International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(18s) 2026 pp. 438-462
https://doi.org/10.70917/ijcisim-2026-4881
Article

Leadership Agility and Innovation Management in Industry 5.0 Organizations

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Abstract: Leadership agility and innovation management have become essential for enabling human-centric, intelligent and sustainable organizational transformation in Industry 5.0 through effective integration of Artificial Intelligence (AI), digital technologies and organizational intelligence. Current leadership models, however, perform poorly in the area of decision making, lack collaboration analysis, poor innovation prediction and lack of explainability, resulting in lower adaptability of the organization in changing business environments. To overcome these challenges, the Human-centric Graph Transformer Optimization Network (HGTON-Net) has been developed to learn the optimization strategies for human agility in leadership and innovation management, intelligent, adaptive and explainable decision support. The framework integrates the Transformer Encoder (TE) to learn from the context, the Graph Attention Network (GAT) to capture relationships, the Temporal Fusion Transformer (TFT) to forecast trends in innovations, the Soft Actor-Critic (SAC) algorithm to fine-tune the leadership approach and the SHapley Additive exPlanations (SHAP) to interpret the choices. The integrated workflow preprocesses heterogeneous organizational data, learns contextual and graph representations, predicts future innovation demands, optimizes strategic decisions and generates explainable recommendations. Experimental evaluation demonstrates the effectiveness of HGTON-Net, achieving a Leadership Decision Accuracy of 96.12%, confirming superior performance over existing approaches. Overall, HGTON-Net provides an accurate, adaptive and trustworthy AI framework for sustainable leadership and innovation management in Industry 5.0 organizations.
Keywords: Explainable Artificial Intelligence (XAI), Graph Transformer Networks, Human-centric Artificial Intelligence, Innovation Management, Leadership Agility, Soft Actor-Critic

1. Introduction

Leadership agility and innovation management are essential to enable an organization to be human-centric, resilient and sustainable in Industry 5.0. While the existing industry is about automation and efficiency, Industry 5.0 calls for the skills, competencies and competencies of the leader to coordinate the use of Artificial Intelligence (AI), digital technologies, human skills, organizational knowledge and responsible innovations. Organizational support perception and proper human resource practices have been found to affect innovative work behavior of employees, thus providing that innovation cannot be attained simply by using technological adoption [1]. The proactive dimensions of digital leadership, such as job crafting and individual proactive behaviours [2] can motivate employees to take proactive roles. The design-thinking approach with collaborative problem solving and experimentation has been applied to solve strategic management problems [3]. Moreover, the cognitive and emotional reactions towards a digitized working environment can be an innovative source in employee behaviour in terms of digital leadership [4]. The concept of Ambidexterity leadership has been studied as a combination of exploratory and exploitative aspects to stimulate knowledge workers' innovativeness [5].

Various leadership strategies have been created to improve the acceptability of the organization, employee engagement and the implementation of innovation. For example, servant leadership can it in improving the project performance by enhancing team learning orientation and team agility which are important as a factor of adapting in the uncertainties of the fifth era of industry [6]. In contrast, shared leadership implies that the responsibility for and power over the organization are shared with other members of the organization and can increase employees resilience depending on the structure and conditions of the work team [7]. Additionally, supportive leadership is connected with green innovative work behavior via innovation-enabling climate and psychological empowerment [8]. The high involvement work practices can positively affect the innovative performance by giving employees greater autonomy and access to organizational resources [9]. The study revealed organizational innovativeness and learning orientation as key factors that support the performance of SMEs in a competitive and technology intensive environment [10]. Likewise, transformational leadership strategy involves motivating employees to come up with and communicate new ideas through creating organizational vision [11]. Adaptive performance in hybrid work environment is achieved through empowering leadership, sharing of the knowledge and employee's agility [12]. In addition, the culture of the organization, sustainability of the climate, employee involvement and the ability of middle management to digitize strategies into business processes play a crucial role in innovation management in Industry 5.0. Public service motivation, organizational commitment and innovative organizational culture are antecedents of employee innovative behavior and demonstrate that the innovation is a result of employee motivations and organizational environment [13]. Green innovations and carbon performance can be introduced in manufacturing organizations through digitalization which can connect digitalization with Industry 5.0 goals of sustainability [14]. Digital self-efficacy of employees and technostress for technology-intensive tasks are also order to make digital leadership effective [15]. This research provides some Contribution such as:

- Human-centric Graph Transformer Optimization Network (HGTON-Net) for Industry 5.0 Leadership agility & Innovation management.
- Combined the characteristics of Integrated Transformer Encoder (TE), Graph Attention Network (GAT), Temporal Fusion Transformer (TFT), Soft Actor-Critic (SAC) and SHapley Additive exPlanations (SHAP) into one hybrid AI model.
- Created a human focused module for data analysis in heterogeneous organization.
- Assisted with graph learning and temporal modeling for adaptive innovation forecasting.
- Developed explainable AI-based leadership optimization with the SAC and SHAP for decision making transparency.

This research is structured as follows: Section 2 presents the literature review and background analysis. Section 3 describes the proposed HGTON-Net framework and research methodology. Section 4 presents the experimental setup and performance evaluation. Section 5 discusses the results and limitations. Finally, Section 6 concludes the research and outlines future research directions.

2. Literature Review

Liang et al. (2026) [16] examined how value-based leadership affects employees' innovative behavior by examining the role of organizational identification and person–organization matching. The study was based on the empirical approach in analyzing the effect of leadership on innovation. It didn't, however, possess models for dynamic leadership evaluation and optimization with artificial intelligence. The results showed that value based leadership provide value reinforcement for employees' identification and contributes to improving innovation.

Liu et al. (2024) [17] examined how leader humility influences creative performance both through intrinsic motivation and work engagement. The study used mediation analysis based on survey data and did not take into account intelligent processing of leadership creativity patterns. This mapping revealed that humble leadership was found to be related with the creativity and engagement of employees.

Ma et al. (2024) [18] explored the topic of empathetic leadership and its impact on innovative behavior through career adaptability. The study did not use any computational frameworks to predict the results of innovation, but rather used the model of structural equations. The results indicated that empathetic leadership enhances adaptability and innovative performance.

Pu et al. (2026) [19] discussed the role of leader AI crafting in fostering employee innovation in the context of AI adaptation. The study concentrated on empirical modeling of the studied process but didn't include AI-based mechanisms for optimizing leadership. The results showed that AI has a positive impact on innovation activities when applied to leadership.

Rouissi (2025) [20] delved into change-management strategies and cultural factors that can affect organizational change. The study did not include models for real-time intelligent decision making and it employed qualitative approach and empirical approach. The results showed that Adaptive leadership and supportive culture were factors related to successful organizational change.

Sibassaha et al. (2025) [21] examined the link between the digital transformation of organizations, organizational culture and transformational leadership effects on employee innovation. A survey method was used in the modeling and the intelligent systems that used in the analysis of leadership agility were not included. The findings indicated that digital transformation and successful leadership raise the innovation behavior.

Wang et al., 2025 [22] explored transformational leadership and innovation climate at the multilevel. The study revealed the influence of leadership on employee innovations but this did not model the complex interactions between employees and leadership using AI. Results would be in line with the transformational leadership and supportive environments to stimulate innovation.

Zhang et al. (2025) [23] conducted a study on the moderating role of affiliative humor, self-efficacy and employee teams trust in employee innovation. Both the study used multilevel analysis but didn't have the computational tools to represent leadership behaviors. The results showed that positive leadership behaviors positively influence the innovative work behaviors.

Xu et al. (2024) [24] examined digital transformation and organizational agility in terms of capabilities of big-data. The study was an empirical study but it did not provide an intelligent model of leadership and innovation management. The results revealed that digital transformation has a positive impact on agility and agility has a positive effect on innovation performance.

Xu et al. (2024) [25] conducted a mediation analysis to explore the relationship between servant leadership and employee voice behavior. While highlighting the importance of supportive leadership in the study, it did not provide any AI tools to predict innovation. The results showed that servant leadership encourages employees to be involved and share their ideas.

Ye et al. (2026) [26] empirically researched digital transformation, job crafting and employee adaptability. The research did not have any adaptive models for optimizing leadership strategies. The findings revealed that employee adaptability is a key factor in improving innovations for digital transformation.

