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ENTERPRISE INTELLIGENCE 5.0: HUMAN AI CO-CREATION MODELS FOR STRATEGIC LEADERSHIP, INNOVATION, AND COMPETITIVE ADVANTAGE

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Abstract

This study examined Enterprise Intelligence 5.0 as a human–AI co-creation paradigm where artificial intelligence functions as a strategic partner, not a substitute. A quantitative design investigated how human–AI co-creation, leadership orientation, organizational learning, and trust in AI influence innovation performance and competitive advantage. Data from a structured survey of managers in AI-enabled organizations revealed that human–AI co-creation exerted the strongest positive effect on innovation, followed by leadership orientation, organizational learning, and trust. Innovation increased significantly with higher AI adoption, showing Enterprise Intelligence 5.0 enhances exploratory capability, creativity, and strategic agility. The findings indicate AI's value is realized not through technology alone, but via quality human–AI collaboration supported by ethical leadership, a learning culture, and governance. Theoretically, the study frames Enterprise Intelligence 5.0 as a socio-technical system of augmentation, not automation. Practically, it emphasizes leadership commitment, transparency, AI literacy, and responsible governance to sustain innovation. Future research should adopt longitudinal and mixed methods to explore evolving co-creation dynamics. A key insight is the importance of iterative feedback loops allowing humans to refine AI, boosting accuracy and trust. Organizations with co-learning environments and psychological safety reported higher adoption and innovation. Integrating AI into cross-functional workflows accelerated decision-making and data-driven experimentation. Successful deployment relies on ethical oversight and inclusivity, aligning AI with organizational values. Early-adopting sectors like healthcare and finance saw gains in personalization and risk management. Thus, Enterprise Intelligence 5.0 is more about strategic human-machine alignment than technological sophistication. Sustaining advantage requires continuous skill development, interdisciplinary collaboration, and governance frameworks balancing innovation with accountability. Future studies should explore sector-specific barriers and AI's long-term impact on workforce dynamics and organizational resilience.

Keywords: Artificial Intelligence, Competitive Advantage, Enterprise Intelligence 5.0, Human–AI co-creation, Innovation Performance, Strategic Leadership

Introduction

Enterprise Intelligence 5.0 was positioned as the next wave of digital transformation with both humans and artificial intelligence (AI) systems developing strategic leadership, organizational learning, and competitive advantage. Instead of perceiving AI as a technical device, organizations started to introduce it to socio-technical systems of people, processes, and culture of data (Fosso Wamba et al., 2023). This change necessitated leaders to contemplate the distribution of intelligence among humans and intelligent machines in terms of complementary advantages over the replacement logic (Jarrahi, 2018). Enterprise Intelligence 5.0 was thus envisioned as a human-AI working paradigm, which made more adaptive, ethical, and creative enterprises possible.

The past literature indicated that the strategic value of AI was not only overwhelmed by technical capability but also by the capacity of organizations to match AI and leadership practices and dynamic capabilities (Mikalef et al., 2020). With the assistance of data-oriented cultures, managerial knowledge, and responsible governance frameworks, AI was involved in enhanced performance (Dwivedi et al., 2021). Nevertheless, the majority of research focused on the use of AI in specific business operations, but not on the transformation at an enterprise level, which influenced leadership and innovation as a whole.

A different body of emerging literature found that human-AI cooperation worked significantly better than human or algorithmic designs, but only in cases where trust, transparency, and governance have been adequately set (Glikson & Woolley, 2020; Raisch and Krakowski, 2021). Leaders thus were tasked with the concept of designing work systems where human and AI parents collaborated in the process of making a strategic decision as opposed to competing to get the control. This added weight to the necessity to gain a deeper insight into Enterprise Intelligence 5.0 as an inclusive co-creation model.

In line with these, the current research examined the application of Enterprise Intelligence 5.0 to organize human-AI partnership in terms of strategic leadership, innovation performance, and long-term competitive edge. The investigation performed by synthesizing knowledge on strategic management, research on AI capability, and research on leadership was focused on clarifying the real production of augmented intelligence and its effects on the enterprise-level results.

