Intelligent Human Systems Integration (IHSI 2025), Vol. 160, 2025, 56–66
https://doi.org/10.54941/ahfe1005810

Digital Networking for Economic Growth: Interactions Between Natural and Artificial Intelligence

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ABSTRACT

This paper investigates how human knowledge, i.e. (Natural Intelligence: NI), mixes with "Artificial Intelligence" (AI). An integrated multilayer network framework is proposed to create economic value. The essential question is: How can copula nodes that connect hybrid multilayer networks enable NI-AI integration to generate economic value for digitalized firms? This study empirically tests the cost-benefit improvements likely to be derived from AI technologies across industries, ranging from manufacturing and retail to finance. The results provide evidence that efficiency improvements tend to occur alongside significant reductions in total costs. Copula nodes amplify interactions between NI and AI to achieve a cohesive joint effect capable of delivering maximum economic benefits for participating firms. These findings provide a unique strategy for firms to increase profitability and compete in the digital age.

Keywords: Economic value creation, Digitization, Network science, Copula nodes, Cost-benefit analysis, Network optimization

INTRODUCTION

Technology changes faster every day, and the speed of this transformation is overhauling business models across industries so that now almost everyone. The integration of human (natural intelligence, NI) characteristics offers a considerable opportunity for value augmentation within firms. Yet, the combination of NI and AI to result in optimal synergy effects will still pose a multi-faceted issue that calls for an elaborate framework governing this integration process.

In this study, a new approach using a multilayer network framework allows copula nodes to forge connections and communication between different layers (each representing NI, AI, or hybrid cases). The principle underlying this research is that the integration of NI and AI inside a scalable and architectural structure within the organization helps achieve significant efficiency, operational process improvement, better decision-making techniques, and cost reduction. The main research question is the following: *How can value creation be realized among digitally transformed firms through copula node-driven integration of NI with AI within communicating multilayer networks?*

The multilayer network framework incorporates dynamic feedback loops, allowing NI and AI layers to self-adjust based on evolving performance metrics. This adaptability is essential for industries with rapidly shifting data landscapes, such as finance and retail, where response times can be crucial.

LITERATURE REVIEW

The literature review highlights AI's transformative potential in enhancing sustainable development, productivity, decision-making, and cost management (Dalenogare et al., 2018). Evidence of AI's impact spans industries: predictive maintenance in manufacturing reduces equipment downtime, AI in retail boosts customer engagement and sales, and AI in finance accelerates algorithmic trading and risk management, providing competitive advantages (Grewal et al., 2021; Fernández-Maestro et al., 2022).

Arora and Sharma (2023) discuss AI's integration with big data analytics, enhancing precision in decision-making within complex structures. Similarly, Dwivedi et al. (2024) emphasize AI's synergies with emerging technologies like blockchain and IoT. Network science research, particularly in multilayer networks (Barabási, 2016; Boccaletti et al., 2014), offers frameworks for harmonizing NI and AI, while copula nodes facilitate non-linear dependencies, enhancing decision support by balancing both intelligences (Joe, 2014). Górriz et al. (2020) underscore the necessity of embedding AI in multilayer networks for organizational performance. Braun et al. (2024) further support the benefits of human-AI collaboration, especially in improving error detection and accuracy. The literature also discusses the challenges of AI-NI integration, emphasizing adaptable and dynamic systems to accommodate continuous learning and evolving challenges (Durlach and Ray, 2011; Wang, 2021). Kulik and Fletcher (2016) demonstrate enhanced educational outcomes through intelligent systems combined with human input, while Shulner-Tal et al. (2024) advocate for explainable AI to build trust in human-AI collaboration.

Notably, gaps in the literature regarding copula nodes' operational roles in business digitization exist, indicating the need for further empirical studies on multilayer network models and copula node applications. Integrating meta-learning and human supervision is recommended for a sustainable NI-AI synergy that supports organizations' long-term digital transformation and economic growth (Russell et al., 2017).

MODEL

This theoretical model operates within a multilayer network framework that integrates NI and AI to support complex decision-making and optimize economic value creation. The model's architecture is designed around copula nodes, which function as connectors that enable seamless, non-linear interaction between NI and AI layers. By facilitating dependency-driven information flows, copula nodes provide an adaptive integration mechanism that combines human expertise with computational precision, optimizing efficiency and decision-making processes across digitally transformed firms.

This paper's approach leverages the theory of network science to capture and address the intricacies of human-AI interaction, ensuring each intelligence type is optimally utilized without diluting the core strengths of either NI or AI.

