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Retraction

Retracted: Application Analysis of Artificial Intelligence Algorithm in Accounting Field under the Background of Innovation Economy

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Chen, "Application Analysis of Artificial Intelligence Algorithm in Accounting Field under the Background of Innovation Economy," *Mobile Information Systems*, vol. 2022, Article ID 7970237, 9 pages, 2022.

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Research Article

Application Analysis of Artificial Intelligence Algorithm in Accounting Field under the Background of Innovation Economy

Jing Chen

Accounting Department, Jiaozuo University, Jiaozuo 454000, Henan, China

Correspondence should be addressed to Jing Chen; chenjing@hpu.edu.cn

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At present, economic business activities occur to the accounting element confirmation link of the accounting information system (AIS), which still occupies a large amount of manpower and material resources of the enterprise to generate information. This has been restricting the development of modern AIS. Based on this, first, this paper studies the influence of the knowledge economy on accounting innovation and in the innovation economy. The process of confirmation for accounting elements in economic business, under the traditional AIS, is analyzed. Then, the model of the accounting element confirmation, i.e., BPNN, is constructed by combining the backpropagation (BP) neural network (NN) theory with the artificial intelligence (AI) algorithm. Finally, we simulate the confirmation process of accounting elements based on the economic business data of specific online stores. The experimental outcomes illustrate that under the proposed BPNN model, the output value of the accounting entry is also increasing and has been in the interval [0, 0.14] with the continuous increase in the input value of economic business activities. Moreover, the overall simulation error of economic business activity data does not exceed 0.3% in the simulation test of the proposed accounting business data confirmation model based on the BPNN algorithm. The empirical outcomes indicate that the model has high accuracy and reliability. The purpose is to realize the identification of business events by machines and complete the automatic confirmation of accounting elements in the back-end economic business of online stores. This paper provides new ideas for realizing the overall intelligence of the AIS.

1. Introduction

At present, most scholars focus on the study of accounting measurement and reports, and there are few studies on accounting confirmation. It was not until around 1830 that the term “confirmation” was first used. Subsequently, the meaning of “confirmation” was proposed in the “accounting outline” [1]. In the 1970s, the specific meaning of “confirmation” was mentioned, but its concept was not formally proposed [2]. In the 1980s, an authoritative concept and definition of accounting identification were proposed. Once an economic business activity occurred, “confirmation” was the process of recording the events in this economic activity with the names of elements such as assets, liabilities, income, and expenses, and finally reflecting them on the financial statements to be output [3]. Basic issues such as the meaning, function, process, premise, standard, and foundation of accounting identification were discussed starting from the definition of accounting identification. At this time, the research on accounting identification was standardized [4]. Later, the theory of accounting confirmation and measurement in the accounting theoretical system was expounded from the research perspective of the accounting theoretical system.

The theoretical issues related to identification and measurement were also pointed out for further research [5]. From the perspective of cognitive theory, judgments were made through the accounting facts reflected in an event. Scholars believed that this process consisted of three stages. Each stage differently impacted the quality of accounting information, which determined the reliability and relevance of the quality of accounting information [6]. Subsequently, accounting identification in the information environment was emphasized. Scholars proposed that accounting confirmation should be further strengthened to adapt to the characteristics of rapid changes and large business volume under the background of e-commerce. This would be a decisive factor in solving current accounting problems [7].

The artificial neural network (ANN) has experienced a long period of development and gradually formed a relatively complete discipline system. Scholars have combined the ANN theory with many disciplinary theories and successfully applied it to other disciplines. This should be noted that the first neural model was proposed in the 1940s, which prompted many scholars to study ANN [8]. In the early 1950s, Hebb's law was proposed. This law stated that the strength of the connection between neurons and synapses was not fixed in a neural network. This nonfixation established neuron-to-neuron connections, and information was stored in connection weights. This law laid the foundation for establishing the learning function of neural networks [9]. In the mid-1950s, an inference engine for simulating the behavior and conditional firing was proposed. This kind of inference engine was composed of signal processing units. It was applied to adaptive pattern identification. This model could reflect the actual working principle of the neural network [10]. In the late 1960s, the research results of the neural network were questioned with the upsurge of ANN research. Scholars believed that the current ANN could only solve simple linear problems, but they could not effectively solve multilayer network problems. Since then, scholars' research on the ANN had entered a period of low ebb [11].

In 1982, the Hopfield network model theory was pointed out. Scholars had proved that the ANN model could reach a stable state under certain conditions. Under the influence of this theory, many research scholars had rejoined the upsurge of studying ANN. The research on the neural network theory had gradually stepped out of the low ebb and toward the renaissance period [12]. In the 1980s, the research on ANN in various countries in the world gradually recovered. Chinese scholars had also joined the research upsurge of ANN. In the 1990s, the first academic conference on neural networks in China was held, which was a new beginning of research on ANN and neural computers in China [13]. Since the 1990s, scholars at home and abroad have continued to develop and improve the field of neural network research. They especially focus on the research of neural networks in the field of nonlinear control and have made substantial progress [14]. After several decades of development, the ANN has now achieved fruitful results in the fields of automatic control, pattern identification, assisted decision-making, signal processing, and artificial intelligence (AI). At present, the ANN is mainly used in printed and handwritten character identification, speech identification, signature identification, fingerprint identification, face identification, and image processing.

