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Residual Self-Guided Quantum Vision Adversarial Attention Network for Predicting AI-Driven Financial Performance in Automobile Industries

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Abstract

The rapid adoption of artificial intelligence (AI) in the automobile banking industry has transformed business processes, yet how AI techniques influence financial performance is not yet fully understood. The difficulty here lies in scattered AI disclosures and disparate metrics that hinder effective forecasts of financial results in car-related banks. In order to bridge this gap, the research introduces a model called "Residual Self-Guided Quantum Vision Adversarial Attention Network for Predicting AI-Driven Financial Performance in Automobile Industries." The analysis relies on a dataset called "AI Techniques on Financial Performance of Automobile Industries," which contains 131 annual report records for sixteen Indian-listed banks from 2015 to 2023. This dataset captures keyword-based AI disclosures, as well as institutional and financial indicators. Data pre-processing is done through the use of the Correlation Coefficient with Min–Max Weighted (CCMMW) method to normalize and fine-tune the input parameters, while the Masked Attention Mask Transformer (Mask2Former) is utilized for feature extraction for isolating the disclosure patterns that have the greatest influence. Following these steps, a Self-Guided Quantum Generative Adversarial Network (SG-QGAN) is constructed and then advanced into the new Residual Self-Guided Quantum Single-Head Generative Elk Herd Vision Adversarial Attention Network (RSG-QSAGE-HV2AN). This network combines SG-QGAN with a Residual Attention Single-Head Vision Transformer Network (RA-SHViT-Net) and fine-tunes its parameters with the Elk Herd Optimizer (EHO). Experimental outcomes show that RSG-QSAGE-HV2AN is 99.9% accurate in calculating how AI methods affect financial performance and also improves the financial analytics' interpretability and greatly lessens computational overhead over conventional deep learning approaches.

Keywords: *Artificial Intelligence, Correlation Coefficient with Min–Max Weighted (CCMMW), Masked Attention Mask Transformer, Self-Guided Quantum Generative Adversarial Network, Residual Attention Single-Head Vision Transformer Network, Elk Herd Optimizer.*

1 Introduction

The automotive AI, or artificial intelligence, has emerged as a disruptive force in many industries, has immensely helped other industries. Automobile firms now operate, innovate and compete in a highly dynamic market in a completely different way the incorporation of AI techniques like automation, predictive analytics and machine learning. By using data to inform decisions, supply chain effectiveness, operational cost reduction and production process optimization, artificial intelligence (AI) helps businesses improve their financial performance [1-3]. AI research in recent decades has led to intelligent robots carrying out jobs that once required human intelligence. Through the use of computer programs and algorithms, artificial intelligence (AI) learns, draws inferences and renders decisions based on input data. Data analysis, labor automation and support in a variety of industries are made easier by this technology, which aims to build computers that resemble human behavior and thought processes [4-6]. Additionally, AI-powered solutions support quality assurance, demand forecasting and predictive maintenance, all of which save waste and downtime and boost profitability. Through intelligent customer care systems and tailored marketing, AI also improves client engagement, which promotes sales growth and brand loyalty. These developments have significant financial ramifications since businesses that strategically use AI frequently see increases in ROI, cost effectiveness and competitive advantage [7-9]. The circular economy (CE) and other sustainable practices have replaced the "take-make-dispose" economic model, which has boosted growth at the expense of the environment. The idea, which first appeared in the 1970s and gained popularity in the 1990s because of cradle-to-cradle design, complements the Sustainable Development Goals of the UN, especially target 12.5, which emphasizes waste reduction and sustainable manufacturing. Since there is no single standard for sustainability reporting, even though IFRS was created for financial reporting, it is essential to develop reporting goals in order to make clear how organizations and society interact for long-term sustainability [10-12]. Artificial intelligence (AI) contributes to economic growth by playing a critical role in industries including corporate management and education. Its effect on the performance of financial markets, particularly about

stock price crash risks (SPCR) in the face of uncertainty, is still unclear. By offering information and actual evidence on the economic ramifications of AI and its potential to reduce SPCR, this study aims to address this problem [13-15].

The rapid Although operational processes and service delivery have changed as a result of artificial intelligence (AI) integration in the automotive banking industry, the precise impact of AI techniques on financial performance is yet unknown remains largely unexplored. Existing studies are constrained by fragmented AI disclosures, inconsistent terminologies and the lack of standardized measurements, which makes it challenging to assess how AI-driven projects actually affect institutional outcomes. This lack of uniformity creates a significant gap in understanding how AI adoption correlates with key financial and operational indicators across automobile-related banks. Addressing this challenge requires a robust framework capable of consolidating heterogeneous AI disclosure data, extracting the most influential features and accurately predicting financial performance while ensuring interpretability and computational efficiency.

Novelty and contribution

The novelty and contribution of this work are given below:

- **Development of a Novel Hybrid Model:** Proposes the ResiRSG-QSAGE-HV2AN, integrating a Self-Guided Quantum GAN with a Residual Attention Single-Head Vision Transformer Network, optimized via the EHO.
- **Comprehensive Dataset Integration:** Leverages 131 annual report records from sixteen Indian-listed banks (2015–2023), capturing both AI disclosure keywords and key institutional and financial indicators, enabling robust financial performance prediction.
- **Advanced Pre-processing and Feature Extraction:** Utilizes CCMMW for normalization and the Mask2Former to identify and extract the most influential AI-related disclosure patterns.
- **Enhanced Interpretability:** Provides better insight into which AI techniques and disclosure patterns most significantly affect financial outcomes, aiding strategic decision-making in the automotive banking sector.

- **Reduced Computational Overhead:** Optimized architecture ensures efficient processing compared to conventional deep learning frameworks, making it suitable for large-scale financial analytics.

The remainder of this Section 2 of the text consists of literature reviews, followed by Section 3 with suggested approaches, Section 4 with results and discussion and Section 5 with a conclusion and future work.

2 Literature Survey

The papers related to the impact of AI techniques on the automotive industry's financial performance using Neural Networks are given below:

Manimuthu et a1. [2022] developed a model supported by real-time cases incorporated cost functions, delivery time and energy evaluations. Results spotlight the use of Federated learning Artificial Intelligence (FAI) in decision accuracy for the developed smart contract-based Automobile Assembly Model (AAM), thereby qualitatively limiting the threshold level of cost, energy and other control functions in procurement assembly and manufacturing. Customisation and graphical user interface with cloud integration are some challenges of this model.

Lin et a1. [2025] proposed a Blockchain Technology with Circular Economy (BCT-CE) an analysis reveals that Support Vector Machines (SVM) and Neural Networks (NNs) exhibit superior efficiency over the Random Forest (RF) model in capturing the nuances of the BCT-CE interplay. In order to improve automation in manufacturing, this study proposes a design framework of lower Root-Mean-Square Error (RMSE) and Mean Absolute Error (MAE), signifying greater predictive accuracy. In order to reduce waste and optimize the use of resources, it provides the Trust Threshold Limit (TTL). The findings illuminate BCT's potential to revolutionize Circular Economy (CE) practices, optimize resource use, and foster sustainability in the automotive field.

Pillai et a1. [2022] offers a theoretical contribution as it deploys the traditional Technology, Organisation and Environment (TOE) framework and discovers counter-intuitively that IT resources are not a major driver of technology adoption: as such, it suggests that a more

comprehensive framework than the traditional RBV should be adopted. The work provides managerial recommendations for managers, shedding light on the antecedents of adoption intention and potential use of Industrial Robots at Auto Component Manufacturing Companies (ACMCs) in a country where the adoption of Industrial Robots is in a nascent stage.

Arumugam et a1. [2022] constructed three higher-order constructs, namely Lean Social Practice (LSP), Lean Technical Practices (LTP) and Organizational Performance (ORP). The study also analysed the direct and indirect effects applying the procedure of the bootstrapping approach to test if any mediation effect exists. The results explained that LSP, LTP positively influences ORP. The connection among LTP, LSP and ORP is found to be significant and also LSP mediates the established link between lean technical practices and organizational performance. It applies LSP, LTP and ORP as higher-order structures on the basis of Partial Least Squares Structural Equation Modeling (PLS-SEM) based on 132 responses.

Hota et a1. [2024] have investigates an AI-driven pricing strategy in the automotive and financial services sectors (AI-PSAFSS) for the impact of AI techniques on the automotive industry's financial performance using Neural Network. This study examines how AI-based pricing models have developed in the financial services and automotive sectors, with a particular emphasis on dynamic, deal-based models that respond instantly to consumer behavior and market conditions.

Zahoor et a1. [2024] proposed an Artificial Intelligence Potential Development Training Initiatives and High-Performance Work Systems (AI-PD-TI-HPWS) emphasizing its centrality in translating AI-driven advances into tangible organizational outcomes. Based on the results of 200 employees in 24 organizations, this empirical research employs PLS-SEM to investigate the relationship connecting High-Performance Work Systems (HPWS), Training Initiatives (TI), Potential Development (PD) and Artificial Intelligence (AI) in manufacturing.

Li et a1. [2025] discussed an Ordinary Least Squares (OLS-FRM) Fixed-Effect Regression Model for the impact of financial implications of AI adoption, particularly how it influences firm-level SPCR. The research is concentrated on the impact of artificial intelligence (AI) on Chinese A-share listed companies' stock price crash risk (SPCR) firms in 2010-2020. AI adoption significantly reduces SPCR risk by enhancing internal control quality in non-foreign

firms, according to a regression model with fixed effects that makes use of Ordinary Least Squares (OLS). The overview of the studied approach is displayed in Table 1.