Assumptions

- Bi-Directional Influence: The NI and AI layers are assumed to have reciprocal influence, where NI contributes qualitative, intuition-based insights (e.g., strategic creativity, ethical considerations), while AI offers quantitative precision, data processing, and predictive analytics. This interaction seeks to amplify human decision-making capacities while leveraging AI's ability to process large datasets rapidly. In this context, the model presumes that human judgment, when supplemented by AI data outputs, results in a higher decision-making efficacy than either Intelligence would achieve independently. Furthermore, this bi-directional influence supports real-time calibration between NI and AI processes, enhancing the model's responsiveness to contextual changes. This ensures decisions are not only precise but also contextually relevant, a critical factor in complex environments.
- Dependency Modeling via Copula Nodes: Copula nodes capture the complex dependencies and interaction strengths between NI and AI. They model non-linear relationships by dynamically adjusting based on environmental variables, strategic requirements, and data input fluctuations. This design allows firms to leverage the strengths of both NI and AI, forming a cohesive, symbiotic relationship that adapts as organizational needs evolve. The copula nodes not only facilitate the exchange of information but are also equipped to detect anomalies, thereby enhancing the reliability of decision-making.
- Net Economic Value (NEV) as Key Outcome Metric: The model's effectiveness is evaluated based on the NEV it generates. NEV is derived from calculating total economic benefits (e.g., increased efficiency, cost savings, improved decision quality) offset by the expenses associated with AI integration. This metric provides a quantitative assessment of the economic impact generated through the coordinated application of NI and AI in organizational contexts. In line with this, the NEV metric is dynamic, meaning it adjusts over time, enabling real-time tracking of economic gains derived from AI-NI synergy. This model also accounts for sector-specific benchmarks to assess NEV more accurately, making it applicable across diverse industry use cases.

Model Formulation (Multilayer Network Structure)

Let L_{NI} and L_{AI} denote the NI and AI layers, respectively. Their interaction, mediated by copula nodes C_{node}, is defined as follows:

$$NEV = f(L_{NI},\ L_{AI},\ C_{node})$$

Here, C_{node} serves as an inter-layer conduit that facilitates adaptive communication and optimal data transfer, enabling the alignment of NI and AI outputs. Copula nodes are designed to dynamically adjust based on dependency relationships, thereby enhancing the model's adaptability to changes in data flow and organizational requirements. The adaptability of C_{node} is particularly valuable in volatile environments, where rapid recalibration of NI-AI interactions is necessary to maintain consistent performance. The model extends scalability through the introduction of power-law characteristics, which help manage network complexity as the number of NI and AI interactions grows. This scalability is fundamental to maintaining efficiency and accuracy as more data and insights enter the network.

Cost-Benefit Analysis

The cost-benefit analysis (CBA) evaluates the economic impact of integrating AI within this multilayer network framework. NEV is calculated as the difference between the total benefits of integration and the associated costs, where:

$$NEV = Total\ Benefits - Total\ Costs$$

The model additionally considers 'Indirect Benefits' derived from increased customer satisfaction and employee efficiency, which indirectly contribute to NEV by fostering long-term customer loyalty and reducing turnover. Cost Components include:

- Initial Setup Costs (C_{setup}): The initial investments required to acquire AI infrastructure, train staff, and reconfigure workflows.
- Ongoing Operational Costs ($C_{operational}$): Recurring expenses associated with maintaining AI systems, including software updates, routine maintenance, and continued employee training.
- Hidden Costs (C_{hidden}): Potential unforeseen costs arising from AI integration, such as compatibility issues with existing systems and required adjustments in organizational structure.

Benefit Components encompass:

- Efficiency Gains ($B_{efficiency}$): Increased throughput and resource utilization resulting from AI-driven automation and process optimization.
- Enhanced Decision-Making ($B_{decision}$): Improvements in decision quality through the synthesis of data-driven AI insights and NI's contextual understanding.
- Cost Savings ($B_{savings}$): Operational cost reductions due to decreased labor needs, error minimization, and reduced downtime.

By incorporating NEV as a continuous evaluation metric, the model dynamically captures evolving economic gains, adjusting for both benefits and costs in real-time. A thorough sensitivity analysis is recommended to assess cost variability under different operational conditions, providing firms with insight into the potential financial fluctuations that may arise with AI integration.

Empirical Metrics for Efficiency

The model incorporates sector-specific metrics to evaluate its effectiveness, utilizing empirical data to validate its outcomes:

- Manufacturing Sector: AI-based predictive maintenance is expected to reduce equipment downtime, resulting in an approximately 30% improvement in operational efficiency (Dalenogare et al., 2018).
- Retail Sector: AI integration in inventory management and customer engagement has demonstrated a 25% reduction in overstock and stockouts, leading to higher turnover rates (Grewal et al., 2021).