It is found that the application of ANN in the field of accounting has been vigorously developed under the background of the innovation economy through the collection of literature. However, there are still problems such as the large consumption of manpower and material resources from the occurrence of economic business activities to the confirmation of accounting elements in the accounting information system (AIS). Based on this, this paper uses the ANN technology in the AI algorithms to construct a confirmation model for various economic business data in accounting. The innovation is that it adopts the backpropagation (BP) ANN theory to explore the accounting field and applies the pattern identification function of AI to the accounting element confirmation process, realizing the cross-application of different theories. This paper aims to help the accounting field to develop further by realizing a model that consumes less accounting business data. The main points of our research can be shortened as follows: (i) this paper studies the influence of the knowledge economy on accounting innovation and in the innovation economy; (ii) the process of confirming accounting elements in economic business under the traditional AIS is analyzed; and (iii) the model of the accounting element confirmation is constructed through combining the backpropagation (BP) and neural network (NN) theory with the artificial intelligence (AI) algorithm.

The remaining part of this article is structured in the following way. In Section 2, we discuss various methods along with knowledge economy and accounting innovation. Applications of the AI and BP neural networks are also discussed. In Section 3, an automatic accounting confirmation model based on the BPNN model is proposed. The experimental setup and obtained results are analyzed in Section 4. Finally, Section 5 summarizes the paper while shedding lights on the future research.

2. Background and Methods

2.1. Knowledge Economy and Accounting Innovation

2.1.1. Characteristics of the Knowledge Economy. The knowledge economy is founded on knowledge and considers the present technology of science and learning as the fundamental components. In fact, it is an economy built on the construction, packing, practice, and depletion of required knowledge, details, and statistics. The social economy is classified by industrial structure, and it can be divided into the agricultural economy, industrial economy, and knowledge economy. The agricultural economy invests in land and labor. The industrial economy invests in capital and equipment, while the knowledge economy invests in knowledge and information [15]. The specific content of the characteristics of the knowledge economy is shown in Figure 1.

2.1.2. The Influence of the Economy of Knowledge over Innovation in Accounting. According to various characteristics and features related to the knowledge economy, the influence of the economy of knowledge over the accounting innovation is manifested in five aspects, as shown in Figure 2. This includes the innovation of the accounting means, theory, content, financial reporting, and essential accounting education.

2.2. Application of AI Algorithms in the Accounting Field

2.2.1. The BP ANN Model

(1). The BP Neural Network (BPNN) Structure. From the topological organization point of view, the BP neural network is a typical and forward hierarchical network, which is

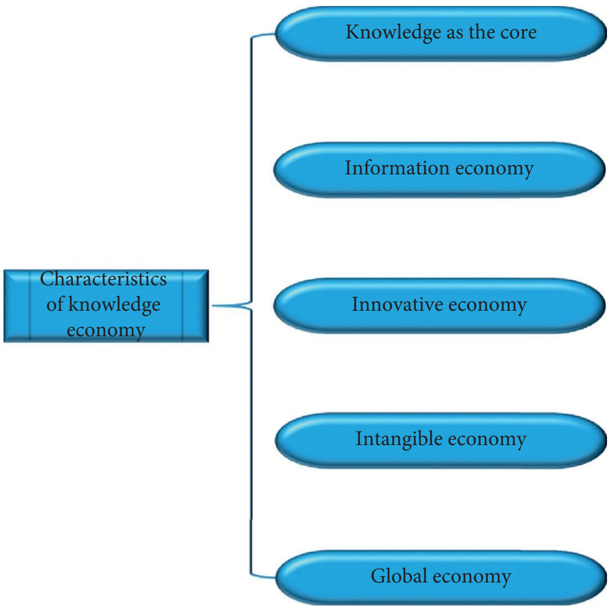

FIGURE 1: Characteristics of the knowledge economy.

distributed into three different layers, i.e., the input layer, the output layer, and the hidden layer. Neuron nodes are not connected in the same layer of the network, and the hidden layer of a BP network can have one or more layers [16]. Figure 3 shows the three-layer BP ANN structure and classical prototype.