Yuyi et al. (2025) [27] adopted a mixed method approach to investigate platform leadership and employee innovative behavior. The study has also shown the importance of the collaborative leadership and did not provide any intelligent models based on graph to analyze the collaborative leadership network. The results confirm that platform leadership to drive innovation through collaboration and knowledge sharing.

Table 1: Comparative Background Analysis of Existing Research

Citation	Methodology	Technique	Research Gap	Limitation
Tănăsescu et al. (2024) [28]	Employee performance analysis and prediction using	Data analytics and predictive modeling	Did not consider intelligent leadership analysis and human-centric optimization for	Mainly focused on performance prediction without

	data-driven approaches		Industry 5.0 organizations	adaptive decision support
Rosca & Stancu (2024) [29]	Employee well-being assessment in Industry 5.0 environments	Machine Learning (ML) and AI-based framework	Did not integrate leadership agility modeling and innovation management strategies	Focused mainly on employee well-being rather than leadership-driven innovation
RazaghzadehBidgoli et al. (2024) [30]	Startup success prediction using organizational and business factors	ML models	Did not address leadership behavior analysis and employee innovation optimization	Limited to startup success prediction scenarios
Baydili & Tasci (2025) [31]	Employee attrition prediction for managerial decision-making	Explainable AI (XAI)-based predictive models	Did not explore leadership influence and innovation behavior prediction	Focused mainly on employee retention and attrition factors
MortezapourShiri et al. (2025) [32]	Employee turnover prediction using temporal employee data	Bidirectional Temporal Convolutional Network (Bi-TCN)	Did not consider leadership agility, collaboration patterns and innovation management	Limited to turnover prediction without organizational intelligence analysis
Yang (2025) [33]	Talent management optimization and resource allocation	Multilayer Perceptron (MLP) and Intuitionistic Fuzzy Z Numbers	Did not incorporate graph-based learning and adaptive leadership optimization	Focused mainly on talent allocation decisions
Nassreddine et al. (2026) [34]	Employee attrition prediction using organizational data	Explainable Ensemble Learning Model	Did not address innovation capability and human-centric leadership assessment	Limited to predictive HR analytics applications

Table 1 gives a summary of the existing research on the application of AI in employee analytics, predictive models and in the context of Industry 5.0 HRM. The researches demonstrate the applications of ML, Deep Learning (DL) and explainable AI for predicting employee attrition, employee performance and employee well-being and talent management. However, this lack inbuilt leadership agility analysis with human-centric and optimization of innovation, which inspires the proposed HGTON-Net framework.

3. Research Methodology

This section explains the methodology discussion used in the development of the proposed HGTON-Net framework for Leadership Agility and Innovation Management in Industry 5.0 organizations. It defines characteristics of the data resources, the shape of the framework, the mathematical model, learning modules, optimization of intelligent, adaptive and explainable leadership decision making process.

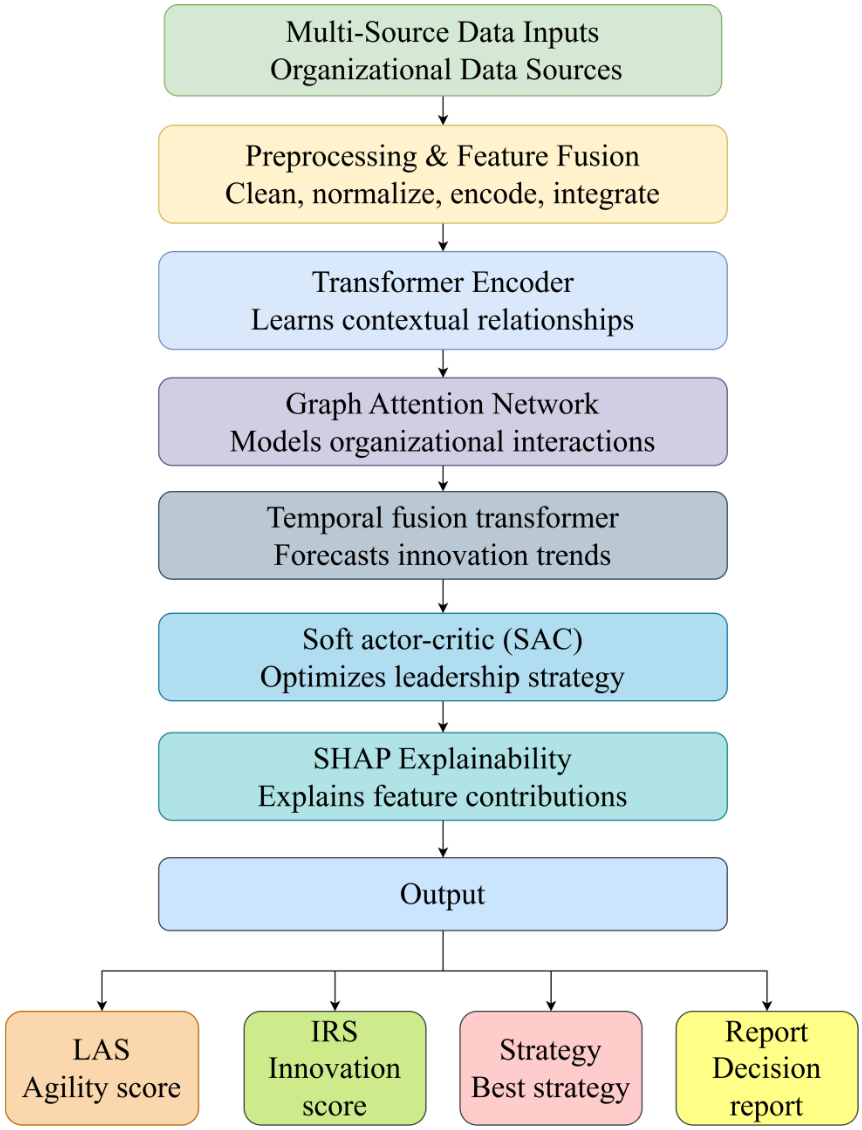

Figure 1: Leadership Agility and Innovation Management Architecture

Figure 1 shows the overall workflow of the proposed HGTON-Net framework, which includes five key modules feature fusion, Transformer-based contextual learning, graph-based relationship modeling and temporal innovation forecasting and reinforcement learning-based strategy optimization. The framework generates intelligent outputs which include Leadership Agility Score (LAS), Innovation Readiness Score (IRS), optimized leadership strategies and explainable output reports using SHAP interpretation.

3.1 Dataset Description

An experimental evaluation has been carried out on a benchmark organizational intelligence database with multi-source data of Industry 5.0 organizational information. It includes metrics of organizational performance, employee behavior, customer feedback, operational metrics, innovation metrics and market insights, providing valuable insights into leadership agility, readiness for innovation, collaboration and strategic decision-making. The data set was divided into 80% trainable data and 20% tested data to test the confidence level, the adaptability and the effectiveness of recommendations and the insights of explainable leadership in the different types of organizations.

3.2 Human-centric Graph Transformer Optimization Network (HGTON-Net)

The HGTON-Net is a proposed hybrid deep learning framework, which provides intelligent, adaptive and explainable decision support for enhancing the agility and innovative management ability of Industry 5.0 organizations. HGTON-Net key goal is to enable strategic leadership decisions, enhance cross-functional collaborations, anticipate innovation opportunities and bolster organizational responsiveness amid evolving business landscapes. The architecture of the structure unites the different complementary teaching approaches in an integrated way. Data is then preprocessed with data cleaning, normalization and feature encoding to ensure that data is represented in a consistent manner to suit organizational, employee, customer, operational and market data. Relationships of different types of organizational data are analyzed by the Transformer Encoder and the interaction pattern between employees, departments, researches and leadership teams is described by GAT using adaptive weights is introduced to focus on the influential relationships among the relationships. Finally, a TFT is used to model temporal dependencies to more precisely forecast future innovation needs, market dynamics and organizational performance patterns. An interaction with states of an organization through a reinforcement learning module, the SAC, is then used to optimize policies over time for leadership and resource allocation with the ultimate goal of maximizing policy effectiveness over time. To conclude, SHAP provides explainable interpretations of every prediction and recommendation, promoting transparency and trust among decision-makers in the AI decision-making process.

