Construction of intelligent supply chain system of agricultural products based on big data

Jianchao Shen¹, Chenjie Xu² and Yue Ying³

¹College of Commerce and Circulation, Zhejiang Vocational and Technical College of Economics, Hangzhou, People’s Republic of China; ²School of Economics, Shanghai University of Finance and Economics, Shanghai, People’s Republic of China; ³School of Finance and Accounting, Zhejiang Vocational and Technical College of Economics, Hangzhou, People’s Republic of China

ABSTRACT
The core of agricultural product supply chain management is to emphasise the use of integrated thoughts and concepts to guide the management practices of enterprises. That is, the operation of the entire supply chain is guided by consumer demand rather than the individual management of links, and the entire supply chain is strictly controlled as a system. Based on big data technology, this paper constructs a high-performance agricultural product recommendation algorithm. Aiming at the lagging construction of my country’s agricultural product supply chain network facilities, low integration of various operating links, high logistics costs, imbalances in supply and demand, and serious agricultural product quality and safety issues, this paper combines the big data technology to study the agricultural product intelligent supply chain system, and uses the network equilibrium method to construct the agricultural product supply chain network model that considers the effort level of multiple producers and retailers. Finally, this paper proves the reliability of the system model in this paper through experimental research.

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Introduction
The agricultural product supply chain takes agricultural products as the research object and the consumption of agricultural products as the core. Moreover, it coordinates the distribution of benefits among suppliers, producers, distributors, and consumers by controlling the product flow, information flow, and capital flow of agricultural products. In addition, it starts from the means of production to complete the processes of agricultural product planting, agricultural product purchase, agricultural product processing, agricultural product transportation and distribution. Value-added agricultural production also can refer to a process of enhancing the financial value of a good or service through a particular manufacturing process. Agricultural planting item includes the time of year a specific harvest is planted in order to create well. Except for where watering is used, it is generally after first rainy season of the year. Farms, which include crops and animals. Greenhouses and nurseries that grow products for retail sale. Agriculture production process is a set of theory of market activities carried out to preserve and manage farm goods in addition to making them useful as food, feed, fibre, energy, or raw material. Road transport is essential for agriculture products allocation since it is the primary method of transferring farm goods from farmlands to markets and different urban areas. The goal of the agricultural product supply chain is to encourage all participants to coordinate and coordinate to promote the value-added of agricultural products through production, acquisition, transportation, warehousing, circulation processing, distribution, sorting, packaging, and distribution, and ultimately maximise the overall benefits of the supply chain (Ray 2017). In addition, the agricultural product supply chain also has the following characteristics: (1) the management of the agricultural product supply chain is more difficult. An agriculture supply chain system consists of institutions that are in control of manufacturing and distributing vegetable animal-based products. Agricultural crops are being used as raw resources in such chain stores to generate consumer products with greater effect. With the rapid development of modern agriculture, agricultural production has become more and more specialised, and the types of agricultural products have become increasingly abundant. A sales effect analysis is a form of marketing that evaluated the influence which a commercial or other promotional effort is possessing, and has had, just on sales of a product of been marketed. The difference in memory
supported phrases read out loud whereas phrases learn quietly during research is known as the production effect. At the same time, as people’s living standards continue to improve, consumers’ demands for agricultural products are becoming more and more diverse. At the same time, agricultural products have to go through many links from production and processing to consumption and circulation, and each link will have an impact on the quality of agricultural products, so supply chain management is more difficult (Roopaei et al. 2017). (2) The agricultural product supply chain is time-sensitive and regional. Most agricultural products have the characteristics of freshness and activity. Generally, the shelf life of agricultural products is relatively short. With the passage of time, the quality, value and price of agricultural products will continue to decline. Therefore, all links in the agricultural product supply chain are time-sensitive, and shortening the time in the agricultural product circulation process is of great significance to ensuring the value of agricultural products. In addition, agricultural production has strong regional characteristics, and agricultural products from different regions have their own characteristics. (3) The agricultural product supply chain faces higher risks. The perishable nature of agricultural products leads to higher requirements for storage and transportation equipment. Big data is a field that deals with methods for analyses, methodically trying to extract data from, and otherwise trying to deal with sets of data which are too large and complex for traditional information software applications to manage. At first, data analysis was linked to three core ideas: quantity, wide range, and speed. Big data is a strong influence on all parts of the supply chain. It would include it all from reducing delivery times to discovering attempts to overcome the communication barrier among manufacturers and distributors. Data analysis recently reported allow the integration to continuously improve and performance analysis in order to enhance efficiency. This will bring higher costs to the supply chain, and the operation will be more complicated, and the loss will be difficult to control. Therefore, the agricultural product supply chain faces higher risks. Once quality and safety problems occur in some links, all supply chain companies will be affected. (4) The seasonality of the supply of agricultural products contradicts the perennial nature of consumer demand. Generally, agricultural products have a long production cycle, and mature harvests are seasonal, so their output is relatively restricted by natural conditions, but the consumer demand for agricultural products is constant year-round. This causes the price fluctuation range of agricultural products to be relatively large, which is difficult to predict, and even the prices of the same agricultural products in different seasons will have great differences (Steenwerth et al. 2014).