In Figure 3, point i is the input layer neuron of the network. Moreover, node j is the hidden layer neuron and the number of hidden layers may vary subject to the depth of the network. Similarly, node k is the output layer neuron. After the input layer of the ANN is stimulated by the external environment (such as economic business data that need to be processed), each input layer transmits the stimulation signal to the subsequent hidden layer. As the internal information processing center, the hidden layer is extremely important in the pattern identification function of the BPNN model. There is an existing input pattern X_{pi}, and each input of the hidden layer can be expressed as given by the following equation:

$$I_{pi} = \sum_i W_{ji} O_{pi}, \tag{1}$$

where W_{ji} is the weight coefficient of the hidden layer node j and the input layer node i, and O_{pi} is the output vector value of the node i. If the threshold of node j is θj, the excitation function is sigmoid, and $A = I_{pj} - \theta j$; then, the output value of node j is computed using the following equation:

$$O_{pj} = \frac{1}{1 + e^{-A}}. \tag{2}$$

The output of the ANN produces the final output vector, and the input value of the node k of the output layer is given by the following equation:

$$O_{pk} = \frac{1}{1 + e^{-A}}. \tag{3}$$

If the threshold of the output layer node k is θ_k, the transfer function between the hidden layer and the output layer is sigmoid, and $B = I_{pk} - \theta_k$; then, the output vector value of node k is given by the following equation:

$$O_{pk} = \frac{1}{1 + e^{-B}}, \tag{4}$$

where O_{pk} is the final output vector produced by the output layer, and e represents the constant.

(2). The BP Algorithm Training Process. The BPNN algorithm can be divided into forward propagation and BP techniques. The forward propagation of the network model means that the input samples are transmitted from the input layer to the hidden layer units and finally to the output layer. In the process of signal transmission and processing, the output of neurons in the upper layer only affects the neurons in the lower layer. When the resulting value is output, the neural network will compare the actual output value with the expected output value. If there is an error between the actual result and the expected output value, then the network model enters the process of feedback adjustment. The error signal value is transmitted in the reverse direction according to the forward propagation path, and the connection weight coefficient between neurons is corrected. The error signal between the final actual output and the expected output reaches the expected setting [17].

The ANN algorithm used in the accounting element classification process is mainly divided into sample training and pattern identification. The first step is to select appropriate training samples. The training samples refer to the economic feature attributes in the economic business activity data that distinguish their categories, so the machine can distinguish different economic business activities. Many ANN models are trained according to the actual collected economic and business data. Existing research shows that the quality and quantity of training samples greatly affect the effects and impacts of the ANN as a classifier, and the selection of sample category feature vector impacts the classification results. The second step is pattern identification. The economic features that distinguish economic business activity categories are used as input vectors. The accounting entries of the business process are obtained as the output vector value by looking up the relevant accounting standards. Figure 4 shows the information dissemination route of the neural network. One is the work signal represented by the solid line, which is the forward propagation from economic business data to accounting entries. The other is the error signal represented by the dotted line, which is the feedback propagation of the error signal in the accounting entry. The accounting entries under the corresponding economic business activities and accounting standards are obtained through the continuous feedback training of the neural network [18, 19].

(3). The BP Algorithm Calculation Steps. The learning steps of the BP ANN are shown in Figure 5.

The first step is to input training samples (Xk, $Y*k$) and $k = 1, 2, \ldots, N$. The second step is to build the network model

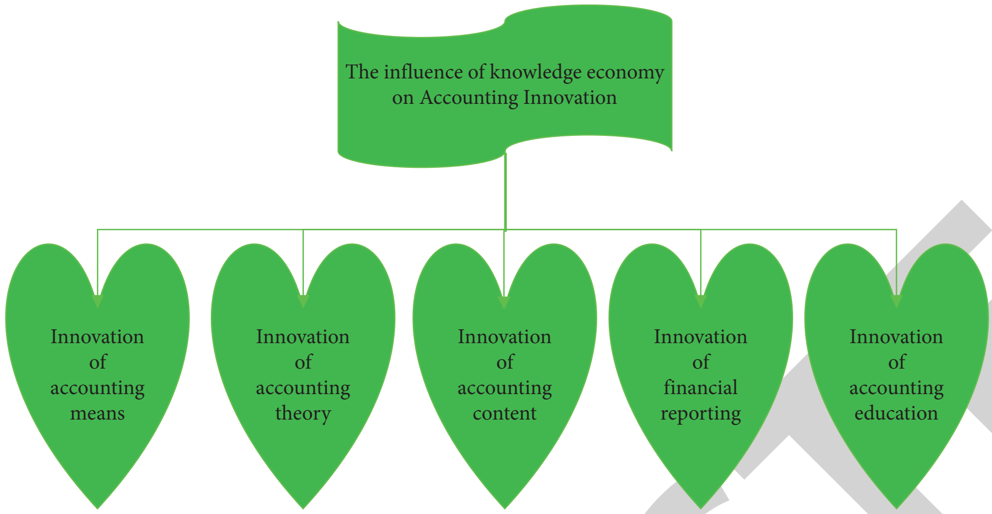

Figure 2: The specific performance of the knowledge economy affecting accounting innovation.

