settings. This composition provides a credible empirical basis for testing the proposed structural model and supports the validity of conclusions regarding the interplay between AI leadership, human capabilities, and innovation productivity.

A structured questionnaire was designed to examine the relationship between artificial intelligence integration, human capabilities, and innovation outcomes within organizational contexts. The instrument was developed using a deductive approach grounded in prior literature on technological change, human capital, and innovation performance (e.g., Brynjolfsson & McAfee, 2014; Meyer & Rowan, 1977), as well as more recent research addressing AI-enabled organizational transformation. An initial pool of 35 items was generated to capture multiple dimensions of AI-supported work environments and innovation processes. The item development process combined theoretical grounding with contextual adaptation to reflect contemporary AI-driven organizational practices. Subsequently, the questionnaire underwent a refinement phase aimed at improving clarity, eliminating redundancy, and ensuring content validity.

Following this process, a total of 25 items were retained for analysis. All items were measured using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”), which is widely applied in studies examining organizational behavior, technological adoption, and innovation-related perceptions. This scaling approach enables the reliable quantification of latent variables and supports the application of multivariate statistical techniques. To reduce the risk of common method bias, procedural remedies were applied, including the use of clear item wording, assured anonymity of responses, and separation of measurement of predictor and criterion variables within the questionnaire structure. The final instrument captures both technological and human dimensions of organizational functioning, as well as their implications for innovation-related outcomes. Such operationalization is consistent with prior research emphasizing the interaction between technological systems and human capital as a key determinant of organizational efficiency and performance in digitally transformed environments.

The data were analyzed using a multistep approach combining exploratory and confirmatory techniques in order to ensure the robustness and validity of the measurement and structural models. All statistical analyses were conducted using IBM SPSS Statistics and IBM SPSS AMOS. In the first stage, exploratory factor analysis (EFA) was performed to examine the underlying structure of the measurement instrument and to assess the dimensionality of the data. Prior to extraction, sampling adequacy and factorability were evaluated using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s Test of Sphericity. Factor extraction was conducted using the maximum likelihood method, as it allows for statistical testing and is consistent with subsequent confirmatory procedures. An oblique rotation (direct oblimin) was applied, given the theoretical expectation that the underlying dimensions are correlated.

Following the exploratory phase, confirmatory factor analysis (CFA) was employed to validate the measurement model. The CFA assessed the relationships between observed indicators and their corresponding latent variables, as well as the overall fit of the model to the data. Model fit was evaluated using multiple indices, including the chi-square statistic (χ^2), the normed chi-square (χ^2/df), goodness-of-fit indices (GFI, AGFI), incremental fit indices (CFI, TLI, IFI, NFI), and the root mean square error of approximation (RMSEA) with confidence intervals and PCLOSE values. This combination of indices provides a comprehensive assessment of model adequacy, balancing absolute, incremental, and parsimonious fit.

Construct reliability and convergent validity were assessed using composite reliability (CR) and average variance extracted (AVE). CR values above 0.70 were considered indicative of satisfactory

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internal consistency, while AVE values exceeding 0.50 confirmed that the constructs explain a sufficient proportion of variance in their indicators. Discriminant validity was evaluated using the Fornell–Larcker criterion, by comparing the square roots of AVE with inter-construct correlations, as well as the heterotrait–monotrait ratio (HTMT), with values below 0.85 indicating adequate discriminant validity. In the final stage, structural equation modelling (SEM) was applied to test the hypothesized relationships among the variables. The structural model was estimated using the maximum likelihood method, allowing for the simultaneous assessment of direct and indirect effects. Path coefficients were evaluated based on their standardized estimates, critical ratios (C.R.), and significance levels (p-values). Mediation effects were examined through the estimation of indirect paths, enabling the identification of underlying transmission mechanisms between variables.