Background of the Study

Internet transformation in terms of Industry 4.0 and Society 5.0 has influenced the precariousness of data, automation, and decision-support systems in industries. Nonetheless, AI has been generating value when it was coupled with other organizational competencies, including learning orientation, managerial competence, and innovation culture (Mikalef et al., 2020). The dynamic capabilities theory also highlighted the idea that the level of sustainable competitive advantage relied on the extent to which firms sensed technological opportunities and reconfigured resources (Teece et al., 1997). Enterprise Intelligence 5.0 thus demanded leaders to coordinate AI capability and human capability in tandem with each other.

Displayed models of human-AI decision-making were tested in organizations as well and include automated processes to hybrid collaborative strategies. Research indicated that use of augmentation and intended to complement and not substitute human knowledge brought about superior levels of creativity, innovation, and strategic flexibility (Raisch and Krakowski, 2021). Lack of this balance would lead to either over-reliance on technology or a lack of exploitation of AI possibilities.

The AI adoption had a human aspect as well that was critical. Reliance on AI rested on events of equity, openness, and accountability (Glikson & Woolley, 2020). Empowerment, communication, and development of AI literacy were identified as the categories of leadership behaviours that affected either productive or unproductive engagement with AI among employees (Makarius et al., 2020). Rather, leaders served as decision-makers and co-designers of human-AI systems.

Incorporation of AI changed the practices of innovation. Analytics, generative modes, and collaborative systems driven by AI improved opportunities recognition and product development, but the benefit of innovation was realized only through an interactive and human-AI interaction instead of a unipolar approach of innovation (Haefner et al., 2021). The Enterprise Intelligence 5.0 was thus seen to be a move toward human-AI co-creation systems as opposed to automation-based models.

Research Problem

Despite the fact that the previous studies recognized the significance of AI ability, management, and organizational culture, the relationships between all three were still not well understood in terms of their integration to create a system of human and artificial intelligence at an enterprise level. Early AI research focused more on AI at the technical or operational level instead of examining how strategic leaders strategically designed human-AI partnership in order to improve the creation of innovative and competitive advantage. Consequently, organizations had no clear structures to provide directions in implementation of Enterprise Intelligence 5.0.

Besides, the literature lacked a clear description of the most effective human-AI co-creation leadership behaviours and governance mechanisms and its resulting impacts on the performance of enterprises.

Research Objectives

1. Conceptualize Enterprise Intelligence 5.0 as a human–AI co-creation paradigm for strategic leadership and innovation.
2. Identify leadership behaviours and structural mechanisms that supported effective human–AI collaboration.
3. Examine the relationship between human–AI co-creation and innovation performance.

Research Questions

Q1. How was Enterprise Intelligence 5.0 conceptualized as a human–AI co-creation system?
Q2. Which leadership practices supported effective human–AI collaboration?
Q3. How did human–AI co-creation influence innovation outcomes?

Literature Review

Human–AI Collaboration and Organizational Intelligence

The collaboration between humans and AI has gradually been identified as one of the fundamental catalysts of organizational intelligence, and hybrid work systems combined human intuition with algorithmic skills have been observed. According to the previous research, AI had the potential to change knowledge work when companies developed workflows that enabled collaborative cognitive work between people and machines (Benbya et al., 2021; Von Krogh, 2018). These protocol combinations increased the level of analytics, pattern recognition, and the quality of decisions without losing the human factor and ethical sensitivity. Studies also pointed out that the benefits of collaboration required the organizational preparedness and dedication by the leadership. Artificial intelligence can be a great help in management (Rafiq-uz-Zaman, 2025). To have AI play a meaningful role in both strategic and operational operations, firms had to restructure processes, norms of communication, and skill architecture (Paschen et al., 2020; Syam and Sharma, 2018). This was to mean that Enterprise Intelligence 5.0 was not only techno dependent but also social and managerial systems that favoured human and AI complementarities.