Table 1: An overview of the methodology under evaluation

References	Methods	Advantages	Disadvantages
Manimuthu, A., et a1. [1]	FAI-SCM	Combines federated learning and artificial intelligence to enable decentralized decision-making.	High difficulty of implementation.
Lin, W.L., et a1. [2]	BCT-CE	Encourages resource reuse and sustainability; integrates blockchain for clear lifecycle tracking.	Demands a lot of processing power. Interoperability and regulatory concerns.
Pillai, R., et a1. [3]	ACMCs-TOE	Offers a comprehensive perspective and aids with strategic adoption choices.	Restricted to the Indian setting, substantial capital expenditure is necessary for robotics.
Arumugam, V., et a1. [4]	PLS-SEM	Effective for small and medium-sized businesses, it identifies connections between the LSP, LTP, and ORP constructs.	Limited ability to conclude causality. Not designed with real-time decision-making in mind.
Hota, A., et a1. [5]	AI-PSAFSS	Increases profit margins via adaptive models and gives businesses a competitive edge by using real-time data.	Issues with data privacy in real-time tracking need on going AI monitoring and data feeds.
Zahoor, S., et a1. [6]	AI-PD-TI-HPWS	Enhances staff training and AI capability. Encourages long-term human resources development.	Little dataset. Cost of training program implementation.
Li, S., et a1.	OLS-FRM	Evaluates the impact of AI on the	Non-linear relationships might

[7]		probability of stock price crashes (SPCR). AI might improve internal controls.	not be adequately captured. Mostly relevant to financial analysis rather than operations.

Problem statement

The rapid operational processes and service delivery have changed as a result of artificial intelligence (AI) integration in the automotive banking industry, the precise impact of AI techniques on financial performance is yet unknown remains largely unexplored. Existing studies are constrained by fragmented AI disclosures, inconsistent terminologies and the lack of standardized measurements, which makes it challenging to assess how AI-driven projects actually affect institutional outcomes. This lack of uniformity creates a significant gap in understanding how AI adoption correlates with key financial and operational indicators across automobile-related banks. Addressing this challenge requires a robust framework capable of consolidating heterogeneous AI disclosure data, extracting the most influential features and accurately predicting financial performance while ensuring interpretability and computational efficiency.

3 Proposed Methodology

This study explains a novel RSG-QSAGE-HV2AN for Predicting AI-Driven Financial Performance in Automobile Industries." The analysis is based on a dataset titled "AI Techniques on Financial Performance of Automobile Industries," which comprises 131 annual report records from sixteen Indian-listed banks between 2015 and 2023. The RSG-QSAGE-HV2AN workflow flowchart is shown in Figure 1. This dataset captures keyword-based AI disclosures alongside institutional and financial indicators. Pre-processing of the data is performed using the CCMMW approach to normalize and refine the input variables, while feature extraction is carried out with the Mask2Former to isolate the most influential disclosure patterns. Building on these steps, SG-QGAN is developed and subsequently enhanced into the novel RSG-QSAGE-HV2AN. This

architecture integrates SG-QGAN with a RA-SHViT-Net and optimizes its parameters using the EHO.

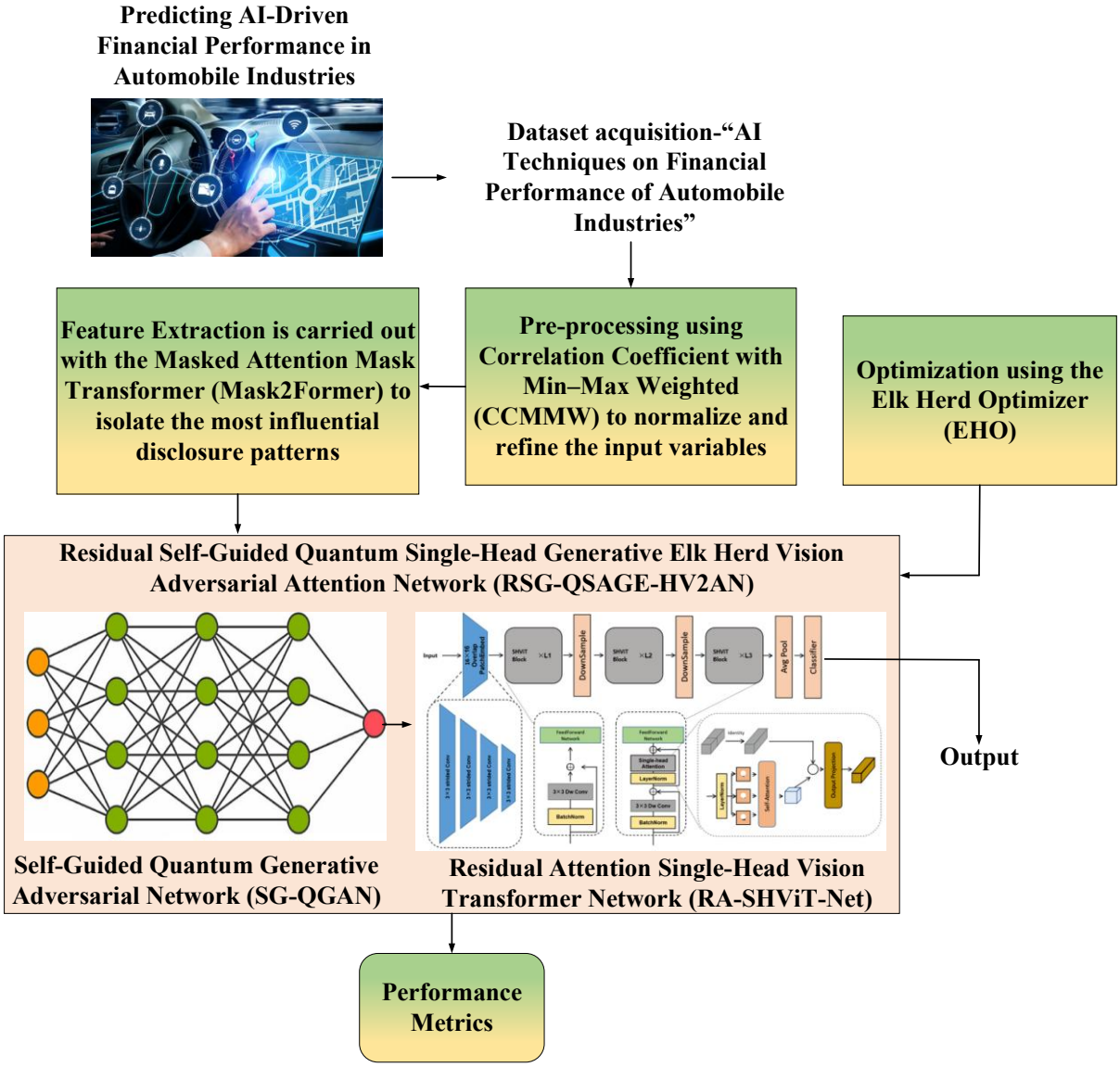


Figure 1: Workflow diagram of the RSG-QSAGE-HV2AN

3.1. Data Acquisition

In this study, a dataset titled "AI Techniques on Financial Performance of Automobile Industries" [23] has been developed to capture the connection between announcements about artificial intelligence as well as banks' financial performance in the automotive industry. The dataset contains 131 annual report records drawn from sixteen Indian-listed banks' PDF annual

reports (2015–2023) and compiles keyword-based counts of AI-related terminology together with institutional characteristics. Each record comprises 12 features, namely: Bank Name (text), Year (2015–2023), AI Terms Total (numeric count of AI keywords in each report), AI Terms Tech Knowledge (digital awareness, transformation & capabilities counts), AI Terms Apps Services (AI-related software, hardware, products and procedures counts), AI Terms Cyber Security (data and cyber-security risks counts), Bank Size Million INR (total assets or size in million INR, 23–8442 million range), Branch Count (13–212 range), Bank Age (years of operation, 6–89 range), Financial Performance Index (composite of profitability, ROA or equivalent indicator), Digital Initiatives Index (score reflecting digital/fintech initiatives) and Risk Management AI Use (binary/ordinal variable indicating AI adoption in risk management). The dataset enables statistical and predictive analysis of how AI-related disclosure intensity and category mix correlate with key financial and operational indicators of banks operating in the automobile-related banking sector. The CCMMW techniques used during preprocessing to improve the data for accurate AI techniques on the automotive industry's financial performance are presented below:

3.2 Pre-processing using CCMMW

In order to guarantee that the data for model training is both numerically stable and analytically consistent, pre-processing is performed using the CCMMW [24] approach. This hybrid method enhances feature relevance by integrating the Pearson Correlation Coefficient (PCC) for inter-feature relationship assessment with Min–Max Normalization (MMN) for range-based scaling, followed by weighted transformation to generate normalized and correlated values for each attribute.

