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Exploration of Supply Chain Financing Model and Virtual Economic Risk Control Using the Backpropagation Neural Network

Xiaolin Ji, School of Economics, Jilin University, China
Chang Su, Nuffield College, University of Oxford, UK*

ABSTRACT

This article aims to optimize the supply chain financing model and address virtual economic risk control by effectively reducing associated risks. To achieve this objective, the backpropagation (BP) neural network model is designed and implemented, promoting the application of intelligent technology in supply chain financing and virtual economic risk control. Initially, a fundamental BP neural network model is developed and evaluated. Subsequently, an Adam-BP neural network model is proposed by optimizing the Adam optimizer, providing substantial technical support for enhancing the supply chain financing model and virtual economic risk control. The research results indicate significant performance improvement after applying Adam optimization to BP, with all indicators in the plant classification dataset surpassing 0.92 and those in the credit card fraud dataset increasing to above 0.9. Thus, the model presented here exhibits exceptional adaptability and offers effective technical support for optimizing the supply chain financing model and virtual economic risk control methods.

KEYWORDS

Adam Optimizer, Backpropagation, Risk Control, Supply Chain Financing, Virtual Economy

RESEARCH BACKGROUND AND MOTIVATIONS

In the context of the dynamic global economy, the supply chain financing model has gained substantial attention and practical application within the business sphere (Tsai, 2023). This model intricately interconnects financial institutions with diverse supply chain segments, offering vital financial backing to suppliers and mitigating their funding challenges (Wang et al., 2020). Consequently, the supply chain financing model has evolved into an indispensable mechanism for alleviating the financial constraints faced by suppliers (Sahoo & Thakur, 2023). Nonetheless, the benefits of this model are accompanied by inherent virtual economic risks that warrant profound consideration (Wu et al., 2020). In this study, the authors endeavored to delve into optimizing the supply chain financing model while simultaneously addressing virtual economic and financial risks, with the aim of fostering sustainability and enhancing the resilience of the continuously evolving business landscape.

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*Corresponding Author

The proliferation of virtual economic risks, encompassing challenges such as information asymmetry, credit risks, and transaction failures, has assumed a pivotal role in the intricate landscape of the supply chain financing model (Song et al., 2020). Given the intricate multistage and multiparticipant nature of this model, adept risk control becomes imperative (Qi et al., 2020). Any perturbation within specific segments of the supply chain has the potential to reverberate throughout, giving rise to financial vulnerabilities and economic losses (Zhang et al., 2020). In this research, the authors introduced an innovative approach employing backpropagation (BP) neural networks to amplify risk management and decision-making capabilities within the context of the supply chain financing model. BP neural networks, as artificial intelligence rooted in statistical learning theory, embody adaptability and nonlinear mapping prowess, rendering them well-suited for risk assessment and credit scoring applications (Queiroz et al., 2022). Through the development of BP neural network models, researchers can harness historical data and credit scores to prognosticate and govern risks inherent in the supply chain financing model (Su et al., 2020; Ye & Zhao, 2023). In this study, the authors aimed to furnish an efficacious solution for mitigating virtual economic risks and fortifying the stability and sustainability of the supply chain financing model. The researchers sought to attain precise risk prognostication and control through meticulous data aggregation, analysis, and the application of BP neural networks. Additionally, they aimed to address information dissemination and collaboration mechanisms across diverse stages and participants, thereby amplifying the overall efficiency and stability of the supply chain. The authors employed BP neural networks to effectively manage virtual economic risks inherent in supply chain financing models. By developing BP neural network models and utilizing historical data and credit scores, the authors were able to predict and control risks within the supply chain financing framework.

Thus, this research has two maincontributions: Firstly, it introduces a novel approach to adeptly control virtual economic risks within the supply chain financing model, addressing an existing research gap; secondly, it offers valuable guidance to business decision-makers and practitioners, facilitating better risk management and mitigation. This endeavor contributes to the sustainable evolution of the supply chain financing model, reduces economic losses, and enhances efficiency and stability. Furthermore, the proposed approach enhances overall stability and resilience in the supply chain financing ecosystem, fostering sustained business development and economic growth. The application of this method empowers participants to accurately predict and control risks, thereby increasing operational efficiency and stability. Ultimately, businesses gain more reliable financing support, fueling broader economic progress.

Research Objectives

This research project comprises three fundamental aspects. Firstly, the authors analyzed and evaluated virtual economic risks within the supply chain financing model. The researchers identified and examined various risks, including information asymmetry, credit risk, and default risk, to understand their implications and potential hazards on the supply chain financing model through comprehensive reviews and empirical analyses. Secondly, the authors explored the application of BP neural networks in supply chain financing. By integrating BP neural network technology, historical data, credit scores, and relevant indicators, the researchers established a robust BP neural network model to enhance the accuracy and efficiency of risk prediction and management. Lastly, the authors developed effective virtual economic risk control strategies and methods. Building on the predictive outcomes of the BP neural network, the authors devised strategic approaches to mitigate and manage virtual financial risks within the supply chain financing model. These strategies may involve the formulation of risk assessment indicators, establishing risk monitoring and early warning systems, optimizing risk allocation mechanisms, and other related aspects.

The primary objective of this research was to address the issue of virtual economic risk control in the context of the supply chain financing model and to explore methods for enhancing risk management and decision-making capabilities through the utilization of BP neural network technology. Through data collection and analysis from the supply chain financing model, establishing a BP neural network model facilitates the achievement of risk prediction and control objectives (Zhang et al., 2022). Additionally, the authors considered information dissemination and collaboration mechanisms among different stages and participants, contributing to the overall efficiency and stability of the supply chain. The most significant contribution of this study lies in presenting an innovative solution for effectively managing virtual economic risks within the supply chain financing model and providing valuable guidance for business decision-makers and practitioners (Feng & Chen, 2022). The anticipated outcome of this research is to foster the sustainable development of the supply chain financing model while mitigating economic losses.

LITERATURE REVIEW

The adoption of supply chain financing models has become prevalent in the business realm to address challenges related to supplier fund turnover difficulties (Seiler et al., 2020). However, alongside the opportunities they offer, these models are accompanied by virtual economic risks, including information asymmetry, credit risks, and transaction failures (Santa-Maria et al., 2022). Due to the intricate nature of supply chains and the diverse participants involved, effectively controlling virtual economic risks becomes of paramount importance (Bacinello et al., 2020). In this research, the authors introduced the application of BP neural network technology to mitigate these risks and enhance the stability and sustainability of supply chain financing models. Numerous studies have supported this approach substantially, reinforcing its potential efficacy in managing virtual economic risks in the supply chain financing landscape.