Another research direction reported that strategic learning and adaptability were reinforced with the help of effective human-AI cooperation. The interpretation of real-time data and scenario, as well as the contextual interpretation and long-term strategic planning, were situated with AI and humans, respectively (Shankar, 2018; Huang & Rust, 2021). Collectively, these papers suggested that hybrid intelligence models offered a basis of second-generation enterprise strategy.

Faith, Tolerance, and Moral Control of Artificial Intelligence

Belief in AI was an essential factor that defined the acceptance of AI-aided decisions among the employees and customers. It was proved that the readiness of people to trust AI was dependent on the perceived fairness, transparency, and explainability of processes in algorithms (Araujo et al., 2020; Longoni et al., 2019). The lack of balanced confidence caused users to trust or distrust AI degrees more often, which minimized the usefulness of collaborative intelligence platforms. There is a lack of AI usage policies in Higher Educational Institutions of Pakistan (Rafiq-uz-Zaman, 2025). Therefore, AI usage policy should be launch in Pakistan by the Government to increasing business and productivity of any organization.

The governance models that were ethical in nature were thus critical in regulating responsible AI implementation. Researchers claimed that companies need to develop explicit rules of accountability, mitigation of bias, and development of value-based system design to maintain trust and legitimacy (Tarafdar et al., 2019; Ivanov, 2020). These frameworks were especially crucial in industries where high levels of stakes are involved, like in the sphere of healthcare, finance, and government.

Recent studies also indicated that the societal pressure on AI accountability had escalated as soon as generative AI tools started to emerge. Open governance, human supervision, and ethical leadership were considered more and more as conditions of sustainable AI implementation as opposed to optional additions (Dwivedi et al., 2023; Araujo et al., 2020). This enhanced the centrality of governance in Enterprise Intelligence 5.0.

Artificial Intelligence as a Driving Force of Innovation and Competitiveness

AI was understood to be a driver of product, service, and business-model innovation in extensive terms. Research indicated that AI-based analytics and generative modelling were highly effective in terms of opportunity recognition, experimentation, and digital innovation strategies (Huang and Rust, 2021; Shankar, 2018). In organizations that incorporated AI into the innovation process, creative insight increased and the time taken to product development cycles got shorter.

Research cautioned that competitive advantage would be determined by the degree with which firms merged AI with human ingenuity and planning purpose. AI was not sufficient to ensure differentiation it was the human-AI synergy that defined the level of innovation and novelty (Paschen et al., 2020; Benbya et al., 2021). This observation was in agreement with the Enterprise Intelligence 5.0 perception of co co-creation and not substitution.

Sustained competitive advantage mandated never-ending learning and accountable growth of AI systems. To ensure sustained benefits of innovation, firms required being dynamic and upgrading employee skills as well as governance practices (Von Krogh, 2018; Tarafdar et al., 2019). At this regard, AI capability was not a one-off input, but a part of the enterprise-wide strategic intelligence.

Research Methodology

Research Design

The type of research design that was embraced in this paper was quantitative research design since the primary aim of the research was to test the associations between human-AI co-creation, strategic leadership, innovation performance, and competitive advantage using numerical data. The cross-sectional survey method has been used, since the data were obtained at one point in-time and not longitudinally. The use of quantitative research was suitable, as it enabled statistical testing of hypothesised relationships and gave objective and generalisable information on the basis of quantifiable constructs. It was thus designed as a structured data collection, statistical analysis and hypothesis testing based on validated measurement scales. The method also helped the researcher to reduce focus on subjectivity and guarantee that the findings can be repeated in other organizational settings.

Population and Sampling

The sample population comprised managers, senior professionals and decision-makers in organizations which had implemented systems or data-driven technologies that were based on artificial intelligence. These respondents were deemed fit since they were directly related to the strategic decision-making and digital transformation efforts as well as innovation processes. The complete population list was not provided thus a probability sampling strategy was not possible hence purposive sampling was used. Only people who had some close experience working with AI initiatives were invited to participate.