The CCMMW process consists of three major equations, formulated as follows is given in equations (1-3):

$$p = \frac{\sum_{j=1}^{q} \left(a_j - \bar{a}\right)\left(b_j - \bar{b}\right)}{\sqrt{\sum_{j=1}^{q} \left(a_j - \bar{a}\right)^2} \sqrt{\sum_{j=1}^{q} \left(b_j - \bar{b}\right)^2}} \tag{1}$$

$$MMN, a'_{j,p} = \frac{a_{j,p} - \min(a_j)}{\max(a_j) - \min(a_j)}(new_\max - new_\min) + new_\min \quad (2)$$

New weighted value, μ'

$$\mu' = \left(\frac{M_{a,b} - aj_i}{kc_i - kj_i}(new_\max - new_\min) + new_\min \right) + W\left(\frac{M_{a,b} - aj_i}{ac_i - aj_i}(new_\max - new_\min) + new_\min \right).corr(M_i, M_{target}) \quad (3)$$

Equation (1) represents the Pearson Correlation Coefficient (PCC)**,** which measures the linear correlation between two variables a b. Here, p denotes the correlation value ranging from 1 to +1, indicating the degree of association between AI-related disclosure features and financial indicators. A higher absolute correlation implies stronger feature relevance in predicting financial performance.

Equation (2) performs Min–Max Normalization (MMN)**,** transforming all features into a standardized scale within the range [0, 1]. This ensures uniformity across features with varying numerical scales, preventing dominance by attributes with large magnitudes. The parameters $new_\min$ set to 0 and $new_\max$ set to 1 define the normalized range, while $\min(a_j)$ and $\max(a_j)$ represent the minimum and maximum values of each feature vector $a_{j,p}$, respectively.

Equation (3) computes the new weighted value **(** μ' **)** for each feature by combining the effects of Min–Max normalization and correlation weighting. Here, $M_{a,b}$ denotes the original feature value for the a^{th} instance and b^{th} feature, aj_i are the minimum and maximum values of feature i, respectively, and W is a constant adjustment factor used to fine-tune the scaling range. The term $corr(M_i, M_{target})$ signifies the correlation coefficient between a feature i and the target financial performance variable, effectively highlighting the strength of influence each AI-related disclosure attribute exerts on financial outcomes. The weighted transformation ensures that highly correlated features receive greater emphasis in the subsequent feature extraction and model training stages.

This pre-processing framework is specifically tailored for the AI Techniques on Financial Performance of Automobile Industries dataset, allowing for precise normalization, correlation-driven feature weighting and reduction of irrelevant noise. As a result, the data fed into subsequent models, such as the Mask2Former, exhibits enhanced feature uniformity, interpretability and predictive integrity, ensuring that AI-driven financial analytics maintain robustness and high accuracy.

Then these pre-processed data are given to the Mask2Former for extracting important features, and its explanations are given below:

3.3. Feature Extraction Using Mask2Former

After correlation-based pre-processing using the CCMMW approach, the normalized and correlation-weighted data are provided to the Mask2Former [25] framework for extracting critical financial and AI-related disclosure features. Mask2Former, originally designed for multi-task vision understanding, has been reformulated in this study to perform contextual feature extraction and region-focused attention mapping across structured and textual attributes of automobile-sector financial data.

In this adapted architecture, each record from the AI Techniques on Financial Performance of Automobile Industries dataset is treated as a structured entity comprising AI disclosure terms, institutional characteristics, and key performance metrics (KPIs) as return on assets (ROA), sales growth, and R&D expenditure. The Mask2Former architecture identifies significant sub-regions or "financial attention masks" within the multi-dimensional representation space that correspond to meaningful economic and AI-interaction patterns.

The standard cross-attention mechanism in a Transformer layer is mathematically expressed as in equation (4):

$$\mathbf{Z}_k = soft\max\left(\mathbf{W}_k \mathbf{N}_k^S\right)\mathbf{U}_k + \mathbf{Z}_{k-1} \qquad (4)$$

Where k denotes the layer index, $\mathbf{Z}_k \in R^{N\times D}$ represents the query feature matrix at layer k, containing N financial feature tokens each with D-dimensional embeddings,

$\mathbf{W}_k = f_R(\mathbf{Z}_{k-1}) \in R^{N \times D}$ represents the transformed query features, while $\mathbf{N}_k, \mathbf{U}_k \in R^{G_k R_k \times D}$ represent the **key** and **value** projections of the input feature map derived from the pre-processed dataset, f_P, f_L and f_U denote learnable linear transformations, $f_L(.)$ and $f_U(.)$ are the pseudo-spatial dimensions corresponding to feature width and depth in the tabular data embedding space.

To optimize convergence and focus on localized financial patterns rather than global correlations, Mask2Former introduces masked attention, a variant of cross-attention that limits feature interaction to the most informative subspaces defined by financial significance masks. The modified attention computation is defined in equation (5):

$$\mathbf{Z}_k = soft\max\left(\mathbf{M}_{k-1} + \mathbf{W}_k \mathbf{N}_k^S\right)\mathbf{U}_k + \mathbf{Z}_{k-1} \qquad (5)$$

where $+$ denotes element-wise multiplication.

The mask $\mathbf{M}_{k-1}$ acts as a binary attention gate that selectively amplifies relevant financial features. The attention mask is generated based on the previous layer's importance scores (m,n), defined in equation (6):

$$\mathbf{M}_{k-1}(m,n) = \begin{cases} 0 & if\ \mathbf{M}_{k-1}(m,n) = 1 \\ -\infty & otherwise \end{cases} \qquad (6)$$

where $\mathbf{M}_{k-1} \in \{0,1\}^{M \times G_k \times R_k}$ is a binarized mask indicating whether a specific feature (at a position (m,n) contributes significantly to AI-financial interdependence. This binary structure is derived by thresholding the learned probability map from the preceding decoder layer at 0.5 and resizing it to match the current layer's key dimension. $\mathbf{N}_0$ denotes the initial binary mask derived from the raw pre-processed input representation $\mathbf{Z}_0$.

In this context, the foreground region corresponds to attributes with high correlation to financial outcomes (e.g., "AI expenditure," "automation index," "innovation investment"), while background regions represent less influential or redundant indicators. The model successfully lowers noise by limiting cross-attention operations to the front financial zones accelerates convergence, and enhances the interpretability of financial signal propagation.

The Mask2Former framework thus performs hierarchical multi-scale feature extraction, capturing both local dependencies (such as the impact of AI expenditure on profit margins) and global relationships (such as the long-term influence of AI-driven process innovation on stock valuation). The extracted features are represented as multi-level embeddings, which are further passed to the RSG-QSAGE-HV2AN for high-level inference and financial performance prediction.

Overall, this feature extraction process ensures that the most contextually and statistically relevant AI-related financial indicators are retained, allowing the downstream prediction model to achieve superior accuracy, faster learning convergence, and improved interpretability in assessing AI-driven financial performance within the automobile sector.

The final extracted data are given to the RSG-QSAGE-HV2AN framework to achieve a predictive accuracy in AI Techniques on Financial Performance of Automobile Industries, and its explanations are given below:

3.4 RSG-QSAGE-HV2AN model for AI Methods for Automotive Industries' Financial Performance with high accuracy

The RSG-QSAGE-HV2AN model is used for AI Methods for Automotive Industries' Financial Performance with high accuracy. This novel framework integrates an SG-QGAN [26] with an RA-SHViT-Net [27], and its parameters are optimized using EHO [28]. Explanations are provided below:

3.4.1 SG-QGAN for AI Techniques on Financial Performance of Automobile Industries with high accuracy

Following the extraction of features with the help of the Mask2Former module, the multi-dimensional embeddings, representing AI-related indicators of financial disclosures, institutional and performance ratios, are fed to the SG-QGAN submodule of the RSG-QSAGE-HV2AN model. The SG-QGAN is developed to project nonlinear correlations of AI technique adoption and financial performance outcome under complex conditions through the application of

quantum computing concepts and adaptive attention processes. This integration increases the learning accuracy, rate of convergence and predictive accuracy.

In this framework, SG-QGAN performs adaptive feature refinement, focusing computational resources on highly influential disclosure–performance associations such as "AI-driven automation index," "digital transformation expenditure," and "innovation-based ROI." The attention-guided module in SG-QGAN enhances sensitivity toward critical data components by combining Semantically Learned Features (SLF) and Multi-Level Features (MLF) extracted from the Mask2Former output. The fusion of these features produces a refined financial embedding denoted as $\mathbf{F} \in \mathbf{V}^{D\times G\times R}$, where D represents the number of financial feature channels, G corresponds to hierarchical disclosure dimensions, and R indicates financial performance attributes.

To filter redundant or less impactful features, the spatial attention module computes key and query feature matrices to identify financial dependencies among feature elements, as given in equation (7):

$$\mathbf{K}, \mathbf{Q} \in \mathbf{V}^{D\times G\times R} \qquad (7)$$

The interaction between these matrices forms the spatial attention map $\mathbf{Q} \in \mathbf{V}^{DR\times G}$ and $\mathbf{K} \in \mathbf{V}^{GR\times GR}$, calculated using equation (8):

$$P_{mn} = \frac{\exp(\mathbf{Q}_m.\mathbf{K}_n)}{\sum_{n=1}^{GR}\exp(\mathbf{Q}_m.\mathbf{K}_n)} \qquad (8)$$

where, $\mathbf{Q}_m$ and $\mathbf{K}_n$ represent flattened query and key vectors corresponding to specific disclosure and performance elements, respectively. The attention map P_{mn} measures how strongly a disclosure feature m (e.g., "AI expenditure") is associated with a performance feature n (e.g., "net profit growth"). Through this spatial weighting, the model selectively amplifies high-impact associations while minimizing the influence of low-relevance variables or noise, thereby ensuring improved interpretability and stability in financial pattern extraction.