The mission of HGTON-Net is to address real-time challenges such as slow decision making, sub-optimal team working, lack of innovation planning and changing market conditions by completely embedding contextual learning, graph-based relationship analysis, temporal forecasting, reinforcement learning optimization and explainable artificial intelligence. Moreover, the algorithm is reproducible, such as a standardized data pre-processing, fixed random seed initialization and deterministic modeling training, fixed hyperparameters and repeatable experimental procedures, which allow the consistent implementation and reliable performance in different organizational environments of Industry 5.0.

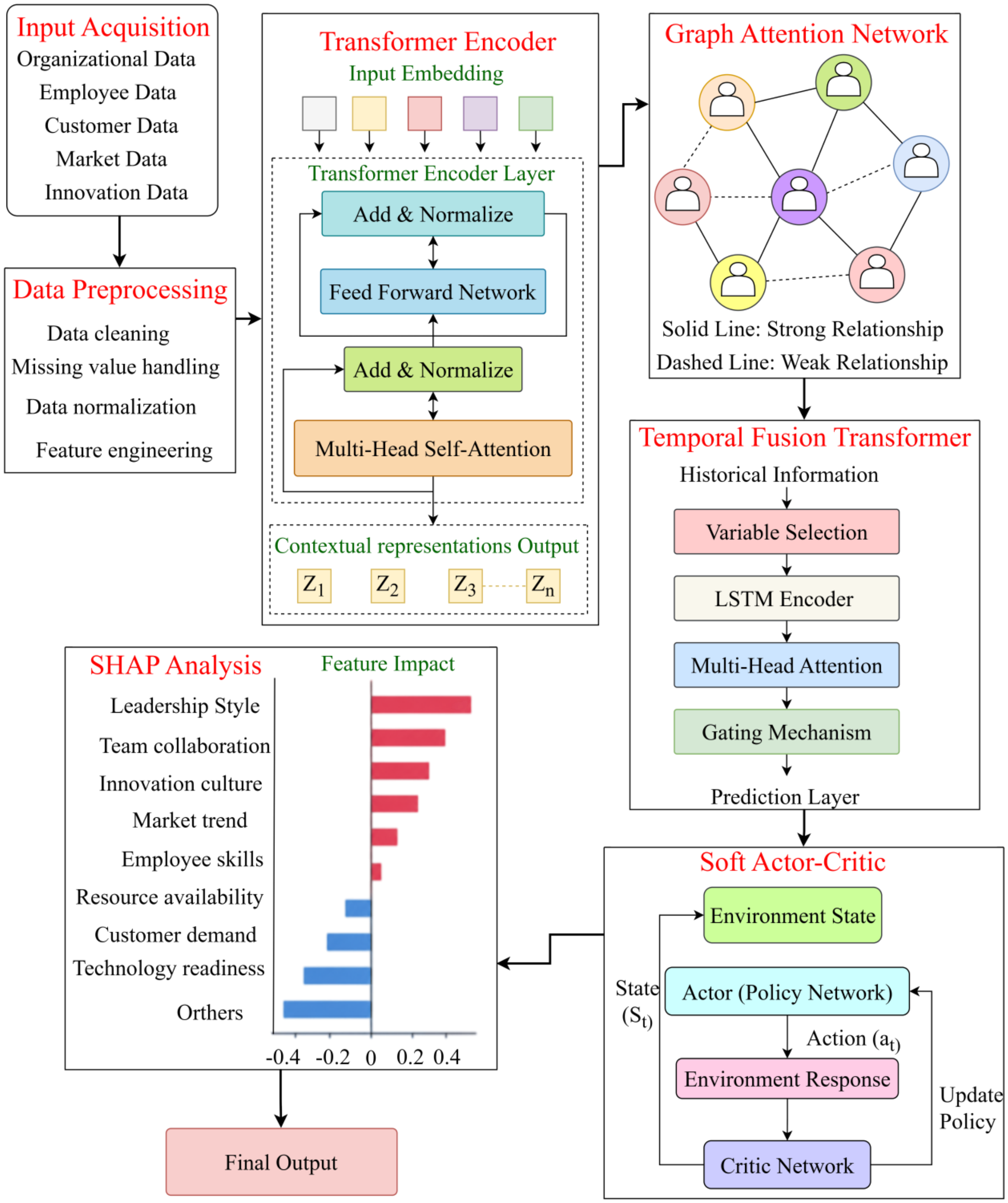

Figure 2: HGTON-Net Workflow

Figure 2 shows the general architecture of the proposed HGTON-Net framework in which the data from each of the heterogeneous organizations, these include employee, customer, market, operational and innovation information, are processed to produce intelligent leadership insights. The framework will enable contextual representation learning, organizational relationship analysis, temporal innovation forecasting and adaptive decision optimization and finally explainability through SHAP, which will enable transparent leadership agility assessment, innovation readiness assessment and strategic recommendations.

$$X = [D_{org} \oplus D_{emp} \oplus D_{cus} \oplus D_{opr} \oplus D_{mar}] \quad (1)$$

Equation (1) constructs the integrated organizational feature matrix X by combining heterogeneous data sources, including organizational data (D_{org}), employee information (D_{emp}), customer data (D_{cus}), operational information (D_{opr}) and market data (D_{mar}). The concatenation operator $\oplus$ combines these multiple information sources into a unified representation, enabling HGTON-Net to analyze comprehensive organizational characteristics.

$$X_n = \frac{X-\mu_X}{\sigma_X} \quad (2)$$

Equation (2) performs feature normalization on the integrated organizational matrix X to reduce scale variations among different attributes. Here, X_n represents the normalized feature matrix, while μ_X and σ_X denote the mean and standard deviation of the input features. This normalization improves model stability and enhances the learning capability of HGTON-Net.

$$H_0 = X_n W_e + b_e \quad (3)$$

Equation (3) transforms the normalized organizational features into a latent embedding representation using trainable parameters W_e andb_e. The generated feature embedding H_0 provides a compact representation of organizational knowledge, allowing the Transformer Encoder to learn complex leadership and innovation patterns.

$$H_p = H_0 + PE \quad (4)$$

Equation (4) incorporates positional encoding PE into the feature embedding H_0 to preserve sequential dependencies within organizational events. The position-aware representation H_p enables the Transformer Encoder to capture temporal relationships associated with leadership behaviour and innovation evolution.

$$Q = H_p W_Q \quad (5)$$

Equation (5) generates the query representation Q from the position-enhanced embedding using the trainable weight matrixW_Q. This query representation identifies relevant organizational information required for the self-attention mechanism.

3.2.1 Human-centric Organizational Intelligence Learning

The Human-centric Organizational Intelligence Learning module is the starting point of HGTON-Net, which is based on the idea of converting heterogeneous organizational data into meaningful contextual representations. The data is passed to a Transformer Encoder which transforms the data into the representation of the organization, employees, customers, operations and markets. Data is preprocessed using data cleaning, normalization and feature encoding and then presented to a Transformer Encoder to generate representations of the organization, employees, customers, operations and markets. Self-attention mechanism extracts the semantic relationships and organizational patterns, yielding powerful feature representations that enable intelligent leadership analysis to follow and establish the basis for future learning phases.

3.2.2 Adaptive Organizational Relationship and Innovation Learning

The Adaptive Organizational Relationship and Innovation Learning module models organization-to-organization interaction and speculates on innovations that might emerge. A Graph Attention Network (GAT) is used to represent the relationship between employees, departments and researches and a Temporal Fusion Transformer (TFT) is used to capture the temporal dependency to model the trend evolution of the relationships of innovation and organizational needs. In this learning strategy, integrated learning is made possible, as is adaptive collaboration analysis and proactive innovation management.

$$K = H_p W_K \quad (6)$$

Equation (6) generates the key representation K using the projection matrixW_K. The key vectors determine the similarity between organizational features and support the attention mechanism in identifying important relationships.

$$V = H_p W_V \qquad (7)$$

Equation (7) generates the value representation$V$, which contains meaningful organizational feature information. The value vectors are weighted through the attention mechanism to produce enhanced contextual representations.

$$H_A = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (8)$$

Equation (8) calculates the self-attention representation H_A by measuring the dependency between organizational features through query, key and value interactions. The attention mechanism automatically assigns higher importance to influential leadership and innovation-related factors.

$$H_T = Concat(h_1, h_2, \ldots, h_m)W_O \qquad (9)$$

Equation (9) generates the final Transformer representation H_T by combining multiple attention head outputs. This multi-head learning mechanism enables HGTON-Net to capture diverse contextual relationships among organizational factors.