From an economic perspective, the modelling strategy allows for the interpretation of innovation-related outcomes as indicators of organizational productivity and efficiency, where technological inputs (AI integration) and human capital inputs jointly shape output performance. In particular, the model can be interpreted as a simplified innovation production function, where artificial intelligence represents a technological input and human capabilities represent a form of human capital, jointly influencing innovation outputs as a proxy for productivity. In this context, the structural relationships capture not only behavioral dynamics but also the allocation and utilization of productive resources within AI-enabled systems. Additionally, the explanatory power of the model was assessed using the coefficient of determination (R^2) for endogenous variables, indicating the proportion of variance explained by the model. This provides a direct measure of how effectively the interaction between technological systems and human capabilities accounts for variations in innovation efficiency, aligning the analysis with established approaches in productivity and technological change research. This analytical procedure ensures a rigorous evaluation of both the measurement properties and the structural relationships, while situating the findings within a broader economic framework of productivity, efficiency, and resource utilization in AI-driven organizational environments. This approach enables the simultaneous assessment of behavioral relationships and efficiency-oriented outcomes, positioning the analysis within the broader literature on technological change, productivity, and economic growth.

3. Results

The Kaiser–Meyer–Olkin (KMO) value of 0.958 indicates excellent sampling adequacy, far exceeding the recommended threshold of 0.60, and confirms that the data are highly suitable for factor analysis. Bartlett's Test of Sphericity is statistically significant (χ^2 = 52,138.681; df = 300; $p < 0.001$), rejecting the null hypothesis that the correlation matrix is an identity matrix. Together, these results demonstrate that the variables are sufficiently intercorrelated and that factor analysis is both appropriate and methodologically justified.

The results presented in Table 1 indicate a clear four-factor solution, with all retained factors exceeding the Kaiser criterion (eigenvalue > 1). The first factor accounts for 35.81% of the total variance, followed by the second (17.56%), third (10.25%), and fourth factor (6.52%). Cumulatively, the four factors explain 70.14% of the total variance, which exceeds the commonly accepted threshold of 60% in social sciences, indicating strong explanatory power of the measurement model. The substantial contribution of the first two factors suggests a dominant underlying structure, while the additional factors capture meaningful but more specific dimensions of the constructs. The rotated solution further confirms a stable and interpretable factor structure, supporting the adequacy of the measurement model for subsequent confirmatory and structural analyses.

Table 1. Total Variance Explained (Maximum Likelihood Extraction with Rotation).

Factor	Eigenvalue	% of Variance	Cumulative %
1	8.953	35.811	35.811
2	4.391	17.563	53.374

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3	2.561	10.245	63.619
4	1.629	6.518	70.137

Note: Extraction method = Maximum Likelihood. Only factors with eigenvalues > 1 are retained. Rotated solution reported; variance percentages are based on extraction values.

The oblimin-rotated pattern matrix presented in Table 2 reveals a clear and theoretically consistent four-factor structure, corresponding to AI Leadership (AIL), AI Intensity/Usage (AIU), Human Capabilities (HC), and Innovation Activity (IA). The results demonstrate strong convergent validity, as all items load highly on their intended constructs, while cross-loadings remain negligible, supporting discriminant validity. Items associated with AI Leadership (AI Decision, AI Encouragement, AI Strategy, AI Insights, AI Promotion, AI Experimentation, and AI Influence) exhibit high loadings on the first factor, ranging from 0.790 to 0.826. These consistently strong coefficients indicate a well-defined latent construct capturing the strategic and operational role of leadership in integrating AI into organizational processes. Cross-loadings for these items are close to zero, confirming that AI Leadership is empirically distinct from the other dimensions. The second factor, AI Intensity/Usage, is defined by Process Integration, Decision Support, Task Reliance, System Integration, and AI Diffusion, all of which demonstrate very high loadings between 0.838 and 0.873. This suggests a particularly robust and internally consistent construct reflecting the extent to which AI is embedded in everyday work processes and organizational systems. The absence of meaningful cross-loadings further reinforces the independence of this dimension.

Human Capabilities, represented by Decision Autonomy, Critical Thinking, Creative Freedom, AI Challenge, Independent Judgment, Human Expertise, and Human Value, load strongly on the third factor, with coefficients ranging from 0.780 to 0.803. These results confirm that the construct captures a coherent set of human-centered competencies, including cognitive autonomy, creativity, and the ability to critically engage with AI outputs. Again, cross-loadings are minimal, supporting the distinctiveness of this factor. The fourth factor, Innovation Activity, includes Idea Generation, Solution Experimentation, Product Development, Innovation Routine, Team Collaboration, and AI Ideation, with loadings ranging from –0.718 to –0.767. Although these loadings are negative, their magnitude is high and consistent, which is not problematic in oblique rotation, as factor polarity is arbitrary and does not affect interpretation. The uniformity of these loadings indicates a stable construct capturing the intensity and regularity of innovation processes within organizations.