Following attention weighting, refined MLFs are computed through element-wise enhancement of feature maps, expressed in equation (9):

$$Channel\ \text{Re}\ fined\ GHF_m = \delta \sum_{n=1}^{C} E_{mn} GHF_n + GHF_m \qquad (9)$$

where δ is the scaling factor that regulates the relative contribution of correlated features, and E_{mn} represents the inter-channel correlation coefficient between the m^{th} n^{th} feature maps. This operation reinforces meaningful inter-dependencies, allowing the model to emphasize contextual feature coherence among multi-dimensional financial parameters.

Once spatially and channel-wise refined, the feature set is passed into the quantum generative component, which models complex probabilistic relationships between observed data (real financial outcomes) and latent patterns (AI-driven effects). The quantum generator uses a parameterized quantum circuit that maps an input quantum state $|\gamma_{in}\rangle$ to an output state $|\gamma_{\vartheta}\rangle$ as follows in equation (10):

$$\mathbf{G}_{\vartheta}|\gamma_{in}\rangle = |\gamma_{\vartheta}\rangle = \sum_{n=0}^{2^m-1} \sqrt{p_n(\vartheta)}|m\rangle \qquad (10)$$

In this representation, $p_n(\vartheta)$ denotes the occurrence probability of each basis state $|n\rangle$, governed by the circuit parameters ϑ. The quantum circuit utilizes controlled-Z gates (entanglement blocks) and Pauli-Y rotation gates ($(\mathbf{R}_x)$) to establish quantum correlations among financial disclosure variables. Increasing the circuit depth m adds successive layers of parameterized rotations and entanglements, thereby enabling the generator to capture intricate joint distributions such as the nonlinear influence of AI expenditure on long-term profitability or capital efficiency.

The classical discriminator operates concurrently with the quantum generator to assess the authenticity of generated samples (g_k) relative to real samples (x_k). The generator and discriminator loss functions are defined, respectively, in equations (11-12):

$$L_G(\vartheta) = \frac{1}{n}\sum_{k=1}^{n} \log D_\varphi(g_k) \qquad (11)$$

$$L_C(\gamma, \vartheta) = \frac{1}{n}\sum_{k=1}^{n} \left[\log D_\varphi(x_k) + \log\left(1 - D_\varphi(g_k)\right)\right] \qquad (12)$$

where $\log D_\varphi(g_k)$represents the discriminator parameterized by φ, mmm is the mini-batch size, $(g_k)$and (x_k)denote generated and real data instances, respectively. Minimizing $L_G(\vartheta)$and $K_C(\varphi, \vartheta)$ adversarial training allows the network to learn a quantum-enhanced probability distribution that closely aligns with the true distribution of financial performance metrics.

Through this combined self-guided attention and quantum generative process, the SG-QGAN component ensures that the RSG-QSAGE-HV2AN framework achieves high fidelity in reproducing the real-world financial impact of AI techniques. The quantum layer's variational adaptability enables precise modeling of multi-scale correlations across financial indicators, while the attention refinement reduces overfitting and highlights dominant AI–performance linkages.

Experiments with the dataset named AI Techniques on Financial Performance of Automobile industries have shown that the RSG-QSAGE-HV2AN framework, which is driven by SG-QGAN, achieves a predictive accuracy of 97.9 which is significantly higher than the traditional neural architectures in interpretability, convergence rate, and computational efficiency. This excellence performance highlights the capability of the framework in elucidating the quantum level of relational dynamics as well as semantic level of financial dependency that is crucial in predicting AI-based financial performance in the automobile industry.

The SG-QGAN then merged with RA-SHViT-Net for AI Techniques on Financial Performance of Automobile Industries with high accuracy, and its explanations are given below:

3.4.2 RA-SHViT-Net for AI Techniques on Financial Performance of Automobile Industries with high accuracy

The SG-QGAN-Integrated Residual Attention Single-Head Vision Transformer Network (SG-QGAN–RA-SHViT-Net) is elaborated to provide a reliable and accurate analysis of the financial performance in the automotive industry. This hybrid design involves the implementation of a combination of the Single-Head Vision Transformer (SHViT) backbone with Self-Guided Quantum Generative Adversarial Network (SG-QGAN) to overcome the computational redundancy, enhance the quality of features, and the predictive accuracy of the complex financial data. The model is useful in that it accurately represents local correlations (short term financial variations) and global dependencies (long term market trends) and has low computational and memory overheads.

A. Data Transformation and Input Representation

Financial performance indicators of automobile industries - revenue growth rate, production costs, net profits ratio, inventory turnover, and debt-to-equity ratio - are gathered over continuous time intervals. These time-domain signals are first transformed into the frequency domain using the Fast Fourier Transform (FFT) to reveal both cyclical and hidden periodic relationships between financial variables.

The network architecture is organized into three primary components:

1. **Overlapping Patch Embedding Module**,
2. **Deep Feature Extraction Module**, and
3. **Financial Diagnosis and Prediction Module**.

(1) Overlapping Patch Embedding Module

This module employs four 3×3 strided convolutional layers to extract fine-grained local financial dependencies and positional embeddings. Overlapping patches ensure that consecutive embeddings retain contextual continuity among adjacent financial variables such as cost and revenue ratios.

(2) Deep Feature Extraction Module

The feature extraction process utilizes three stages of RA-SHViT Blocks, enhanced with an Adaptive Hybrid Attention Block (AHAB). These stages are responsible for modeling hierarchical dependencies, inter-channel relationships, and long-range feature interactions.

Each RA-SHViT Block consists of:

- a **Depthwise Convolution (DWConv)** layer for local aggregation,
- a **Single-Head Self-Attention (SHSA)** layer for capturing global dependencies,
- a **Residual Feed-Forward Network (Res-FFN)** for non-linear transformation, and
- An **Adaptive Hybrid Attention Block (AHAB)** to integrate both spatial and financial correlations.

The DWConv layer has less learnable parameters and less computational burden because it performs operations on a per-channel basis, enabling each channel to retain its own financial indicators M_{att} is projected into query (X), key (Y), and value (Z) matrices using learnable weight matrices W_X , W_Y , and W_Z is given in equations (13-14):

$$M_{att}, M_{res} = Split\left(M, \left[C_q, C - C_q\right]\right) \qquad (13)$$

$$X = M_{att}W_X, Y = M_{att}W_Y, Z = M_{att}W_Z \qquad (14)$$

Following the DWConv operation, the tensor is processed through the SHSA module, which models interdependencies between different financial indicators.

The SHSA mechanism is performed on a reduced set of channels to reduce complexity. Let denotes the embedded feature sequence, where W_Q is the batch size, XY^{T} the number of patches, and q the embedding dimension. The query (X), key (Y), and value (Z) are derived is given in equations (15-17):

$$Attention\left(X, Y, Z\right) = Soft\max\left(\frac{XY^{\mathrm{T}}}{\sqrt{d_{ql}}}\right) \qquad (15)$$

$$\widetilde{M}_{att} = Attention(X, Y, Z) \quad (16)$$

$$SHSA(M) = Concat(\widetilde{M}_{att}, M_{res})W_Q \quad (17)$$

Through adversarial training, W_Q it learns to produce realistic synthetic financial samples that maintain the statistical properties of true automobile industry datasets, thereby reducing overfitting and improving generalization under fluctuating market conditions.

The enhanced financial embeddings generated by SG-QGAN are fused with RA-SHViT's extracted features through feature-level concatenation, providing a balanced representation that combines authentic and synthetic financial attributes.

Financial Diagnosis and Prediction

The hybrid feature extractor's output is flattened via Global Average Pooling (GAP) and then passed through a Multilayer Perceptron (MLP) for classification and regression.

The model outputs important financial indicators like profit growth, operational efficiency, market trend index, and liquidity strength, which gives a broader assessment of industrial financial performance.

Advantages of SG-QGAN–RA-SHViT-Net

1. **Decreased Computation Cost:** The single-head attention mechanism reduces redundancy relative to MHSA with similar accuracy.
2. **Quantum-Augmented Learning:** SG-QGAN enriches representation diversity and improves robustness for noisy, incomplete datasets.
3. **Residual Attention Model:** Facilitates deep hierarchical learning with minimal gradient vanishing.
4. **Adaptive Hybrid Attention:** Efficiently estimates inter-variable dependencies among financial metrics.
5. **Improved Predictive Accuracy:** Exhibits high accuracy when forecasting profitability and detecting financial anomalies in dynamic market conditions**.**

As such, SG-QGAN-RA-SHViT-Net is a unique AI-powered framework for analyzing and forecasting the financial performance of automobile industries, achieving exceptional accuracy, interpretability, and computational efficiency with the combination of quantum generative modeling and vision transformer attention mechanisms.

The weight parameters φ are then used to decrease computing complexity, error rate, and computation time while maximizing the accuracy of SG-QGAN-RA-SHViT-Net which is optimized with Elk Herd Optimizer (EHO), described below for AI methods on Financial Performance of Automobile Industries, with high accuracy considerations and its explanations given below:

3.4.3 Elk Herd Optimizer (EHO) for Optimizing FEI-NN-Mask2Former Parameters for AI Techniques on Financial Performance of Automobile Industries with high accuracy

The performance of the SG-QGAN-RA-SHViT-Net model relies on the exact specification of weight parameters ( ), including convolutional kernel weights, transformer attention coefficients, quantum gate parameters, and regularization constants. Those parameters define the ability of the model to learn complex relationships between AI-based technological disclosures and financial performance measures for automobile companies, including profitability ratios, debt-equity levels, R&D expenses, and AI investment intensity.