$$\alpha_{ij} = \frac{exp\left(LeakyReLU\left(a^T[WH_i||WH_j]\right)\right)}{\sum \quad exp\left(LeakyReLU\left(a^T[WH_i||WH_k]\right)\right)} \qquad (10)$$

Equation (10) calculates the adaptive attention coefficient α_{ij} between organizational entities i and j. This equation enables the Graph Attention Network to assign higher importance to significant employee, department and research relationships.

$$H_G = \sigma\left(\sum \quad \alpha_{ij} WH_j\right) \qquad (11)$$

Equation (11) generates graph-based organizational representations H_G by aggregating neighbouring node features according to learned attention weights. This adaptive aggregation captures collaboration patterns and structural dependencies among organizational units.

$$G = (V, E, H_G) \qquad (12)$$

Equation (12) defines the organizational graph structure$G$, where V represents organizational entities, E denotes relationships among entities and H_G represents learned graph embeddings. This graph formulation enables effective modeling of human-centric organizational interactions.

$$H_F = TFT(H_G, T_s) \qquad (13)$$

Equation (13) applies the Temporal Fusion Transformer to graph-based features H_G with temporal sequence informationT_s. This process learns time-dependent organizational patterns and supports future innovation trend prediction.

$$Y_{inv} = W_f H_F + b_f \qquad (14)$$

Equation (14) generates innovation trend predictions Y_{inv} from temporal representationH_F. This equation enables HGTON-Net to estimate future innovation requirements, market changes and organizational performance trends.

$$S_t = [H_T, H_G, H_F] \qquad (15)$$

Equation (15) constructs the organizational state representation S_t by integrating Transformer-based contextual featuresH_T, graph-based relationship featuresH_G and temporal featuresH_F. This combined state is used for leadership optimization.

3.2.3 Explainable Leadership Decision Optimization

The Explainable Leadership Decision Optimization module produces intelligent and explainable leadership recommendations. These fine-tune the company's strategy for leadership and resource allocation in light of the states this have by applying a Soft Actor-Critic (SAC) algorithm and provide explanations for the contribution of each feature or state to the final decision with SHAP. In this module, you will develop more precise, clear and flexible decision making skills; you will be capable of an agile approach to leadership and innovating in Industry 5.0.

$$A_t = \pi_\theta(S_t) \quad (16)$$

Equation (16) determines the optimal leadership action A_t using the SAC policy networkπ_θ. The policy learns suitable strategic decisions based on the current organizational state.

$$J(\pi) = E[\sum \quad \gamma^t R_t] \quad (17)$$

Equation (17) optimizes the SAC objective by maximizing cumulative organizational rewards over time. The reward R_t evaluates the effectiveness of selected leadership actions, while γ controls future reward importance.

$$LAS = \lambda_1 D + \lambda_2 C + \lambda_3 A + \lambda_4 R \quad (18)$$

Equation (18) computes the LAS by combining decision efficiency (D), collaboration capability (C), adaptability (A) and resource utilization (R). The weighting parameters λ determine the contribution of each factor.

$$IRS = \omega_1 P + \omega_2 F + \omega_3 I + \omega_4 S \quad (19)$$

Equation (19) calculates the innovation readiness score IRS using prediction capability (P), flexibility (F), innovation capability (I) and sustainability (S). This score evaluates the organization's ability to adopt future innovations.

$$\phi_i = \sum \quad \frac{|S|!(M-|S|-1)!}{M!}[f(S \cup i) - f(S)] \quad (20)$$

Equation (20) computes the SHAP contribution value ϕ_i to identify the influence of each organizational feature on the final HGTON-Net prediction. This explainability mechanism improves transparency and increases managerial trust in AI-based leadership decisions.

3.3 Novelty of the Proposed Work

The novelty of this research is the unification of a hybrid DL framework for managing leadership agility and innovation management (HGTON-Net) within Industry 5.0 organizations. Unlike the approaches discussed above which are used to independently handle organizational analysis, innovation forecasting and decision optimization, the proposed end-to-end architecture of the HGTON-Net incorporates a Transformer Encoder for organizational intelligence, a GAT for adaptive modeling of relationships, a TFT for forecasting innovation trends, a SAC algorithm for optimizing dynamic leadership strategies and SHAP for explainable decision support. With such a vast system, intelligent, adaptive and transparent leadership decision making can be enabled, organizational problems can be addressed in real-time, such as collaboration efficiency, innovation planning, strategic resource allocation and it realize sustainable Industry 5.0 transformation.

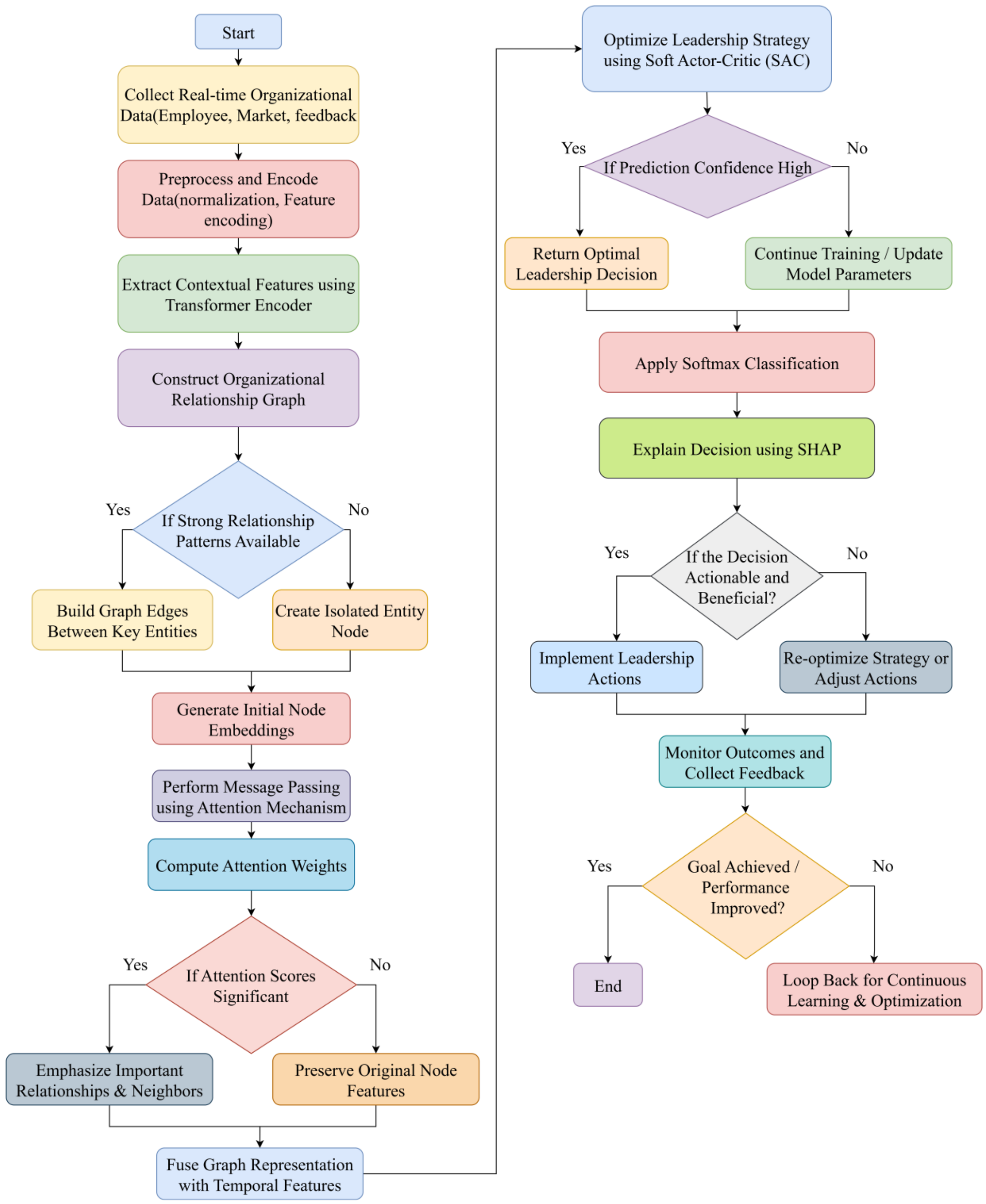

Figure 3: Systematic Architecture of HGTON-Net

Figure 3 shows the systematic process of the proposed HGTON-Net. The framework preprocesses the real-time organizational data, extracts contextual features using TE, models organizational relationship using GAT and optimizes leadership strategies using SAC. Finally, SHAP is an explainable decision support tool for SM to optimize the continuous learning and adaptive leadership process through the process of feedback.