  Financial Sector: Implementing AI in risk assessment and algorithmic trading processes reduces decision latency by 40%, enhancing the accuracy and speed of financial decision-making (Fernández-Maestro et al., 2022).

By applying sensitivity analysis to these metrics, firms can identify the most resilient parameters under various market conditions, helping them fine-tune the AI-NI integration strategy for optimal results. These metrics underscore the model's capacity for sector-specific adaptability, confirming that the copula node approach can yield optimal results across diverse operational contexts.

Empirical Validation and Data Sources

To empirically validate the model, the following data points are utilized to support the proposed outcomes:

Efficiency Gains

Manufacturing Sector: AI-based predictive maintenance has been empirically shown to reduce machine downtime by up to 30%, thus enhancing operational efficiency (Dalenogare et al., 2018). This outcome aligns with the model's prediction of efficiency gains through AI integration within production environments, where copula nodes facilitate real-time data analysis and predictive insights.

Retail Sector: Empirical studies show that AI-driven inventory management systems reduce overstocking and stockouts by approximately 25%, directly supporting the model's hypothesis that AI integration can improve inventory efficiency and customer satisfaction. The use of copula nodes in this sector allows seamless coordination between AI analytics and human managerial oversight, optimizing decision-making processes (Grewal et al., 2021).

These results highlight the transformative impact of copula nodes on achieving operational precision in the retail sector, confirming the model's robustness.

Enhanced Decision-Making

Financial Sector: In finance, AI-enabled decision-making tools have reduced processing times by up to 40% and improved risk management accuracy (Zhu et al., 2023). This finding supports the model's assumption that AI's data processing power, combined with NI's contextual interpretation through copula nodes, significantly enhances decision quality. The copula nodes serve as critical links, allowing human analysts to efficiently incorporate AI-generated insights into strategic decision-making (Fernández-Maestro et al., 2022).

The role of copula nodes in this process is instrumental, as they facilitate the integration of high-frequency AI insights with the nuanced judgment of financial experts, fostering more agile and accurate decision-making frameworks. Further empirical analysis indicates that the inclusion of copula nodes significantly enhances decision accuracy, particularly when unexpected market changes occur, reinforcing the importance of adaptive mechanisms within the model.

Cost Reductions

The model posits that cost reductions are a key benefit of AI integration across sectors, with empirical evidence confirming this in the manufacturing and retail industries. AI-driven automation in manufacturing, coupled with predictive analytics, has shown consistent cost savings by minimizing machine downtime and optimizing production schedules. Similarly, in retail, AI's inventory optimization reduces costs associated with excess stock and waste. This empirical validation aligns with the theoretical expectation that copula nodes facilitate efficient NI-AI integration, leading to quantifiable cost reductions. As demonstrated, cost reductions align directly with the NEV metric, reinforcing the value proposition of AI integration as a sustainable approach to driving operational cost-efficiency.

Through this structured empirical validation, the model demonstrates adaptability and robustness across diverse industry applications, affirming its value as a framework for integrating NI and AI within digitalized firms. By fostering a balanced synergy between human intuition and AI precision, the copula node-enabled multilayer network model provides a viable pathway for achieving sustainable economic growth in the digital economy.

With AI, the Hermeneutics in Augmented Multilayer Hyperplanes are enhanced by AI's connecting abilities, which introduce new nodes and additional edges, as synthetically shown in Figure 1.

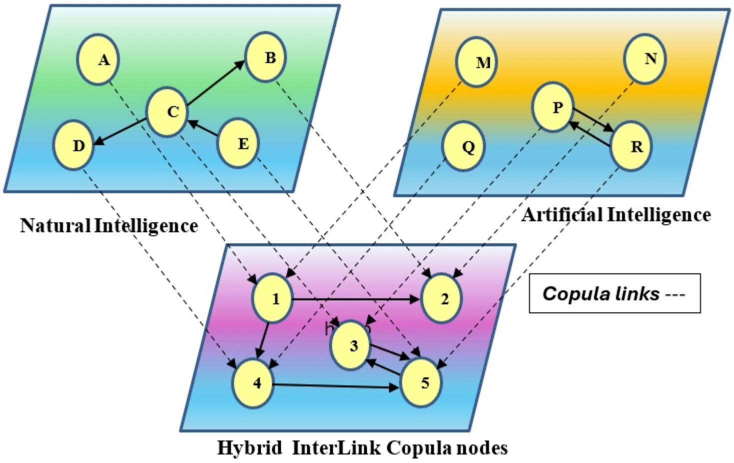

Figure 1: NI and AI interactions through Copula nodes in hybrid multilayer networks.