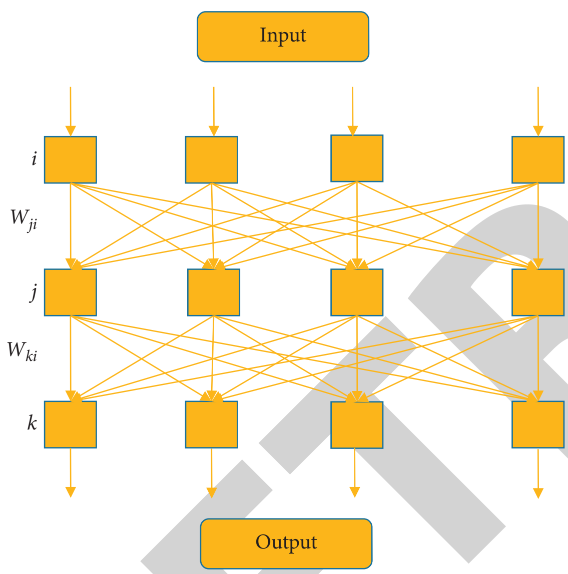

Figure 3: Schematic diagram of the three-layer BP ANN structure.

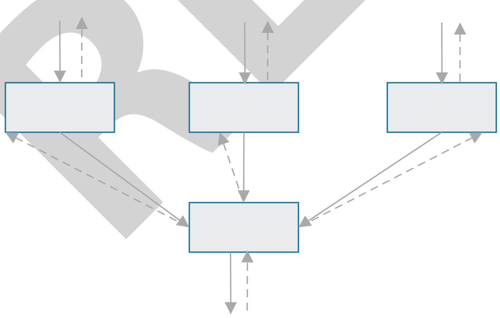

Figure 4: Information dissemination route of the neural network.

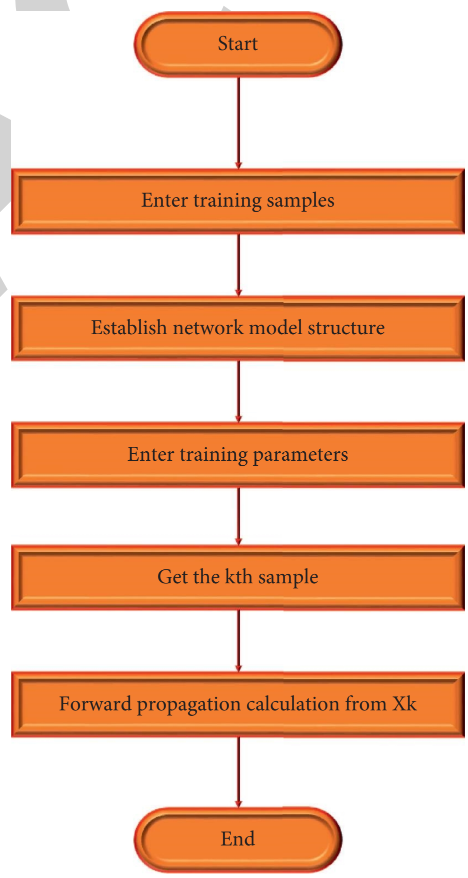

Figure 5: Learning process of BP ANN.

structure. This should be noted that the input vector of the training samples decides the amount of nodes in the input layer of the proposed network model. Similarly, the vector that defines the training sample output determines the total amount of nodes in the output layer of the network. The third step is to input network model parameters, for instance, the learning rate η and the allowable error ε. The serial number of the training sample is $k = 1$, and the number of initialization iterations of the model is $t = 1$. The fourth step is to obtain the kth training sample $(Xk, Y{*}k)$, $Xk = (x_{1k}, x_{2k}, \ldots, x_{nk})$, and $Y{*}k = (y{*}_{1k}, y{*}_{2k}, \ldots, y{*}_{mk})$. The fifth step is to start the forward propagation calculation from X_k, and the output of each node of the input layer is calculated as given by the following equation:

$$O_{ik}^{(l)} = f\left(x_{jk}\right), \quad j = 1, 2, \ldots, n. \tag{5}$$

The sixth step is to calculate the input and output of each node of each layer using the following equations, respectively.

$$I_{jk}^{(l)} = \sum_{i=1}^{n(l-!)} w_{ij}^{(l-1)} O_{ik}^{(l-1)}, \tag{6}$$

$$O_{jk}^{(l)} = f\left(I_{jk}^{(l)}\right). \tag{7}$$

In equations (6) and (7), $l = 2, \ldots, L$ and $j = 1, 2, \ldots, m$. The seventh step is that if any sample K in the training sample has an error value $E_{jk} \leq \varepsilon$ and $j = 1, 2, \ldots, m$, the learning process is terminated. On the contrary, the model performs error backpropagation and weight correction adjustment between neurons. The final step is to calculate the backpropagation error [20].

(4). The Working Process of the BPNN Classification. When the BP ANN is applied to the construction of the automatic accounting element confirmation mechanism, its working principle can be divided into the following: (i) the preparation stage, (ii) the learning stage, and (iii) the classification stage [21, 22]. The three stages and specific steps within each stage are as follows:

(1) *Preparation*. The first is the preparation stage. The tasks of the preparation stage are the selection of training samples and the determination of the initial weights and parameters of the network model. The training samples are generally the typical economic feature vector values of each category on the economic business activities to be classified. The determination of the network structure means that when the classification of accounting elements is applied, the amount of nodes, which as specified in the input layer, is generally selected as the amount of economic feature vectors of business activities. In the output layer, the total amount of nodes is identical to the category of accounting entries to be distinguished. Moreover, the selection of nodes and their amount within the hidden layer can be based on experience. There is no specific and accurate theory to guide [17]. The determination of the initial weights and control parameters of the network means that the random function of the computer can generate the initial weight matrix of the ANN. The classification of the network model requires control parameters such as accuracy, the maximum number of cycles, or learning factors, which can also be selected based on experience [23].