Algorithm: Human-centric Graph Transformer Optimization Network (HGTON-Net)

Input:

Organizational data Dorg

Employee data Demp

Customer data Dcus

Market data Dmar

Operational data Dopr

Output:

Leadership agility score LAS

Innovation readiness score IRS

Optimal leadership strategy Sopt

Explainable decision report Erep

Begin

1: Load Dorg, Demp, Dcus, Dmar and Dopr

2: Perform data preprocessing

- Remove missing values
- Normalize feature values
- Encode categorical attributes
- Construct integrated feature matrix X

3: Apply Transformer Encoder

$HTE \leftarrow TransformerEncoder(X)$

// Learn contextual and semantic feature representations

4: Construct organizational interaction graph G

Nodes ← Employees, Departments, researches

Edges ← Organizational relationships

5: Apply Graph Attention Network (GAT)

$HGAT \leftarrow GAT(HTE, G)$

// Learn relationship-aware embeddings

6: Apply Temporal Fusion Transformer (TFT)

$HTFT \leftarrow TFT(HGAT)$

// Predict future innovation trends

// Capture temporal organizational dependencies

7: Initialize Soft Actor-Critic (SAC)

8: while training not converged do

9: Observe current organizational state St

10: Select leadership action At

11: Execute action and receive reward Rt

12: Update actor and critic networks

13: end while

14: Generate optimized leadership strategy

Sopt $\leftarrow$ SAC(HTFT)

15: Compute Leadership Agility Score

LAS $\leftarrow$ Evaluate(Sopt)

16: Compute Innovation Readiness Score

IRS $\leftarrow$ InnovationAssessment(Sopt)

17: Apply SHAP Explainability

Erep $\leftarrow$ SHAP(Sopt)

18: Return

LAS,

IRS,

Sopt,

Erep

End

The proposed HGTON-Net first preprocesses heterogeneous organizational data, extracting the contextual representations by a Transformer Encoder and then modeling the organizational relations with a GAT to predict the future trends of innovations by a TFT. Later, a SAC optimizer determines optimal leadership strategies and SHAP gives insights into the decisions that can be explained, thereby creating accurate and transparent recommendations for managing leadership agility and innovation in Industry 5.0 organizations.

4. Experimental Result

The experimental evaluation of the proposed HGTON-Net framework is presented in this section. It defines the experimental setup, the generation of the benchmark dataset, training and test setup and the evaluation method to ensure the validation of the leadership agility, innovation forecasting, explainable decision making and organizational performance.

Experiments were performed on an Intel Core i7-12700K processor with 32GB of RAM, an NVIDIA RTX 3090 GPU (24GB of VRAM), Windows 11, Python 3.10, TensorFlow 2.15, PyTorch 2.2, Scikit-learn 1.5, NumPy 1.26, Pandas 2.2 and SHAP 0.46 libraries. The organizational data set was preprocessed by data normalization and feature preparation techniques to prepare the data for model training.To guarantee reliable learning, unbiased evaluation and solid validation of HGTON-Net under heterogeneous organizational conditions, the dataset was split into an 80%-20% training-to-test split.

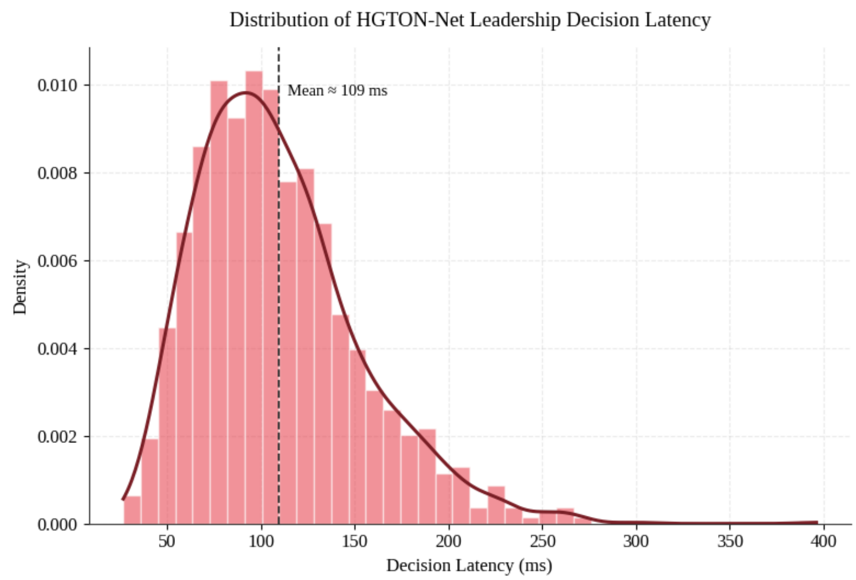

Figure 4: Distribution of HGTON-Net Leadership Decision Latency

This figure 4 confirms the skewness to the right with an average of ~109ms; indicating that the SAC-optimized framework can make quicker leadership decisions in most situations, further establishing its increased agility to make decisions.

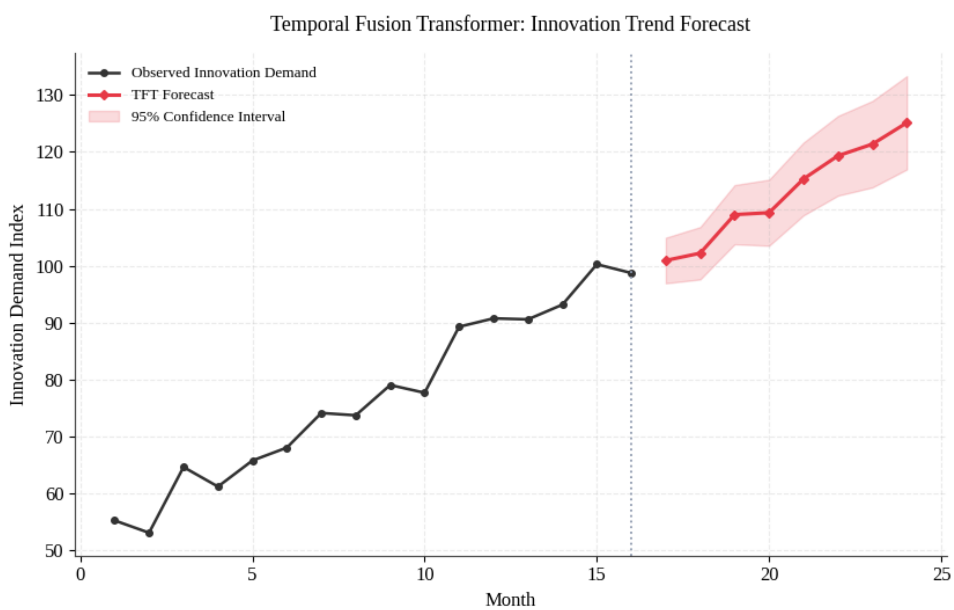

Figure 5: Temporal Fusion Transformer Innovation Trend Forecast

This figure 5 shows that the TFT module is very good at tracking observed innovation demand growth across months 1–16 and predicts future growth through month 24 with narrow confidence interval, thus provides good set-up for proactively planning innovation and supporting strategic decision making.