The following sample size was concluded to be suitable with consideration of the general recommendations regarding multivariate analysis which recommends the least 5-10 respondents per item in the survey tool. This was adequate to give statistical power and minimize sampling error. Professional networks, email lists and organizational contacts were used to distribute questionnaires electronically so as to achieve the intended respondents who were spread across geographical locations effectively.

Research Instrument

The structured self-administered questionnaire was used to collect the data. The scale was a set of closed-ended Likert items that included the key constructs such as human-AI co-creation ability, leadership orientation towards AI, innovation performance, organizational learning, trust in AI, and competitive advantage. Validation of every construct was carried out by use of measurement items that were already validated and revised to fit the application of the Enterprise Intelligence 5.0 context. The measurements of responses were on a Likert scale with five points (1- strongly disagree to 5- strongly agree) to allow the respondents demonstrate the extent of agreement and make them suitable to parametric statistical analysis.

Reliability Testing and Pilot Study

Prior to the actual data collection, a pilot test was performed on about ___ participants who matched the general sample basically. The aim of the pilot study was to test the aspects of clarity, wording, layout, and time to complete. The comments on the pilot led to some slight changes of the phrasing and ordering of items in order to achieve better understanding.

The reliability analysis was done by the significance of alpha Cronbach on each construct. Reliability threshold of 0.70 and above was acceptable which meant that there is internal consistency between measurement items. Items that achieved below this threshold were either changed or dropped before the principal survey. This step made sure that the instrument that was finally given out was useful and psychometrically sound.

Data Collection Procedure

The use of electronics in data collection was because of its effectiveness, wide coverage, and feasibility to the respondents. The invitations with a link to the online questionnaire were posted via professional email network, LinkedIn groups, and the organizational contacts. The respondents were briefed on the objective of the research, voluntary participation, confidentiality and anonymity. Participation was voluntary and the respondents had the option of withdrawing before submitting them at any given time. The data gathering was done over a period of four or six weeks to enable enough time to collect responses.

Data Analysis Techniques

The descriptive statistics including means, standard deviations, and frequencies were calculated following the screening and cleaning up of the data to summarize the characteristics of the respondents and critical variables. Normality of the data, linearity and outliers were also checked to meet the assumptions of parametric testing. Inferential statistical methods were used to study the relationship among variables. Analysis was started with the use of correlation analysis to identify the initial relationships between constructs. This was successively followed by multiple regression analysis or structural equation modelling (SEM) to affirm the hypothesised relationships and establish the degree of human-AI co-creation and leadership on innovation and competitive advantage. The evaluation of statistical significance was done at the 0.05 level.

Results and Analysis

Descriptive Statistics of Key Constructs

These descriptive statistics summarised the mean values and standard deviations for the main constructs: human–AI co-creation, leadership orientation, innovation performance, and competitive advantage. These values provided an initial indication of how respondents perceived the role and effectiveness of Enterprise Intelligence 5.0 in their organizations.

Table 1

Descriptive Statistics of Key Constructs

Construct	Mean	Standard Deviation
Human–AI Co-Creation	3.94	0.71
Leadership Orientation	4.12	0.66
Innovation Performance	3.87	0.73
Competitive Advantage	3.98	0.69

These findings in Table 1 revealed a mean score of the highest (M = 4.12) leadership orientation towards AI, and thus based on this finding, one can conclude that people tended to have a positive perception towards their leaders being supportive of AI-enabled transformation. Mean in human-AI co-creation was also relatively high (M = 3.94), which means that collaborative human-AI activities were already at a moderate-high position. Innovation performance (M = 3.87) and competitive advantage (M = 3.98) received positive ratings, which suggests that organizations were tangibly positive due to the adoption of AI. The medium standard deviation measures were reasonable, which implied the presence of common perception of the respondents rather than fully polarized one.