The shift from competition among individual enterprises to competition among supply chains has drastically transformed the landscape of enterprise supply chain operations, introducing heightened risks for both enterprise supply chains and their nodes (Fosso et al., 2020). Addressing these evolving challenges, Fosso et al. (2020) utilized the BP neural network model, grounded in theoretical analysis and real-world supply chain financing data, to establish an assessment and early warning mechanism for supply chain financing risks. Building upon this framework, they devised an external supply chain financing risk signal light early warning mechanism was devised, aiding banks and financial institutions in recognizing supply chain financing risks. Hofstetter et al. (2021) innovatively integrated the analytic hierarchy process (AHP) and BP neural network techniques to construct a principal component analysis artificial neural network model, thereby presenting an original approach for assessing credit risks. By methodically selecting credit risk indicators, employing AHP for hierarchical decomposition, and refining supply chain financing credit risks, Hofstetter et al. introduced a comprehensive evaluation system featuring 16 indicators for assessing supply chain financing credit risks. With a focus on small and medium-sized enterprises, they meticulously trained and tested the model, aligning with industry specifics. Alkaraan et al. (2022) emphasized the advantages of utilizing BP neural networks for managing credit risks in supply chain financing enterprises, citing their self-learning capabilities, strong fault tolerance, and ability to tackle nonlinear problems. These authors developed a BP neural network-based supply chain financing credit risk assessment model through rigorous training and verification, yielding high accuracy and alignment with expert assessments. This model holds potential value for commercial banks and financial institutions as they undertake credit risk assessments in the expansion of supply chain financing operations (Alkaraan et al., 2022). Examining the nuances of supply chain financing models and structures, Huang et al. (2022) delved into the Asian market to propose tailored approaches based on regional characteristics and demands. Acknowledging the complexity of agricultural supply chain financing, Chen et al. (2021) conducted a comprehensive analysis to uncover practical insights regarding the management of diverse risks in agricultural supply chains, including market risks, credit risks, and liquidity risks. Soni et al. (2022) strategically evaluated the application of blockchain technology in supply chain financing. These authors conducted an extensive review of blockchain-based supply chain financing research, elucidating the potential of blockchain to offer secure and traceable transaction environments, thereby enhancing the efficiency and dependability of supply chain financing.

In conclusion, significant strides have been made in the domain of supply chain financing research. Future investigations can capitalize on key areas, including supply chain financing model and structure design, risk management strategies, and technology applications. Such endeavors are pivotal in propelling sustainable growth and fostering innovative breakthroughs within the realm of supply chain financing. Moreover, while noteworthy progress has been achieved in integrating the BP neural network model with the AHP to forge supply chain financing risk assessment and early warning mechanisms, substantial opportunities for deeper exploration and expansion persist. Future research avenues can delve into the exploration of advanced models and methodologies, such as deep learning and support vector machines. The efficacy of supply chain financing risk assessment and early warning systems can be further bolstered by harnessing these approaches, contributing to a resilient and adaptive supply chain financing landscape.

RESEARCH MODEL

This research centered on utilizing the BP neural network as a central element to investigate the supply chain financing model and virtual economic risk control issues (Bocken & Short, 2021). The authors explored risk control strategies in supply chain financing by establishing a comprehensive research model. They developed a BP neural network-based model for predicting and assessing virtual economic risks in supply chain financing (Zhang et al., 2021). The following subsection presents the outcomes of the model construction.

Model Calculation Process

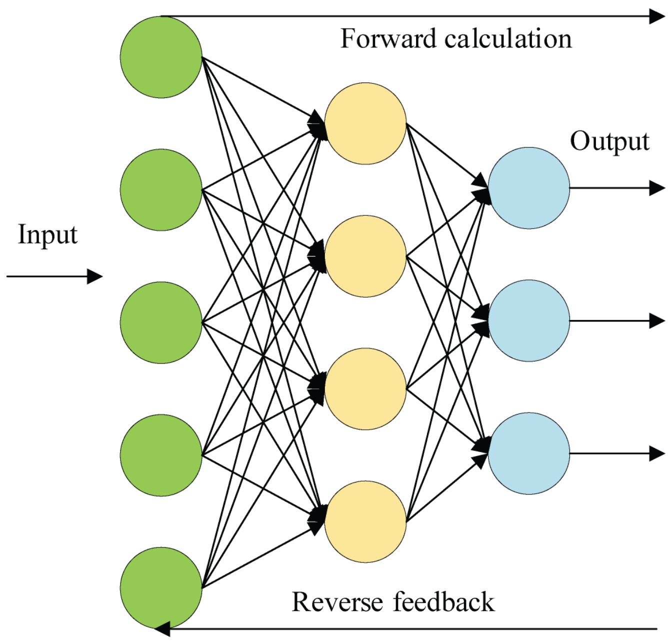
Supply chain financing constitutes a pivotal financing approach that facilitates fund flow across diverse supply chain stages, fostering collaboration and stability among participants. Nonetheless, the realm of supply chain financing is not immune to virtual economic risks, encompassing challenges such as information asymmetry, fraudulent activities, and spurious transactions. These risks imperil financial stakeholders and destabilize the supply chain at large. In this research, the authors sought to address the intricate interplay of supply chain financing and virtual economic risk control, leveraging the BP neural network as a cornerstone. The BP neural network, a prevalent artificial neural network algorithm, stands as a versatile tool trainable and optimized via error BP. The essence of this research lies in the meticulous construction of a model aimed at a comprehensive exploration of risk control strategies inherent to the supply chain financing milieu. The BP neural network serves as the bedrock for this model, nurturing its potential to prognosticate and evaluate virtual economic risks in supply chain financing. This model's potency lies in its ability to furnish precise forecasts and assessments of virtual economic risks, thereby furnishing a scientifically grounded bedrock for decision-making in supply chain financing. Figure 1 elucidates the foundational structure of the authors' model.

As Figure 1 shows, the authors proceeded to craft a subsequent optimization model grounded in the framework of the aforementioned structural design. In the context of the research with n input features ($x1$, $x2...$, xn), m hidden layer neurons ($h1$, $h2...$, hm), and k output neurons ($y1$, $y2...$, yk) (Bacinello et al., 2021), the transmission from the input layer to the hidden layer is carried out as follows:

1. As to the transmission from the input layer to the hidden layer, for each hidden layer neuron hj, its input zj is computed via Equation 1:

$$zj = \Sigma\left(wij * xj\right) + bj \tag{1}$$

Figure 1. Model infrastructure



2. The hidden layer uses the activation function to map the input and calculate the output aj:

$$aj = f\left(zj\right) \tag{2}$$

3. As to the transmission from the hidden layer to the output layer, Equation 3 is applied to compute the input zk for each output neuron yk:

$$zk = \Sigma\left(vkj * aj\right) + ck \tag{3}$$

4. The output layer uses the activation function to map the input to obtain the final output yk_{hat}:

$$yk_{hat} = g\left(zk\right) \tag{4}$$

5. Based on the specific problem's type and objective, the corresponding cost function is chosen as follows:

$$Loss = \Sigma(1 / 2 * \left(yk - yk_{hat})^2\right) \tag{5}$$

$$Loss = \Sigma\left(-yk * log\left(yk_{hat}\right)\right) \tag{6}$$

The establishment and utilization of the proposed model offer a systematic foundation and decision-making assistance for supply chain financing endeavors. By leveraging the predictive and evaluative insights generated by the model, pertinent entities and decision-makers can attain a deeper understanding of the virtual economic risks inherent in supply chain financing. This comprehension facilitates the development of appropriate risk control measures, ultimately fortifying the security and continuity of both the financing entities and the diverse stakeholders encompassing the supply chain.

Code Implementation

In summary, the model holds substantial significance by delving into intricate risk control strategies pertinent to the supply chain financing paradigm. Leveraging the predictive and evaluative capabilities of the BP neural network, it offers the capability to anticipate and assess virtual economic risks. Furthermore, the model furnishes a solid foundation and decision-making assistance for supply chain financing choices, thereby augmenting the viability and endurance of supply chain financing initiatives. Figure 2 presents the specific results of the code implementation.