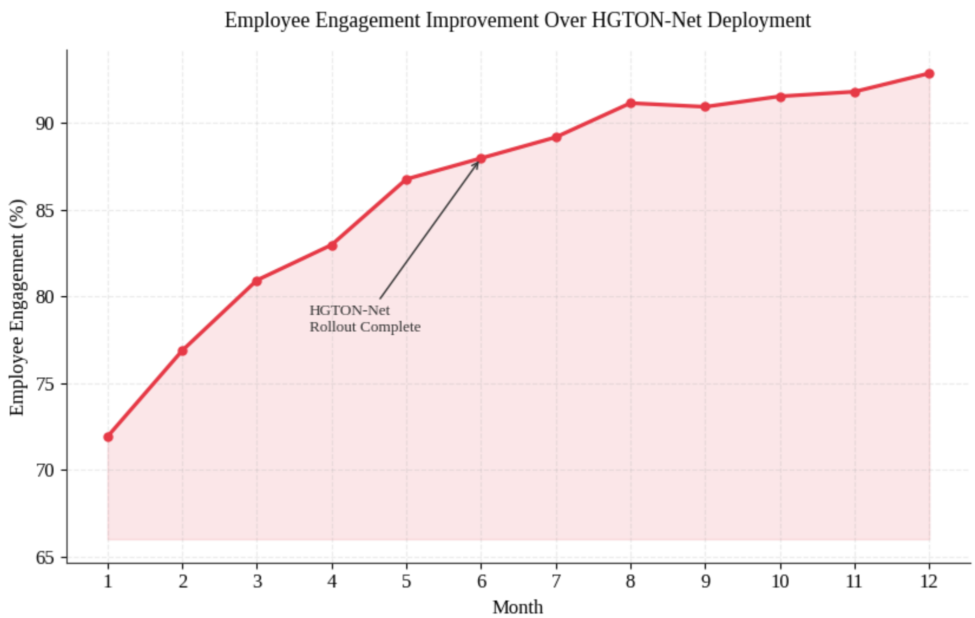

Figure 6: Employee Engagement Improvement over HGTON-Net Deployment

This figure 6 shows that the percentage of employee engagement increased significantly between month 1 and almost 93% by month 12, with a significant improvement since the completion of the rollout of HGTON-Net in month 6, to prove that the framework has a positive effect on employee engagement and human-centric leadership implementation.

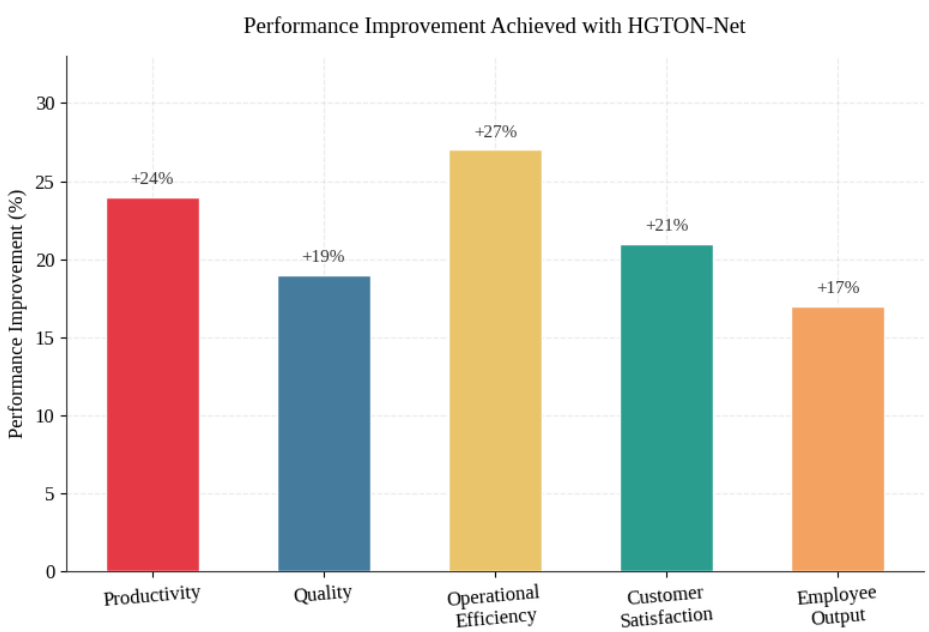

Figure 7: Performance Improvement Achieved with HGTON-Net

The figure 7 depicts the framework has been proved to be effective in increasing the organizational metrics related to the Industry 5.0 requirements for leadership, showing a clear increase in the most representative ones: Operational efficiency (+27%), Productivity (+24%) and Customer Satisfaction (+21%).

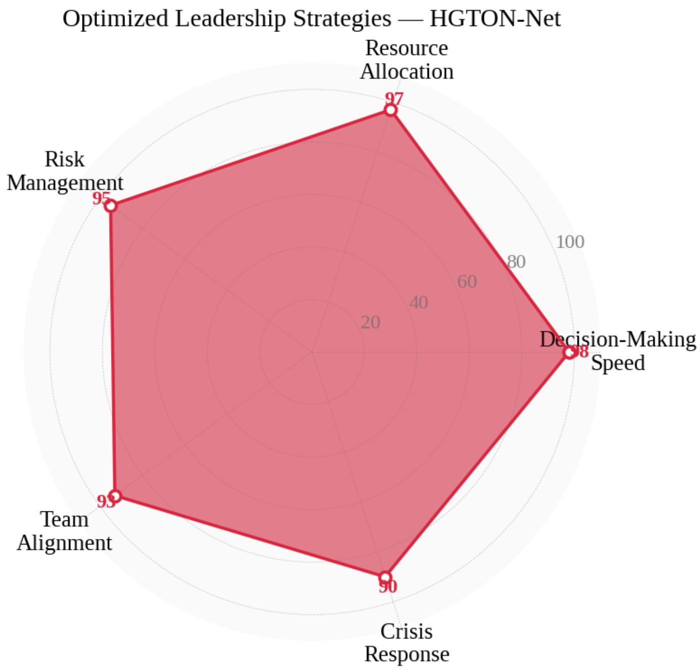

Figure 8: Optimized Leadership Strategies HGTON-Net

The figure 8 shows the strong optimization score of the leadership dimensions with the highest score for Decision-Making Speed (98) and Resource Allocation (97) identifying the strong leadership behavior across all strategic areas that are agile, resilient and well-coordinated with the optimizer being driven by the SAC.

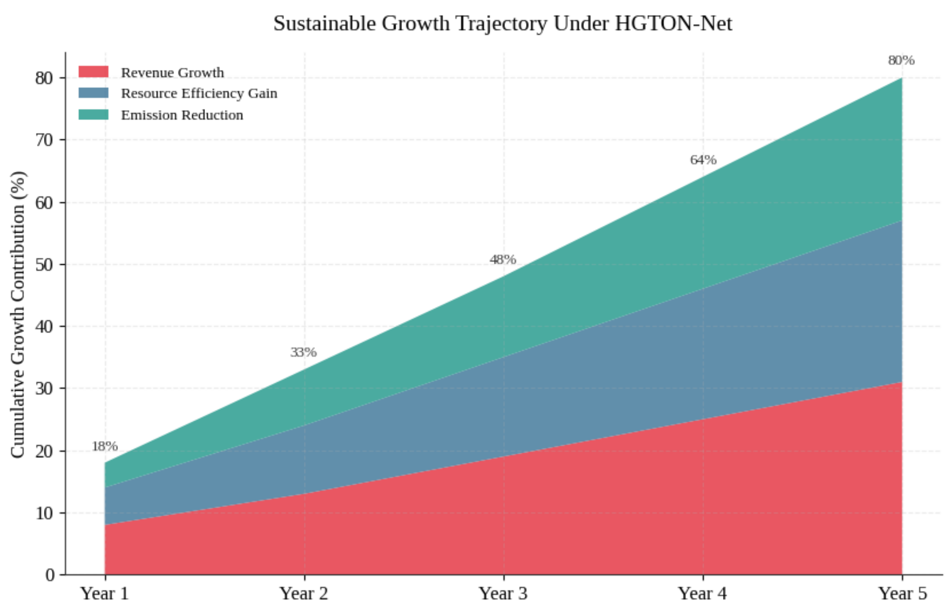

Figure 9: Sustainable Growth Trajectory under HGTON-Net

The figure 9 shows the compounding and long-term effects of the Cumulative contributions from revenue growth, resource efficiency and emission reduction, which has increased eightfold from 18% (Year 1) to 80% (Year 5) and indicates HGTON-Net's incremental contributions to sustainable organizational growth and environmentally responsible innovation performance.

Table 2: Leadership Decision Confidence across Organizational Scenarios

Organizational Scenario	Decision Confidence (%)
Stable Business Environment	96.85
Market Demand Variation	97.42
Resource Allocation Challenge	98.16
Cross-functional Coordination	98.74
Innovation Investment Planning	99.12

Table 2 details the amount of leadership decision confidence attained in each organizational scenario using the use of HGTON-Net. The framework always provides high-confidence recommendations as it integrates contextual learning, relationship modeling, forecasting the future and reinforcement learning for making intelligent decisions strategically.