(2) *Learning*. The second is the learning stage. At this stage, the training samples are fed as responses into the proposed network model for training, and the network weight function is updated according to the selected training samples. The training sample input means that the economic business feature vector value passes through each hidden layer. Moreover, in each layer it obtains the actual output value and error value in the output layer [24]. Updating the network weight function means that if the actual output error value meets the parameter requirements, the model stops training [25, 26]. Otherwise, the model will return to the first step until the output meets the requirements. If the number of cycles exceeds the initial maximum number of cycles, the training is not as expected. The neural network stops training and repeats the first step of training by setting new model parameters.

(3) *Classification*. The last is the classification stage. This stage is the automatic classification process of confirming the accounting elements of economic business activities with the help of the results of the BP network model. The characteristic attribute values of the new economic business activities are calculated in turn according to the model weight coefficients accumulated in the training process. In addition, each accounting entry output by the economic business event is classified into the category with the smallest error according to the comparison among the real output value and the anticipated output result. This should be noted that the BP network has some defects, for instance, easy to fall into the local minima, very difficult to determine the network structure, and more importantly slow convergence speed. In the actual accounting confirmation process, many repetitions are often required to obtain satisfactory classification results [27].

2.2.2. Analysis and Design of Accounting Confirmation Mechanism Based on BP Network

(1). Automatic Accounting Confirmation Process Based on BPNN. After the data of internet economic business activities are standardized, the AIS automatically collects the original vouchers or agreements of related businesses and stores them in the system's event voucher database. The computer automatic accounting confirmation processing platform converts these standardized data into accounting information according to relevant information [28, 29]. Figure 6 demonstrates the confirmation process of the accounting elements based on the proposed BP ANN model.

(2). Input and Output Vector Analysis of Automatic Accounting Confirmation Based on BPNN. In the internet environment, economic business activities mainly include internal business and external business. The economic entities involved in enterprise procurement and sales include suppliers, buyers, logistics companies, and banks. From the specific online store transaction process, the accounting entries involved in the commodity procurement business

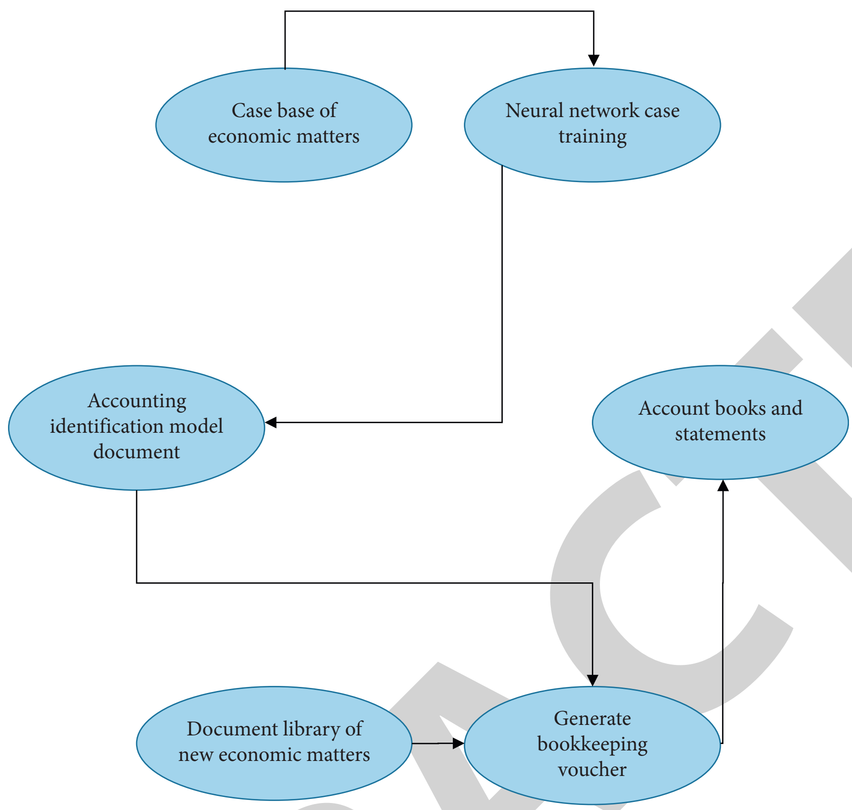

Figure 6: Schematic diagram of the accounting element confirmation process.

mainly include the automatically generated trigger mechanism or agreement for the commodity purchase invoice and the payment slip. According to the above information, an automatic accounting confirmation model based on BP ANN is constructed. The input vector analysis in the purchase payment business link is revealed in Table 1.