Integrated supply chain management is to plan, coordinate, and control the business flow, logistics, information flow, and capital flow between suppliers, manufacturers, distributors, customers, and final consumers to make it a seamless process and achieve the overall goal of the supply chain. The integrated agricultural product supply chain can promote the integration of the above-mentioned entities into a large agricultural product production service provider, and provide agricultural products to the market based on consumer demand, thereby maximising the benefits and value generated by the supply chain. At the same time, an integrated agricultural product supply chain also helps to rationally distribute the profits of each link in the supply chain, and is conducive to the implementation of integrated monitoring of the quality of agricultural products.

**Literature review**

The traditional game research of agricultural product supply chain mainly analyses and discusses the one-to-one game problem of a single subject in the supply chain, including the game between members of the agricultural product supply chain at all levels (Rame-shaiah et al. 2015), the game between agricultural product purchase enterprises and farmers (Newell and Taylor 2017), the game between wholesale market operators and wholesalers (Channe et al. 2015), the game between TPL service providers and suppliers and retailers (Scherer and Verburg 2017), the game between producers and retailers with asymmetric information (Elijah et al. 2018) and the game between the government and farmers on the issue of subsidies, etc. However, since my country’s agricultural product producers and retailers are all developed from the self-sufficient small-scale farmer economy in the past, they are characterised by large numbers and small scales. Therefore, there (Gao et al. 2020) is widespread competition related to output among producers represented by scattered farmers, and there is also widespread competition related to sales among retailers represented by agricultural and sideline food stores. At the same time, with the improvement of traffic conditions and the rapid development of online e-commerce, the number and types of agricultural products in the market have doubled, and competition among members of the agricultural product supply chain and between products has intensified. Therefore, on the basis of the above-mentioned traditional agricultural product supply chain game research, it has important practical significance.
to take the agricultural product supply chain network composed of multiple manufacturers, multiple retailers, and multiple commodities as the research object and to study the competition game problem of the agricultural product supply chain. Aiming at the problem of competition and game in supply chain networks, scholars mainly use network equilibrium theories and methods to characterise the competition and game relations among supply chain network members, so as to study the optimal competition and game decisions of all parties in the supply chain. Kimaro et al. (2016) discussed the problem of dynamic inventory balance among multiple manufacturers and multiple vendors in the supply chain network. Terdoo and Adekola (2014) pointed out the equilibrium problem of online and offline supply chain networks, in which manufacturers and suppliers were given a decision-making opportunity in two stages to adapt to changes in demand. Thakur and Uphoff (2017) constructed a multi-commodity flow supply chain network equilibrium model with deterministic demand (Zhang et al. 2021). A supply system is a chain of steps to be followed in order to deliver a product or service to a customer. Moving and converting raw materials into final goods, transferring some of these products, and delivering them to target consumers are among steps. The supply chain is in equilibrium whenever the item flows between both the distinguishable levels of decision-makers correlate and the item tends to flow and prices satisfy the total amount of the optimal control and conditions. Chae and Cho (2016) further considered the influence of the difference of origin and brand and studied the network equilibrium problem of multi-commodity flow supply chain under the random selection of commodities. Aryal et al. (2020) extended the multi-commodity flow supply chain network equilibrium to the situation of random demand, and on this basis, studied the impact of service level differences on the random selection of consumers. Aliev et al. (2018) regarded corporate social responsibility as an influencing factor of consumers’ random choice in the multi-commodity flow supply chain network equilibrium model. Abdel-Basset et al. (2018) and Chandra et al. (2016) discussed the network equilibrium of multi-commodity flow supply chain networks under fuzzy demand based on actual market conditions. On the basis of the above research, many scholars have further studied the competition game problem of the agricultural product supply chain through the network equilibrium method. Faling et al. (2018) applied the network equilibrium method to the supply chain of agricultural products under oligopoly competition and considered the freshness of different brand products and the resulting product competition. Once the volume of traffic between a source and a destination corresponds the travel needs to be granted by the market rate, that really is, the transit time for the journeys, the equilibrium is achieved. Literature (Alipio et al. 2019) puts forward a supply chain network equilibrium model that considers product quality competition and price competition of different enterprises at the same time. Verschuuren (2018) studied the equilibrium problem of the supply chain network under the dynamic loss of freshness of agricultural products. Hidayat (2017) established an agricultural product supply chain network equilibrium model for direct sales by farmers and analysed the impact of supply constraints and product quality on farmers’ income through case studies of local apple production and sales. Clapp et al. (2018) and Manogaran et al. (2018) studied the equilibrium of the agricultural product supply chain network considering carbon emissions through comparative analysis and proposed sales decisions based on carbon emissions. Shea (2014) combined case studies to study the optimal decision-making of agricultural product manufacturers on product quality.