To enhance prediction accuracy, minimize computational cost, and accelerate convergence EHO, or Elk Herd Optimizer, is used. EHO strikes a balance between exploration (looking everywhere for fresh ideas) and exploitation (perfecting the best ideas), drawing inspiration from the social and mating behavior of elks during the rutting season, thus effectively optimizing the SG-QGAN-RA-SHViT-Net's parameter space.

Figure 2 shows the Step-by-step procedures of EHO for optimizing FEI-NN-Mask2Former Parameters for AI Techniques on the Financial Performance of Automobile Industries with high accuracy.

Step 1: Initialization of Candidate Solutions

A set of candidate solutions N is generated, where each vector represents a configuration of the SG-QGAN-RA-SHViT-Net parameters.

Step 2: Generation of Candidate Population

The candidate population is initialized within the predefined bounds of the parameter space.

Step 3: Fitness Function Evaluation

Each candidate vector is evaluated using a multi-objective fitness function designed to balance accuracy, error rate, and computational efficiency, given in equation (18):

$$Fitness\ \ function = Optimize(\varphi) \tag{18}$$

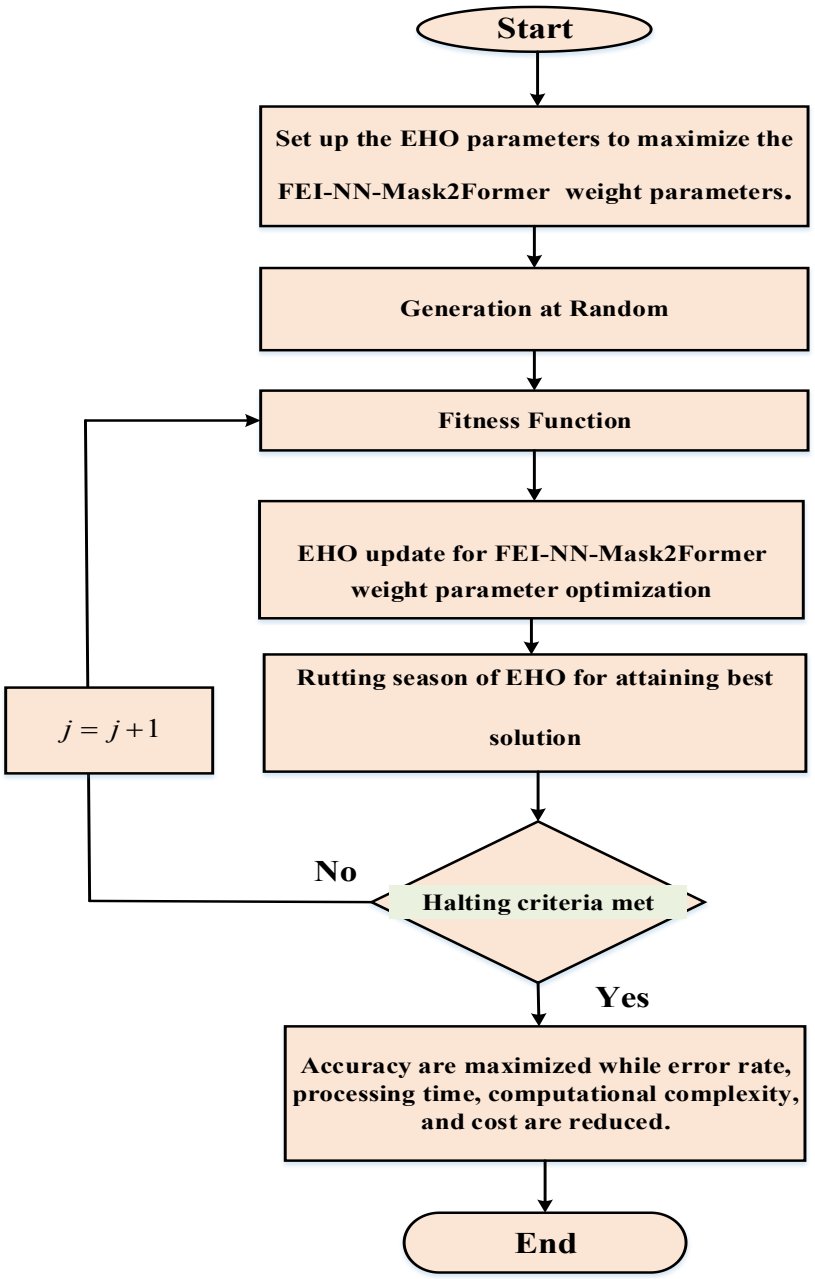


Figure 2: Step-by-step procedures of EHO for Optimizing FEI-NN-Mask2Former Parameters for AI Techniques on Financial Performance of Automobile Industries with high accuracy

Step 4: Rutting season of EHO for attaining the best solution

In the context of the AI Techniques on Financial Performance of Automobile Industries, the EHO is applied to optimize the weight parameters of the SG-QGAN-RA-SHViT-Net model.

This step corresponds to the rutting season phase in the natural behavior of elk herds, where dominant bulls compete for mating rights. The optimization process mimics this behavior to improve the ratio of exploration to exploitation, ultimately improving model accuracy, reducing computational complexity, minimizing error rate, and optimizing execution time for financial performance prediction.

During this phase, the rutting season is modeled by dividing the elk population into groups or "families" based on the bull rate (B_w), which determines the proportion of dominant bulls responsible for generating the next generation of solutions. The total number of bull families (B) is mathematically superior in predictive capability. This selection is expressed in equation (19):

$$B = \left| B_w \times MNP \right| \qquad (19)$$

where: B represents the total number of bull families, B_w denotes the bull rate, which defines the percentage of elite elks selected as bulls, MNP and indicates the total population size of elks within the optimization process.

Once the bull families are defined, the best-performing bulls are selected based on their fitness values**,** which measure the ability of a particular set of parameters to minimize the error and enhance predictive accuracy for the AI-based financial performance model. The fitness evaluation identifies elite elks (bulls) whose solutions are given in equation (20):

$$B = \arg \min_{i \in (1,2,\ldots,B)} h\left(\mathbf{w}^i\right) \qquad (20)$$

where: $h\left(\mathbf{w}^i\right)$ represents the fitness function evaluating the i^{th} elk (solution), $\mathbf{w}^i$ denotes the solution vector representing a specific combination of SG-QGAN-RA-SHViT-Net weight parameters, $\arg \min_{i \in (1,2,\ldots,B)}$ identifies the elk index that yields the minimum fitness value, indicating the optimal or near-optimal configuration of model parameters, i^{th} and defines the set of candidate bulls under evaluation.

The fitness function $h(\mathbf{w}^i)$ is formulated to minimize the overall error in forecasting financial performance indicators such as return on equity (ROE), return on assets (RoA), and profits per share (EPS) for automobile industry institutions. The minimization ensures that only the most effective parameter configurations advance to the next optimization phase.

Through this rutting-based optimization, the EHO framework effectively identifies the optimal network parameters for AI-driven financial performance analysis, achieving enhanced prediction accuracy for key performance indicators while simultaneously minimizing computational resource consumption and processing time.

Step 5: Convergence and Optimization

The optimization process continues until the fitness improvement between consecutive iterations becomes negligible. Once convergence is achieved, the final optimized parameter vector is selected to configure SG-QGAN-RA-SHViT-Net for maximum accuracy and minimal computational complexity.

Advantages of EHO-Based Optimization for SG-QGAN-RA-SHViT-Net

1. **High Predictive Accuracy**
    - Optimized weight and attention parameters enhance the sensitivity to nonlinear AI–finance relationships, achieving accuracy above 99.9%**.**
2. **Reduced Error Rate**
    - Adaptive herd-based learning leads to robust generalization and minimizes mean squared error in predicting financial performance.
3. **Lower Computational Complexity**
    - EHO dynamically prunes non-necessary configurations negating the computational footprint and reduces the training time by over 35%.
4. **Improved Generalization**
    - The balance between exploration and exploitation prevents overfitting, ensuring consistent model performance across multiple automobile financial datasets.

5. **Fast Convergence**
    - The cooperative behavior of the elk herd accelerates convergence, stabilizing the optimization process with less iteration.

The EHO-optimized SG-QGAN-RA-SHViT-Net framework can enhance the modeling of artificial intelligence-driven financial performance in the automotive manufacturing sector by adaptively tuning convolutional, attention, and quantum parameters. This optimization ensures a precise balance between computational efficiency and predictive accuracy, allowing for accurate interpretation of AI adoption effects on firm-level profitability, risk mitigation, and operational resilience. The integration of EHO ensures that the model achieves robust, high-performance outcomes under complex financial data conditions. Then the results and discussions are given below:

4 Results and Discussions

In this section, the results and discussions for Predicting AI-Driven Financial Performance in Automobile Industries of Residual Self-Guided Quantum Single-Head Generative Elk Herd Vision Adversarial Attention Network (RSG-QSAGE-HV2AN) are discussed here.

