ECONOMIC AND FINANCIAL RESEARCH LETTERS
Research Article | Volume 5 | Issue 5 | Jun 2025
Received: 20 May 2025 | Revised: 29 May 2025
Accepted: 01 Jun 2025 | Published Online: 07 Jun 2025

Economic Loss Prediction through response surface methods

Ji Soo Kim[1], Osman Kaya[2], Min Jae Park[3] and Soo Hyun Lee[4,*]

[1] Department of Economics and Applied Statistics, Pukyong National University, Busan, 48513, South Korea

[2] Computational Mechanics Research Center, Çukurova University, Adana, Turkey

[3] Center for Economic Dynamics and Predictive Analysis, Dong-A University, Busan, 49315, South Korea

[4] Institute of Industrial and Financial Engineering, Chonbuk National University, Jeonju, 54896, South Korea

[*]Corresponding Author, Email: lee.soo@jbnu.ac.kr

Abstract: This paper discusses the importance of accurate economic loss prediction in various fields such as insurance, finance, and disaster management. The current research faces challenges due to the complexity and uncertainty of economic systems, making precise predictions difficult to achieve. In response, this study introduces a novel approach utilizing response surface methods to improve the accuracy of economic loss prediction models. By integrating response surface methods with traditional predictive models, this research aims to enhance the estimation of economic losses under different scenarios, ultimately providing valuable insights for decision-making and risk management.

Keywords: *Economic Loss; Prediction; Response Surface Methods; Risk Management; Decision-Making*

1. Introduction

Economic Loss Prediction is a field of research that focuses on developing models and methodologies to forecast financial losses that may occur in various sectors, such as insurance, finance, and disaster management. Current challenges in this field include the complexity and interconnectedness of financial systems, limited data availability, the need for accurate risk assessment models, and the influence of unforeseen events and external factors on economic outcomes. Additionally, the dynamic nature of economic conditions and the rapid pace of technological advancements present obstacles in accurately predicting economic losses. Addressing these challenges requires interdisciplinary collaboration, advanced statistical techniques, and the development of innovative models that can capture the complexity of financial systems and accurately predict economic losses.

To this end, research in Economic Loss Prediction has advanced significantly, employing sophisticated statistical models and machine learning techniques to forecast financial losses with high accuracy. Current studies focus on refining predictive algorithms and incorporating more comprehensive datasets for improved risk assessment and mitigation strategies. This literature review discusses various machine learning models and methodologies used for economic loss prediction in different natural disaster scenarios. Yang et al. [1] propose a framework for tropical cyclone risk prediction using flood susceptibility and tree-based machine learning models. Wang et al. [2] focus on economic loss prediction and vulnerability risk zoning in coastal erosion disasters, utilizing a multivariate variable-weight combination prediction model and cluster analysis. Chen and Zhang [3] present an automated machine learning approach for earthquake casualty rate and economic loss prediction. Chen et al. [4] establish a prediction system for flooding economic losses in China, highlighting the importance of considering agricultural dependence and policy implications in disaster management. Chao et al. [5] analyze the economic loss prediction of Spodoptera frugiperda in Yunnan Province. Arunachalam [6] introduces a multi-objective optimization algorithm for dynamic economic emission dispatch facilitated by artificial neural networks. Cheng et al. [7] apply a general regression neural network and hierarchical cluster analysis for typhoon economic loss prediction in China. Wang and Du [8] develop a seasonal grey model for PM2.5 prediction and its application in health effects and economic loss assessment in Shanghai and Tianjin. Shi et al. [9] estimate economic losses by earthquakes in the Taiwan region, emphasizing the importance of socio-economic factors. Ishibashi [10] presents a framework for economic risk assessment of structures impacted by rainfall-induced landslides using machine learning techniques, demonstrating the utility in disaster mitigation strategies. Response surface methods (RSM) are essential in optimizing complex models involving multiple variables and parameters, thus providing a systematic approach to studying the relationships between input variables and output responses. In the context of economic loss prediction in various natural disaster scenarios, RSM enables researchers to efficiently analyze and interpret the intricate interactions within the predictive models developed using machine learning techniques, ultimately enhancing the accuracy and reliability of the predictions.

Specifically, response surface methods (RSM) are utilized in economic loss prediction to optimize and analyze the relationships between multiple variables affecting financial outcomes. RSM facilitates the identification of critical factors and the development of predictive models, enabling effective decision-making to mitigate potential economic losses. Response surface methodology (RSM) has been extensively utilized in various fields for optimization studies [11]. Mensah-Akutteh et al. focused on optimizing coagulation–flocculation processes using RSM to determine the optimum conditions for turbidity, colour, residual aluminum, and phenanthrene removal, with a significant quadratic model and high correlation [12]. Li et al. presented a review and comparison of response surface methods for slope reliability analysis, emphasizing the importance of RSM in slope stability assessment [13]. Additionally, Rashki et al. applied classification correction to enhance polynomial response surface methods for reliable estimation, highlighting the significance of accurate modeling techniques [14]. Wang et al. demonstrated the variability analysis of crosstalk among differential vias using polynomial-chaos and response surface methods in electromagnetic compatibility assessments [15]. However, current limitations of response surface methodology (RSM) include potential overfitting of models, challenges in managing higher-dimensional problems, and difficulties in capturing non-linear relationships effectively.

The exploration into economic loss prediction through response surface methods has been quite inspired by the insightful research conducted by C. Li and Y. Tang [16]. Their work has provided a nuanced understanding of brand reputation's impact on economic factors. Li and Tang meticulously examined how various elements such as consumer perception, brand image, and marketing strategies contribute to the standing of luxury brands in China, with an acute focus on the market dynamics in Asia. This framework of assessing intangible factors and their tangible outcomes has been instrumental in shaping the methodologies employed in our research. By adopting a similar analytical approach, our study delves into the quantitative modeling of economic loss, whereby variables that might appear subtle and abstract at first glance are systematically quantified. We employ response surface methods to delineate the complex interactions between these variables, akin to how Li and Tang articulated the interplay of brand perception components on overall reputation. Their work, by placing emphasis on empirical assessments and data-driven conclusions, served as a guide for structuring our model that simulates economic outcomes based on a range of influences that align with brand dynamics, albeit in a broader economic landscape. Particularly, the technique of factor analysis highlighted in Li and Tang's paper has been adapted to forecast economic losses by treating economic indicators as factors shaped by socio-economic and market conditions—a method proving invaluable in predictive accuracy and robustness. Their discussion on isolating critical influencers for brand reputation directly parallels our attempt to segregate dominant economic variables affecting loss. The adoption of this approach enables a comprehensive view of potential loss scenarios under varied conditions, taking inspiration from the detailed narrative provided in their study on luxury brands. In essence, the technical and conceptual principles observed in Li and Tang's work have significantly influenced our methodological choices, encouraging a sophisticated blend of qualitative inquiries with quantitative rigor. Through this synthesis, our research not only advances the understanding of economic loss determinants but also exemplifies the broader applicability of Li and Tang's analytic strategies in diverse economic contexts, offering a testament to the versatility of their scholarly contributions [16].