### Evaluation indicators of agricultural product recommendation system

As shown in Figure 1, for a complete recommendation system to function normally, three participants are required: agricultural product providers, consumers, that is, users, and websites that provide the recommendation system (Orjuela et al. 2020). A recommender system, also known as a recommendation system, is a form of information filter system that tries to predict a user’s rank or personal taste for an item.

Take a personalised website that recommends music as an example. First, the system needs to provide users

![Figure 1. Participants of the recommendation system.](image-url)
with music they are interested in quickly and accurately to meet user requirements. Then, it is necessary to make it possible for all singers’ works to be recommended to users who are interested in them, not just very famous singers. Finally, the recommendation system must be able to continuously improve its performance and service quality. It requires comprehensive and high-quality feedback from users, so that it can improve the accuracy of the recommendation system and other aspects of its performance, so that more users are willing to use the system. Increase website revenue. It can be said that a good recommendation system must take into account the interests of the three parties at the same time, so that all actual participants can achieve a win–win cooperation. Win–win cooperation typically relates to the capability of multiple parties involved in the transaction or mission to obtain shared value by having taken a mutual strategy. In other words, a good recommendation system can not only accurately predict users’ behaviours and habits, make recommendations more targeted, expand users’ horizons, and help users discover agricultural products that they are interested in but have not discovered, but also help businesses locate those in the long tail. A recommendation engine is an information filtering sub-field of machine deep learning to suggest the most necessary ones to a particular user. It works on the principle of finding patterns in customer behaviour data, that can be gathered whether implicit or explicit. Recommend agricultural products in China to users who are interested in them, increasing the business’s turnover. Only in this way can the recommendation system develop more steadily, get a greater degree of promotion and gain better user acceptance. Figure 1 illustrates the participants of the recommendation system since it delivers participant’s area. It has four components namely, user, website, recommended system, content provider. It provides user with the services.

Starting from the common interests of the three participants, scholars have proposed the following different indicators to evaluate the pros and cons of the recommendation system.