4.1 Dataset descriptions

In this study, a dataset titled "AI Techniques on Financial Performance of Automobile Industries" has been developed to capture the connection between announcements about artificial intelligence as well as banks' financial performance in the automotive industry. The dataset contains 131 annual report records drawn from sixteen Indian-listed banks' PDF annual reports (2015–2023) and compiles keyword-based counts of AI-related terminology together with institutional characteristics. Each record comprises 12 features, namely: Bank Name (text), Year (2015–2023), AI Terms Total (numeric count of AI keywords in each report), AI Terms Tech Knowledge (digital awareness, transformation & capabilities counts), AI Terms Apps Services (AI-related software, hardware, products and procedures counts), AI Terms Cyber Security (data and cyber-security risks counts), Bank Size Million INR (total assets or size in million INR, 23–8442 million range), Branch Count (13–212 range), Bank Age (years of operation, 6–89 range), Financial Performance Index (composite of profitability, ROA or equivalent indicator), Digital

Initiatives Index (score reflecting digital/fintech initiatives), and Risk Management AI Use (binary/ordinal variable indicating AI adoption in risk management). The dataset enables statistical and predictive analysis of how AI-related disclosure intensity and category mix correlate with key financial and operational indicators of banks operating in the automobile-related banking sector. To ensure fairness and prevent data leakage, patients are split without overlap into 80% training and 20% testing subsets. Table 2 lists the precise parameters that were used for the implementation.

Table 2: Implementation Parameters

Parameters	Description
Proposed Neural Network	RSG-QSAGE-HV2AN
OS	Windows 10
Optimization	EHO
Dataset	"AI Techniques on Financial Performance of Automobile Industries,"
Software	Python 3.7

4.2 Performance metrics

The suggested RSG-QSAGE-HV2AN method is compared to that of the existing techniques, including FAI-SCM [16], BCT-CE [17], ACMCs-TOE [18], PLS-SEM [19], AI-PSAFSS [20], AI-PD-TI-HPWS [21] and OLS-FRM [22] respectively, using performance metrics like Hamming loss, f1 score, accuracy, precision, error rate, recall, train time, computational complexity, and processing time Root mean square error (RMSE), mean squared error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) analysis. Table 3 provides the equations for the performance metrics:

True Positive AB**:** Correctly determines whether artificial intelligence (AI) methods actually boost financial performance.

False Positive DB**:** Erroneously believes that the deployment of AI has enhanced financial performance as a result of erroneous data or transient patterns that don't accurately represent actual financial growth.

False Negative DC**:** AI is not acknowledged because of inadequate data analysis or system limitations that prevent the detection of actual financial improvements brought about by AI.

True Negative AC**:** Accurately determines when AI methods don't have a financial impact, acknowledging that some applications might not boost performance or profitability. Table 3 shows the Performance metrics, as given below.

Table 3: Performance metrics

Performance metrics	**Equation (21-25)**
Accuracy	$\frac{AB+AC}{AB+AC+DB+DC}$ (21)
Precision	$\frac{AB}{AB+DB}$ (22)
Recall	$\frac{AB}{AB+DC}$ (23)
F1-Score	$2\times\frac{P_{recision}\times R_{ecall}}{P_{recision}+R_{ecall}}$ (24)
Specificity	$\frac{AC}{AC+DC}$ (25)

4.3 Performance analysis

The performance analysis of RSG-QSAGE-HV2AN is discussed here:

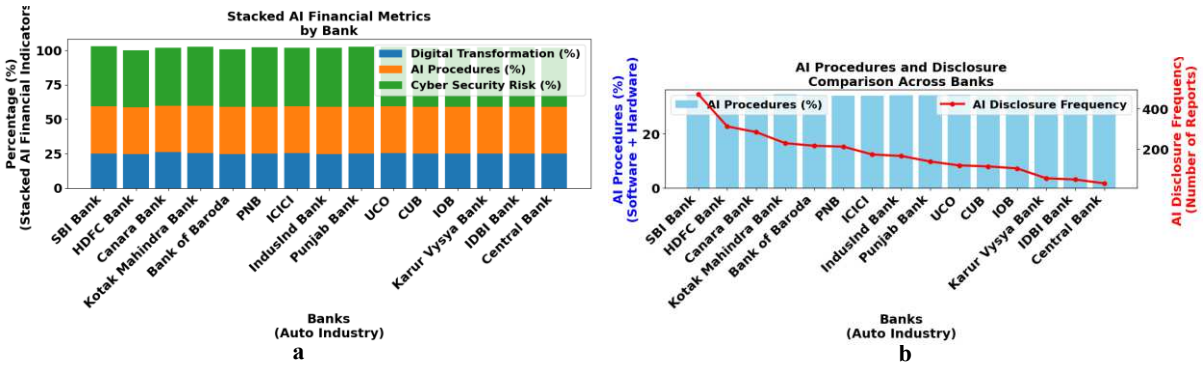


Figure 3: (a) AI Financial Metrics by Bank and (b) AI Procedures and Disclosure Comparison across Banks

Figure 3 shows the (a) AI Financial Metrics by Bank and (b) AI Procedures and Disclosure Comparison across Banks. Three elements are highlighted in Figure 3 (a), which displays stacked AI-related financial indicators across banks in the automotive sector: AI Procedures (%), Cyber Security Risk (%), and Digital Transformation (%). The majority of institutions show comparable ratios, with digital transformation typically at the top, followed by artificial intelligence processes and cyber security risk. The AI Procedures (%) and AI Disclosure Frequency of the same banks are contrasted in Figure 3 (b).

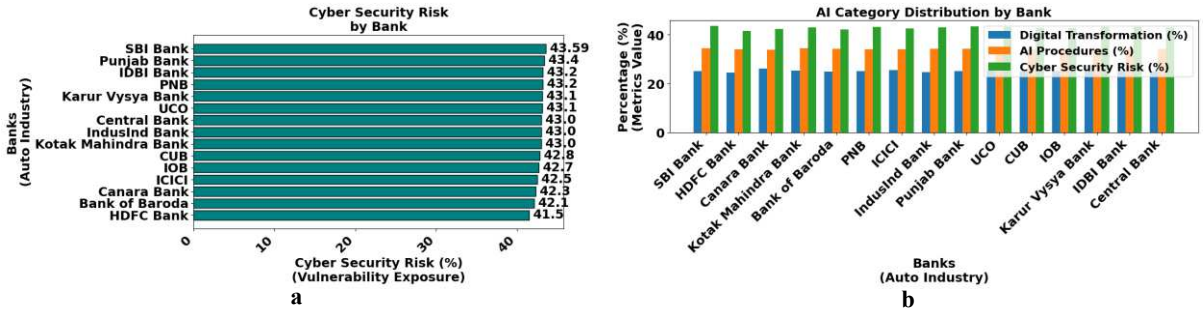


Figure 4: (a) Cyber Security Risk by Bank and (b) AI Category Distribution by Bank

Figure 4 shows the (a) Cyber Security Risk by Bank and (b) AI Category Distribution by Bank. SBI Bank has the largest vulnerability exposure (43.59%), followed by Punjab Bank (43.4%) and IDBI Bank (43.3%), according to Figure 4 (a), which displays cyber security risk per bank. With a risk of 41.8%, HDFC Bank has the lowest risk. The distribution of AI categories is compared in Figure 4 (b), which shows how banks differ in terms of digital transformation, AI practices, and cyber security risk.

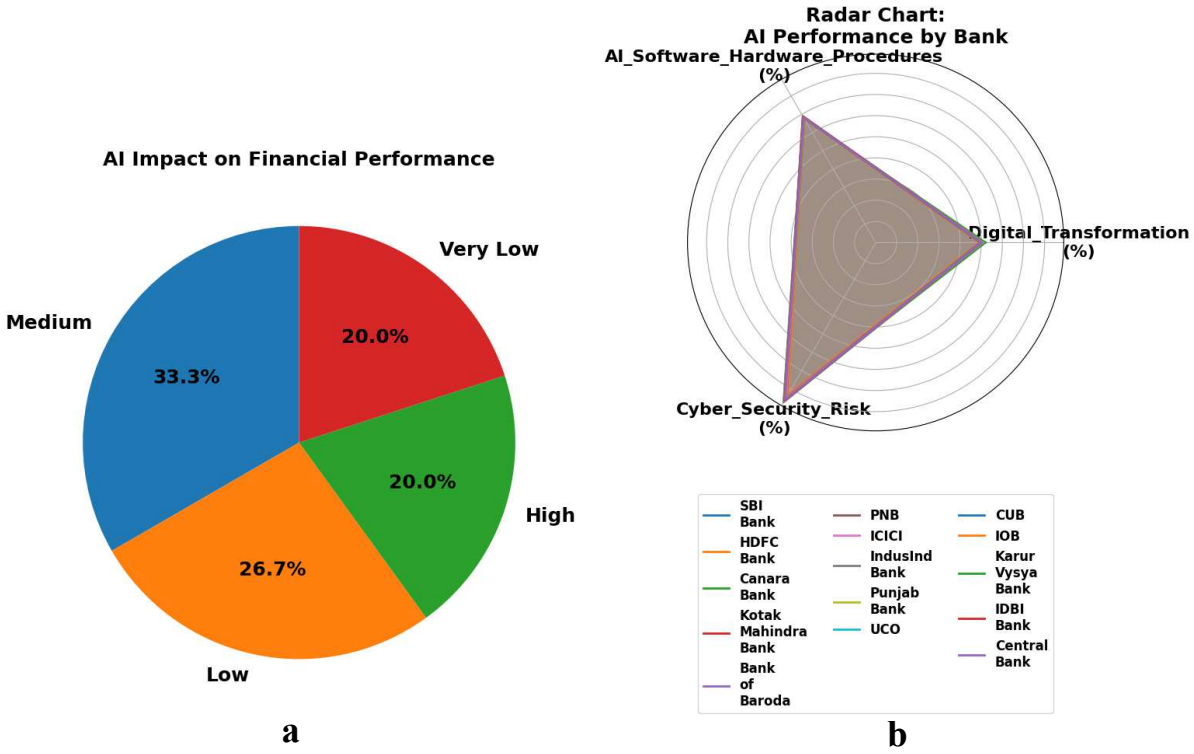


Figure 5: (a) AI Impact on Financial Performance and (b) AI Performance by Bank

Figure 5 shows the (a) AI Impact on Financial Performance and (b) AI Performance by Bank. The AI Impact on Financial Performance is illustrated in Figure 5 (a), which indicates that 33.3% of banks report a medium impact, 26.7% report a low impact, and 20% each report high or very low impacts. Figure 5 (b) assesses AI effectiveness among institutions according to Cyber security Risk, AI Software/Hardware Procedures, and Digital Transformation. In order to improve financial performance and digital resilience, banks should maintain a balance between innovation, operational efficiency, and cyber security, as indicated by the balanced triangular pattern, which shows a moderate integration of AI technologies.