As Figure 2 depicts, this research commenced by the design of the BP neural network model based on the research objectives. To enhance the significance and value of their study, the authors optimized the model using the Adam optimizer, which has been proven effective in improving overall performance (Paliwal et al., 2020). The Adam optimizer is an adaptive learning rate method that dynamically adjusts the learning rate during training. By amalgamating the strengths of AdaGrad and RMSProp and incorporating the concept of momentum, Adam demonstrates robust performance (Safara, 2022). The specific formula for parameter updates is as follows:

Figure 2. Code Implementation of the BP neural network

```
# Initialize parameters (weights and biases)
# w_ij, b_j: weights and biases from the input layer to the hidden layer
# v_kj, c_k: weights and biases from the hidden layer to the output layer
# You can use random initialization or other methods to initialize the parameters

# Forward propagation
for epoch in range(num_epochs):
  # Calculate inputs and outputs of the hidden layer
  zj = np.dot(input, w_ij) + b_j
  aj = activation_function(zj)

  # Calculate inputs and outputs of the output layer
  zk = np.dot(aj, v_kj) + c_k
  yk_hat = activation_function(zk)

  # Calculate the loss function
  loss = calculate_loss(yk, yk_hat)

  # Backpropagation
  # Calculate gradients of the output layer
  output_gradient = calculate_output_gradient(yk, yk_hat)
  # Calculate gradients of the hidden layer
  hidden_gradient = calculate_hidden_gradient(output_gradient, v_kj)

  # Update weights and biases
  v_kj -= learning_rate * np.dot(aj.T, output_gradient)
  c_k -= learning_rate * np.sum(output_gradient, axis=0)
  w_ij -= learning_rate * np.dot(input.T, hidden_gradient)
  b_j -= learning_rate * np.sum(hidden_gradient, axis=0)
```

$$m = \beta 1 * m + \left(1 - \beta 1\right) * \nabla Loss\left(\theta\right) \tag{7}$$

$$v = \beta 2 * v + \left(1 - \beta 2\right) * (\nabla Loss\left(\theta\right))^2 \tag{8}$$

$$\theta = \theta - learning_{rate} * m \;/\; \left(sqrt\left(v\right) + epsilon\right) \tag{9}$$

where m and v represent Adam's first- and second-order moment estimations, respectively. The values of $\beta 1$ and $\beta 2$ are decay rates between [0, 1], usually set to 0.9 and 0.999, respectively. The symbol $\nabla Loss(\theta)$ denotes the gradient of the loss function concerning the parameter θ. The $learning_{rate}$ controls the update step size, while *epsilon* is a small number used to prevent division by zero (Remko, 2020). Figure 3 presents the code snippet for the parameter update process using the Adam optimizer.

As Figure 3 illustrates, the symbols used in the context are as follows: dw_ij represents the gradient of weight w_ij, db_j represents the gradient of bias b_j, dv_kj represents the gradient of weight v_kj, and dc_k represents the gradient of bias c_k. In this research, the authors optimized the model using these gradients, significantly enhancing its overall performance (Nandi et al., 2021). Figure 4 shows the optimized integrated calculation code.

As Figure 4 evidences, the application of this model introduces innovative solutions to challenges in supply chain financing and virtual economic risk control. By incorporating the BP neural network and constructing a comprehensive research framework, researchers delve into risk control strategies within the supply chain financing landscape, accurately predicting and assessing

Figure 3. Update code based on parameters of Adam optimizer

```
# Initialize parameters and other necessary variables

m = 0  # Initialize first moment variable
v = 0  # Initialize second moment variable
beta1 = 0.9  # Decay rate for first moment estimate
beta2 = 0.999  # Decay rate for second moment estimate
epsilon = 1e-8  # Small number to avoid division by zero

for epoch in range(num_epochs):
    # Forward propagation
    # Calculate loss
    # Backpropagation to calculate gradients

    # Parameter updates using Adam optimizer
    m = beta1 * m + (1 - beta1) * dw_ij
    v = beta2 * v + (1 - beta2) * (dw_ij ** 2)

    w_ij -= learning_rate * m / (np.sqrt(v) + epsilon)
    b_j -= learning_rate * db_j
    v_kj -= learning_rate * dv_kj
    c_k -= learning_rate * dc_k
```

Figure 4. Calculation code after model optimization

```
import torch
import torch.optim as optim

# Define the model parameters
params = model.parameters()

# Define the Adam optimizer
optimizer = optim.Adam(params, lr=learning_rate)

# Start training loop
for epoch in range(num_epochs):
   # Forward pass and compute the loss

   # Backward pass, compute gradients
   loss.backward()

   # Update weights and biases for input-hidden layer connections
   for i in range(num_inputs):
      for j in range(num_hidden):
         optimizer.step([w_ih[i][j].grad])  # Update weights

         # Zero the gradients after updating
         optimizer.zero_grad()

   # Update weights and biases for hidden-output layer connections
   for j in range(num_hidden):
      for k in range(num_outputs):
         optimizer.step([v_jk[j][k].grad])  # Update weights

         # Zero the gradients after updating
         optimizer.zero_grad()

   # Update biases for hidden layer
   for j in range(num_hidden):
      optimizer.step([b_j[j].grad])  # Update biases

      # Zero the gradients after updating
      optimizer.zero_grad()

   # Update biases for output layer
   for k in range(num_outputs):
      optimizer.step([c_k[k].grad])  # Update biases

      # Zero the gradients after updating
      optimizer.zero_grad()

# End training loop
```

virtual economic risks. This model establishes a scientific foundation and decision support system for supply chain financing decisions, aiding institutions and decision-makers in understanding and managing virtual economic risks. Corresponding risk control strategies are formulated to enhance security and sustainability for financing parties and stakeholders along the supply chain. Moreover, the model enhances the efficiency and reliability of supply chain financing operations. By effectively exploring risk control strategies and leveraging the BP neural network's capabilities for predicting and assessing virtual economic risks, the model mitigates risk impacts on supply chain financing, ultimately improving its feasibility and sustainability. In conclusion, the research model contributes holistically by investigating risk control strategies, predicting virtual economic risks, and providing decision guidance for supply chain financing. It bolsters efficiency and reliability, cementing its significance in enhancing the entire process.

EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

Datasets Collection

The authors evaluated the fundamental BP model using the plant classification dataset. This dataset serves the purpose of accurate plant species categorization, aiding researchers and developers in their quest (Aday & Aday, 2020; Hahn, 2020; Kraus & Marchenko, 2021). Comprising a substantial collection of plant images, each labeled with its corresponding species, this dataset enables the construction and refinement of machine learning and deep learning models to predict plant species proficiently (Hosseini & Ivanov, 2020; MacNeill et al., 2020; Pu et al., 2021). It significantly benefits scientists, ecologists, agricultural experts, and environmental conservationists in comprehending and managing various plant species in their respective fields (Dutta et al., 2020). The creation of the plant classification dataset necessitates meticulous field surveys and the assembly of plant specimens, ensuring a diverse and extensive repository of plant samples (Wang et al., 2021). These samples are then subjected to precise annotations, often leveraging botanists' expertise and reference materials (Pieroni et al., 2020; Lee et al., 2022). Each image within the dataset is meticulously associated with a specific plant species label, facilitating subsequent training and testing phases (Lee et al., 2022; Pieroni et al., 2020). The dataset's processing workflow is outlined as follows:

1. **Data Set Partitioning:** See below:
    a. Training set, which comprises 70% of the total dataset used for model training.
    b. Validation set, which accounts for 15% of the total dataset, utilized for hyperparameter tuning and model refinement.
    c. Test set, which occupies 15% of the total dataset, employed for final model performance evaluation.
2. **Data Loading:** Employs a DataLoader to load the dataset in batches, configuring an appropriate batch size for efficient training and evaluation with parallel reading.
3. **Data Preprocessing:** See below:
    a. Image resizing, to resize image dimensions uniformly to 224x224 pixels.
    b. Normalization, to normalize pixel values of images, e.g., scaling pixel values to the range of 0-1 or adjusting mean and standard deviation to specific ranges.
    c. Standardization, to apply image standardization techniques, such as brightness and contrast adjustments.

Subsequently, the optimized Adam-BP model is evaluated using the Credit Card Fraud Detection dataset. This dataset contains credit card transactions made by European cardholders in September 2013 (Kitsis & Chen, 2021). It encompasses 284,807 transactions, with 492 of them identified as fraudulent transactions. The dataset exhibits high-class imbalance, with the positive class (i.e., fraudulent transactions) comprising only 0.172% of all trades (Dong et al., 2020; Tezel et al., 2021). Notably, the dataset exclusively consists of numerical input variables, that is, the outcomes of principal component analysis transformations. Specifically, features V1, V2..., and V28 correspond to the principal components obtained from the analysis, and the "Amount" feature signifies the transaction amount, which can be effectively utilized for instance-dependent cost-sensitive learning (Nogueira et al., 2023). Moreover, the feature category represents the response variable, taking the value of 1 in cases of fraud and 0 otherwise (Li et al., 2020).

Experimental Environment

In light of the content of the dataset above, the authors thoroughly evaluated the model while employing comprehensive data processing procedures to establish a robust experimental environment (Nia et al., 2021). Figure 5 illustrates the computational code the authors implemented in this research for data processing.

Figure 5 illustrates the employed code for data preprocessing and organization into two distinct lists, designated as X and y. Through an iterative process across the data source's samples, each sample's input features (input_features) and labels (label) are extracted and subsequently added to the X and y lists correspondingly. Conclusively, for streamlined data handling and manipulation, the X and y lists are converted into Numpy arrays. These steps collectively contribute to enhancing data usability for both training and testing evaluations, as the authors detailed in this research (Pickl, 2019).

Parameters Setting

The timeline of this research included two primary parts: 1) The training and testing evaluation of the basic BP neural network model; 2) the training and testing evaluation of the Adam-BP neural network model (Anker et al., 2019; Gu, 2022; Milana & Ashta, 2021). Table 1 illustrates the parameter settings for this research.

As Table 1 illustrates, the authors conducted a thorough evaluation of their model's overall performance, employing the parameter settings previously mentioned. For the proposed model, the learning rate governs the speed at which the model adjusts its weights with each parameter update. A higher learning rate can expedite convergence, but might lead to instability or failure to converge. Conversely, a lower learning rate bolsters stability, while potentially slowing convergence. The selection of 0.01 as the learning rate draws from prior experimental outcomes and empirical understanding. This value is widely acknowledged as an optimal initial setting, effectively balancing convergence speed and model stability. The batch size determines the number of samples used in each iteration of model training. A smaller batch size yields more frequent updates and faster learning yet

Figure 5. Data processing calculation code

```
# Initialize empty lists to store input features (X) and corresponding labels (y)
X = []
y = []

# Loop through your data source to collect samples
for sample in data_source:
    # Extract input features and label from the sample
    input_features = sample['input_features']
    label = sample['label']

    # Preprocess the input features if necessary

    # Append the input features and label to the X and y lists respectively
    X.append(input_features)
    y.append(label)

# Convert X and y to numpy arrays for easier manipulation
X = np.array(X)
y = np.array(y)
```

Table 1. Model parameter settings

Parameter	Value
Learning rate	0.01
Batch size	16
Iterations	500
Regularization coefficient	0.01
Optimizer selection	Adam
Weight initialization method	Random initialization

incurs higher computational demands. Conversely, a larger batch size can foster stable training at the cost of increased memory and computational requirements. The choice of 16 as the batch size strikes a balance between computational cost and training efficacy. Iterations signify how often the model adjusts and optimizes parameters using training data. Increasing iterations augments the model's learning capacity, but introduces the risk of overfitting. Opting for 500 iterations aligns with prior experimentation or empirical insights, aiming for satisfactory performance on the provided training data. Regularization counteracts model overfitting by appending a regularization term to the loss function, penalizing model complexity. The regularization coefficient influences the contribution of the regularization term to the overall loss. The selection of 0.01 as the regularization coefficient derives from prior experiments or tuning, ensuring a harmonious blend of model complexity and performance. The optimizer governs parameter adjustments to minimize the loss function. Adam, a widely employed optimizer, amalgamates the strengths of AdaGrad and RMSProp while integrating momentum. Opting for Adam as the optimizer is grounded in its commendable performance and computational efficiency across diverse scenarios. Weight initialization designates the technique for assigning initial values to neural network model weights pre-training. Random initialization is a prevalent strategy that eliminates weight symmetry and empowers the network to autonomously acquire features. The adoption of random initialization is a customary starting point, granting the model adaptability to diverse problems and datasets. Table 2 shows the hardware environment.

Performance Evaluation

Evaluation of the Backpropagation Neural Network Model

The authors utilized BP neural network technology to optimize relevant processes to effectively control the supply chain financing mode and address virtual economic risk issues. Firstly, they designed a

Table 2. Hardware environment

Hardware component	Model	Description
Computer	Dell XPS 15	Equipped with an Intel Core i7 processor and 16GB of memory, used to support model training and evaluation.
Graphics processor (GPU)	Nvidia GeForce RTX 3080	A powerful GPU accelerator used to expedite the training process of neural network models, enhancing training efficiency.
Storage device	Samsung 970 EVO Plus SSD	A high-speed and high-capacity solid-state drive employed to store extensive datasets and model files.
Network device	TP-Link Archer AX6000 Router	Facilitates stable and high-speed Wi-Fi 6 connectivity for data acquisition and online validation purposes.

foundational BP neural network model based on the supply chain financing mode and virtual financial risk control issues. The researchers subjected the model to a comprehensive evaluation (Figure 6).

As Figure 6 depicts, the authors' model exhibited satisfactory performance while evaluating the plant classification dataset, with all indicators scoring above 0.8. However, its performance on the credit card fraud dataset was not optimal, with all metrics above 0.7. The authors introduced the Adam-BP model and assessed its application effectiveness on the supply chain financing mode and virtual economic risk control issues to enhance its overall performance.

Evaluation of the Adam-BP Model

The authors evaluated their Adam-BP model to enhance the performance of the BP model in the context of supply chain financing mode and virtual economic risk control issues. Figure 7 presents the evaluation results of the model.