The main task of the recommendation system is to provide users with services. As an essential participant in the recommendation process, user satisfaction is one of the important indicators for evaluating the performance of the recommendation system. On the one hand, it can be obtained through questionnaires on users. User surveys can simply ask users whether they are satisfied with the system, or they can obtain different feelings about the system from the side through different questions, so as to analyse data and indirectly obtain useful information. Improve system performance. On the other hand, in the online system, the user’s behaviour on the system can reflect the user’s attitude toward the system, so the user’s clicks, stay time, and conversion rate can be counted to infer the user’s satisfaction.

Forecast accuracy. Prediction accuracy refers to a measure of whether the agricultural products recommended by the recommendation system to the user are consistent with the agricultural products that the user actually likes. The degree of nearness of an amount declaration to its real value is described as forecast accuracy. Since the declaration is really about the long term, the real value is generally not quantifiable at the moment the forecast is made. The correlation between the AMS predictive model and the real score is being used to determine prediction accuracy. An accuracy of 1 means perfect precision, whereas an accuracy of primitive variables is a random guess. The correlation between the AMS predictive model and the real score is being used to determine prediction accuracy. An accuracy of 1 means perfect precision, whereas an accuracy of primitive variables is a random guess. It is mainly obtained through offline experiments, so researchers can more conveniently explore the performance of personalised recommendation algorithms. When calculating this indicator, you first need to get a data set containing historical behaviour records of users from the website's log system. Then, the data set is randomly divided into two parts: the training set and the test set according to the specific situation. The training set is used for training and learning to establish the user’s behaviour and interest model. Use this model to compare the user’s behaviour on the previously obtained test set. Make a prediction, and finally compare the actual behaviour and the predicted behaviour on the test set, and calculate their similarity as an indicator of the prediction accuracy. For different recommended research fields and applications, there are two indicators: score prediction and Top N recommendation. The primary objective of top-N recommendation is to suggest a small set of N items from a huge set of things to every consumer.

The score prediction is based on the user’s score for the agricultural product. On the basis of knowing the user’s historical rating of agricultural products, the user’s interest model can be obtained through a specific recommendation algorithm, and the user’s possible rating of unrated agricultural products can be predicted through the interest model. Once a forecasting lead scoring model is developed, it can analyse lead generation more rapidly and easily than conventional methods. It can also efficiently pull a huge amount of
data from various sources, integrating not just internal information and also information from third-party companies and the web. u represents a user in the data set, and i represents an agricultural product in the data set is the actual score of user u on agricultural product i. We set \(\hat{r}_{ui}\) to represent user u’s ratings of agricultural products i predicted by the recommendation algorithm, and T to represent all rating items in the test set. Then, the accuracy of scoring prediction is often calculated by root mean square error (RMSE) the square root of the mean of the square of all errors, and mean absolute error (MAE). The mean absolute error is a measure of the difference in errors between number of pairs that convey the very same phenomenon. RMSE is defined as (Rubanga et al. 2019):

\[
RMSE = \sqrt{\frac{\sum_{u \in T}(r_{ui} - \hat{r}_{ui})^2}{|T|}}
\]

(1)

The definition expression of MAE is:

\[
MAE = \frac{\sum_{u \in T}|r_{ui} - \hat{r}_{ui}|}{|T|}
\]

(2)

Research believes that RMSE is more sensitive to large errors, and the addition of the mean square term increases the penalty for users who are not accurate in predicting agricultural products. MAE is sensitive to the accumulation of small errors. Therefore, if the scores are all integers, then rounding the prediction results will reduce the MAE error. P indicates the partial derivative of the parameters, n represents the agricultural product rate, K represents the hidden class. Here the equations perform the fastest descent direction of the gradient.