From the analysis of the business process, the input vectors in the commodity procurement process include commodity name, commodity code, invoice type, supplier, department name, and salesperson. The input vector of the commodity purchase payment link consists of the supplier, department name, salesperson, settlement number, settlement method, currency, exchange rate, and amount.

In addition, a total of 62 input vectors in the economic business can be obtained using the same method to analyze sales collection business, fixed asset purchase payment business, and other types of businesses.

After the economic and business activities occur, the accounting process is performed according to the obtained original voucher information to generate accounting entries, which are used as the expected output of the neural network model, as shown in Table 2.

(3). Input and Output Design. Outputs are results produced by the system or accounting information provided to users. The purpose of output design is to reflect the output information of the system accurately and timely. Information can meet the needs of users, which is directly related to the use effect of the system and the success of system development. The appropriate input form or vector is determined according to the characteristics of different economic and business activities. The purpose of the input design is to determine the ANN input value. According to the inherent characteristics of the network model, an intelligent accounting information processing platform with a stable structure and pattern identification is trained. In the experiment, the data related to the economic and business characteristics of the online shopping transaction activity are captured as the input vector of the network model according to the actual transaction. Furthermore, different accounting entries are used as expected output values to conduct model training according to the results of different business accounting processing.

3. Automatic Accounting Confirmation Model Based on BPNN

3.1. The BP Network Structure Design. This paper adopts the basic three-layer BP ANN model. It is finally determined that 62 economic features are selected as input vectors by analyzing the business process, so the number of nodes in the input layer is 62. The number of nodes in the output layer is equal to the number of different accounting entry types to be divided into results. There are 13 types of accounting entries in this study, so the number of nodes in the output layer is 13. For the selection of the number of hidden layer nodes, the number of hidden layer nodes is set under the condition of comprehensively considering the error accuracy and the complexity of the network structure. Usually, the global error tends to be the smallest or smaller than the predetermined allowable error, which will be used as an

Table 1: The purchase-to-pay business input vector.

Eigenvalues of the input vector	1	2	3	4	5	6	7	8	9	10	11
Name of the input vector	Commodity name	Commodity code	Invoice type	Supplier	Unit name	Salesperson	Statement number	Payment method	Currency	Exchange rate	Amount

Table 2: The output vector for business link.

Output vector number	1	2	3	4	5	6	7	8	9
Output vector name	Goods purchase settlement business	Purchase of fixed assets	Provision for impairment of fixed assets	Collection of goods sold	Capital increase business	Profit division business	Employee payroll preparation business	Utility bill payment business	Housing rental business
Expected output value	1	2	3	4	5	6	7	8	9

indicator for the selection of the number of hidden layer nodes. The last step is to determine the excitation function. The excitation function of the neural network chosen here is the logarithmic function of the sigmoid. The sigmoid function is the first derivative and is continuously differentiable. For the three-layer BPNN, the region divided by the sigmoid excitation function is composed of a nonlinear hyperplane, rather than a linear division. This excitation function has a smooth and soft arbitrary interface, so its classification is more reasonable and accurate than the linear excitation function. Moreover, the model has good fault-tolerant characteristics.

3.2. The BP Network Learning Design. For the design of the BP network learning, the first is the selection of the initial weight a of the model. The settings of the initial weights of the network model are generally randomly generated within a fixed range according to a uniform distribution. This fixed range is between zero and one. The size of the initial weights influences the convergence speed of the model and the prevention of local minima. Therefore, the initial value will be set according to the specific network mode and different training samples in the actual situation. The second is the determination of the learning rate factor η. This paper selects a small learning rate factor η to ensure the convergence of the training results. The selection of the initial value of η is the same as that of the normal algorithm, and just defines a positive number between zero and one. The last step is the selection of the global error E. In this paper, the error threshold is predetermined according to the actual situation in the training process of the suggested BP network prototype. In fact, when the error threshold is set small, the training effect is good. However, the speed of the network convergence decreases, but the number of training times increases. If E is large, the opposite is true.

3.3. Simulation Experiment Design. In this paper, the MATLAB software was used to build a BPNN model with given parameters as described, i.e., (62 nodes in the input layer while 13 nodes in the output layer, and we assume 1 hidden layer only). The parametric value for initial weight takes $a = 0.1$, the learning speed takes $\eta = 0.1$, and the given network global error takes $E = 0.000001$.

4. Results and Analysis

4.1. The Training Results of the BP Network Model. The BP network model constructed here is trained through the MATLAB platform, and the results acquired are shown in Figure 7.

From Figure 7, in the BP ANN constructed here, different input values of economic business activities correspond to different output values of accounting entries. There are twists and turns in the curve, but the input value continues to increase with the business activity. The accounting entry output value is also increasing and has been in the interval [0, 0.14].

4.2. The Effect of the Automatic Accounting Confirmation Model Based on the BPNN. Figure 8 reveals the simulation test error results obtained through the MATLAB platform for the accounting confirmation of economic and business activity data.