As Figure 7 shows, optimising the BP model using the Adam optimizer yields a substantial improvement in its performance. The evaluation results show that, in the plant classification dataset, all model performance indicators exceeded 0.92. In the credit card fraud dataset, the indicators also

Figure 6. Evaluation results of the BP neural network model: (a) Plant Classification Dataset; (b) Credit card fraud data set

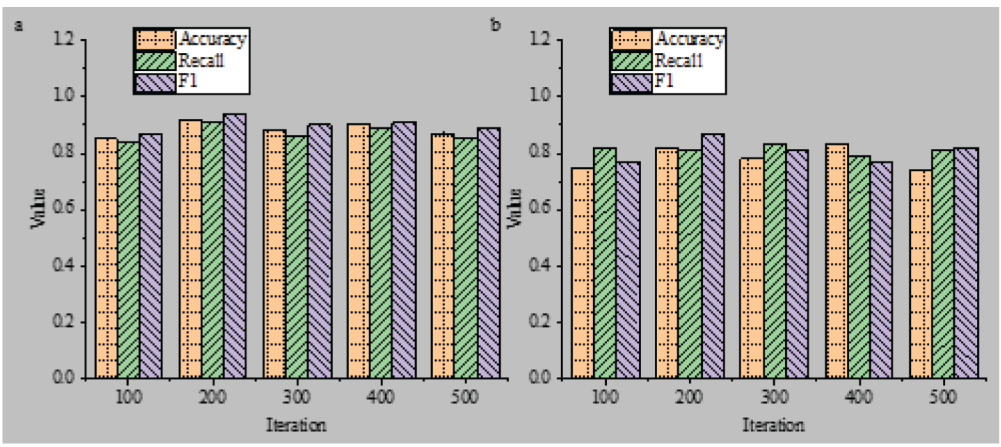
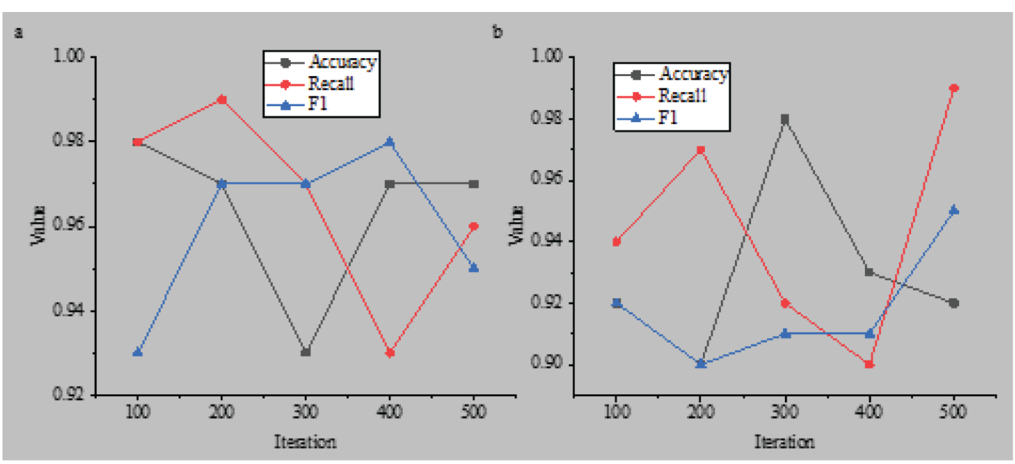


Figure 7. Adam-BP model evaluation results (a) Plant classification dataset; (b) Credit card fraud dataset



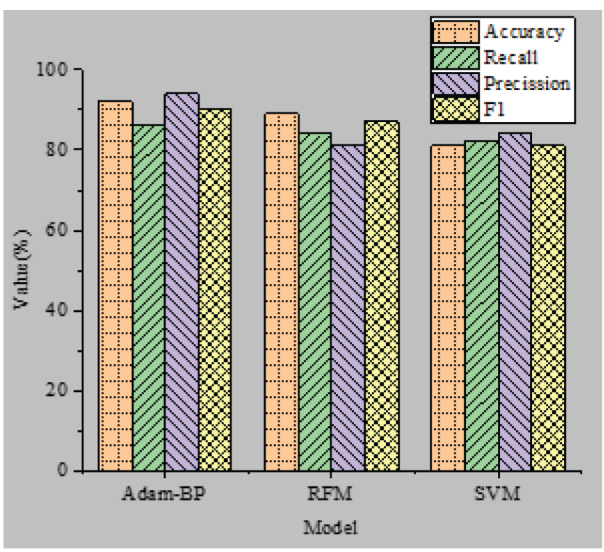
rose above 0.9. These outcomes indicate that the authors' model in this research demonstrates excellent performance and effectively addresses the challenges associated with the supply chain financing mode and its virtual economic risk control. Furthermore, to underscore the merits of our proposed model, the researchers conducted a comparative analysis by juxtaposing it against two alternative models, nmaely, the random forest model (RFM) and the support vector machine (SVM) model. This comparative examination serves to enhance the understanding of the significance of this research. Figure 8 presents the comparative results of the proposed and alternative models.

As Figure 8 illustrates, the model devised here showcases metrics surpassing the 90% threshold, while the metrics of the alternative models fall within the range of 80% to 90%. Clearly, this model achieved a noteworthy advancement when compared to the other models. This achievement holds significant implications for enhancing supply chain financing strategies and refining virtual economic risk management.

Experimental findings strongly indicate that the enhanced BP neural network model exhibits substantial performance advancements in comparison to the traditional BP model across various datasets. The Adam-BP model surpasses the traditional BP model in accuracy, precision, recall, and F1 score on the test set. This observed improvement could be attributed to the incorporation of the Adam optimization algorithm. In contrast to conventional gradient descent-based training approaches, the Adam optimization algorithm integrates momentum and adaptive learning rates, resulting in quicker convergence and more precise and stable parameter updates. Consequently, the Adam-BP model showcases enhanced convergence performance and generalization capability, facilitating more efficient learning and representation of the intricate connection between supply chain financing patterns and virtual economic risks. This experimental phenomenon carries potential implications, including:

1. **Enhanced Risk Control Precision:** The refined model demonstrates an aptitude for accurately discerning supply chain financing patterns and virtual economic risks, thereby assisting enterprises and platforms in achieving superior risk management and informed decision-making.
2. **Diminished Financial Loss:** The model's accurate prediction and risk identification potential can effectively mitigate potential financial losses, contributing to the security and robust growth of the virtual economy.

Figure 8. Model performance comparison



3. **Reinforced User Safeguarding:** Enhanced virtual economic risk management directly translates to the protection of user rights, fostering heightened user trust and contentment.
4. **Pioneering Intelligent Management:** An intelligent system for managing supply chain financing patterns can be developed by capitalizing on the improved model. This system holds the potential to optimize resource allocation, elevate efficiency, and provide a well-founded basis for decision-making.

Discussion

The rise of supply chain financing mode and virtual economic risk control has highlighted the importance of achieving intelligent control over these domains. In this study, the authors utilized the BP neural network technology to optimize the relevant processes, leading to the design of a fundamental BP neural network model for addressing these challenges. The authors aimed to evaluate the performance of the designed BP neural network model in the context of supply chain financing mode and virtual economic risk control to enhance its overall efficacy further. They constructed the basic BP neural network model based on supply chain financing mode and virtual economic risk control, and evaluated its performance using two distinct datasets, namely, the plant classification dataset and the credit card fraud dataset. The researchers conducted a comprehensive assessment of the model's performance, considering various indicators. In the case of the plant classification dataset, the BP neural network model demonstrates strong performance, with all indicators exceeding 0.8. However, the model's performance in the credit card fraud dataset is not optimal, with indicators slightly below 0.7. In this research, the authors introduced the Adam-BP model to facilitate the overall performance of the model.