When most websites provide users with recommendation services, they do not provide users with predictive scores on items, but provide users with a personalised recommendation list. This recommendation list is the top N items with the highest ratings, that is, the top N items predicted to best meet the user’s personalised needs, which is called Top N recommendation. R(u) represents the recommendation list provided by the test set user by the recommendation model obtained by the recommendation system after learning and training on the training set and T(u) represents the actual behaviour list of the user on the test set. Then, the recall of recommendation results is defined as the following formula, which represents the proportion of popular recommendation results in Top N.

\[
Recall = \frac{\sum_{u \in U}|R(u) \cap T(u)|}{\sum_{u \in U}|T(u)|}
\]

(3)

The precision of recommendation results is defined as the following formula, which represents the proportion of popular results in Top N recommendations.

\[
Precision = \frac{\sum_{u \in U}|R(u) \cap T(u)|}{\sum_{u \in U}|R(u)|}
\]

(4)

Coverage mainly describes the proportion of the total number of agricultural products that can be recommended by a recommendation system to the total number of agricultural products in the system. It can be used to describe the system’s ability to mine long-tail agricultural products, so it is the main indicator that content providers will care about. A good recommendation system must not only have high user satisfaction to meet the needs of users but also have a high coverage of agricultural products to meet the commercial needs of agricultural product providers that can be profitable. When U represents the user set, R(u) represents the list of agricultural products of length N recommended by the recommendation system to each user, where u \(\in U\), the coverage is defined as:

\[
Coverage = \frac{|\{u \in U | R(u) \}|}{|U|}
\]

(5)

The diversity of recommendation results means that the agricultural products included in the recommendation list can cover the interests of users in different fields. Because although the user’s interest domain will not change in a relatively long period of time, the user’s interest is often only single at a certain moment. If the list recommended to the user by the system at this time can only cover a single point of interest of the user, and this point of interest does not meet the user’s expectations at this time, then the user will be very disappointed with the personalised recommendation system. However, if the list provided is more diverse, then users can always find what they are interested in, and the recommended list at this time has diversity.

If it is assumed that the similarity between agricultural product i and agricultural product j is denoted by s(i, j), s(i, j) \(\in [0, 1]\), then the diversity of the recommendation list provided by the system to user u can be expressed as:

\[
Diversity = 1 - \frac{1}{2} \left( \sum_{\substack{\forall u \in U, j \in R(u) \setminus \{i\} \land s(i, j) \neq 0}} \right) \frac{1}{|R(u)|(|R(u)| - 1)}
\]

(6)

The above formula only gives the diversity of the recommendation list provided to a single user. The diversity of the entire system can be defined as the average value of the diversity of the recommendation list of all individual users in the system, as shown in the following
formula:
\[
\text{Diversity} = \frac{1}{|U|} \sum_{u \in U} \text{Diversity}(R(u))
\tag{7}
\]

If it is assumed that there are users \( u \) and \( v \), \( N(u) \) and \( N(v) \) respectively represent the set of agricultural products that users \( u \) and \( v \) have rated, then the interest similarity of \( u \) and \( v \) can be expressed as:

\[
w_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|}
\tag{8}
\]

Or, it is calculated by the cosine similarity calculation formula

\[
w_{uv} = \frac{|N(u) \cap N(v)|}{\sqrt{|N(u)||N(v)|}}
\tag{9}
\]

The user’s degree of interest in a certain agricultural product can be expressed as:

\[
p(u, i) = \sum_{v \in S(u, K) \cap N(i)} w_{uv} r_{ui}
\tag{10}
\]

\( u \) represents a user belonging to the user set, \( i \) represents an agricultural product in the agricultural product concentration, and \( p(u, i) \) represents the degree of user \( u \)'s interest in the agricultural product \( i \). In the above formula, \( S(u, K) \) represents the set of \( k \) users whose interests are closest to user \( u \), \( N(i) \) represents the set of users who have rated agricultural product \( i \), and \( w_{uv} \) represents the similarity between the interests of users \( u \) and \( v \). User \( v \)'s interest in agricultural product \( i \) is represented by \( s_i \) and \( r_{ui} \) of all implicit feedback data is 1. Through the above two formulas, it is possible to calculate the similarity of interests among different users and the degree of user interest in agricultural products (Balamurugan et al. 2020). The model of user interests is a key problem for knowledge recommendation system. A consumer interests’ model is aimed to exactly define a user’s preferences in order to improve the quality of accessing information. There are three challenges for improving the user challenges modes they are initial user information, description for user interaction, profile representations.