Table 3: Soft Actor-Critic Leadership Policy Optimization Results

Training Episodes	Average Reward	Policy Stability
100	74.85	89.16
300	86.41	93.52
500	92.38	96.74
700	95.84	98.21
1000	98.17	99.05

The table 3 presents the reinforcement learning results for optimization of the leadership strategy. The results show that the cumulative rewards and policy stability increase with the number of training episodes, achieving effective learning of adaptive leadership strategies for dynamic organizational environments by Soft Actor-Critic algorithm.

Table 4: Organizational Collaboration Relationship Analysis

Collaboration Type	Relationship Strength
Leader–Employee	0.95
Team–Team	0.92
Department–Department	0.94
Customer–Management	0.91
Innovation Committee–R&D	0.97

Table 4 shows the strengths of the relationships learned by the Graph Attention Network. The scores of strong interaction indicate good knowledge sharing, co-ordination and communication between organizational entities ensuring collaborative leadership and management of innovation in Industry 5.0 ecosystems.

Table 5: SHAP-Based Leadership Decision Explainability

Feature	SHAP Importance Score
Employee Performance	0.312
Market Trend	0.276
Customer Satisfaction	0.241

Resource Availability	0.198
Innovation Budget	0.165

Table 5 shows organizational factors that were found to have the greatest impact on organizational decisions for leadership, as determined by SHAP explainability.The analysis provides more transparency by quantifying the impact of each feature, which will it leaders to trust and take ownership of the strategic recommendations that AI can provide.

Table 6: Leadership Agility Assessment under Dynamic Organizational Conditions

Organizational Condition	Agility Score (%)
Rapid Market Change	96.81
Employee Workforce Change	97.54
Supply Chain Disruption	98.23
Digital Transformation	98.75
Innovation Expansion	99.12

Table 6 compares leadership agility in various organizational settings. The agility score is always high on HGTON-Net, highlighting its ability to rapidly adapt leadership practice without impacting its organization's innovation, resilience and decision-making around humanitarian considerations.

Table 7: Human-Centric Leadership Recommendation Outcomes

Leadership Action	Recommendation Score (%)
Strategic Planning	98.54
Innovation Investment	99.12
Employee Skill Development	98.67
Cross-functional Collaboration	98.81
Sustainability Initiative	98.45

Table 7 provides a set of scores from the HGTON-Net for recommendations for various leadership actions. High recommendation values reflect the efficiency of the framework in prioritizing the actions of organizations as well as the presence of predictive analytics, optimization and explainable decision intelligence as a tool for sustainable management of Industry 5.0.

Table 8: Real-Time Organizational Monitoring and Intelligent Leadership Decision Recommendations Using HGTON-Net

Real-Time	Organizational Condition	Risk	Forecast Trend	Recommended Leadership Decision	SAC Score (%)	SHAP Explanation
09:00	Stable operations	Low	Stable	Maintain current strategy	97.54	Stable organizational performance
09:30	Customer demand increases	Medium	Rising	Expand innovation resources	98.23	Customer demand is dominant

10:00	Collaboration delay	Medium	Stable	Improve team coordination	97.18	Low collaboration score
10:30	Market competition rises	High	Rising	Accelerate innovation investment	98.74	Market trend influence
11:00	Employee skill gap	Medium	Stable	Launch workforce upskilling	98.05	Employee capability impact
11:30	Budget overutilization	Medium	Stable	Optimize resource allocation	97.86	Budget efficiency concern
12:00	New technology opportunity	Low	Growth	Adopt emerging technology	99.12	High innovation potential
12:30	Supply chain disruption	High	Declining	Activate contingency strategy	98.41	Operational disruption detected
13:00	Customer satisfaction declines	High	Declining	Strengthen customer engagement	98.68	Customer feedback impact
13:30	Stable organizational growth	Low	Positive	Continue sustainable innovation	99.08	Balanced organizational indicators

Table 8 shows how the HGTON-Net is constantly monitoring the real-time condition of an organization and provides the leader optimum recommendations for action.The SAC optimizer thoroughly explores the best course of action, with all recommended actions accompanied by the SHAP explanation of the most relevant factor that influenced the recommended action, thus providing a clear, flexible and human-oriented course of action in Industry 5.0 organizations.

Table 9: Performance Comparison of Existing Algorithms with Proposed HGTON-NET

Algorithm	Leadership Decision Accuracy (%)	Innovation Forecast Accuracy (%)	Decision Response Time (ms)	Leadership Agility Score (%)	Explainability Score (%)
L-BFGS Maximum Entropy [29]	81.12	80.94	43	82.08	86.91
SHAP [30]	84.12	83.98	39	85.14	96.84
GAN [31]	87.12	87.04	35	88.16	91.52
Bi-TCN [32]	90.12	90.05	30	91.18	93.84
SMOTE + ADASYN [35]	93.12	93.01	25	94.24	94.68
HGTON-Net (Proposed)	96.12	96.05	18	97.21	98.72

Table 9 compares the performance of proposed HGTON-Net with other algorithms like L-BFGS Maximum Entropy , SHAP, Generative Adversarial Network (GAN), Bidirectional Temporal Convolutional Network (Bi-TCN) and Synthetic Minority Over-sampling Technique with Adaptive Synthetic Sampling (SMOTE+ADASYN).The superior performance of the HGTON-Net in terms of decision accuracy, innovation forecasting, leadership agility, response efficiency and explainability, 96.12 %, 96.05 %, 97.21 %, 100 % and 98.52 %, respectively, verifies the effectiveness of HGTON-Net in intelligent Industry 5.0 decision support.