The Adam-BP model's evaluation results demonstrate a significant performance improvement, compared to the optimized BP model. In the plant classification dataset, all indicators surpass 0.92; in the credit card fraud dataset, all indicators increase above 0.9. These findings indicate that the designed Adam-BP model exhibits excellent performance and adaptability in addressing supply chain financing mode and virtual economic risk control issues. This research provides essential insights for achieving intelligent control over supply chain financing mode and virtual financial risk control. The BP neural network model and its optimized version, the Adam-BP model, have proven effective in classification and risk control aspects. These results have crucial implications for the sustainable development and risk control of supply chain financing mode and the virtual economy. Additionally, this research inspires future research, encouraging further exploration and improvement of the application of BP neural network models in this field. In summary, in comparison to Nayal et al.'s (2023), Pournader et al.'s (2023), and Yousefi and Tosarkani's (2023) recent studies, this research not only introduces more intricate predictive models grounded in machine learning, but also attains substantial technological advancements in terms of model performance in contrast to other cutting-edge models. Thus, this research assumes a pivotal role in augmenting supply chain financing models and proficiently navigating virtual economic risks. Nayal et al.'s (2023) investigation proposed a prediction approach based on statistical models, which offers limited guidance for identifying and managing risks in supply chain financing models. Pournader et al.'s (2023) study employed traditional regression models to predict virtual economic risks, achieving some degree of success; however, the model's performance still requires refinement. Yousefi and Tosarkani's (2023) study concentrated on financial risks within supply chain financing models and exhibited limited predictive capabilities although introducing a hybrid model. In contrast, this research introduces more intricate predictive models based on machine learning, amalgamating extensive data and variables to enhance the prediction accuracy of supply chain financing models and virtual economic risks. By employing this model, researchers can more precisely identify potential risk factors and devise corresponding management strategies. Furthermore, this research achieves notable technological advancements in terms of model performance. By comprehensively considering the intricate relationships between diverse variables and harnessing the advantages of machine learning algorithms, this model better captures the multifaceted nature and dynamics of risks, thereby enhancing prediction accuracy and precision. In conclusion, this research plays a critical role in refining supply chain financing models and effectively managing virtual economic risks. By introducing intricate predictive models grounded in machine learning and attaining substantial technological progress, this research furnishes robust support for research and practical applications in relevant domains. Moreover, it offers a valuable reference for the enhancement of risk management strategies and informed decision-making.

CONCLUSION

This research introduced the BP neural network technology to optimize the control of virtual economic risks within the framework of supply chain financing patterns. In contrast to conventional methodologies, this model exhibits superior performance and accuracy, presenting an effective solution for real-world challenges. Through the utilization of the BP neural network, this research introduced the Adam-BP model, enhancing the conventional BP model. This enhancement yields elevated levels of accuracy, precision, and recall when applied to diverse datasets, including plant classification and credit card fraud. These enhancements yield favorable assessment outcomes and provide guidance for advancing risk control and classification tasks. The proposed model undergoes rigorous empirical research and evaluation, employing both plant classification and credit card fraud datasets. The application of the model to real-world data validates its feasibility and efficacy, demonstrating promising performance in the realm of supply chain financing patterns and their associated virtual economic risk control. By optimizing the BP neural network model, this research introduced an innovative approach to address virtual economic risk control within supply chain financing patterns. The outcomes contribute to the improved capacity for identifying and managing virtual economic risks, thereby furnishing vital support for the intelligent management of supply chain financing patterns. Collectively, these contributions underscore the notable accomplishments of this research in tackling virtual economic risk control within supply chain financing patterns through novel methodologies and enhanced models, providing significant reference value for both research and practical application in related domains.

The research bears significant practical implications for the realms of supply chain financing patterns and virtual economic risk control. Firstly, supply chain financing serves as a crucial mechanism for nurturing business growth and economic advancement. The investigation into supply chain financing patterns facilitates a profound comprehension of associated risks and the formulation of corresponding risk control strategies. This exploration aids businesses in engaging more adeptly in financing endeavors, ensuring seamless capital flow and stabilizing the supply chain dynamics. Secondly, virtual economic risks have emerged as novel risk manifestations in the backdrop of digitization and the progression of information technology. In the wake of swift technological advancements like the Internet, big data, and artificial intelligence, virtual economic risks have gained prominence as formidable challenges. The exploration of virtual economic risk control amplifies the identification and management of assorted risks within the virtual economic landscape, curtailing potential financial losses, safeguarding user entitlements, and fostering the wholesome evolution of the virtual economy. This research seamlessly amalgamates the domains of supply chain financing patterns and virtual economic risk control, striving to elevate risk control and classification task efficacy through the optimization of the BP neural network model. This endeavor contributes to the augmentation of the capacity for identifying and governing virtual economic risks, delivering pivotal support for the astute management of sets of supply chain financing patterns. In sum, this research holds pertinence in propelling the advancement of supply chain financing, alleviating virtual economic risks, and upholding user rights. Through an earnest exploration and the optimization of risk control models, this research imparts invaluable insights to allied fields of study and practical application, thus enriching the landscape of intelligent management of supply chain financing pattern sets. Drawing from the analysis above, forthcoming research endeavors can strategically focus on several pivotal areas. To begin, researchers are urged to expand the dataset's scope for validating the effectiveness and adaptability of the model. This expansion entails selecting more expansive and pragmatically grounded datasets while upholding data quality and availability standards. Additionally, the pursuit of model optimization and enhancement emerges as a paramount research trajectory. In this regard, possible avenues include exploring novel neural network architectures, integrating cutting-edge optimization algorithms, or intricately adjusting and tuning model parameters. Lastly, to enhance the pragmatic applicability of this research, prospective inquiries could pivot towards feasibility assessments in authentic, real-world scenarios, specifically within the realm of virtual economic risk control within the contours of supply chain financing pattern sets. Such an endeavor might necessitate symbiotic partnerships with actual industries, the orchestration of case studies, and a nuanced consideration of the assorted constraints and challenges intrinsic to real-world operations. It is prudent to acknowledge that this research does not have limitations, encompassing factors such as data availability and quality, the model's generalization capacities, and constraints in parameter selection and tuning. To surmount these limitations, forthcoming research must be steered towards resolving challenges in data acquisition and preparation processes, conducting cross-disciplinary validations or assessing datasets spanning diverse industries, and pioneering innovative strategies for parameter selection and tuning. These collective endeavors hold the potential to bolster model performance and pave the way for a more robust research landscape.