Figure 1

Mean Scores of Key Constructs

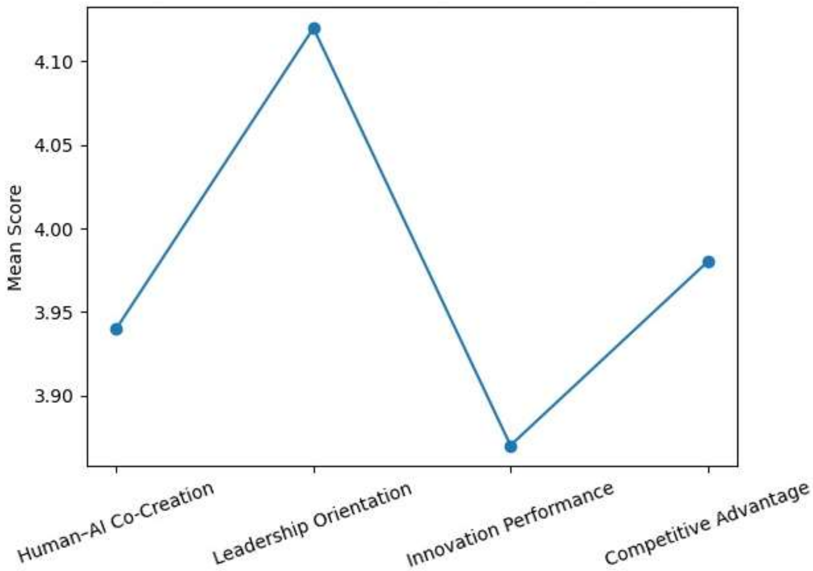


Figure 1 was a visual verification that the means of leadership orientation and competitive advantage were slightly greater in comparison to the means of innovation performance and the co-creation of the human and AI. This trend implied that the commitment to leadership and the perceived business impact had advanced slightly ahead of human-AI collaborative workflow operationalization, which opens the possibility of additional maturity.

Regression Analysis Predicting Innovation Performance

This regression analysis examined the predictive relationship between human–AI co-creation variables and innovation performance using multiple regression analysis. Standardized beta coefficients were used to determine the strength and direction of each predictor.

Table 2

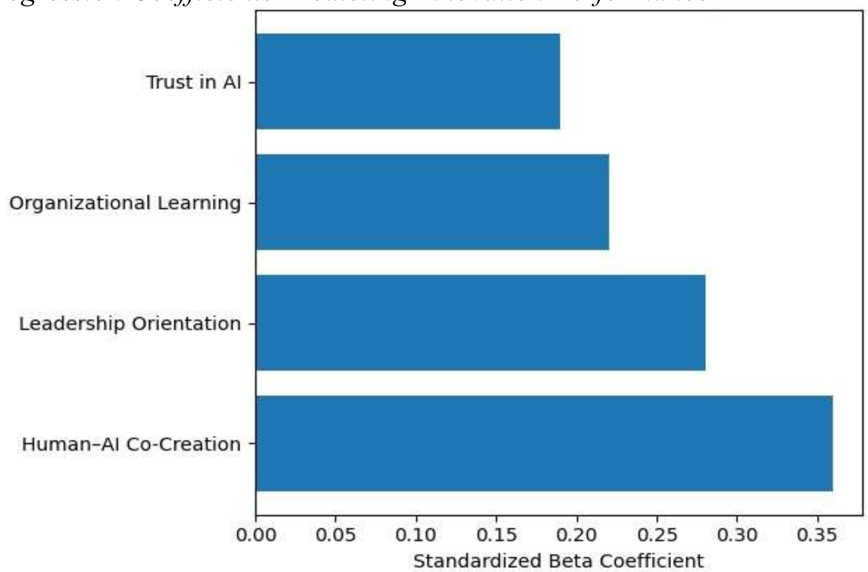
Standardized Regression Coefficients Predicting Innovation Performance