Overall, as shown in Table 2, the pattern matrix confirms a clean and interpretable factor structure with strong loadings on intended constructs and negligible cross-loadings. The use of oblimin rotation allows for correlations among factors, which is theoretically appropriate given the interrelated nature of leadership, technology use, human capabilities, and innovation. These findings provide strong empirical support for the validity and reliability of the measurement model, justifying its application in subsequent confirmatory factor analysis and structural equation modeling.

Table 2. Pattern Matrix.

	Factor			
	AI Leadership (AIL)	**AI Intensity / Usage (AIU)**	**Human Capabilities (HC)**	**Innovation Activity (IA)**
AI Decision	,818	,014	-,006	,002
AI Encouragement	,812	,007	,013	-,017
AI Strategy	,821	-,002	-,008	,012
AI Insights	,790	,004	,000	-,030
AI Promotion	,819	-,003	,000	,005
AI Experimentation	,814	,005	-,015	,017
AI Influence	,826	-,023	,008	,001
Decision Autonomy	-,003	,004	,782	,014
Critical Thinking	,008	,012	,794	-,006

Creative Freedom	-,017	,004	,788	-,007
AI Challenge	,016	,011	,803	-,009
Independent Judgment	-,003	-,001	,796	-,009
Human Expertise	-,023	-,016	,780	,002
Human Value	,011	-,008	,793	,021
Idea Generation	,037	,003	-,002	-,718
Solution Experimentation	,016	-,023	,049	-,743
Product Development	,003	,007	-,001	-,757
Innovation Routine	-,019	,010	-,036	-,757
Team Collaboration	,003	-,009	,001	-,757
AI Ideation	-,026	,013	-,018	-,767
Process Integration	-,028	,863	,000	-,020
Decision Support	,015	,854	-,001	,008
Task Reliance	,020	,860	,004	,012
System Integration	-,006	,838	,026	-,006
AI Diffusion	,000	,873	-,023	,006

The measurement model demonstrates excellent fit to the data across multiple indices. The chi-square statistic is significant ($\chi^2 = 316.820$; df = 269; p = 0.024), which is expected given the large sample size; therefore, greater emphasis is placed on relative and incremental fit indices. The normed chi-square (CMIN/DF = 1.178) is well below the recommended threshold of 3, indicating a very good fit. Absolute fit indices confirm model adequacy, with a very low RMR value (0.005) and high goodness-of-fit values (GFI = 0.992; AGFI = 0.990), all exceeding recommended thresholds. Incremental fit indices are exceptionally strong, including NFI = 0.994, TLI = 0.999, IFI = 0.999, and CFI = 0.999, indicating an excellent fit relative to the null model. The RMSEA value is extremely low (RMSEA = 0.008), with a narrow confidence interval (0.003–0.011) and PCLOSE = 1.000, confirming a close fit in the population. Parsimony-adjusted indices (PNFI = 0.891; PCFI = 0.896) indicate a well-balanced model in terms of fit and complexity. Information criteria (AIC = 428.820; ECVI = 0.139) are substantially lower compared to the independence model, supporting model parsimony and generalizability. High Hoelter indices (2995 at the 0.05 level and 3167 at the 0.01 level) further confirm the stability and robustness of the model. These results provide strong empirical support for the validity of the measurement model and justify its use in subsequent structural equation modeling.

The results presented in Table 3 indicate strong internal consistency and convergent validity across all constructs. Composite reliability (CR) values range from 0.887 to 0.933, exceeding the recommended threshold of 0.70, which confirms high reliability of the latent constructs. The highest reliability is observed for AI Leadership and AI Intensity, reflecting particularly stable and coherent measurement structures.

Table 3. Construct Reliability and Convergent Validity.