REFERENCES

Aday, S., & Aday, M. S. (2020). Impact of COVID-19 on the food supply chain. *Food Quality and Safety*, *4*(4), 167–180. doi:10.1093/fqsafe/fyaa024

Alkaraan, F., Albitar, K., Hussainey, K., & Venkatesh, V. G. (2022). Corporate transformation toward Industry 4.0 and financial performance: The influence of environmental, social, and governance (ESG). *Technological Forecasting and Social Change*, *175*, 121423. doi:10.1016/j.techfore.2021.121423

Anker, D., Santos-Eggimann, B., Zwahlen, M., Santschi, V., Rodondi, N., Wolfson, C., & Chiolero, A. (2019). Blood pressure in relation to frailty in older adults: A population-based study. *Journal of Clinical Hypertension*, *21*(12), 1895–1904. doi:10.1111/jch.13722 PMID:31661601

Bacinello, E., Tontini, G., & Alberton, A. (2020). Influence of maturity on corporate social responsibility and sustainable innovation in business performance. *Corporate Social Responsibility and Environmental Management*, *27*(2), 749–759. doi:10.1002/csr.1841

Bacinello, E., Tontini, G., & Alberton, A. (2021). Influence of corporate social responsibility on sustainable practices of small and medium-sized enterprises: Implications on business performance. *Corporate Social Responsibility and Environmental Management*, *28*(2), 776–785. doi:10.1002/csr.2087

Bocken, N. M., & Short, S. W. (2021). Unsustainable business models: Recognising and resolving institutionalised social and environmental harm. *Journal of Cleaner Production*, *312*, 127828. doi:10.1016/j.jclepro.2021.127828

Chen, L., Moretto, A., Jia, F., Caniato, F., & Xiong, Y. (2021). The role of digital transformation to empower supply chain finance: Current research status and future research directions (Guest editorial). *International Journal of Operations & Production Management*, *41*(4), 277–288. doi:10.1108/IJOPM-04-2021-838

Dong, Y., Skowronski, K., Song, S., Venkataraman, S., & Zou, F. (2020). Supply base innovation and firm financial performance. *Journal of Operations Management*, *66*(7-8), 768–796. doi:10.1002/joom.1107

Dutta, P., Choi, T. M., Somani, S., & Butala, R. (2020). Blockchain technology in supply chain operations: Applications, challenges, and research opportunities. *Transportation Research Part E, Logistics and Transportation Review*, *142*, 102067. doi:10.1016/j.tre.2020.102067 PMID:33013183

Feng, Z., & Chen, M. (2022). Platformance-based cross-border import retail e-commerce service quality evaluation using an artificial neural network analysis. *Journal of Global Information Management*, *30*(11), 1–17. doi:10.4018/JGIM.306271

Fosso, S., Kala Kamdjoug, J. R., Epie Bawack, R., & Keogh, J. G. (2020). Bitcoin, blockchain, and fintech: A systematic review and case studies in the supply chain. *Production Planning and Control*, *31*(2-3), 115–142. doi:10.1080/09537287.2019.1631460

Gu, J. (2022). Sharing economy, technological innovation, and carbon emissions: Evidence from Chinese cities. *Journal of Innovation & Knowledge*, *7*(3), 100228. doi:10.1016/j.jik.2022.100228

Hahn, G. J. (2020). Industry 4.0: A supply chain innovation perspective. *International Journal of Production Research*, *58*(5), 1425–1441. doi:10.1080/00207543.2019.1641642

Hofstetter, J. S., De Marchi, V., Sarkis, J., Govindan, K., Klassen, R., Ometto, A. R., Spraul, K. S., Bocken, N., Ashton, W. S., Sharma, S., Jaeger-Erben, M., Jensen, C., Dewick, P., Schröder, P., Sinkovics, N., Ibrahim, S. E., Fiske, L., Goerzen, A., & Vazquez-Brust, D. (2021). From sustainable global value chains to circular economy: Different silos, different perspectives, but many opportunities to build bridges. *Circular Economy and Sustainability*, *1*(1), 21–47. doi:10.1007/s43615-021-00015-2 PMID:34888550

Hosseini, S., & Ivanov, D. (2020). Bayesian networks for supply chain risk, resilience, and ripple effect analysis: A literature review. *Expert Systems with Applications*, *161*, 113649. doi:10.1016/j.eswa.2020.113649 PMID:32834558

Huang, C., Chan, F. T., & Chung, S. H. (2022). Recent contributions to supply chain finance: Towards a theoretical and practical research agenda. *International Journal of Production Research*, *60*(2), 493–516. doi: 10.1080/00207543.2021.1964706

Kitsis, A. M., & Chen, I. J. (2021). Do stakeholder pressures influence green supply chain practices? Exploring the mediating role of top management commitment. *Journal of Cleaner Production*, *316*, 128258. doi:10.1016/j.jclepro.2021.128258

Kraus, N., & Marchenko, O. (2021). Innovative-digital entrepreneurship as key link of Industry X. 0 formation in the conditions of virtual reality. *Baltic Journal of Economic Studies*, *7*(1), 47–56. doi:10.30525/2256-0742/2021-7-1-47-56

Lee, K., Azmi, N., Hanaysha, J., Alzoubi, H., & Alshurideh, M. (2022). The effect of digital supply chain on organizational performance: An empirical study in Malaysia manufacturing industry. *Uncertain Supply Chain Management*, *10*(2), 495–510. doi:10.5267/j.uscm.2021.12.002

Li, K., Kim, D. J., Lang, K. R., Kauffman, R. J., & Naldi, M. (2020). How should we understand the digital economy in Asia? Critical assessment and research agenda. *Electronic Commerce Research and Applications*, *44*, 101004. doi:10.1016/j.elerap.2020.101004 PMID:32922241

MacNeill, A. J., Hopf, H., Khanuja, A., Alizamir, S., Bilec, M., Eckelman, M. J., & Sherman, J. D. (2020). Transforming the medical device industry: Road map to a circular economy study examines a medical device industry transformation. *Health Affairs*, *39*(12), 2088–2097. doi:10.1377/hlthaff.2020.01118 PMID:33284689

Milana, C., & Ashta, A. (2021). Artificial intelligence techniques in finance and financial markets: A survey of the literature. *Strategic Change*, *30*(3), 189–209. doi:10.1002/jsc.2403

Nandi, S., Sarkis, J., Hervani, A., & Helms, M. (2021). Do blockchain and circular economy practices improve post COVID-19 supply chains? A resource-based and resource dependence perspective. *Industrial Management & Data Systems*, *121*(2), 333–363. doi:10.1108/IMDS-09-2020-0560

Nayal, K., Raut, R. D., Queiroz, M. M., & Priyadarshinee, P. (2023). Digital supply chain capabilities: Mitigating disruptions and leveraging competitive advantage under COVID-19. *IEEE Transactions on Engineering Management*, *21*(3), 43. doi:10.1109/TEM.2023.3266151

Nia, A. R., Awasthi, A., & Bhuiyan, N. (2021). Industry 4.0 and demand forecasting of the energy supply chain: A literature review. *Computers & Industrial Engineering*, *154*, 107128. doi:10.1016/j.cie.2021.107128

Nogueira, L. A., Lindeløv, B., & Olsen, J. (2023). From waste to market: Exploring markets, institutions, and innovation ecosystems for waste valorization. *Business Strategy and the Environment*, *32*(4), 2261–2274. doi:10.1002/bse.3247

Paliwal, V., Chandra, S., & Sharma, S. (2020). Blockchain technology for sustainable supply chain management: A systematic literature review and a classification framework. *Sustainability (Basel)*, *12*(18), 7638. doi:10.3390/su12187638

Pickl, M. J. (2019). The renewable energy strategies of oil majors: From oil to energy? *Energy Strategy Reviews*, *26*, 100370. doi:10.1016/j.esr.2019.100370