In Figure 8, when the model is simulated and tested, the simulation errors of different economic and business activity data are 0.21%, 0.01%, 0.23%, 0.01%, 0, 0.01%, 0.13%, 0.01%, 0.01%, 0.02%, 0.01%, 0.01%, and 0, respectively. The overall error does not exceed 0.3%. The above data show that the model has high accuracy and reliability.

5. Conclusions and Future Work

At present, there are some problems in the confirmation link of accounting elements from the occurrence of economic business activities to the AIS. Therefore, this paper integrates the BPNN technology into the accounting field. In addition, an automatic accounting confirmation model is constructed

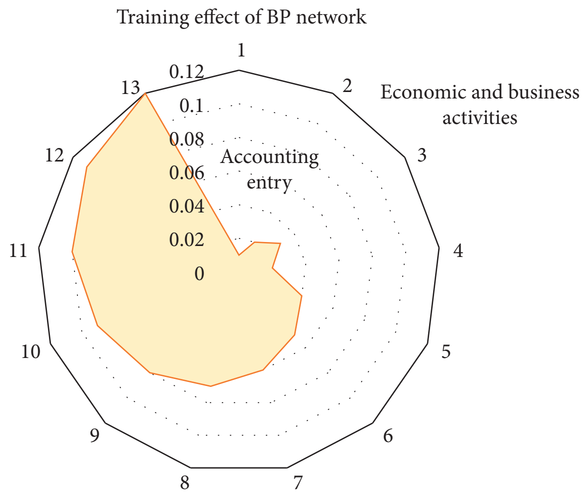

FIGURE 7: The effect of the BP network training process.

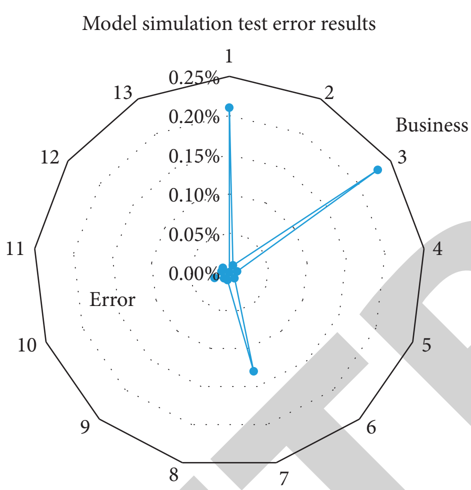

FIGURE 8: Model simulation test error results.

combined with the economic business scope of accounting. The simulation analysis of the model shows that the BP ANN established here has a good training effect, and the overall test error is less than 0.23% when the automatic accounting confirmation model based on the BPNN is used to simulate the data. It indicates that the model has high accuracy, reliability, and applicability. The shortcoming is that the business covered is not wide enough, and the accounting entries in the basic accounting theory cannot be discussed one-to-one when the business links are analyzed. Furthermore, the content of the case is not rich enough and needs to be supplemented.

This paper will carry out extended research and discussion on the above problems in the future. The determination of this research is to establish a spontaneous identification mechanism for data input and accounting information output in economic business activities to efficiently process business data generated in e-commerce activities and provide a choice for the real-time accounting information output. In the future, we will compare other deep learning techniques over a large amount of data. The impact of activation functions of the obtained results should also be investigated. Finally, this study was conducted over a dataset that consists of several attributes and records. In the future, larger datasets should be used to generalize the outcomes obtained in this work.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] C. M. Brunoro, I. Bolis, T. F. Sigahi, B. C. Kawasaki, and L. I. Sznelwar, "Defining the meaning of "sustainable work" from activity-centered ergonomics and psychodynamics of Work's perspectives," *Applied Ergonomics*, vol. 89, no. 10, Article ID 103209, 2020.

[2] A. Temme, F. Guzzetti, J. Samia, and B. B. Mirus, "The future of landslides' past—a framework for assessing consecutive landsliding systems," *Landslides*, vol. 17, no. 7, pp. 1519–1528, 2020.

[3] H. Jia, "Research on accounting recognition and measurement related to energy management contract," *IOP Conference Series: Earth and Environmental Science*, vol. 440, no. 3, Article ID 032069, 2020.

[4] H. Kohler, C. Pochet, and A. Le Manh, "Auditors as intermediaries in the endogenization of an accounting standard: the case of IFRS 15 within the telecom industry," *Accounting, Organizations and Society*, vol. 91, no. 1, Article ID 101227, 2021.

[5] A. Moung Yin Chan, P. Lo, and N. Kong, "An analysis of management accounting system development from the structuration theory viewpoint," *Journal of Accounting Business and Management (JABM)*, vol. 27, no. 1, 2020.

[6] D. Wu, H. Gu, S. Gu, and H. You, "Individual motivation and social influence: a study of telemedicine adoption in China based on social cognitive theory," *Health Policy and Technology*, vol. 10, no. 3, Article ID 100525, 2021.

[7] Q. Yao and Y. Gao, "Analysis of environment accounting in the context of big data," *Journal of Physics: Conference Series*, vol. 1650, no. 3, Article ID 032081, 2020.