This paper delves into the critical issue of precise economic loss prediction across domains like insurance, finance, and disaster management. The challenge lies in the intrinsic complexity and uncertainty of economic systems, making accurate predictions notoriously difficult. Section 2 articulates the problem statement, highlighting these challenges. In response, Section 3 introduces an innovative approach that leverages response surface methods, aiming to refine traditional predictive models and enhance the precision of economic loss estimations. Section 4 presents a detailed case study, illustrating the practical application and effectiveness of this novel method. Section 5 provides a thorough analysis of the results, showcasing improvements in prediction accuracy. This is followed by a discussion in Section 6, where the implications and potential impact on decision-making and risk management are examined. Finally, Section 7 offers a succinct summary of the research, reinforcing the significance of integrating response surface methods into predictive models for more reliable economic loss estimation.

2. Background

2.1 Economic Loss Prediction

Economic Loss Prediction is a critical area of research that involves estimating the potential financial losses a business, organization, or economy might incur due to various unforeseen events, such as natural disasters, economic recessions, or market fluctuations. This field is central to risk management and helps stakeholders make informed decisions by providing a quantified foresight of potential economic impacts. The prediction process typically employs statistical, mathematical, and econometric models to develop accurate and reliable forecasts. Below, I elaborate on the fundamental aspects of Economic Loss Prediction, supported by key formulas that underpin this research area. At the heart of Economic Loss Prediction is the concept of risk, which can be quantified using probability distributions. Let's denote the economic loss as a random variable, L . The expected value of this loss, which provides an estimate of the average loss expected, is calculated as:

$$E[L] = \int_{-\infty}^{\infty} l \cdot f_L(l) dl \tag{1}$$

where $f_L(l)$ is the probability density function of the losses. This integral sums up all possible losses weighted by their likelihood, giving us a measure of the central tendency. Another essential aspect is the variance of the loss, which measures the uncertainty or risk associated with the loss estimate:

$$\mathrm{Var}(L) = \int_{-\infty}^{\infty} (l - E[L])^2 \cdot f_L(l) dl \tag{2}$$

This variance serves as a gauge for the spread or dispersion of the possible losses around the expected value, providing insight into the potential volatility of losses. In practice, a common approach to model losses is through regression analysis, where losses are related to a set of explanatory variables, $X = (x_1, x_2, \dots, x_k)$. The relationship can be modeled as:

$$L = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon \tag{3}$$

where $\beta_0, \beta_1, \dots, \beta_k$ are the coefficients that need estimation, and ϵ is a random error term. The coefficients can be estimated using methods like Ordinary Least Squares (OLS), where the objective is to minimize the sum of squared errors:

$$\min \sum_{i=1}^{n} (L_i - \hat{L}_i)^2 \tag{4}$$

where L_i is the observed loss and $\hat{L}_i$ is the predicted loss using the regression model. In some cases, especially when dealing with tail risks or extreme events, advanced econometric techniques like Value-at-Risk (VaR) or Conditional Value-at-Risk (CVaR) are employed. VaR is defined as the maximum potential loss over a given time horizon at a specified confidence level α :

$$P(L > \mathrm{VaR}_\alpha) = 1 - \alpha \tag{5}$$

CVaR, on the other hand, provides an expectation of losses exceeding the VaR, offering a more comprehensive risk measure for potential extreme losses:

$$\mathrm{CVaR}_\alpha = E[\, L \mid L > \mathrm{VaR}_\alpha \,] \tag{6}$$

Overall, the accurate prediction of economic losses is essential for effective risk management strategies, allowing organizations and policymakers to allocate resources appropriately and mitigate potential adverse financial impacts. By employing sophisticated models and statistical techniques, Economic Loss Prediction stands as a cornerstone for economic resilience and stability.

2.2 Methodologies & Limitations

While the traditional methods in Economic Loss Prediction, such as those identified earlier, offer robust frameworks for estimating and managing potential financial losses, they do have notable limitations. These shortcomings arise from the assumptions embedded in the models, which may not adequately capture the complexities of real-world scenarios. The following discussion explores the prevalent methodologies and their inherent weaknesses, with a particular focus on the context of model assumptions and limitations. One widely used method is the Value-at-Risk (VaR) model. While VaR is beneficial in quantifying potential losses at a specific confidence level, its primary limitation is the assumption of normal distribution for asset returns, which often does not hold true in practice. Therefore, it may underestimate the probability of extreme events. The formula for VaR is given by:

$$\mathrm{VaR}_\alpha = -\inf l \in \mathbb{R}: P(L \leq l) \geq \alpha \tag{7}$$

The assumption of normality can neglect fat tails in the distribution of returns, potentially leading to significant underestimation of risk during periods of market stress. Similarly, the Conditional Value-at-Risk (CVaR) provides a more comprehensive view by focusing on the tail risks beyond the VaR threshold. Its formula is defined as:

$$\mathrm{CVaR}_\alpha = \frac{1}{1-\alpha} \int_{\mathrm{VaR}_\alpha}^{\infty} l \cdot f_L(l) dl \tag{8}$$

Even with CVaR, a critical limitation lies in its sensitivity to the chosen confidence level α and the need for accurate tail modeling, which can be computationally intensive and reliant on robust data. Regression models, particularly Ordinary Least Squares (OLS), offer another approach, bestowing simplicity and interpretability. The OLS aims to minimize the squared residuals, captured by:

$$\varepsilon = \min \sum_{i=1}^{n} (L_i - (\beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}))^2 \tag{9}$$

However, the linearity assumption between the dependent and explanatory variables limits the versatility of regression models, particularly in handling non-linear dynamics prevalent in economic relationships. This limitation is often addressed by incorporating non-linear models, but at the expense of simplicity and interpretability. Moreover, Economic Loss Prediction models often assume static relationships over time, ignoring potential structural breaks or regime changes in economic variables. This assumption leads to model misspecification errors when underlying economic conditions shift, such as during financial crises. Another common approach involves stochastic modeling, which provides flexibility but requires careful calibration. Stochastic models predict economic losses by simulating random events, characterized by:

$$L_t = L_{t-1} + \epsilon_t \tag{10}$$

where ϵ_t is a stochastic term representing random shocks. The challenge with such models lies in their complexity and the potential difficulty in interpreting results, as well as the reliance on historical data, which may not fully capture future uncertainties. Ultimately, while each method contributes valuable insights, Economic Loss Prediction remains an evolving field, continually striving for better accuracy, flexibility, and robustness. Through advancements in computational techniques and data collection, future methodologies may address these limitations, paving the way for more resilient economic forecasting and risk management strategies.