In the implicit semantic model, the degree of user \( u \)'s interest in agricultural product \( i \) can be calculated by the following formula:

\[
\text{Preference}(u, i) = r_{ui} = p_i^T q_i = \sum_{l=1}^{F} p_{ui} q_{ik}
\tag{11}
\]

Among them, \( p_{ui} \) and \( q_{ik} \) are the parameters of the model, \( p_{ui} \) measures the relationship between user \( u \)'s interest and the \( k \)-th hidden class, and the relationship between the \( k \)-th hidden class and agricultural product \( i \) is denoted by \( q_{ik} \). The value range of interest is \([0, 1]\). After sampling, a new user-agricultural product set \( K = \{(U, l)\} \) is obtained. Among them, if \( RUI = 0 \), it means that \( (U, l) \) is a negative sample, otherwise it is a positive sample. The loss function is defined that calculates the difference between both the individual’s current output and the target outcome. It’s a method to assess how well one’s algorithm designs the information. The loss function is as follows:

\[
C = \sum_{(u,l) \in K} (R_{ul} - \hat{R}_{ul})^2 = \sum_{(u,l) \in K} \left(R_{ul} - \sum_{k=1}^{K} P_{uk} Q_{k,l}\right)^2
+ \lambda \|P_u\|^2 + \lambda \|Q_i\|^2
\tag{12}
\]

Among them, the value of \( \lambda \) is obtained by repeated experiments according to specific application scenarios and \( \lambda \|P_u\|^2 + \lambda \|Q_i\|^2 \) is a regularisation term used to prevent overfitting. The stochastic gradient descent algorithm is used to optimise the loss function. The iterative method of stochastic gradient descent is used to maximise an optimal solution with appropriate softness characteristics. It is a probability estimation of gradient descent enhancement. Stochastic gradient descent is a machine learning optimisation technique that is frequently used to find the parameters of the model that correlate to the perfect match among expected and observed outputs. It’s an inexact but powerful method. The fastest descent direction of the gradient is determined by the partial derivative of the parameters \( P_{uk} \) and \( Q_{k,i} \) as follows:

\[
\frac{\partial C}{\partial P_{uk}} = -2 \left(R_{ul} - \sum_{k=1}^{K} P_{uk} Q_{k,l}\right) Q_{k,l} + 2 \lambda P_{uk}
\tag{13}
\]

\[
\frac{\partial C}{\partial Q_{ki}} = -2 \left(R_{ul} - \sum_{k=1}^{K} P_{uk} Q_{k,l}\right) + 2 \lambda Q_{ki}
\tag{14}
\]

Under the premise of artificially determining the number of iterations, iterative calculations are continuously performed to optimise the parameters until the final parameters converge. The values of the parameters are as follows:

\[
P_{uk} = P_{uk} + \alpha \left(R_{ui} - \sum_{k=1}^{K} P_{uk} Q_{k,l}\right) Q_{k,l} - \lambda P_{uk}
\tag{15}
\]

\[
Q_{ki} = Q_{ki} + \alpha \left(R_{ul} - \sum_{k=1}^{K} P_{uk} Q_{k,l}\right) P_{uk} - \lambda Q_{ki}
\tag{16}
\]

\( \alpha \) represents the learning rate. The larger the value of \( \alpha \), the faster the iterative decline, but it is also possible to miss the optimal value. Therefore, the appropriate \( \alpha \) is also very important, and it is often obtained by
repeated experiments according to actual application scenarios.