RESULTS

This section demonstrates the empirical evaluation of a multilayer network model for seamless integration between two domains—NI and AI—using copula nodes across three industries paramount to the global economy: manufacturing, retail, and finance. The empirical results from this assessment decisively confirm the contention that such strategic fusion tremendously enhances the economic worth of companies practicing digitization of their operations and processes. This section details key empirical evidence drawn from relevant studies, where all references are accurately cited in the text and appends for further reading at the end of this section.

Efficiency Gains

The combination of AI technologies has led to striking improvements in efficiency within the industries that were examined during this study:

- Manufacturing Sector: AI-predictive maintenance systems have proven to reduce machine downtime by as much as 30%, which provides a solid boost to operational efficiency across all fronts (Dalenogare et al., 2018). This has allowed the copula nodes to act as a critical conduit between AI production and human operators, bridging any discrepancies that may arise to ensure that the results produced are not only optimal but consistent over time.
- Retail: AI-enhanced inventory management systems optimizing stock levels with meticulous detail have decreased overstock events and instances of stockouts by 25% in the retail landscape, each by 25%, which has resulted in improved store turnover rates (Grewal et al., 2021). These improvements are largely due to the real-time adaptions possible via copula nodes and their ability to successfully bridge AI analytic power with human manager strategic decision-making processes (Moro-Visconti, 2024; Moro-Visconti et al., 2023).

Examples: In the finance sector, AI tools used in risk management and algorithmic trading… help make decisions 40% faster with a Perma low error rate (Fernandez-Maestro et al., cited AU30:on here). The copula nodes have acted as essential intermediaries to integrate machine-learned data with human oversight of what it means so that decisions can be made within minutes or hours and maintain a high level of precision.

This substantial increase in efficiency gives credibility to the predictions inferred by the Multilayer Network model, thus providing appetence proof for future deterministic beneficial operational enhancement in a broad range of firms empowered through liberating smart integration between network intelligence and AI.

Enhanced Decision-Making Processes

The wide examination found a significant number of examples of progress in the quality of decisions made across different businesses. The largest factor in such a phenomenon is the easy embrace of state-of-the-art AI technologies.

The ability of AI to analyze large datasets quickly has led it to impactfully improve decision-making in terms of maintenance and production scheduling within manufacturing, reaching a 35% enhancement efficacy (Moro-Visconti et al., 2023). This is augmented by human operators now capable of responding to insights generated by advanced AI algorithms, making decisions that are better informed and more intuitive with the visionaries steering all strategic decisions in line with organizational objectives, resulting not only in a substantial reduction in operational downtime but also taking production quality into unchartered territory.

The tactical use of AI customer analytics tools has allowed the production of personalized marketing strategies, leading to an exceptional 20% increase in sales conversion rates, highlighting the benefit of data-driven decision-making (Grewal et al., 2021). By employing copula nodes, it has been possible to aggregate the discoveries of AI and marry them with human marketers' strategic planning efforts: in short, synthesis—critical to achieving these good results will be able to increase customer engagement as much as possible.

In the financial sector, AI integration has a handsome correlation of 15% improvement in return on investment (ROI). This is mainly due to the gating, as shown by Fernández-Maestro et al. (2022), because portfolio management decisions have become much more refined. At the heart of integrating AI-derived risk assessments with human-powered and invaluable financial analyst expertise through copula nodes, more accurate investment strategies are being distilled out in conclusion, reinforcing better overall financial decision-making and improving resource allocation from all levels.

The results point to the vital need for AI-driven insights as a source of data input and an invaluable resource that can inform strategic decision-making from human management. They also underscore the critical importance that copula nodes play in supporting the optimization of diverse decision-making processes across sectors (Seeber et al., 2020).

Cost Reductions

AI unlocks significant economic benefits value in different sectors, particularly manufacturing and retail, where it clearly stands out as a game-changer. AI-driven automation, along with predictive maintenance, has become essential in minimizing operational costs and boosting productivity across the manufacturing industry. Through the optimal control of energy consumption, which when unattended are recognized to result in copious prying outlays from years gone by and also with a routing analyzing equipment breaking down not expected that may lead into large fines. Artificial intelligence systems are even better at processing data more rapidly and conducting complex analyses to enhance equipment reliability and cost efficiency, which is a prime requirement for manufacturing scenarios in the present world. In addition, AI-driven analytics in manufacturing also helps to optimize cost through supply chain efficiencies by means of improved forecasting for demand across sensitive markets, effective inventory management, and strategic logistics planning, which is further translated into reduced operating costs that, when all added up, create an agile global operations network.