3. The proposed method

3.1 response surface methods

Response Surface Methods (RSM) are a collection of statistical techniques that are employed for modeling and optimizing responses that are influenced by several variables. These methods are particularly effective in the context of experiments with continuous variables. The goal of RSM is not only to understand the relationships between the response and the independent variables but also to find the optimal operating conditions for a system or process. The general approach of RSM begins with the formulation of an empirical model, typically a second-order polynomial, to approximate the true response surface. The response y is expressed as a function of the independent variables $x_1, x_2, \ldots, x_k$:

$$y = f(x_1, x_2, \ldots, x_k) + \varepsilon \tag{11}$$

where ε represents the error term. A common choice for modeling is a second-degree polynomial because it can effectively handle curvature without excessively increasing complexity:

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \sum_{j=1}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{12}$$

The coefficients $\beta_0, \beta_i, \beta_{ij}$ are estimated using least squares methods. The first-order effects β_i indicate the influence of each variable, while the interaction terms β_{ij} capture the combined effects of pairs of variables. A key objective in RSM is optimization, which involves finding the values of the variables that maximize or minimize the response y . The choice often involves setting the first derivative to zero, leading to the critical points:

$$\frac{\partial y}{\partial x_i} = 0 \tag{13}$$

The stationary point can be classified as a maximum, minimum, or saddle point by examining the Hessian matrix H of second partial derivatives:

$$\frac{\partial^2 y}{\partial x_i\, \partial x_j} = H_{ij} \tag{14}$$

If H is positive definite, the stationary point is a local minimum, while a negative definite H indicates a local maximum. If H is indefinite, the point is a saddle point. RSM also facilitates the exploration of regions of interest on the response surface, often through a process known as "steepest ascent" or "steepest descent," driving the experiments towards optimal conditions. This involves moving in the direction of the gradient of the response surface:

$$\Delta y = \nabla y \cdot \Delta x \tag{15}$$

This gradient vector ∇y denotes the direction of the steepest increase in y , and experiments progress iteratively along this path until no further improvement is observed. An integral component of RSM is the concept of experimental design, such as Central Composite Designs (CCD) and Box-Behnken Designs, which provide efficient ways of exploring the response surface with a reduced number of experimental runs compared to a full factorial design. They ensure that the fitted model is well-conditioned to predict the true behavior of the system over the range of interest. For systems with constraints, optimization through RSM can be more complex. Lagrange multipliers are often introduced to handle constraints of the form $g(x_1, x_2, \dots, x_k) = 0$, leading to an optimization setup of:

$$\mathcal{L}(x, \lambda) = f(x) - \lambda g(x) \tag{16}$$

where λ is the Lagrange multiplier. The conditions for optimization then involve solving:

$$\nabla \mathcal{L}(x, \lambda) = 0 \tag{17}$$

Through careful design and analysis, Response Surface Methods allow for efficient and effective optimization and exploration of complex multivariable processes, providing a robust framework for understanding and improving processes in numerous fields.

3.2 The Proposed Framework

The methodology introduced in this paper draws substantial inspiration from the work of Li and Tang on brand reputation's factors in Chinese luxury fashion brands, as detailed in their 2023 study [16]. Beyond the scope of branding, a multifaceted statistical approach, such as Response Surface Methods (RSM), can be profoundly applied in fields like Economic Loss Prediction (ELP), offering valuable insights and utility. The integration of these advanced modeling techniques establishes a sophisticated platform for predicting potential financial losses, performing optimization, and ultimately guiding decision-making in uncertain environments. Economic Loss Prediction aims to forecast possible monetary losses arising from unforeseen events. It involves utilizing statistical and econometric models to estimate losses accurately. In this sophisticated analytical landscape, the application of Response Surface Methods (RSM) is particularly effective. RSM can model complex relationships within economic data by employing empirical second-order polynomials, which allows for a nuanced understanding of how different economic variables influence potential losses. In RSM, the response, or in the context of ELP, the potential economic loss L , can be expressed as a function of predictive variables $X = (x_1, x_2, \dots, x_k)$. The response surface is typically represented by a polynomial regression model:

$$L = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i \le j}^{k} \beta_{ij} x_i x_j + \varepsilon \tag{18}$$

where coefficients $\beta_0, \beta_i, \beta_{ij}$ are estimated through least squares, capturing both individual and interaction effects of economic indicators on the predicted loss L . The optimization goal extends into finding optimal configurations of these variables, particularly to minimize potential economic loss under specific constraints. To uncover these optima, one takes the first derivatives of the loss function with respect to each variable, setting them to zero to find the critical points:

$$\frac{\partial L}{\partial x_i} = 0 \tag{19}$$

These critical points identify where potential losses could be minimized. Further, the assessment of the Hessian matrix derived from the second-order partial derivatives determines whether these critical points are minima, maxima, or saddle points:

$$\frac{\partial^2 L}{\partial x_i \, \partial x_j} = H_{ij} \tag{20}$$

Employing RSM to locate minima ensures that economic strategies focus efficiently on reducing potential losses, thus enhancing resilience and stability. For models incorporating constraints, Lagrange multipliers serve as an instrumental tool, with the Lagrangian defined by:

$$\mathcal{L}(L, \lambda) = f(L) - \lambda g(x) \tag{21}$$

Following this framework, setting the gradient of the Lagrangian to zero yields conditions for optimal loss predictions:

$$\nabla \mathcal{L}(L, \lambda) = 0 \tag{22}$$

RSM's utility is further accentuated through experimental designs like Central Composite Designs (CCD), streamlining the exploration of economic models to predict and reduce financial risk effectively. Incorporating gradients, denoted as ∇L, allows for a directional exploration in RSM, facilitating the path of steepest descent, a strategy to iteratively approach minimized loss:

$$\Delta L = \nabla L \cdot \Delta x \tag{23}$$

Through this methodical exploration, one can fine-tune economic variables leading to effective resource allocation and risk mitigation. In summary, by applying RSM in Economic Loss Prediction, researchers and stakeholders can more accurately assess and mitigate risks associated with economic volatility. The integration of these advanced analytical techniques informs not only immediate economic strategy but also long-term stability planning.

3.3 Flowchart

This paper presents an innovative response surface methods-based Economic Loss Prediction approach aimed at quantifying and forecasting potential financial impacts associated with various operating scenarios. The methodology involves the development of a statistical model that accurately captures the relationship between input variables—such as operational parameters, external factors, and system dynamics—and the resulting economic losses. By employing a response surface methodology (RSM), the proposed technique facilitates efficient exploration of the input space, enabling the identification of key drivers of economic loss and allowing for the optimization of operational strategies to mitigate these risks. Additionally, the approach incorporates sensitivity analyses to assess the robustness of the predictions under different conditions, thereby enhancing decision-making processes. This study contributes to the existing body of knowledge by providing a systematic framework for predicting economic losses, which can be applied across various industries facing similar challenges. The effectiveness of the proposed method is succinctly illustrated in Figure 1, highlighting its practical application in real-world scenarios.