[8] A. Aggarwal, V. Vinayak, S. Bag, C. Bhattacharyya, U. V. Waghmare, and P. K. Maiti, "Predicting the DNA conductance using a deep feedforward neural network model," *Journal of Chemical Information and Modeling*, vol. 61, no. 1, pp. 106–114, 2021.

[9] S. Napitupulu and Z. Situmorang, "Optimization of giving employee craft assessment using artificial neural network with Hebb algorithm," *IOP Conference Series: Materials Science and Engineering*, vol. 725, no. 1, Article ID 012111, 2020.

[10] Z. Wang, S. Yang, L. Li, Y. Tang, and G. Xu, "A 3D Voronoi clump based model for simulating failure behavior of brittle rock," *Engineering Fracture Mechanics*, vol. 248, no. 2, Article ID 107720, 2021.

[11] L. A. Do, P. G. Synnott, S. Ma, and D. A. Ollendorf, "Bridging the gap: aligning economic research with disease burden," *BMJ Global Health*, vol. 6, no. 6, Article ID e005673, 2021.

[12] G. Liu, W. P. Ma, H. Cao, and L. D. Lyu, "A quantum Hopfield neural network model and image recognition," *Laser Physics Letters*, vol. 17, no. 4, Article ID 045201, 2020.

[13] X. Zhang, Q. Xie, and M. Song, "Measuring the impact of novelty, bibliometric, and academic-network factors on citation count using a neural network," *Journal of Informetrics*, vol. 15, no. 2, Article ID 101140, 2021.

[14] Y. Cao and R. B. Gopaluni, "Deep neural network approximation of nonlinear model predictive control," *IFAC-PapersOnLine*, vol. 53, no. 2, Article ID 11319, 2020.

[15] S. Xing, G. Zhai, H. Mo et al., "Study of ignition and combustion characteristics of consecutive injections with isooctane and n -heptane as fuels," *Energy & Fuels*, vol. 34, no. 11, Article ID 14741, 2020.

[16] L. Meng, Z. Gu, F. Li, X. Liu, G. Zeng, and X. He, "Application of BP neural network on quantitative evaluation of curriculum reform in advanced education-A case study of signal and system," *Journal of Physics: Conference Series*, vol. 1774, no. 1, Article ID 012047, 2021.

[17] S. Chen, "The impact of artificial intelligence and data fusion technology on the accounting industry and its countermeasures," in *Proceedings of the 3rd International Conference on Artificial Intelligence and Advanced Manufacture*, Manchester United Kingdom, October 2021.

[18] D. Zhang and S. Lou, "The application research of neural network and BP algorithm in stock price pattern classification and prediction," *Future Generation Computer Systems*, vol. 115, pp. 872–879, 2021.

[19] J. Qiu, "Analysis of human interactive accounting management information systems based on artificial intelligence," *Journal of Global Information Management*, vol. 30, pp. 1–13, 2021.

[20] C. Lavor, R. Alves, M. Souza, and L. A. Jose, "NMR protein structure calculation and sphere intersections," *Computational and Mathematical Biophysics*, vol. 8, no. 1, pp. 89–101, 2020.

[21] G. S. Chadha, A. Panambilly, A. Schwung, and S. X. Ding, "Bidirectional deep recurrent neural networks for process fault classification," *ISA Transactions*, vol. 106, pp. 330–342, 2020.

[22] Y. Zhang, F. Xiong, Y. Xie, X. Fan, and H. Gu, "The impact of artificial intelligence and blockchain on the accounting profession," *IEEE Access*, vol. 8, Article ID 110461, 2020.

[23] Y. Xu and N. Xiao, "Research on the application of Internet technology in adaptive education of accounting major," in *Proceedings of the 2nd International Conference on E-Commerce and Internet Technology (ECIT)*, March 2021.

[24] G. Zeba, M. Dabic, M. Cicak, T. Daim, and H. Yalcin, "Technology mining: artificial intelligence in manufacturing," *Technological Forecasting and Social Change*, vol. 171, Article ID 120971, 2021.

[25] D. Mhlanga, "Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: lessons from emerging economies?" *Sustainability*, vol. 13, 2021.

[26] A. Musleh Al-Sartawi, K. Hussainey, A. Razzaque, and R. Anjum, "The role of artificial intelligence in sustainable finance," *Journal of Sustainable Finance & Investment*, pp. 1–6, 2022.

[27] A. Feizi, "A gated convolutional neural network for classification of breast lesions in ultrasound images," *Soft Computing*, vol. 26, no. 11, pp. 5241–5250, 2022.

[28] K. Zhou, J. Zhang, X. Qi, W. Xu, and X. Long, "Fault diagnosis of spraying workshop based on BP neural network," *Journal of Physics: Conference Series*, vol. 1952, Article ID 032074, 2021.

[29] M. C. Pietronudo, G. Croidieu, F. Schiavone, and F. Schiavone, "A solution looking for problems? A systematic literature review of the rationalizing influence of artificial intelligence on decision-making in innovation management," *Technological Forecasting and Social Change*, vol. 182, Article ID 121828, 2022.