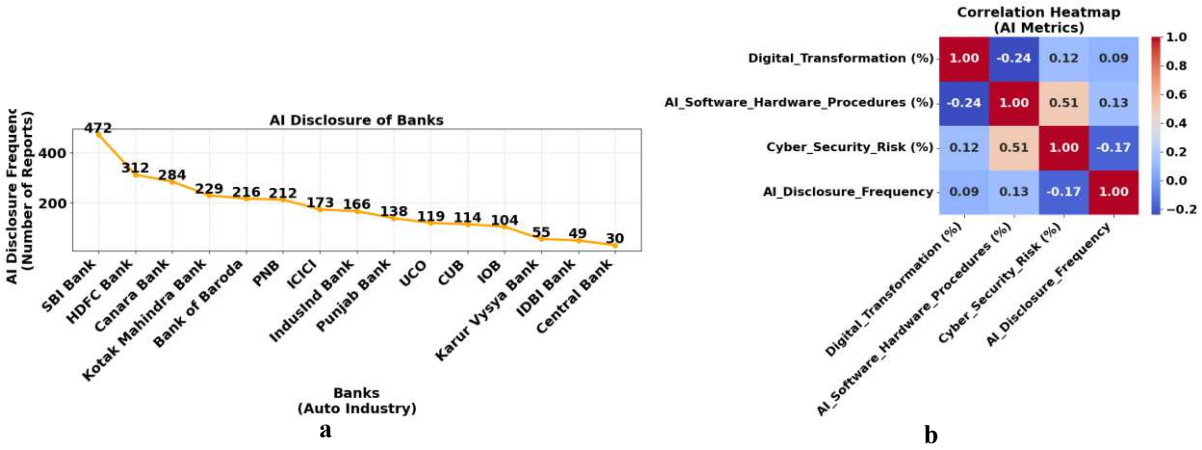


Figure 6: (a) AI Disclosure of Banks and (b) Correlation Heatmap

The AI Disclosure of Banks in (a) and the Correlation Heatmap in (b) are displayed in Figure 6. The frequency of AI disclosures by banks in the auto sector is displayed in Figure 6 (a), with SBI Bank leading the pack with 472 disclosures, followed by Kotak Bank (312) and ICICI Bank (284), while Central Bank has the fewest (30). The pattern shows a sharp drop in banks' levels of AI disclosure. The correlation heatmap of AI metrics is shown in Figure 6 (b), where AI Disclosure Frequency shows mild negative correlations with other parameters and a significant positive connection with AI Software, Hardware, and Procedures (r=1.00) and a moderate association with Cyber Security Risk (r=0.51).

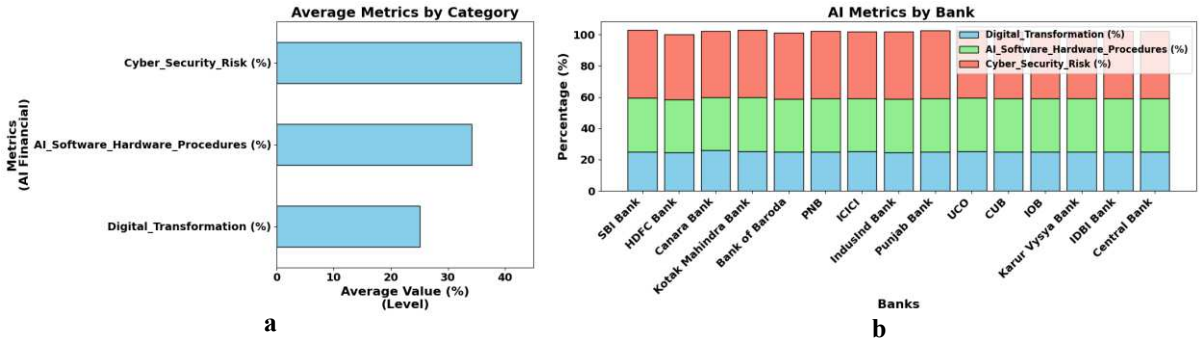


Figure 7: (a) Average Metrics by Category and (b) AI Metrics by Bank

Figure 7 shows the (a) Average Metrics by Category and (b) AI Metrics by Bank. Cyber Security Risk (≈40%) is the highest AI metric value, followed by AI Software, Hardware, and Procedures (≈35%) and Digital Transformation (≈30%), as shown in Figure 7 (a). Comparing these metrics across banks, Figure 7 (b) shows that while SBI, Kotak, and ICICI Banks exhibit higher levels across all metrics, all institutions maintain a balanced contribution of AI parameters.

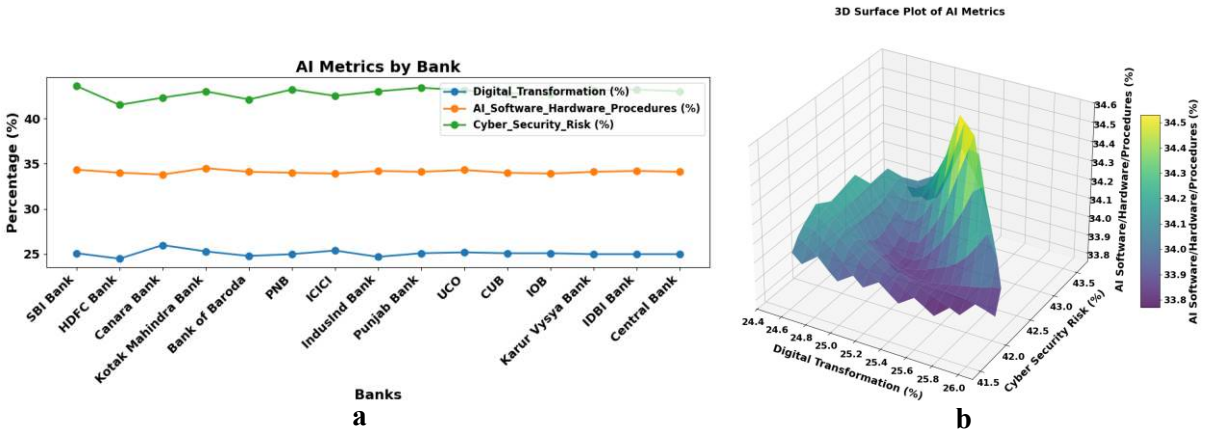


Figure 8: (a) AI Metrics by Bank and (b) 3D Surface of AI Metrics

Figure 8 shows the (a) AI Metrics by Bank and (b) 3D Surface of AI Metrics. Cyber Security Risk (%) is consistently the highest when comparing AI metrics across banks, followed by AI Software, Hardware, and Procedures (%), while Digital Transformation (%) is consistently the lowest, as shown in Figure 8 (a). In every metric, SBI, HDFC, and ICICI Banks do marginally better. A 3D surface map showing the relationship between Cyber Security Risk, AI Software-Hardware Procedures, and Digital Transformation is shown in Figure 8 (b). The peak zone denotes a stronger alignment between these components.