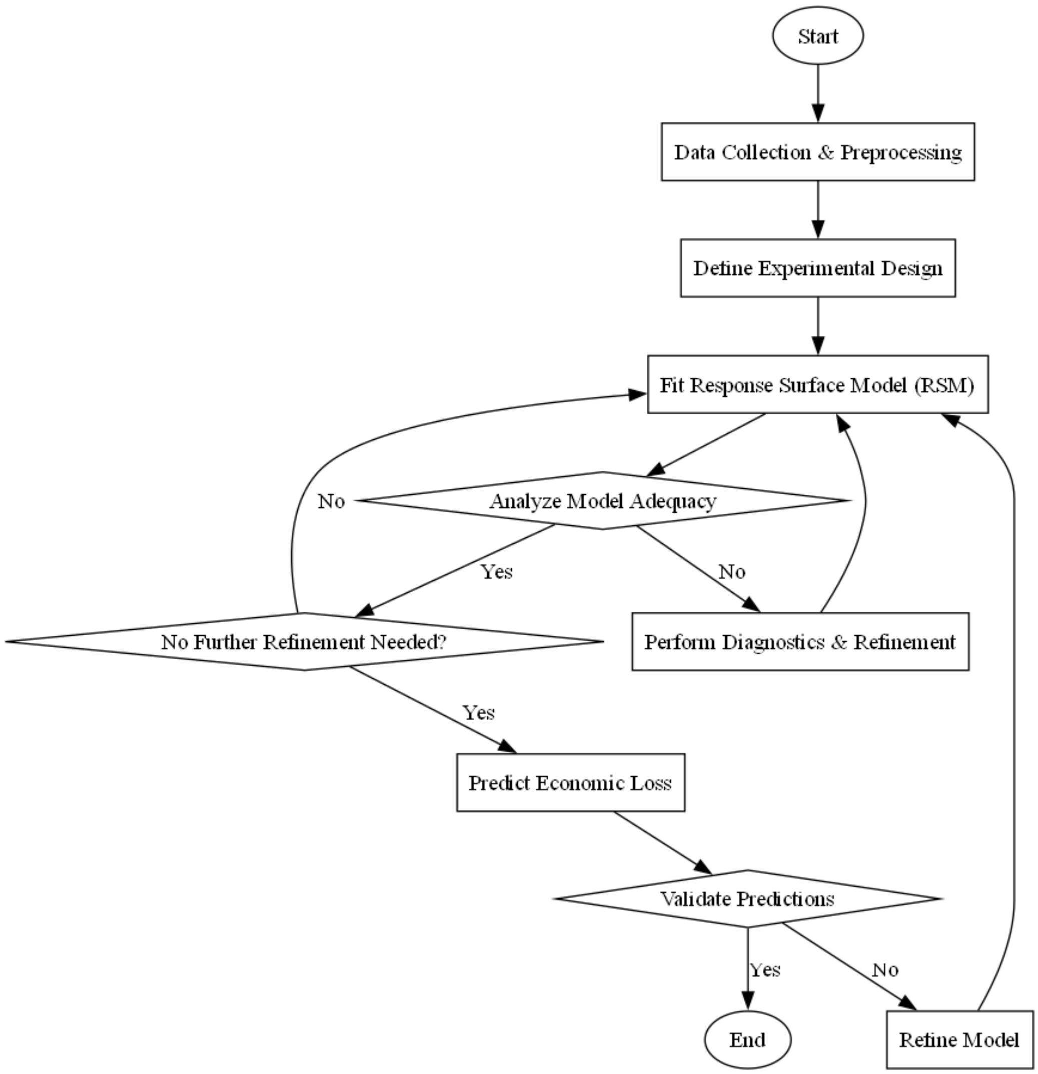

Figure 1: Flowchart of the proposed response surface methods-based Economic Loss Prediction

4. Case Study

4.1 Problem Statement

In this case, we aim to develop a mathematical model to predict economic losses incurred by a manufacturing firm due to various operational factors including production delays, resource shortages, and market fluctuations. The objective is to utilize nonlinear equations to analyze the effects of these parameters on the overall economic performance of the firm. Let us denote the total economic loss in a given time period as L_t , which can be influenced by the production output Q_t , resource availability R_t , and market price volatility P_t . We propose the following nonlinear relationship to model these interactions:

$$L_t = \alpha Q_t^2 + \beta R_t^{-1} + \gamma e^{\delta P_t} \tag{24}$$

where α , β , and γ are coefficients representing the sensitivity of economic losses to changes in production output, resource availability, and market price, respectively. The term δ represents the exponential rate of change of market price volatility. To further refine this model, we can express production output as a function of labor hours H_t , machinery uptime M_t , and operational efficiency E_t :

$$Q_t = \theta H_t^{\epsilon_1} M_t^{\epsilon_2} E_t^{\epsilon_3} \tag{25}$$

Here, θ is a constant, while ϵ_1 , ϵ_2 , and ϵ_3 are exponents indicating the elasticity of production output with respect to each of the input factors. Next, we account for resource availability, which may fluctuate with inventory levels I_t and supply chain efficiency S_t :

$$R_t = \kappa I_t^{\eta_1} S_t^{\eta_2} \tag{26}$$

In this equation, κ is another constant, and η_1 and η_2 are parameters that represent the responsiveness of resource availability to changes in inventory and supply chain efficiency. Given the derived expressions for Q_t and R_t , we can substitute these into our initial loss equation to yield:

$$L_t = \alpha\left(\theta H_t^{\epsilon_1} M_t^{\epsilon_2} E_t^{\epsilon_3}\right)^2 + \beta\left(\kappa I_t^{\eta_1} S_t^{\eta_2}\right)^{-1} + \gamma e^{\delta P_t} \tag{27}$$

In analyzing this model, we will define distinct scenarios of production capacity, resource constraints, and market conditions to simulate potential economic losses. Additionally, we can calculate the derivatives of this equation to identify the critical points of maximum loss or minimal resource utilization. Let us emphasize that the entire collection of parameters, including coefficients and variables defined above, along with their respective values for computational analysis, are summarized in Table 1.