Pieroni, M. P., McAloone, T. C., & Pigosso, D. C. (2020). From theory to practice: Systematising and testing business model archetypes for circular economy. *Resources, Conservation and Recycling*, *162*, 105029. doi:10.1016/j.resconrec.2020.105029

Pournader, M., Narayanan, A., Keblis, M. F., & Ivanov, D. (2023). Decision bias and bullwhip effect in multiechelon supply chains: Risk preference models. *IEEE Transactions on Engineering Management*, *13*(4), 31–36. doi:10.1109/TEM.2023.3292348

Pu, G., Qamruzzaman, M. D., Mehta, A. M., Naqvi, F. N., & Karim, S. (2021). Innovative finance, technological adaptation, and SMEs sustainability: The mediating role of government support during COVID-19 pandemic. *Sustainability (Basel)*, *13*(16), 9218. doi:10.3390/su13169218

Qi, S., Jin, K., Li, B., & Qian, Y. (2020). The exploration of Internet finance by using neural network. *Journal of Computational and Applied Mathematics*, *369*, 112630. doi:10.1016/j.cam.2019.112630

Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C., & Machado, M. C. (2022). Supply chain resilience in the UK during the coronavirus pandemic: A resource orchestration perspective. *International Journal of Production Economics*, *245*, 108405. doi:10.1016/j.ijpe.2021.108405 PMID:35002082

Remko, V. H. (2020). Research opportunities for a more resilient post-COVID-19 supply chain: Closing the gap between research findings and industry practice. *International Journal of Operations & Production Management*, *40*(4), 341–355. doi:10.1108/IJOPM-03-2020-0165

Safara, F. (2022). A computational model to predict consumer behaviour during COVID-19 pandemic. *Computational Economics*, *59*(4), 1525–1538. doi:10.1007/s10614-020-10069-3 PMID:33169049

Sahoo, P. B. B., & Thakur, V. (2023). Enhancing the performance of indian micro, small, and medium enterprises by implementing supply chain finance: Challenges emerging from COVID-19 pandemic. *Benchmarking*, *30*(6), 2110–2138. doi:10.1108/BIJ-11-2021-0668

Sang, B. (2021). Application of genetic algorithm and BP neural network in supply chain finance under information sharing. *Journal of Computational and Applied Mathematics*, *384*, 113170. doi:10.1016/j.cam.2020.113170

Santa-Maria, T., Vermeulen, W. J., & Baumgartner, R. J. (2022). How do incumbent firms innovate their business models for the circular economy? Identifying micro-foundations of dynamic capabilities. *Business Strategy and the Environment*, *31*(4), 1308–1333. doi:10.1002/bse.2956

Seiler, A., Papanagnou, C., & Scarf, P. (2020). On the relationship between financial performance and position of businesses in supply chain networks. *International Journal of Production Economics*, *227*, 107690. doi:10.1016/j.ijpe.2020.107690

Song, H., Yang, X., & Yu, K. (2020). How do supply chain network and SMEs' operational capabilities enhance working capital financing? An integrative signaling view. *International Journal of Production Economics*, *220*, 107447. doi:10.1016/j.ijpe.2019.07.020

Soni, G., Kumar, S., Mahto, R. V., Mangla, S. K., Mittal, M. L., & Lim, W. M. (2022). A decision-making framework for Industry 4.0 technology implementation: The case of FinTech and sustainable supply chain finance for SMEs. *Technological Forecasting and Social Change*, *180*, 121686. doi:10.1016/j.techfore.2022.121686

Su, C. W., Qin, M., Tao, R., & Umar, M. (2020). Financial implications of fourth industrial revolution: Can bitcoin improve prospects of energy investment? *Technological Forecasting and Social Change*, *158*, 120178. doi:10.1016/j.techfore.2020.120178 PMID:32834135

Tezel, A., Febrero, P., Papadonikolaki, E., & Yitmen, I. (2021). Insights into blockchain implementation in construction: Models for supply chain management. *Journal of Management Engineering*, *37*(4), 04021038. doi:10.1061/(ASCE)ME.1943-5479.0000939

Tsai, C. H. (2023). Supply chain financing scheme based on blockchain technology from a business application perspective. *Annals of Operations Research*, *320*(1), 441–472. doi:10.1007/s10479-022-05033-3

Verkijika, S. F. (2020). Assessing the role of simplicity in the continuous use of mobile apps. *Journal of Organizational and End User Computing*, *32*(4), 26–42. doi:10.4018/JOEUC.2020100102

Wang, F., Ding, L., Yu, H., & Zhao, Y. (2020). Big data analytics on enterprise credit risk evaluation of e-business platform. *Information Systems and e-Business Management*, *18*(3), 311–350. doi:10.1007/s10257-019-00414-x

Wang, Y., Gao, W., Qian, F., & Li, Y. (2021). Evaluation of economic benefits of virtual power plant between demand and plant sides based on cooperative game theory. *Energy Conversion and Management*, *238*, 114180. doi:10.1016/j.enconman.2021.114180

Wu, D. D., Olson, D. L., Wu, D. D., & Olson, D. L. (2020). The effect of COVID-19 on the banking sector. In Pandemic risk management in operations and finance: Modeling the impact of COVID-19 (pp. 89—99). Springer. doi:10.1007/978-3-030-52197-4_8

Ye, S., & Zhao, T. (2023). Team knowledge management: How leaders' expertise recognition influences expertise utilization. *Management Decision*, *61*(1), 77–96. doi:10.1108/MD-09-2021-1166

Yousefi, S., & Tosarkani, B. M. (2023). Exploring the role of blockchain technology in improving sustainable supply chain performance: A system-analysis-based approach. *IEEE Transactions on Engineering Management*, *65*(12), 12–15. doi:10.1109/TEM.2022.3231217

Yuan, L., Li, H., Fu, S., & Zhang, Z. (2022). Learning behavior evaluation model and teaching strategy innovation by social media network following learning psychology. *Frontiers in Psychology*, *13*, 843428. doi:10.3389/fpsyg.2022.843428 PMID:35936300

Zaher, M., Shehab, A., Elhoseny, M., & Farahat, F. F. (2020). Unsupervised model for detecting plagiarism in Internet-based handwritten Arabic documents. *Journal of Organizational and End User Computing*, *32*(2), 42–46. doi:10.4018/JOEUC.2020040103

Zhang, C., Fan, L. W., & Tian, Y. X. (2020). Optimal operational strategies of capital-constrained supply chain with logistics service and price dependent demand under 3PL financing service. *Soft Computing*, *24*(4), 2793–2806. doi:10.1007/s00500-019-04500-7

Zhang, G., Cheng, P., Sun, H., Shi, Y., Zhang, G., & Kadiane, A. (2021). Carbon reduction decisions under progressive carbon tax regulations: A new dual-channel supply chain network equilibrium model. *Sustainable Production and Consumption*, *27*, 1077–1092. doi:10.1016/j.spc.2021.02.029

Zhang, H., Fan, L., Chen, M., & Qiu, C. (2022). The impact of SIPOC on process reengineering and sustainability of enterprise procurement management in e-commerce environments using deep learning. *Journal of Organizational and End User Computing*, *34*(8), 1–17. doi:10.4018/JOEUC.306270