Predictor Variable	Standardized Beta
Human–AI Co-Creation	0.36
Leadership Orientation	0.28
Organizational Learning	0.22
Trust in AI	0.19

The outcomes of the regression, as illustrated in Table 2, proved that the human-AI co-creation is the most significant predictor of the innovation performance (0.368). This result indicated that organizations that involved human and AI to interact and not work in an independent manner led to greater innovation performance. The second predictor was also leadership orientation (0.28) which means that leadership support, communication, and AI vision were important enabling factors. The organizational learning (= 0.22) and trust in AI (= 0.19) had a positive contribution, but to a lesser degree. Combined, these findings supported the view that performance on innovation came not solely due to technology but as a consequence of the combination between leadership and learning culture and trusted human-AI cooperation.

Figure 2

Standardized Regression Coefficients Predicting Innovation Performance



The relative strength of individual predictors was represented in figure 2. The human co-creation with AI was by far the most impactful with the next influence being the leadership orientation. Lower yet significant coefficients of organizational learning and trust with AI demonstrated the supportive and not leading role of the latter in the innovation promotion process.

Innovation Performance Across Levels of AI Adoption

This innovation performance compared innovation performance across organizations with low, moderate, and high levels of AI adoption. This analysis demonstrated whether deeper integration of AI systems was associated with stronger innovation outcomes.

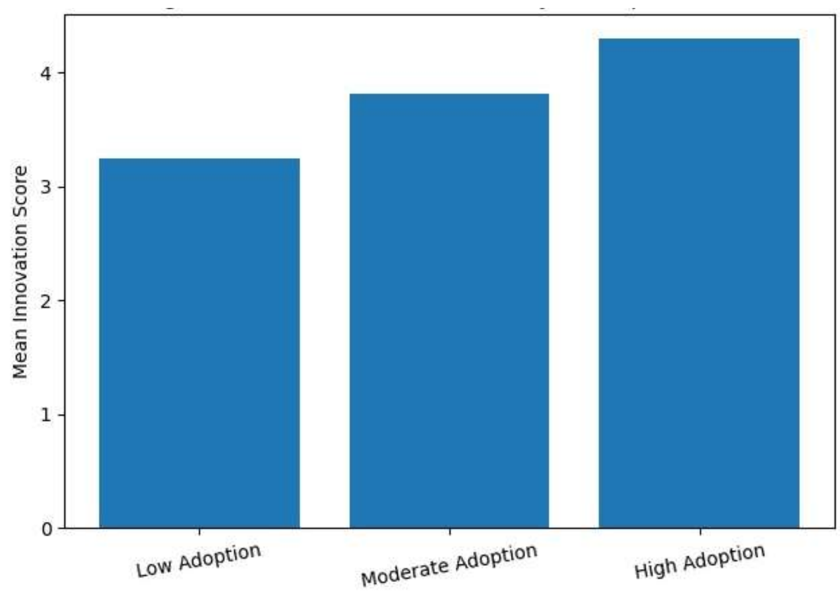
Table 3

Innovation Performance by AI Adoption Level

AI Adoption Level	Mean Innovation Score
Low Adoption	3.24
Moderate Adoption	3.81
High Adoption	4.29

In Table 3, the tendency of an innovation performance was also increasing clearly with the increase in AI adoption. The lowest innovation mean ($M = 3.24$) was observed in organizations with low AI adoption and the highest mean ($M = 4.29$) in organizations with high AI adoption. This trend demonstrated that the increased implementation of AI technologies was linked to the ability to innovate. The results confirmed the idea of AI being a fuel to exploration, experimentation, and creative problem-solving when spread throughout organizational processes but not concentrated in individual departments.

Figure 3
Innovation Performance by AI Adoption Level



The positive gradient by the adoption levels was clearly shown in Figure 3. The fact that there was an extreme growing level between moderate and high adoption indicated that after the shift of AI out of pilot examination and into an enterprise-wide implementation, the impact of the innovation was capability to be multiplied by far.