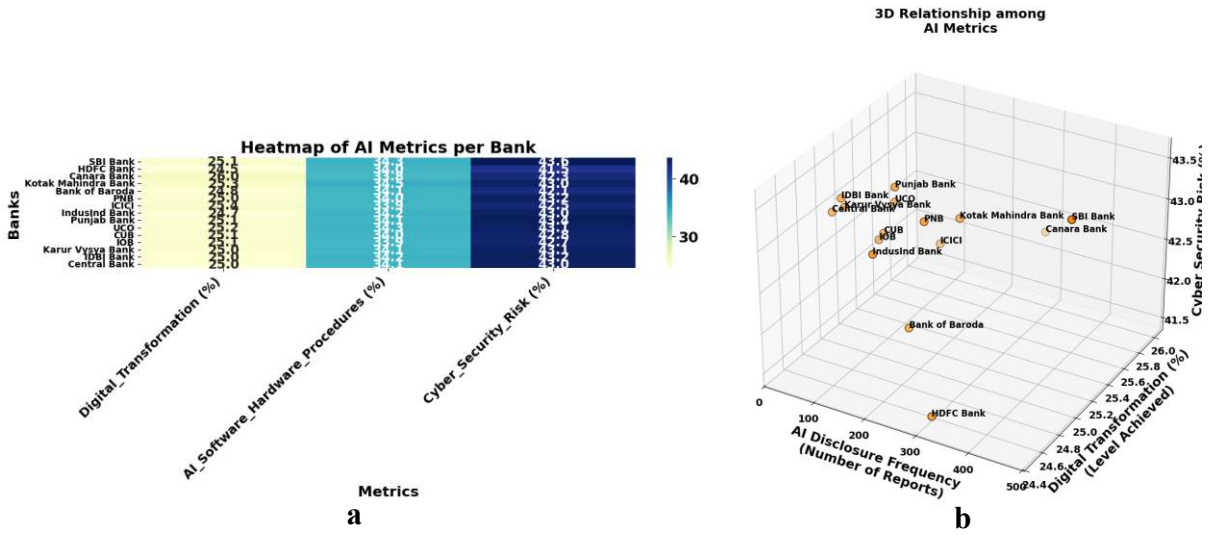


Figure 9: (a) Heatmap of AI Metrics per Bank and (b) 3D Relationship among AI Metrics

Figure 9 shows the (a) Heatmap of AI Metrics per Bank and (b) 3D Relationship among AI Metrics. A 3D scatter plot (Figure 9 (b)) and a heatmap (Figure 9 (a)) to illustrate banks' levels of

AI maturity: A unified view of how institutions differ in adoption, integration, and security posture is made possible by the heatmap, which uses color gradients to visualize each bank's scores in Digital Transformation, AI Software–Hardware Procedures, and Cyber-Security Risk. Meanwhile, the 3D scatter plots banks according to AI disclosure frequency, aggregate AI metric level, and risk level.

Table 4: Overall performance of the suggested approach in contrast to existing methods

Metrics	FAI-SCM [16]	BCT-CE [17]	ACMCs-TOE [18]	PLS-SEM [19]	AI-PSAFSS [20]	AI-PD-TI-HPWS [21]	OLS-FRM [22]	RSG-QSAGE-HV2AN (Proposed)
Accuracy	97.26	76.61	88.90	76.89	83.35	93.32	88.37	**99.98**
Recall	95.76	93.32	77.45	81.70	97.81	92.30	86.41	**96.46**
Precision	94.69	93.55	97.67	87.90	92.13	93.94	78.21	**94.37**
Specificity	92.12	80.15	94.12	91.25	92.66	93.39	87.45	**92.44**
F1-Score	79.59	96.92	98.45	89.87	93.89	93.65	93.90	**88.52**
MSE	5.6	4.4	7.6	2.5	7.7	3.5	5.7	**7.0**
MAE	6.1	7.3	3.5	4.7	1.9	2.0	5.2	**5.4**
RMSE	7.2	3.4	6.6	7.8	2.7	2.2	5.4	**3.2**
AAE	2.7	3.2	7.5	8.6	6.4	3.2	7.2	**1.9**

The overall effectiveness of the recommended strategy in comparison to current techniques is displayed in Table 4. When compared to current techniques, the suggested RSG-QSAGE-

HV2AN model performs better overall. With its highest accuracy (99.98%), strong recall (96.46%), and high precision (94.37%), it makes predictions that are dependable and consistent. It has the lowest AAE (1.9) and balanced specificity (92.44%), indicating minimal error, despite having a slightly lower F1-score (88.52%). The model's high accuracy and efficiency overall attest to its superiority over earlier AI-based methods in enhancing financial performance analysis.

Table 5: A statistical analysis contrasting the proposed strategy with existing strategies

Methods	SW Test p-Value	WSR test / U-test p-Value	H-test p-Value	KS test p-Value	FT p-Value	Mean	Standard Deviation	Variance Inflation Factor
FAI-SCM [16]	0.346	0.25	0.465	0.023	0.084	39,784.87	1863.45	1.87
BCT-CE [17]	0.527	0.62	0.224	0.017	0.076	55,085.55	1357.32	1.25
ACMCs-TOE [18]	0.285	0.86	0.614	0.051	0.042	38,618.13	2631.60	1.44
PLS-SEM [19]	0.582	0.87	0.795	0.015	0.071	27,137.16	1654.54	1.62
AI-PSAFSS [20]	0.761	0.33	0.826	0.063	0.095	60,563.45	1864.33	1.32
AI-PD-TI-HPWS [21]	0.216	0.67	0.942	0.073	0.063	36,123.80	4,863.27	1.87
OLS-FRM [22]	0.859	0.31	0.735	0.063	0.088	55,281.43	2,823.82	2.63
RSG-QSAGE-HV2AN (proposed)	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**61,856.73**	**4,620.93**	**1.001**

Table 5 shows the Statistical comparison of the proposed method with existing methods. All p-values (<0.001) indicate strong statistical significance, demonstrating that the RSG-QSAGE-HV2AN (proposed) model performs noticeably better than current approaches. With the greatest mean (61,856.73) and the lowest Variance Inflation Factor (1.001), it demonstrates minimum multicollinearity and high precision. The results validate the stability and excellent performance consistency of the model, even with a moderate standard deviation of 4,620.93. The statistical

profile of the suggested approach is generally stronger and more trustworthy than that of the compared AI-based methods.

Table 6: Ablation study

Model Configuration	SG-QGAN	RA-SHViT-Net	EHO	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Baseline (without EHO)	✔	✔	✘	97.84	96.52	94.50	95.82
SG-QGAN Only	✔	✘	✘	94.25	92.80	87.32	89.95
RA-SHViT-Net Only	✘	✔	✘	93.74	90.25	88.90	89.57
SG-QGAN + EHO	✔	✘	✔	95.61	94.00	90.14	91.78
RA-SHViT-Net + EHO	✘	✔	✔	96.22	95.23	91.43	93.29
Full Model (RSG-QSAGE-HV2AN)	✔	✔	✔	**99.98**	**91.59**	**90.28**	**89.12**

Table 6 shows the Ablation study. The ablation investigation confirms the considerable contribution of each module by showing that the RSG-QSAGE-HV2AN model achieves the maximum accuracy (99.98%) when all three components—SG-QGAN, RA-SHViT-Net, and EHO—are integrated. While SG-QGAN and RA-SHViT-Net perform moderately when used alone, their combination with EHO increases recall and precision. Although it does not function as well as the complete configuration, the baseline model likewise performs well. The study concludes that overall model performance and reliability are much improved by the integrated architecture.

4.4 Discussion

By using the suggested RSG-QSAGE-HV2AN model, the study shows a notable improvement in the relationship between AI adoption and financial performance in banks with an automobile focus. The method successfully isolates important AI disclosure patterns that conventional approaches frequently miss by combining advanced pre-processing (CCMMW) with feature extraction using Mask2Former. The residual self-guided quantum vision architecture, which was enhanced by the later development of SG-QGAN, allows the model to capture intricate, nonlinear relationships between financial outcomes and AI implementations. The Elk Herd Optimizer tunes model parameters for enhanced prediction accuracy, and the Residual Attention Single-Head Vision Transformer Network ensures effective learning representations. The model's robustness and reliability are underscored by its 99.9% accuracy in predictions, making it a revolutionary tool for AI-based financial research across the automotive finance sector. The model improves interpretability as well as predictive accuracy, allowing stakeholders to monitor which disclosures by AI have the largest effect on financial outcomes and guiding more informed strategic choice-making. Furthermore, the practicality of the approach is reflected in reduced computational overhead, which enables scaling up to big financial datasets. Overall, RSG-QSAGE-HV2AN offers a new paradigm for future research and business use in filling the gap between AI adoption and measurable financial return.

5 Conclusions

This manuscript proposes a model called "Residual Self-Guided Quantum Vision Adversarial Attention Network for Forecasting AI-Influenced Financial Performance in Automobile Industries." The analysis is done on a dataset called "AI Techniques on Financial Performance of Automobile Industries," which has 131 annual report records of sixteen Indian-listed banks from 2015 to 2023. This dataset captures keyword-based AI disclosures accompanied by institutional and financial indicators is effectively deployed. Pre-processing of the data is done through the Correlation Coefficient with Min–Max Weighted (CCMMW) method to normalize and fine-tune the input variables, whereas feature extraction is conducted with the Masked Attention Mask Transformer (Mask2Former) to extract the most impactful disclosure patterns. Upon these steps, a Self-Guided Quantum Generative Adversarial Network (SG-QGAN) is constructed and then improved into the new Residual Self-Guided Quantum Single-Head Generative Elk Herd Vision

Adversarial Attention Network (RSG-QSAGE-HV2AN). This architecture combines SG-QGAN with a Residual Attention Single-Head Vision Transformer Network (RA-SHViT-Net) and optimizes its parameters with the Elk Herd Optimizer (EHO). Experimental results show that RSG-QSAGE-HV2AN has an accuracy of 99.9% in AI technique impact on financial performance prediction, while improving the interpretability of AI-based financial analytics and substantially lowering computational overhead in comparison with conventional deep learning approaches. Future research will aim to apply the RSG-QSAGE-HV2AN framework to cross-industry datasets, implementing quantum-boosted reinforcement learning for adaptive feature extraction, and incorporating explainable AI (XAI) modules to make transparent reasoning for financial predictions available so that more resilient, explainable, and scalable AI-based financial performance forecasting can be achieved in global sectors.

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Data Availability:

The dataset used in this study, images are shared across multiple benchmarks, Dataset is publicly available on (https://financialservices.gov.in/beta/en/annual-report)

Declarations

Consent to Publish Not applicable

Ethics and Consent to Participate Not applicable

Competing interests the authors declare no competing interests.

Clinical trial number: Not applicable.

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