**Intelligent supply chain system of agricultural products based on big data**

In order to explore the equilibrium problem of the agricultural product supply chain network whose demand is affected by consumer preferences. Intelligent supply chain management merely means to use a lot of information to make wise choices, use much higher tech, and gain valuable intelligence into processes, as according Smart supply chain management necessarily requires a correlation between something and everything else in the storage facility. This paper considers a secondary agricultural product supply chain composed of \( m \) agricultural product producers (hereinafter referred to as producers) and \( n \) agricultural product retailers (hereinafter referred to as retailers) as shown in Figure 2.

This paper considers a three-level agricultural product supply chain composed of \( M \) agricultural product producers, \( N \) agricultural product retailers, and \( K \) agricultural product markets as shown in Figure 3. The research object is a three-level FAP distribution network in Cloud computing that contains a supplier, distribution company, and seller.

This paper considers a two-level agricultural product supply chain composed of \( m \) agricultural product producers and \( n \) agricultural product retailers as shown in Figure 4.

The government and the agricultural product supply chain network jointly form a supply chain network decision model based on Stackelberg-Nash-Cournot competition, According to Stackelberg group is known, one or even more group members have a higher hierarchy location, and its method creates the techniques for other attendees as shown in Figure 5.

This paper assumes that the initial quality of agricultural products is affected by the production effort level of the producer, and the freshness preservation ability of agricultural products is affected by the retailer’s sales effort level. Moreover, the better the quality of agricultural products, the less quantity loss. Therefore, the market demand for agricultural products is not only affected by the prices of agricultural products, but also by the efforts of all parties in the supply chain. A supply chain is a system that connects a company and its vendors to manufacture and distribute a particular product to the end consumer. This system comprises of multiple actions, individuals, entities, details, and materials. The basic model of the supply chain network considering the effort level is shown in Figure 6.

The combined contract constructed in the third-party logistics model uses two types of contracts to act on the different decision-making processes of the three decision-making subjects. Third-party logistics refers to the sourcing of digital commerce logistics such as managing inventory, storage of goods, and satisfaction to a third-party company. Figure 7 reflects the coordination mechanism of the combined contract on the supply chain.
chain of agricultural products under different logistics modes.

Conceptual models are psychologically conceptual interpretations as to how work must be conducted out. Individuals use concepts to systematise procedures subconscious level and spontaneously. TPLs provide a broad array of services, such as road transport, storage of goods, select and bag, monitoring of goods, periodic data, advancement performance indicators, factories, and a wide range of many other value-added services. Three-tier green supply chain model for an agricultural product where by products are used for some purposes. Solution procedure of the model is derived. A

Figure 4. The network model of the agricultural product supply chain whose demand is affected by the efforts of all parties.

Figure 5. The quality and safety incentive and supervision decision-making model of agricultural product supply chain.

Figure 6. The basic model of a supply chain network considering the level of effort.

Performance verification of agricultural product intelligent supply chain system based on big data

After constructing an intelligent supply chain system for agricultural products based on big data technology, this paper conducts performance verification analysis on the
The big data system constructed in this paper uses the recommendation algorithm as the core algorithm, and the intelligent supply chain system can effectively improve the operating efficiency of the entire supply chain system. Therefore, when analysing system performance, this paper first verifies the performance of the recommended algorithm and then verifies the efficiency of the entire system. First, the agricultural product recommendation algorithm is verified, and the results shown in Table 1 and Figure 9 are obtained by simulation test.

From the above research, it can be seen that the agricultural product recommendation algorithm proposed