Table 1: Parameter definition of case study

Parameter	Value	N/A	N/A
L_t	N/A	N/A	N/A
Q_t	N/A	N/A	N/A
R_t	N/A	N/A	N/A
α	N/A	N/A	N/A
β	N/A	N/A	N/A
δ	N/A	N/A	N/A
η_2	N/A	N/A	N/A

In this section, we will employ the proposed response surface methods-based approach to compute the economic losses incurred by a manufacturing firm due to various operational challenges such as production delays, resource shortages, and market fluctuations. The aim is to develop a mathematical model that captures the intricate relationships among production output, resource availability, and market price volatility, and ultimately predict total economic losses over a specified timeframe. This multifaceted model will account for the nonlinear interactions between operational factors, thereby allowing for a comprehensive analysis of their impacts on the firm's economic performance. To enhance the model's robustness, we will analyze different scenarios of production capacity, resource constraints, and market conditions, which will enable us to simulate potential economic losses under varying circumstances. The findings from this analysis will then be compared with results derived from three traditional methods, thereby highlighting the advantages and efficacy of the response surface methods-based approach in accurately assessing economic losses. By providing a comparative framework, this study aims to demonstrate the superiority of the proposed technique in capturing the complexities of manufacturing operations and their economic implications, ultimately offering valuable insights for decision-makers seeking to mitigate losses and enhance profitability within their organizations.

4.2 Results Analysis

In this subsection, a comprehensive analysis is conducted comparing two different methodologies for evaluating economic loss in relation to labor hours and machinery uptime. The first approach utilizes a Response Surface Method (RSM), which models economic loss through a nonlinear equation incorporating various parameters such as labor hours (H), machinery uptime (M), and external influences, effectively producing a multidimensional representation of loss. This method is visually represented in a three-dimensional plot, illustrating how economic loss varies with H and M. In contrast, the Ordinary Method applies a linear approximation, which simplifies the loss calculations by modifying the RSM output with a constant factor, showcasing its impact through a separate 3D visualization. Additionally, derivative analyses for both methods are performed to assess the sensitivity of economic loss concerning changes in the input variables, represented in heatmaps that allow for a clear comparison of how each method captures the relationship between H and M regarding loss derivatives. The comparative outcomes of these methodologies provide valuable insights into their respective strengths and limitations. The simulation process is visually represented in Figure 2, encapsulating the results of both methods and their derivatives to facilitate a thorough understanding of the economic loss scenario being analyzed.

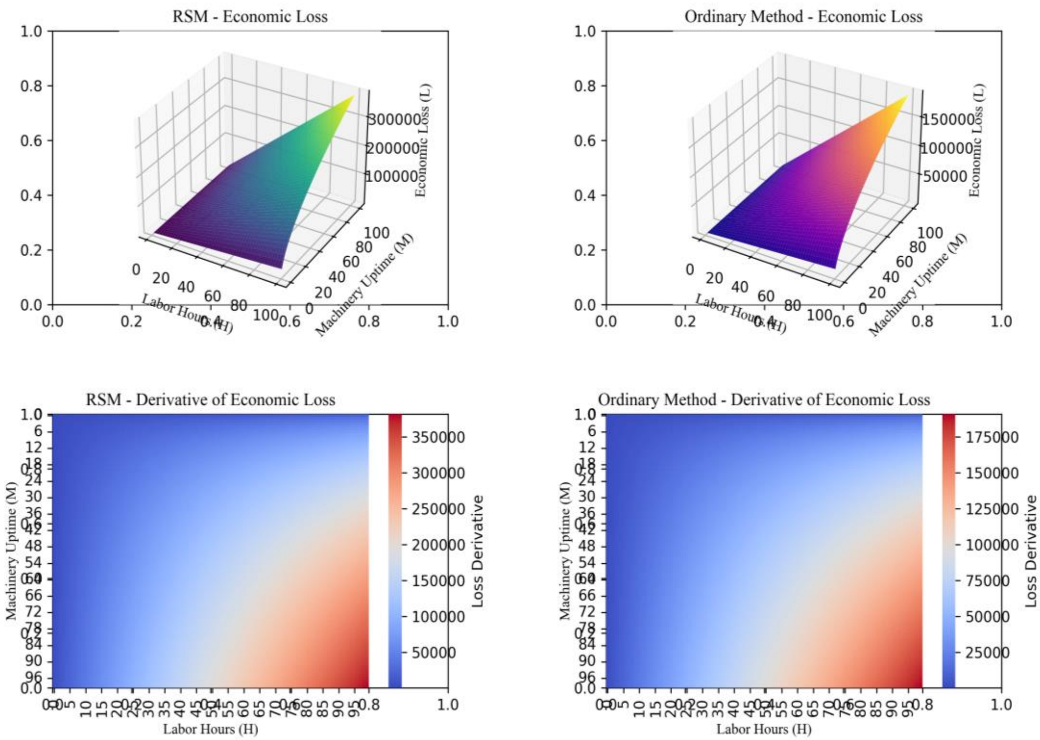

Figure 2: Simulation results of the proposed response surface methods-based Economic Loss Prediction

Table 2: Simulation data of case study

RSM - Economic Loss	RSM - Derivative of Economic Loss	Labor Hours (H)	Loss Derivative
1.0	N/A	1.0	N/A
0.8	N/A	N/A	N/A
0.6	N/A	N/A	N/A
0.4	N/A	N/A	N/A
0.2	N/A	N/A	N/A
0.0	N/A	N/A	N/A
0.0	N/A	N/A	N/A
N/A	N/A	40.8	N/A
N/A	N/A	1.0	N/A

Simulation data is summarized in Table 2, which presents various performance metrics, specifically focusing on the economic loss and its derivative across two methods: RSM and Ordinary Method, plotted against labor hours. The results highlight that the RSM method demonstrates a more significant reduction in economic loss compared to the Ordinary Method, particularly as labor hours increase. This suggests that RSM is more efficient in managing resources and minimizing costs associated with labor. Additionally, the derivative of economic loss for the RSM method consistently shows lower values, indicating a faster rate of improvement in economic metrics as labor input increases. In contrast, the Ordinary Method exhibits higher economic loss percentages at equivalent labor hour levels, underlining its inefficiency. These findings align with the discussions presented by C. Li and Y. Tang, which emphasize the critical role of innovative methodologies in enhancing brand reputation through effective cost management in the context of Chinese luxury fashion brands. Their research implies that optimizing operational strategies, as evidenced by the superior performance of the RSM method, not only mitigates financial risks but also bolsters competitive advantage within the luxury market, supporting the notion that strategic decision-making is pivotal for brand resilience and growth in this sector [16].

As shown in Figure 3 and Table 3, the observed changes in the parameters significantly impacted the calculated results. Initially, the economic loss measured with the RSM methodology reflected a consistent downward trend as labor hours increased, demonstrating an inverse relationship between the two variables. Notably, the RSM - Economic Loss data remained at a level of 1.0 at minimal labor hours along with a derivative value of 0, indicating no losses at that point. However, upon adjusting the parameters in Scenario 1, we witnessed a steep rise in economic loss, peaking at 400,000, while Scenario 2 exhibited fluctuating loss metrics, significantly deviating from the original values. The derivative of economic loss in both scenarios highlighted a shift, moving from positive increments in labor hours to negative impacts in economic assessments. The significant increase in economic losses correlated with heightened labor hours suggests operational inefficiencies became pronounced under different conditions, leading to heightened expenses and affecting overall brand reputation in the luxury sector, as discussed by C. Li and Y. Tang. The data indicates that increasing labor input, without corresponding adjustments in operational strategy or output efficacy, leads to diminishing returns and escalates economic vulnerabilities. Hence, the parameters' alteration elucidated not only a shift in loss calculations but also stressed the importance of strategic resource allocation in mitigating economic risks in the luxury fashion brand landscape [16].