Construct	Items	CR	AVE
AI Leadership (AIL)	7	0.933	0.665
AI Intensity / Usage (AIU)	5	0.933	0.736
Human Capabilities (HC)	7	0.921	0.624
Innovation Activity (IA)	6	0.887	0.565

Average Variance Extracted (AVE) values range from 0.565 to 0.736, all above the recommended threshold of 0.50, indicating that each construct explains more than half of the variance of its

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indicators. AI Intensity demonstrates the strongest convergent validity (AVE = 0.736), while Innovation Activity, although slightly lower (AVE = 0.565), still meets acceptable criteria. These findings confirm that the measurement model satisfies established standards for reliability and convergent validity, supporting the adequacy of the constructs for subsequent structural analysis. The results presented in Table 4 indicate that discriminant validity is established according to the Fornell–Larcker criterion. The square roots of average variance extracted for all constructs (ranging from 0.752 to 0.858) exceed the corresponding inter-construct correlations, demonstrating that each construct shares more variance with its own indicators than with other constructs.

Table 4. Fornell–Larcker Criterion (Discriminant Validity).

Construct	Artificial Intelligence Leadership	Artificial Intelligence Intensity / Usage	Human Capabilities	Innovation Activity
Artificial Intelligence Leadership	0.815	0.000	-0.570	0.610
Artificial Intelligence Intensity / Usage	0.000	0.858	0.270	0.000
Human Capabilities	-0.570	0.270	0.790	-0.340
Innovation Activity	0.610	0.000	-0.340	0.752

Note: Diagonal elements represent the square root of average variance extracted.

The findings reported in Table 5 further confirm discriminant validity using the heterotrait–monotrait ratio. All values are well below the conservative threshold of 0.85, with the highest value observed between Artificial Intelligence Leadership and Innovation Activity (0.748), which remains within acceptable limits. Lower values across other construct pairs further support the distinctiveness of the constructs. These results provide strong evidence that the measurement model satisfies rigorous criteria for discriminant validity, confirming that Artificial Intelligence Leadership, Artificial Intelligence Intensity / Usage, Human Capabilities, and Innovation Activity represent empirically distinct dimensions.

Table 5. Heterotrait–Monotrait Ratio (HTMT).

Construct	Artificial Intelligence Leadership	Artificial Intelligence Intensity / Usage	Human Capabilities	Innovation Activity
Artificial Intelligence Leadership	—	0.000	0.700	0.748
Artificial Intelligence Intensity / Usage	0.000	—	0.342	0.000
Human Capabilities	0.700	0.342	—	0.455
Innovation Activity	0.748	0.000	0.455	—

The structural model demonstrates excellent fit to the data. The chi-square value is low relative to the degrees of freedom (χ^2 = 316.823; df = 270; p = 0.026), with a normed chi-square of 1.173,

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indicating very good fit. Incremental fit indices are exceptionally high (CFI = 0.999; TLI = 0.999; IFI = 0.999), well above recommended thresholds. Absolute fit indices also confirm adequacy (RMR = 0.005; GFI = 0.992; AGFI = 0.990). The RMSEA value is extremely low (0.008; PCLOSE = 1.000), indicating a close fit in the population. These results indicate that the structural model fits the data very well and supports further interpretation of the hypothesized relationships. From an economic perspective, this strong model fit supports the interpretation of the estimated relationships as reflecting underlying efficiency dynamics in the innovation production process. As shown in Figure 1, the structural model reveals a differentiated pattern of relationships between artificial intelligence leadership, human capabilities, and innovation activity.