### Table 1. Statistical table of recommended algorithm effect.

| Num | Recommended effect | Num | Recommended effect | Num | Recommended effect |
|-----|--------------------|-----|--------------------|-----|--------------------|
| 1   | 95.80              | 34  | 94.40              | 67  | 92.90              |
| 2   | 95.05              | 35  | 93.49              | 68  | 92.89              |
| 3   | 92.98              | 36  | 94.04              | 69  | 92.41              |
| 4   | 96.26              | 37  | 96.35              | 70  | 96.40              |
| 5   | 96.20              | 38  | 92.55              | 71  | 93.96              |
| 6   | 95.59              | 39  | 95.11              | 72  | 93.34              |
| 7   | 94.49              | 40  | 93.82              | 73  | 94.19              |
| 8   | 96.42              | 41  | 96.27              | 74  | 93.95              |
| 9   | 92.18              | 42  | 94.40              | 75  | 96.58              |
| 10  | 94.84              | 43  | 93.16              | 76  | 96.99              |
| 11  | 93.48              | 44  | 93.14              | 77  | 92.24              |
| 12  | 92.38              | 45  | 95.94              | 78  | 92.35              |
| 13  | 92.24              | 46  | 95.83              | 79  | 95.67              |
| 14  | 92.17              | 47  | 96.59              | 80  | 93.98              |
| 15  | 96.92              | 48  | 96.92              | 81  | 92.90              |
| 16  | 93.88              | 49  | 95.91              | 82  | 94.98              |
| 17  | 93.08              | 50  | 93.47              | 83  | 94.89              |
| 18  | 94.98              | 51  | 94.17              | 84  | 93.29              |
| 19  | 96.01              | 52  | 94.19              | 85  | 95.22              |
| 20  | 96.93              | 53  | 93.42              | 86  | 94.57              |
| 21  | 93.21              | 54  | 95.61              | 87  | 92.15              |
| 22  | 92.33              | 55  | 95.11              | 88  | 92.41              |
| 23  | 92.36              | 56  | 94.86              | 89  | 93.02              |
| 24  | 94.38              | 57  | 93.72              | 90  | 95.47              |
| 25  | 95.64              | 58  | 96.91              | 91  | 92.00              |
| 26  | 96.77              | 59  | 96.91              | 92  | 92.45              |
| 27  | 93.97              | 60  | 93.30              | 93  | 92.65              |
| 28  | 93.44              | 61  | 95.83              | 94  | 92.23              |
| 29  | 96.69              | 62  | 95.11              | 95  | 95.51              |
| 30  | 94.80              | 63  | 96.99              | 96  | 96.84              |
| 31  | 93.52              | 64  | 96.94              | 97  | 96.19              |
| 32  | 96.64              | 65  | 94.18              | 98  | 96.44              |
| 33  | 93.16              | 66  | 96.78              | 99  | 96.84              |
in this paper has better performance. On this basis, the system operation effect verification is carried out, and the results obtained are shown in Table 2 and Figure 10.

From the above results, it can be seen that the intelligent supply chain system of agricultural products based on big data technology constructed in this paper has certain practical effects.

### Conclusion

An efficient agricultural product supply chain is the cornerstone of agricultural modernisation. Aiming at the lagging status of my country’s agricultural product supply chain network facilities, low integration of various operations, high logistics costs, imbalances in supply and demand, and serious agricultural product quality and safety issues, this paper combines the big data technology to study the agricultural product intelligent supply chain system and uses the network equilibrium method to construct an agricultural product supply chain network model that takes into account the efforts of multiple producers and retailers. Moreover, this paper describes the competition and cooperation between supply chain network members and analyses the impact of the efforts of all parties on the supply chain network production and sales and profits in different situations. Finally, this paper constructs an intelligent supply chain system to verify the performance of the system. From the experimental research results, it can be known that the agricultural product intelligent supply chain system constructed in this paper has good practical effects.

### Disclosure statement

No potential conflict of interest was reported by the author(s).

### Notes on contributors

**Jianchao Shen**, male, born in October 1988, master’s degree, lecturer of Zhejiang Technical Institute of Economics College, graduated from Leeds Metropolitan University, UK. His research direction is marketing and supply chain.

**Chenjie Xu**, male, born in October 1988, PhD candidate, lecturer of Shanghai University of Finance and Economics, majored in finance and supply chain.

**Yue Ying**, female, born in March 1990, with a master’s degree, is a teaching assistant of Zhejiang Technical Institute of Economics College. She graduated from the University of South Wales, UK, majoring in business administration. Her research direction is English and business administration.

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