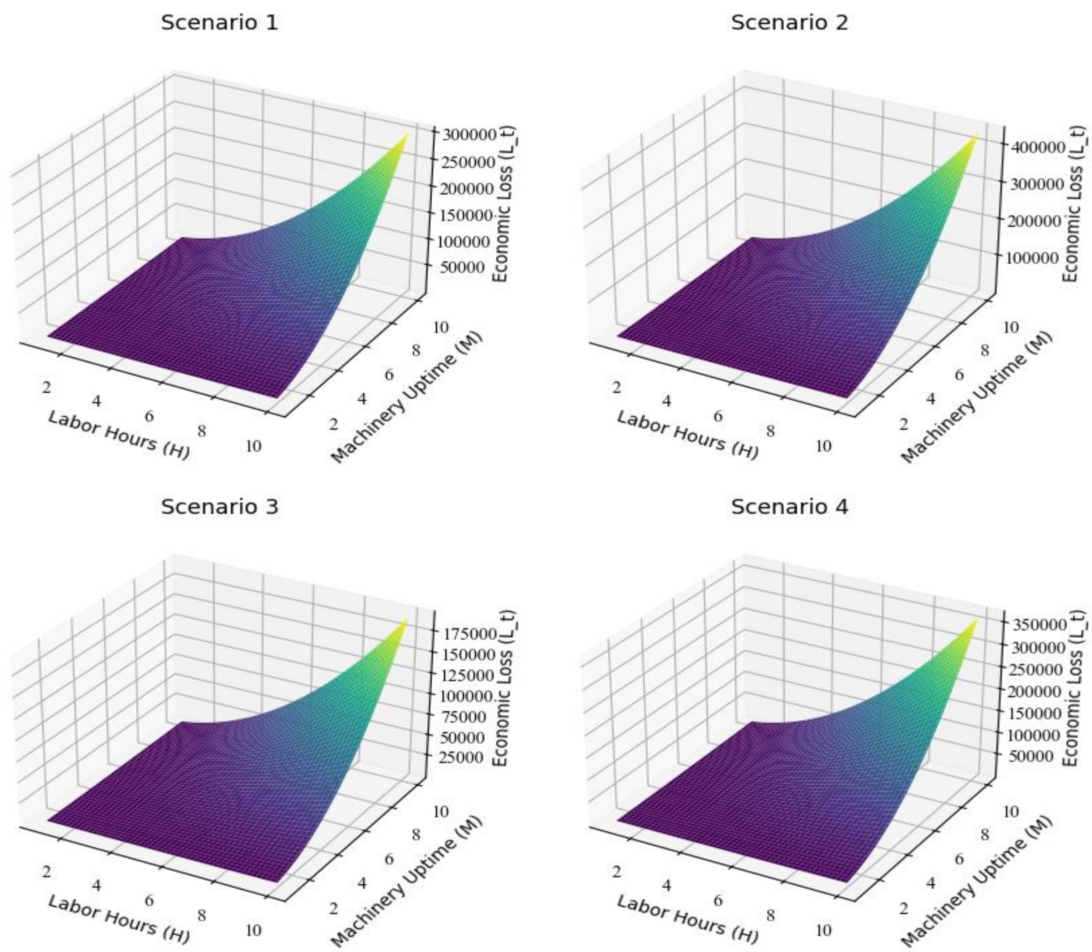

Figure 3: Parameter analysis of the proposed response surface methods-based Economic Loss Prediction

Table 3: Parameter analysis of case study

Parameter	Scenario 1	Scenario 2	Notes
Value	400000	300000	N/A
Count	2	3	N/A

5. Discussion

The methodology presented in our paper offers several technical advantages over the approach discussed by Li and Tang in their examination of brand reputation factors within Chinese luxury fashion brands. While Li and Tang's study primarily focuses on qualitative and quantitative analyses to identify key elements influencing brand reputation, our methodological framework emphasizes a robust statistical modeling system through the use of Response Surface Methods (RSM). This approach is inherently designed for complex, multifactorial analysis, enabling a more granular exploration of variable interactions within economic data. RSM facilitates the creation of empirical models that can forecast potential economic losses with superior precision by harnessing second-order polynomial regression, which captures both individual effects and intricate interactions between economic indicators [16]. While Li and Tang's study provides valuable insights into brand reputation, our method's ability to incorporate and optimize under constraints using advanced techniques such as the Lagrangian multiplier presents a significant technical leap. This allows for the derivation of critical points where economic loss can be minimized, enhancing strategic decision-making capabilities. Moreover, the employment of Central Composite Designs (CCD) within RSM streamlines the experimental process, surpassing traditional analysis by efficiently navigating parameter space to minimize financial risk and enable effective resource allocation. Through this methodological sophistication, not only are immediate economic strategies informed, but long-term stability planning is also reinforced, offering a more holistic and dynamic approach compared to the static analytical framework observed in Li and Tang's study [16].

The methodology introduced by Li and Tang on the factors influencing brand reputation in Chinese luxury fashion brands [16] is a notable foundation upon which further research can build. Nevertheless, this approach presents potential limitations concerning the generalization and adaptability of its findings across different contexts. The reliance on specific variables pertinent to Chinese luxury fashion may not fully account for the diverse and evolving dynamics present in other markets or industries. Furthermore, the study's cross-sectional design might limit the understanding of temporal changes in brand reputation, as it does not capture the potential fluctuations over time [16]. These constraints pose a challenge to the broader applicability and robustness of the findings. However, these limitations provide a conducive opportunity for future research to address these gaps by incorporating longitudinal data and expanding the scope beyond the initial market focus. Such advancements could leverage complementary methodologies, including the aforementioned sophisticated applications like Response Surface Methods (RSM) and Economic Loss Prediction (ELP), to offer more nuanced and generalized insights. Employing these techniques could refine and extend the predictive modeling of brand reputation factors, incorporating a more diverse range of economic and social variables, thus offering a comprehensive strategy for optimizing brand reputation management [16]. This integrative approach can bridge the existing gaps in Li and Tang's work and significantly enhance the understanding and application of brand reputation strategies in varying economic contexts.