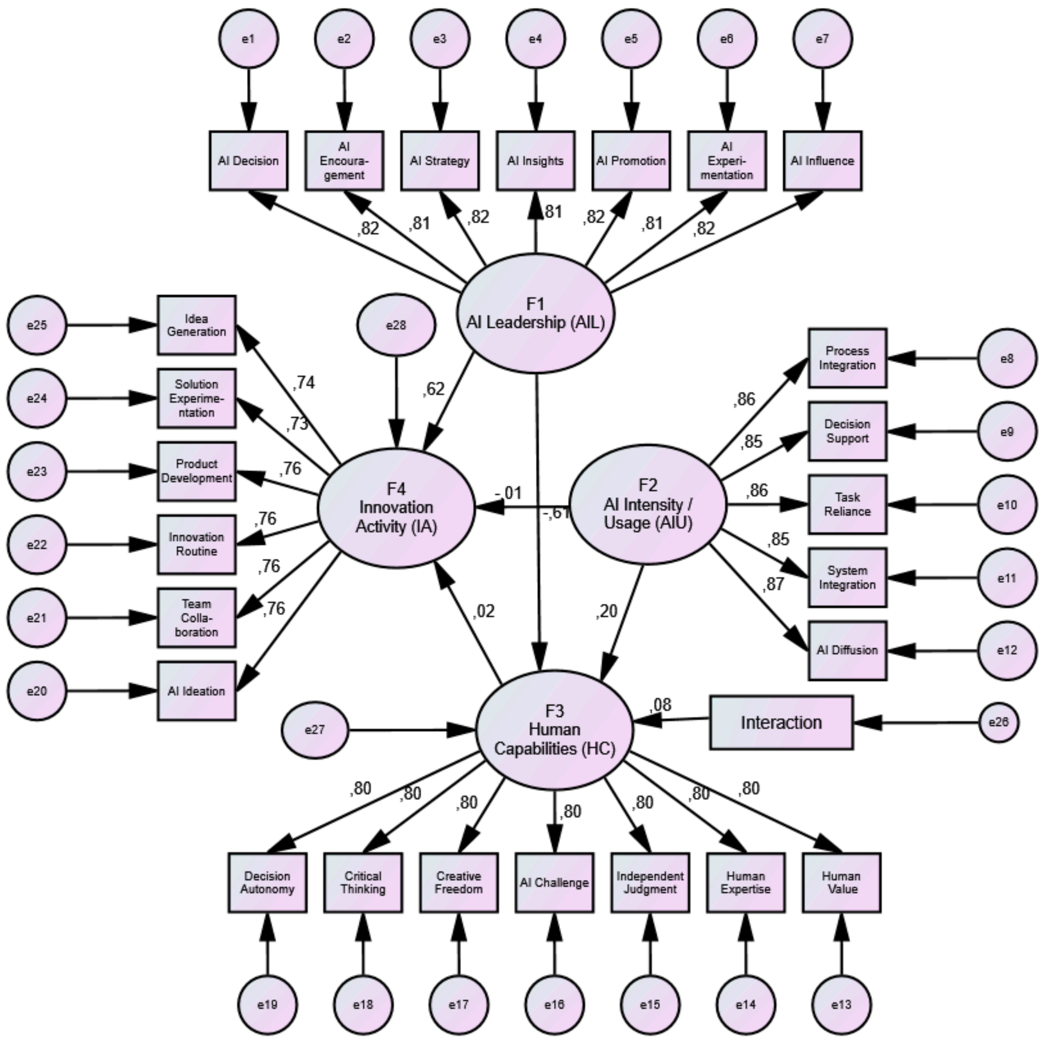

Figure 1. Structural Equation Modeling (SEM). Source: Own elaboration.

Table 6 presents the results of the structural model analysis. The findings indicate that Artificial Intelligence Leadership has a strong and statistically significant positive effect on Innovation Activity (β = 0.616, p < 0.001), thereby supporting H1. This result suggests that the integration of artificial intelligence into leadership practices substantially enhances innovation processes and outcomes, indicating efficiency gains in innovation performance within organizations. At the same time, Artificial Intelligence Leadership exerts a significant negative effect on Human Capabilities (β = −0.568, p < 0.001), confirming H2. This finding implies that increased reliance on AI-driven leadership is associated with a reduction in employees' autonomy, critical thinking, and creative engagement, reflecting a decline in the effective utilization of human capital. In contrast, the effect of Human

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Capabilities on Innovation Activity is not statistically significant (β = 0.011, p = 0.616), leading to the rejection of H3. This result indicates that, within the tested model, human capabilities do not play a direct role in explaining innovation outcomes. Overall, the results reveal a pattern in which Artificial Intelligence Leadership simultaneously strengthens innovation activity while diminishing human capabilities, indicating a shift in the innovation production function toward technology-driven efficiency with limited contribution of human capital.

Table 6. Structural Model Results.

Hypothesis	Path	β (Standardized)	SE	C.R.	p-value	Supported
H1	Artificial Intelligence Leadership → Innovation Activity	0.616	0.016	25.095	***	Yes
H2	Artificial Intelligence Leadership → Human Capabilities	-0.568	0.017	-30.035	***	Yes
H3	Human Capabilities → Innovation Activity	0.011	0.016	0.501	0.616	No

Table 7 presents the results of the mediation analysis. The findings indicate that the indirect effect of Artificial Intelligence Leadership on Innovation Activity through Human Capabilities is negligible and not statistically supported (indirect effect = −0.006). Although Artificial Intelligence Leadership significantly reduces Human Capabilities and exhibits a strong direct positive effect on Innovation Activity, the non-significant relationship between Human Capabilities and Innovation Activity prevents the establishment of a meaningful mediation pathway. Consequently, H4 is not supported, as Human Capabilities do not mediate the relationship between Artificial Intelligence Leadership and Innovation Activity. This result suggests that the influence of AI leadership on innovation operates primarily through a direct pathway, suggesting a misalignment between technological inputs and human capital rather than through changes in human capabilities.