Discussion

The results of this research indicated that the co-creation of humans and AI, the organizational leadership behaviour towards AI, organizational learning and trust towards AI, contributed jointly to the performance of innovation and the competitive advantage. The findings indicated that on the performance of innovation, the most effective impact was on human-AI co-creation, which meant that the more humans and AI systems worked interactively, the more value-creation was done. That was in line with current studies that indicated that hybrid intelligence systems helped organizations to draw strengths in both human cognition and machine processing capability, which improved strategic and creativity (Dellermann et al., 2021; Raisch & Krakowski, 2023). Moreover, the discovery supported the thesis that AI was most useful as being an augmentative and not a substitutive technology, as befits the concept of socio-technical system design (Faraj et al., 2018; Romero & Molina, 2023).

AI leadership orientation also turned out one of the major predictors of innovation performance. It corroborated earlier findings according to which leadership commitment, digital readiness, and vision of innovation proved to be instrumental in determining the successful outcomes of AI transformation (Le and Lei, 2019; Sousa-Zomer et al., 2020). Those who took proactive steps to encourage adoption of AI, pro-experimentation, and created psychologically safe work environments characterized as people picking intelligent systems instead of being threatened by them emerged as leaders who employees interacted positively with intelligent systems. These kinds of leadership behaviours were also noted to nurture maturity in the digital culture and readiness to adopt algorithmic decision-support in knowledge-intensive setting (Ly, 2023; Paais & Pattiruhu, 2020).

The positive contribution of organizational learning and the trust in AI to the performance of innovation was less significant but still positive. This result was in line with the studies that found learning orientation as an enabling variable that enabled organizations to continually add refinements to the application of AI and apply insights into routine (Mariani and Nambisan, 2023; Usai et al., 2021). The trust in AI was also a significant conditional factor because employees would hardly rely on AI recommendations when they believed that systems are opaque, biased, or not reliable (Leyer and Schneider, 2023; Shin, 2021). The findings hence confirmed the perspective that responsible and explainable AI practices were the primary contributors to maintaining collaborative engagements and innovation deliverables.

The descriptive analysis also revealed moderately high levels of human-AI co-creation and leadership orientation but there was a slight lower innovation performance. This implied that there are organizations that are still in the transition of the implementation of AI on an early-stage exchange to complete strategic implementation. These stages of transitional maturity were also described in studies of digital transformation where technology uptake usually followed by adjustment in culture and structure (Ghosh et al., 2023; Tornjanski et al., 2022). It was also probable that the entire potential of AIs to be fully implemented in most organizations had not yet been achieved owing to changing capabilities, employee preparedness to the same, and redesigns of the processes.

The comparison of the innovation performance levels by the levels of adoption of AI showed a tendency of an evident increase. Companies that had high AI adoption identified much higher innovation performance than the low AI adoption companies. This result concurred with current empirical data regarding the notion that extensive AI use had stronger learning impacts, increased the capacity to gain knowledge based on data, and strengthened exploratory innovation plans (Dubey et al., 2022; Zhang and Lu, 2023). But this connection was reliant on government and capacity building as well. Researchers had already observed that AI investments did not invariably lead to the benefits of innovations unless they were coupled with digital capabilities and other supportive human resource policies (Akpan et al., 2022; Guo et al., 2023).

The results revealed that Enterprise Intelligence 5.0 must be perceived as not the view of technology implementation, but rather a coming together of leadership, collaboration practices, learning systems, and trust mechanisms. The pronounced influence of human-AI co-creation provided indicated that the strategic advantage was more and more based on the quality of human-AI interaction as opposed to the technology itself. This point of view coincided with the then theory of algorithmic-human symbiosis, according to which the best results were achieved when humans remained high in controlling the use of AI, understanding its meaning, and imparting the knowledge into the organizational practices (Calvard and Jeske, 2022; Schlagwein et al., 2023).