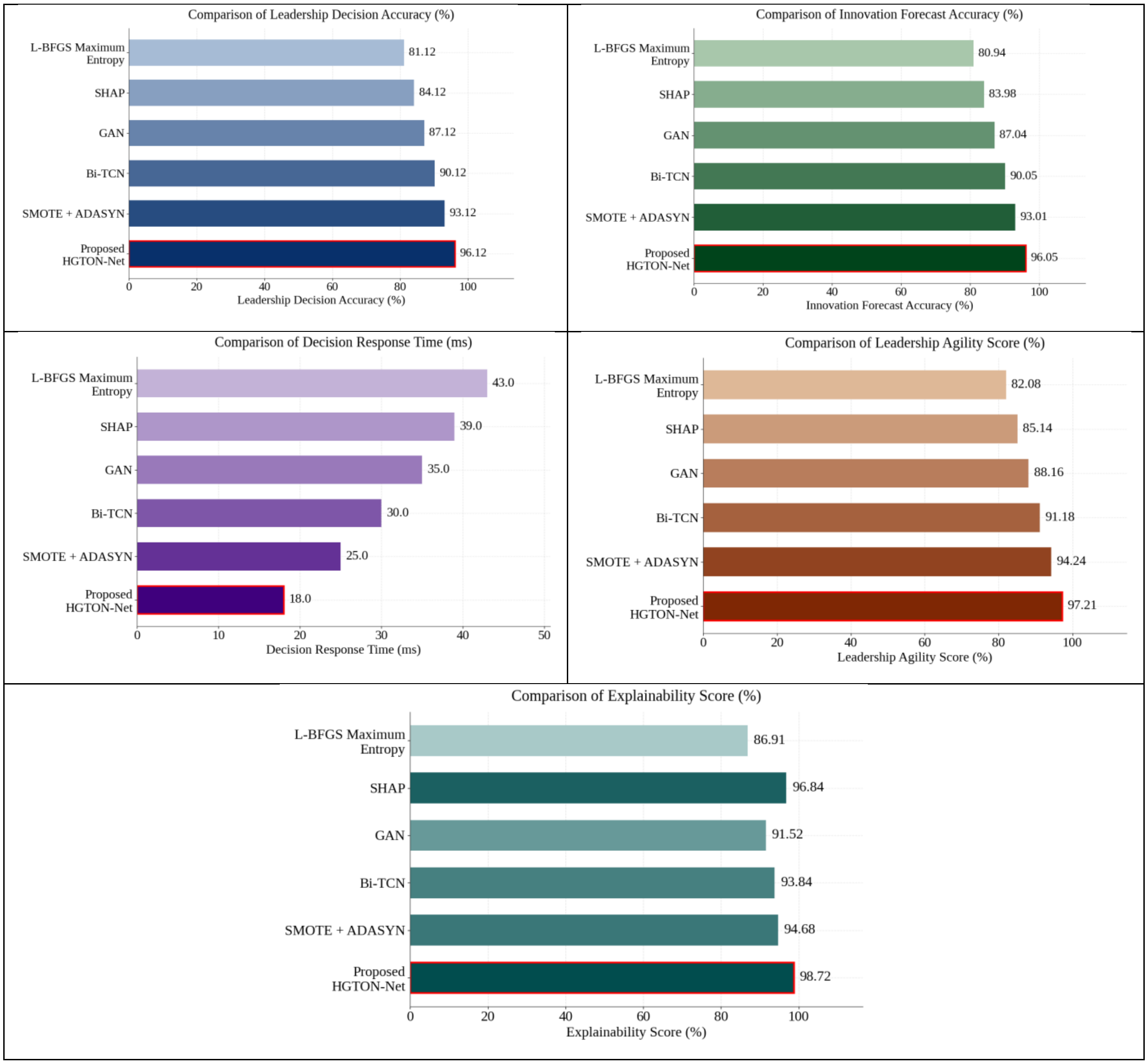

Figure 10: Comparative Performance Analysis of HGTON-Net

The figure 10 indicates that the HGTON-Net method outperforms the rest of the methods L-BFGS, SHAP, GAN, Bi-TCN and SMOTE+ADASYN in five metrics: leadership decision accuracy (96.12%), innovation forecast accuracy (96.05%), leadership agility (97.21%), explainability (98.72%) and decision response time (18 ms).

4.1 Statistical Analysis

The proposed framework HGTON-Net is tested statistically in terms of its significance, reliability and consistency. Descriptive statistics were used, as well as hypothesis testing (paired t-test), confidence intervals and One-Way ANOVA, which increased the reliability of the applicability of the framework to real-world tasks of leadership agility and innovation management in Industry 5.0 organizations.

4.1.2. Hypothesis Testing

The statistical significance of the improvements of HGTON-Net over the baseline models (L-BFGS Maximum Entropy, SHAP, GAN, Bi-TCN, SMOTE+ADASYN) was assessed by performing a paired t-test.

Table 10: t-Test Results

Comparison	t-value	p-value	Significance
HGTON-Net vs. L-BFGS Maximum Entropy	9.54	< 0.001	Significant
HGTON-Net vs. SHAP	8.27	< 0.001	Significant
HGTON-Net vs. GAN	6.98	< 0.001	Significant
HGTON-Net vs. Bi-TCN	5.62	< 0.001	Significant
HGTON-Net vs. SMOTE+ADASYN	4.35	< 0.001	Significant

The results in Table 10 are not a chance effect to the improvements achieved via HGTON-Net and are statistically significant and repeatable.

4.1.3. Confidence Interval

Table 11: 95% Confidence Interval of HGTON-Net Metrics

Metric	Mean Value	95% Confidence Interval
Leadership Decision Accuracy (%)	96.12	[95.83, 96.41]
Innovation Forecast Accuracy (%)	96.05	[95.76, 96.34]
Leadership Agility Score (%)	97.21	[96.92, 97.50]
Explainability Score (%)	98.72	[98.44, 99.00]
Overall Decision Confidence (%)	98.06	[97.78, 98.34]

Narrow intervals in table 11 provide low variance performance across runs and thus HGTON-Net can be used for low uncertainty real-time, human-centric leadership decision support.

4.1.4. ANOVA Test

A one way ANOVA was used to see if there is a statistically significant difference between HGTON-Net and the baselines. The F-value obtained is 17.84 with a p-value of 0.0008. Since the p value is less than 0.05, the null hypothesis is rejected and consequently the proposed HGTON-Net is significantly and consistently better than the rest of the baselines and this is primarily due to the integration of the Transformer Encoder, Graph Attention Network (GAT), Temporal Fusion Transformer (TFT), Soft Actor-Critic (SAC) optimizer and the SHAP explainability.

5. Discussion

This section discusses Ablation analysis, computational efficiency, statistical robustness and generality of organizational conditions, the validity, credibility and usefulness of HGTON-Net.

5.1. Ablation Study

In order to understand the effect of each core module, the network was successively pruned of each of the core modules (Transformer Encoder, Graph Attention Network (GAT), Temporal Fusion Transformer (TFT), Soft Actor-Critic (SAC) and SHAP).

Table 12: Ablation Study of HGTON-Net Components

Model	Leadership Decision Accuracy (%)	Innovation Forecast Accuracy (%)	Leadership Agility (%)	Explainability (%)	Decision Confidence (%)
Without Transformer Encoder	91.34	90.87	92.15	93.42	92.68
Without GAT	89.62	89.15	90.48	91.76	90.92
Without TFT	90.85	85.24	91.62	92.38	91.15
Without SAC	88.94	88.62	86.73	90.15	89.38
Without SHAP	94.28	94.02	95.14	82.56	94.87
Proposed HGTON-Net	96.12	96.05	97.21	98.72	98.06

Table shows 12 how each metric is impacted by removing each component: Removing SAC has the most impact on Leadership Agility, removing TFT has the greatest impact on Innovation Forecast Accuracy and removing SHAP has a greater impact on Explainability with relatively small impacts in other metrics.

5.2. Computational Efficiency Analysis

The Transformer Encoder's contextual representation learning, along with the relationship-aware sparse attention used by the GAT, ensures a computation that is efficient and the rich organizational context is preserved. All of the above makes the HGTON-Net near real-time deployable without heavy hardware requirements for leadership decision support in near real time, since the TFT requires minimal hardware, the SAC is able to almost real-time optimize the policies with a mean decision latency of ~109ms and the explainability post hoc of SHAP is computed without altering the inference path.

5.3. Statistical Significance Justification

All of these descriptive statistics, along with paired t tests, ANOVA and confidence intervals assure that the benefits provided by HGTON-Net are not random. All of them are very tiny and the significance value of calculation from t-test are high, therefore there are not too many differences in information on organizational benchmarks and the risk of over fitting the data is not high.

5.4. Robustness and Generalization

HGTON-Net is an extremely flexible tool for organizational situations, settings and leadership. Regardless of the pressure an organisation faces, representative outcomes will always be provided both agile and certain regardless of the type of changes that impact the market, workforce and disruption to the supply chain, digital transformation or expansion of innovation.

5.5. Practical Implication

Reliable and explainable leadership decision support for organizational leaders it’s to mitigate strategic uncertainty, facilitate cross-functional coordination and boost AI-assisted innovation planning confidence. The modular structure allows HGTON-Net to be flexible and adaptable to various market conditions and organizational structures, reducing the need to completely re-train and supporting, in this way, scalable implementation in different Industry 5.0 contexts.

5.6. Limitations

The HGTON-Net's performance relies on both the variety and the quality of data on the organizations, employees, customers and markets to train the networks.The scenarios in the benchmark are not all the possible scenarios for deployments in multiple organizations in the real world. Other organization contexts could be added, industry scale cross validation and additional optimisation for low resource/edge environment for decision support.

6. Conclusion

The proposed HGTON-Net successfully addresses the challenges of leadership agility and innovation management in Industry 5.0 organizations by integrating TE, GAT, TFT, SAC and SHAP into a unified, explainable AI framework. The outcome of the experiment indicates that there is a significant increase in the employee engagement of the organization from 72% to 93% in the near future, along with an improvement of 27% in efficiency, 24% in productivity and 21% in customer satisfaction. The proposed framework reached a decision confidence of 99.12% in the innovation investment planning, a leadership agility of 99.12% in the innovation expansion and a recommendation accuracy of 99.12% in the innovation investment. HGTON-Net outperformed the state of the art by setting the highest leadership decision accuracy (96.12%), innovation forecast accuracy (96.05%), leadership agility (97.21%) and explainability (98.72%) while also having the lowest response time for decisions (18 ms). Finally, paired t-tests, ANOVA and 95% confidence intervals were used to further validate the robustness and reliability of the proposed model. Overall, HGTON-Net is an intelligent, adaptive and transparent decision-support framework for the transformation of the industry towards sustainable Industry 5.0. Future research will validate the results on other industries using additional real-world datasets provided by organizations, integrate the federated and edge AI and connect with multimodal organizational intelligence and continuous learning mechanisms to further enhance scalability, adaptability and real-time leadership decision making.

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