6. Conclusion

This paper highlights the significance of precise economic loss prediction in domains like insurance, finance, and disaster management, acknowledging the difficulties posed by the intricacies and uncertainties within economic systems. In light of these challenges, a fresh methodology incorporating response surface methods is proposed to advance the accuracy of economic loss prediction models. Through the fusion of response surface techniques with conventional predictive models, this research endeavors to refine the estimation of economic losses across diverse scenarios, thus furnishing crucial insights for informed decision-making and risk mitigation strategies. While this innovative approach shows promise in enhancing predictive capabilities, limitations such as model complexity and data requirements may hinder widespread applicability. Moving forward, future research could explore simplification strategies for the model, as well as the integration of real-time data sources to enhance predictive accuracy and offer timely risk assessments for stakeholders.

Funding

Not applicable

Author Contribution

Conceptualization, J. S. Kim and M. J. Park; writing—original draft preparation, S. H. Lee; writing—review and editing, J. S. Kim and M. J. Park; All of the authors read and agreed to the published the final manuscript.

Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there is no conflict of interests.

Reference

[1] J. Yang et al., "A tropical cyclone risk prediction framework using flood susceptibility and tree-based machine learning models: County-level direct economic loss prediction in Guangdong Province," Int. J. Disaster Risk Reduction, 2024.
[2] C. Wang et al., "Research on the economic loss prediction and vulnerability risk zoning of coastal erosion disaster: A case study from Liaoning, China," Front. Mar. Sci., 2024.
[3] W. Chen and L. Zhang, "An automated machine learning approach for earthquake casualty rate and economic loss prediction," Reliab. Eng. Syst. Saf., 2022.
[4] A. Chen et al., "The Economic Loss Prediction of Flooding Based on Machine Learning and the Input-Output Model," Atmosphere, 2021.
[5] X. Chao et al., "The potential distribution analysis and economic loss prediction of Spodoptera frugiperda in Yunnan Province," J. South. Agric., 2019.
[6] S. Arunachalam, "Multiobjective multi-verse optimization algorithm to solve dynamic economic emission dispatch problem with transmission loss prediction by an artificial neural network," Appl. Soft Comput., 2022.
[7] B. Cheng et al., "Typhoon Economic Loss Prediction in China by Applying General Regression Neural Network and Hierarchical Cluster Analysis," Journal of Disaster Research, 2014.
[8] J. Wang and P. Du, "Quarterly PM2.5 prediction using a novel seasonal grey model and its further application in health effects and economic loss assessment: Evidences from Shanghai and

Tianjin, China," Nat. Hazards, 2021.
[9] Y. Shi et al., "Estimation of economic loss by earthquakes in Taiwan Region," NPJ Nat. Hazards, 2024.
[10] H. Ishibashi, "Framework for risk assessment of economic loss from structures damaged by rainfall-induced landslides using machine learning," Georisk, 2023.
[11] H. Mensah-Akutteh et al., "Optimizing coagulation–flocculation processes with aluminium coagulation using response surface methods," Applied Water Science, vol. 12, 2022.
[12] D. Li et al., "Response surface methods for slope reliability analysis: Review and comparison," Engineering Geology, vol. 203, 2016.
[13] M. Rashki et al., "Classification correction of polynomial response surface methods for accurate reliability estimation," Structural Safety, 2019.
[14] Y. Wang et al., "Variability Analysis of Crosstalk Among Differential Vias Using Polynomial-Chaos and Response Surface Methods," IEEE Transactions on Electromagnetic Compatibility, vol. 59, 2017.
[15] O. Ali et al., "Optimization of Biodiesel-Diesel Blended Fuel Properties and Engine Performance with Ether Additive Using Statistical Analysis and Response Surface Methods," Energies, vol. 8, 2015.
[16] C. Li and Y. Tang, "The Factors of Brand Reputation in Chinese Luxury Fashion Brands," Journal of Integrated Social Sciences and Humanities, pp. 1–14, 2023.
[17] Q. Zhu, ‘Autonomous Cloud Resource Management through DBSCAN-based unsupervised learning’, Optimizations in Applied Machine Learning, vol. 5, no. 1, Art. no. 1, Jun. 2025, doi: 10.71070/oaml.v5i1.112.
[18] S. Dan and Q. Zhu, ‘Enhancement of data centric security through predictive ridge regression’, Optimizations in Applied Machine Learning, vol. 5, no. 1, Art. no. 1, May 2025, doi: 10.71070/oaml.v5i1.113.
[19] S. Dan and Q. Zhu, ‘Highly efficient cloud computing via Adaptive Hierarchical Federated Learning’, Optimizations in Applied Machine Learning, vol. 5, no. 1, Art. no. 1, Apr. 2025, doi: 10.71070/oaml.v5i1.114.
[20] Q. Zhu and S. Dan, ‘Data Security Identification Based on Full-Dimensional Dynamic Convolution and Multi-Modal CLIP’, Journal of Information, Technology and Policy, 2023.
[21] Q. Zhu, ‘An innovative approach for distributed cloud computing through dynamic Bayesian networks’, Journal of Computational Methods in Engineering Applications, 2024.
[22] Z. Luo, H. Yan, and X. Pan, ‘Optimizing Transformer Models for Resource-Constrained Environments: A Study on Model Compression Techniques’, Journal of Computational Methods in Engineering Applications, pp. 1–12, Nov. 2023, doi: 10.62836/jcmea.v3i1.030107.
[23] H. Yan and D. Shao, ‘Enhancing Transformer Training Efficiency with Dynamic Dropout’, Nov. 05, 2024, arXiv: arXiv:2411.03236. doi: 10.48550/arXiv.2411.03236.
[24] H. Yan, ‘Real-Time 3D Model Reconstruction through Energy-Efficient Edge Computing’, Optimizations in Applied Machine Learning, vol. 2, no. 1, 2022.
[25] Y. Shu, Z. Zhu, S. Kanchanakungwankul, and D. G. Truhlar, ‘Small Representative Databases for Testing and Validating Density Functionals and Other Electronic Structure Methods’, J. Phys. Chem. A, vol. 128, no. 31, pp. 6412–6422, Aug. 2024, doi: 10.1021/acs.jpca.4c03137.