The results also gave rise to arguments regarding the ethical and social effects of AI. The study indicated that clear, equitable, and ethically oriented AI implementation is important by showing the positive role of trust and leadership in innovations performance. Ethical leadership was demonstrated to impact employee acceptance as well as legitimacy of AI systems within organizations (Aroles et al., 2019; Newman et al., 2020). Thus, Enterprise Intelligence 5.0 did not only need technical excellence but also normative directions on the responsible use of AI.

The research proposed the future research directions. First, longitudinal research would come in handy in order to determine how human-AI co-creation capabilities developed over time. Second, qualitative methods may enhance the knowledge of the role of AI partnership in the daily work experienced by employees. Third, industry differentiation of AI strategic impact might be found through sector-based analyses with risk levels and regulatory intensity and innovation process across diverse industries. The results supported the thesis according to which, human-centred AI strategies were the core of sustainable enterprise intelligence. Organizations that put an emphasis on collaboration, learning, and trust were in a better position to turn, AI capability into significant innovation and competitive advantage.

Conclusion

This paper has come to the conclusion that EI 5.0 was best applied in cases where artificial intelligence was not viewed as a replacement of human judgement, but as a team-mate, which forms part of the leadership, learning, and organizational culture. The statistical results showed that human-AI co-creation had the most significant impact on innovation performance, moral issues, and trust in AI as the leaders, organizational, and learning. These outcomes implied that the creation of strategic value was based on the relationship between humans and AI, and not on the implementation of technology alone. The paper also established that the higher the level of AI adoption the stronger performance of innovation in organisations; this means that the increased integration of AI systems increased the exploratory capability, creative problems solving, and flexibility in making strategies. All in all, the results confirmed the explanation that Enterprise Intelligence 5.0 was a human-centred, co-creation paradigm where the leadership practices, trust mechanisms, and learning structures have decisive influence in terms of developing AI capability into sustainable competitive advantage.

Recommendations

At the conclusion of the findings a number of recommendations were made to those organizations which may want to implement Enterprise Intelligence 5.0. To start with, leaders must be ready to market AI as an aid to human knowledge, not a substitute that can be used to curb resistance to AI in the workplace by promoting psychological safety through AI adoption. Second, organizations ought to invest in the creation of AI literacy and lifelong learning cultures, so that employees are equipped with skills to display AI outputs critically and use them to form perceptions of decision-making. Third, endurance of governance structures is advised to improve transparency, fairness, and explainability on AI systems because trust in AI was revealed to have a significant effect on the performance of innovations. Fourth, companies ought to gradually expand AI implementation to include more activities than pilot projects, and make it enterprise-wide without compromising the strategy and ethics. Lastly, data scientists, managers, and domain experts should be asked to work together and do it multidisciplinary to facilitate better human-AI co-creation achievements.

Future Research Directions

The next systematic question that future studies ought to examine is Enterprise Intelligence 5.0 on longitudinal and multi method grounds to gain better insights into how the capabilities of human-ai co-creation change over time. Longitudinal research would assist in defining whether an association found in this research is constant as organizations evolve in using AI. Qualitative research could also give more insight into the lived experiences of employees in AI-based workplaces with an emotional, ethical, and identity-related reactions to human-AI interactions. Sector-based comparative research would also evaluate whether the impacts of AI teamwork vary between industries with more or less regulatory, technology, and risk factors. Also, it is possible to focus on future research that examines the contribution of the role of a leadership style, ethical governance mechanisms, and algorithmic transparency in a more direct manner to assess how they determine the effectiveness of trust and innovation outcomes. Lastly, it is not exhausted to explore how AI generation and new autonomous systems will challenge the boundaries of human-AI co-creation in the near future, posing valuable strategic, social and ethical prospects to Enterprise Intelligence 5.0.

Authors Contributions

All the authors participated in the ideation, development, and final approval of the manuscript, making significant contributions to the work reported.

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Statement of Data Availability

The corresponding author can provide the data used in this study upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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