Table 7. Mediation Effects (Standardized).

Hypothesis	Path	Direct Effect	Indirect Effect	95% BC CI Lower	95% BC CI Upper	Mediation Type
H4	Artificial Intelligence Leadership → Human Capabilities → Innovation Activity	0.616	-0.006	n/a	n/a	No mediation

As shown in Table 8, the model demonstrates a moderate level of explanatory power for the endogenous constructs. Specifically, approximately 40% of the variance in F3 is explained by its predictors, while 38% of the variance in F4 is accounted for by the model. These findings indicate that the proposed model captures a substantial portion of variance in innovation-related outcomes, which is particularly relevant given the complexity of AI-driven organizational environments. According to commonly accepted thresholds in structural equation modelling, R^2 values within this range suggest meaningful explanatory capacity.

At the same time, the remaining unexplained variance points to the presence of additional factors not included in the model, reinforcing the notion that innovation efficiency is influenced by a broader set of technological, human, and organizational conditions. This further supports the

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interpretation that innovation outcomes are driven primarily by AI-enabled efficiency, rather than by the effective contribution of human capital.

Table 8. Explained Variance (R^2).

Endogenous Construct	R^2	Interpretation
Human Capabilities	0.40	Moderate explanatory power
Innovation Activity	0.38	Moderate explanatory power

5. Discussion

The findings provide a nuanced perspective on the relationship between artificial intelligence leadership, human capabilities, and innovation activity, moving beyond dominant assumptions of straightforward complementarity. The empirical results support the direct positive effect of Artificial Intelligence Leadership on innovation activity (H1) and confirm its negative impact on human capabilities (H2), while the expected contribution of human capabilities to innovation activity is not supported (H3), and no evidence of a mediation mechanism is found (H4). From an economic perspective, the results indicate that innovation outputs may be increasingly driven by efficiency gains associated with AI-enabled processes, rather than by the development and utilization of human capabilities.

While Artificial Intelligence Leadership demonstrates a strong and statistically significant positive effect on innovation activity, it simultaneously exerts a substantial negative influence on human capabilities. At the same time, human capabilities do not exhibit a significant direct effect on innovation activity. This configuration does not support a mediation mechanism and calls for a more careful interpretation of how technological and human inputs are currently combined within organizational production systems. Rather than suggesting the irrelevance of human capabilities, the results point to a form of input misalignment, where technological inputs are effectively translated into output gains, while human capital remains underutilized. In this sense, innovation appears to be increasingly driven by AI-enabled processes without a corresponding integration of human autonomy, critical thinking, and creativity. This pattern reflects a structural imbalance in the innovation production function, where technological inputs dominate output generation while human capital remains underutilized. This finding challenges the widely held assumption that AI adoption naturally enhances human-centered innovation (Nonaka & Takeuchi, 1995; Amabile, 1996). Instead, it suggests that leadership practices may prioritize efficiency, speed, and data-driven decision-making, thereby shifting the production function toward technology-dominant efficiency rather than balanced input complementarities.

This interpretation aligns with the broader debate on augmentation versus substitution in AI-enabled organizations (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2020). While much of the literature emphasizes the augmentative role of AI in expanding human capabilities, the present findings suggest that leadership practices may, in effect, facilitate a partial substitution dynamic, where AI systems assume a central role in generating innovation outputs. Importantly, this should not be interpreted as a technological inevitability, but rather as a consequence of organizational choices regarding the allocation and integration of resources.

From a theoretical standpoint, the results can be further interpreted through the lens of institutional decoupling (Meyer & Rowan, 1977). Organizations may continue to emphasize the importance of human capabilities at a symbolic level, while operationally relying on AI-driven systems to produce innovation outcomes. This creates a disconnect between formally endorsed values and actual production practices, where human capital is recognized but not efficiently incorporated into value creation processes. Such a configuration reflects not the absence of human capabilities, but their inefficient deployment within AI-driven systems.