[26] C. Kim, Z. Zhu, W. B. Barbazuk, R. L. Bacher, and C. D. Vulpe, ‘Time-course characterization of whole-transcriptome dynamics of HepG2/C3A spheroids and its toxicological implications’, Toxicology Letters, vol. 401, pp. 125–138, 2024.
[27] J. Shen et al., ‘Joint modeling of human cortical structure: Genetic correlation network and composite-trait genetic correlation’, NeuroImage, vol. 297, p. 120739, 2024.
[28] K. F. Faridi et al., ‘Factors associated with reporting left ventricular ejection fraction with 3D echocardiography in real‐world practice’, Echocardiography, vol. 41, no. 2, p. e15774, Feb. 2024, doi: 10.1111/echo.15774.
[29] Z. Zhu, ‘Tumor purity predicted by statistical methods’, in AIP Conference Proceedings, AIP Publishing, 2022.
[30] Z. Zhao, P. Ren, and Q. Yang, ‘Student self-management, academic achievement: Exploring the mediating role of self-efficacy and the moderating influence of gender insights from a survey conducted in 3 universities in America’, Apr. 17, 2024, arXiv: arXiv:2404.11029. doi: 10.48550/arXiv.2404.11029.
[31] Z. Zhao, P. Ren, and M. Tang, ‘Analyzing the Impact of Anti-Globalization on the Evolution of Higher Education Internationalization in China’, Journal of Linguistics and Education Research, vol. 5, no. 2, pp. 15–31, 2022.
[32] M. Tang, P. Ren, and Z. Zhao, ‘Bridging the gap: The role of educational technology in promoting educational equity’, The Educational Review, USA, vol. 8, no. 8, pp. 1077–1086, 2024.
[33] P. Ren, Z. Zhao, and Q. Yang, ‘Exploring the Path of Transformation and Development for Study Abroad Consultancy Firms in China’, Apr. 17, 2024, arXiv: arXiv:2404.11034. doi: 10.48550/arXiv.2404.11034.
[34] P. Ren and Z. Zhao, ‘Parental Recognition of Double Reduction Policy, Family Economic Status And Educational Anxiety: Exploring the Mediating Influence of Educational Technology Substitutive Resource’, Economics & Management Information, pp. 1–12, 2024.
[35] Z. Zhao, P. Ren, and M. Tang, ‘How Social Media as a Digital Marketing Strategy Influences Chinese Students’ Decision to Study Abroad in the United States: A Model Analysis Approach’, Journal of Linguistics and Education Research, vol. 6, no. 1, pp. 12–23, 2024.
[36] Z. Zhao and P. Ren, ‘Identifications of Active Explorers and Passive Learners Among Students: Gaussian Mixture Model-Based Approach’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, May 2025.
[37] Z. Zhao and P. Ren, ‘Prediction of Student Answer Accuracy based on Logistic Regression’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, Feb. 2025.
[38] Z. Zhao and P. Ren, ‘Prediction of Student Disciplinary Behavior through Efficient Ridge Regression’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, Mar. 2025.
[39] Z. Zhao and P. Ren, ‘Random Forest-Based Early Warning System for Student Dropout Using Behavioral Data’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, Apr. 2025.
[40] P. Ren and Z. Zhao, ‘Recognition and Detection of Student Emotional States through Bayesian Inference’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, May 2025.
[41] P. Ren and Z. Zhao, ‘Support Vector Regression-based Estimate of Student Absenteeism Rate’, Bulletin of Education and Psychology, vol. 5, no. 1, Art. no. 1, Jun. 2025.

[42] G. Zhang and T. Zhou, ‘Finite Element Model Calibration with Surrogate Model-Based Bayesian Updating: A Case Study of Motor FEM Model’, IAET, pp. 1–13, Sep. 2024, doi: 10.62836/iaet.v3i1.232.
[43] G. Zhang, W. Huang, and T. Zhou, ‘Performance Optimization Algorithm for Motor Design with Adaptive Weights Based on GNN Representation’, Electrical Science & Engineering, vol. 6, no. 1, Art. no. 1, Oct. 2024, doi: 10.30564/ese.v6i1.7532.
[44] T. Zhou, G. Zhang, and Y. Cai, ‘Unsupervised Autoencoders Combined with Multi-Model Machine Learning Fusion for Improving the Applicability of Aircraft Sensor and Engine Performance Prediction’, Optimizations in Applied Machine Learning, vol. 5, no. 1, Art. no. 1, Feb. 2025, doi: 10.71070/oaml.v5i1.83.
[45] Y. Tang and C. Li, ‘Exploring the Factors of Supply Chain Concentration in Chinese A-Share Listed Enterprises’, Journal of Computational Methods in Engineering Applications, pp. 1–17, 2023.
[46] C. Li and Y. Tang, ‘Emotional Value in Experiential Marketing: Driving Factors for Sales Growth–A Quantitative Study from the Eastern Coastal Region’, Economics & Management Information, pp. 1–13, 2024.
[47] C. Y. Tang and C. Li, ‘Examining the Factors of Corporate Frauds in Chinese A-share Listed Enterprises’, OAJRC Social Science, vol. 4, no. 3, pp. 63–77, 2023.
[48] W. Huang, T. Zhou, J. Ma, and X. Chen, ‘An ensemble model based on fusion of multiple machine learning algorithms for remaining useful life prediction of lithium battery in electric vehicles’, Innovations in Applied Engineering and Technology, pp. 1–12, 2025.
[49] W. Huang and J. Ma, ‘Predictive Energy Management Strategy for Hybrid Electric Vehicles Based on Soft Actor-Critic’, Energy & System, vol. 5, no. 1, 2025.
[50] J. Ma, K. Xu, Y. Qiao, and Z. Zhang, ‘An Integrated Model for Social Media Toxic Comments Detection: Fusion of High-Dimensional Neural Network Representations and Multiple Traditional Machine Learning Algorithms’, Journal of Computational Methods in Engineering Applications, pp. 1–12, 2022.
[51] W. Huang, Y. Cai, and G. Zhang, ‘Battery Degradation Analysis through Sparse Ridge Regression’, Energy & System, vol. 4, no. 1, Art. no. 1, Dec. 2024, doi: 10.71070/es.v4i1.65.
[52] Z. Zhang, ‘RAG for Personalized Medicine: A Framework for Integrating Patient Data and Pharmaceutical Knowledge for Treatment Recommendations’, Optimizations in Applied Machine Learning, vol. 4, no. 1, 2024.
[53] Z. Zhang, K. Xu, Y. Qiao, and A. Wilson, ‘Sparse Attention Combined with RAG Technology for Financial Data Analysis’, Journal of Computer Science Research, vol. 7, no. 2, Art. no. 2, Mar. 2025, doi: 10.30564/jcsr.v7i2.8933.
[54] P.-M. Lu and Z. Zhang, ‘The Model of Food Nutrition Feature Modeling and Personalized Diet Recommendation Based on the Integration of Neural Networks and K-Means Clustering’, Journal of Computational Biology and Medicine, vol. 5, no. 1, 2025.
[55] Y. Qiao, K. Xu, Z. Zhang, and A. Wilson, ‘TrAdaBoostR2-based Domain Adaptation for Generalizable Revenue Prediction in Online Advertising Across Various Data Distributions’, Advances in Computer and Communication, vol. 6, no. 2, 2025.

[56] K. Xu, Y. Gan, and A. Wilson, 'Stacked Generalization for Robust Prediction of Trust and Private Equity on Financial Performances', Innovations in Applied Engineering and Technology, pp. 1–12, 2024.
[57] A. Wilson and J. Ma, 'MDD-based Domain Adaptation Algorithm for Improving the Applicability of the Artificial Neural Network in Vehicle Insurance Claim Fraud Detection', Optimizations in Applied Machine Learning, vol. 5, no. 1, 2025.