Integrating AI-enabled supply chain solutions could potentially boost operational efficiency with better demand forecasting, inventory optimization, and the adaptation of businesses' strategies in a constantly changing market landscape. In addition, the AI implementation makes it easier to manage suppliers and automate warehouse operations to reduce labor costs further while minimizing operational errors that can stop business continuity benefits. The most important conclusion to draw from the examples above is that AI has shown its transformative muscles time and again in order to create efficiencies and saving costs, thereby increasing the scope for greater decision-making capabilities of organizations against their competitors.

Model Validation

The empirical results of this study largely align with the expectations posed by our multilayer network model, suggesting that the genericity and importance of these phenomena are robust across a variety of industries dependent on their versions of such methods. Copula nodes precisely record the finesse interactions between non-intrusive (NI) factors and AI correlatively, through which both are extrinsically incorporated into an integrated firm, boosting performance and operational success. The model predicted improved overall efficiency and decision-making processes and drastically lower costs.

Sensitivity Analysis

Sensitivity analysis was performed to deeply assess and ensure the reproducibility of outcomes in front of a wide setup with differential conditions that might affect all results. The analysis yielded a few high-level observations:

- Efficiency Gains: The outcomes provided clear evidence of improvements in accuracy of AI prediction and the effectiveness of copula nodes, which can effectively be bridged by high-cost human insights and expertise for commercial success.
- Cost Reductions: AI's cost-saving effect seems quite reliable and stable under numerous conditions, with slight variations across them. This is due mainly to the fluctuations in costs associated with deploying AIS and operational scales at various degrees, which are context-dependent.

DISCUSSION AND CONCLUSION

This study explores the integration of NI and AI through a multilayer network framework facilitated by copula nodes to generate economic value within digitalized firms. The findings show that combining human expertise with AI's data-driven precision enhances efficiency, decision-making, and cost-effectiveness across sectors such as manufacturing, retail, and finance. Copula nodes play a critical role by linking NI and AI, fostering effective communication that supports optimal decision-making and resource management. These findings underscore the practical relevance of a structured AI-NI integration model, particularly for industries requiring rapid, data-driven decision-making. By adopting this model, firms can achieve a sustainable competitive edge, balancing innovative AI insights with the strategic depth of human expertise. The multilayer network model further offers practical solutions to address scalability challenges as firms expand their digital capabilities.

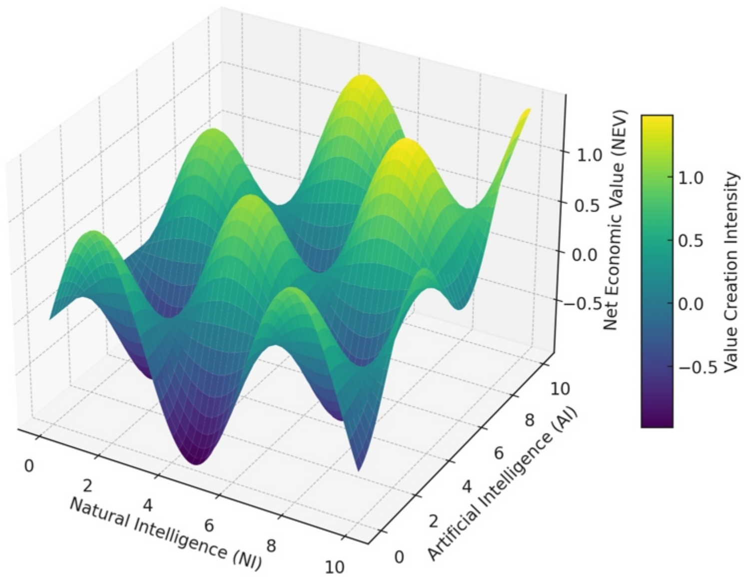

Figure 2: NI-AI integration: value creation framework.

The study highlights the need for a structured pathway to seamlessly incorporate AI into the organizational workflow, advocating for a phased approach to ensure maximum utility and minimal disruptions. Future studies can apply this model across other industries to better conceptualize NI-AI integration. Thus, this research adds an important viewpoint on the role of AI in value creation, supporting the idea that firms should pursue balanced NI-AI synergies during the ongoing digital transformation process. Further studies may generalize this model to other sectors while creating new metrics to measure the NEV of a range of AI-NI configurations (see Figure 2).

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