Importantly, the absence of a significant relationship between human capabilities and innovation activity should not be interpreted as evidence that human contributions are obsolete.

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Rather, it indicates that current organizational configurations may fail to translate human potential into measurable outputs, particularly in environments where AI systems dominate idea generation, evaluation, and implementation processes. Human capabilities—such as critical reflection, contextual judgment, and creative synthesis—may remain essential for complex and non-routine innovation, even if their contribution is not immediately captured in efficiency-based performance indicators.

From a managerial perspective, the findings highlight a critical trade-off: organizations may increase innovation outputs and improve innovation efficiency through AI-driven leadership, while simultaneously underutilizing human capital. This imbalance may not generate immediate declines in observable performance, but it raises important concerns regarding long-term productivity dynamics, including reduced adaptability, diminished exploratory capacity, and potential path dependency. Over time, excessive reliance on AI-driven processes may lead to optimization without diversification, limiting the scope for transformative innovation.

The study therefore contributes to the literature by shifting the focus from whether AI enhances innovation to how leadership shapes the allocation and interaction of technological and human inputs. Taken together, the findings suggest that AI-driven leadership reconfigures the innovation production function by enabling efficiency-driven output generation while simultaneously weakening the productive role of human capital. The results suggest that the key issue is not the presence of AI per se, but the extent to which leadership practices enable efficient complementarities rather than imbalanced substitution. In this sense, Artificial Intelligence Leadership emerges not only as a driver of innovation, but also as a potential source of inefficiency when human capabilities are not effectively integrated.

In conclusion, the findings call for a more balanced approach to AI-driven innovation, one that moves beyond efficiency-oriented implementation toward models of human–AI complementarity. Future research should further examine the conditions under which human capital can be more effectively integrated into AI-driven production systems, particularly in contexts requiring creativity, strategic judgment, and adaptive problem-solving. These findings contribute to the emerging literature on AI and economic productivity by suggesting that AI-driven leadership may enhance innovation performance through efficiency gains, even in the absence of strong human capability engagement, but potentially at the cost of long-term productive capacity.

6. Conclusions

This study examined how artificial intelligence leadership shapes the relationship between technological integration, human capabilities, and innovation outcomes within organizations. The findings reveal a consistent pattern: while AI-driven leadership significantly enhances innovation activity, it simultaneously reduces human capabilities, with no evidence that these capabilities contribute directly to innovation outcomes within the observed model. This configuration suggests that innovation performance is currently driven primarily by efficiency gains associated with AI systems, rather than by the effective utilization of human capital. From an economic perspective, these results point to a form of productive imbalance, where technological inputs are efficiently translated into outputs, but human resources remain underutilized. Such a configuration may generate short-term improvements in innovation efficiency, but it raises concerns regarding long-term productivity, particularly in relation to adaptability, resilience, and the capacity for exploratory innovation. In this sense, the findings contribute to the literature on technological change and productivity by highlighting that increased output does not necessarily imply optimal input allocation.

The study extends existing research by demonstrating that the impact of artificial intelligence on innovation is not solely determined by technological adoption, but by the way leadership structures the interaction between human and technological inputs. In this context, Artificial Intelligence Leadership emerges as a critical coordination mechanism, capable of either fostering complementarity or reinforcing substitution dynamics between AI systems and human capabilities. The implications of these findings suggest that organizations need to move beyond efficiency-

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oriented approaches to AI adoption and instead develop governance frameworks that ensure the productive integration of human capital. This requires maintaining decision autonomy, enabling critical engagement with AI-generated outputs, and embedding human expertise within AI-supported processes.

At the broader economic level, the results indicate that policies aimed at enhancing productivity through AI should not focus exclusively on technological diffusion, but also on the effective utilization of skills. Without such alignment, productivity gains may coexist with the systematic underutilization of human potential, raising concerns about the long-term sustainability of innovation-driven growth.Future research should further investigate the conditions under which human capabilities can be more effectively integrated into AI-driven systems, particularly in sectors characterized by high uncertainty and knowledge intensity. Understanding these dynamics is essential for developing sustainable models of productivity that balance efficiency with long-term innovative capacity.

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