

## Research Article

# Research on Open Innovation Intelligent Decision-Making of Cross-Border E-Commerce Based on Federated Learning

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Product development and innovation is the key issue for cross-border e-commerce operation. It is of great importance to build an intelligent open innovation system and maximize its proximity to market demand with the internationalization and digital advantages of cross-border e-commerce. Cross border e-commerce data is widely distributed among each node enterprise in the supply chain. But the enterprises will not share private data for intelligent learning for the sake of data security, which has become a difficulty problem in intelligent decision-making of open innovation. This paper analyzes the research status of open innovation and the technical basis of federated learning, builds an open innovation intelligent decision-making model of cross-border e-commerce based on federated learning, trains and tests the model using data from two participants, compares the intelligent prediction effects among whole learning, local learning and federated learning, and puts forward the collaborative promotion strategy of open innovation and intelligent optimization of cross-border e-commerce based on federated learning.

## 1. Introduction

The development and growth of cross-border e-commerce has promoted the continuous improvement of supply chain system, the rapid expansion of global market, and the widespread development of digital trade. According to the data of the Ministry of Commerce of China, the size of China's cross-border e-commerce transactions reached 1.98 trillion CNY in 2021, up 15% year-on-year. From 2015 to 2022, China's cross-border e-commerce comprehensive pilot zones have been expanded for six times to reach 132, which have driven the development of new forms of foreign trade through pilot projects. Hindered by the COVID-19 pandemic, the operation of the global supply chain relies more on cross-border e-commerce model, which further promotes the development of global cross-border e-commerce trade. Under the new pattern of "double cycle" development, cross-border e-commerce has become an important way for enterprises to internationalize and a strong driving force for trade upgrading. At present, cross-

border e-commerce has entered the era of branding and intelligent development. The traditional way of directly selling a large number of products on cross-border e-commerce platforms can no longer meet the market demand. It is far from encouraging to evaluate the development of cross-border e-commerce enterprises only by GMV (Gross Merchandise Volume) sales indicators. Instead, it is necessary to use data to effectively drive marketing innovation, product research and development, and customer life cycle management optimization, among which the most critical issue is product development and selection. However, the two types of cross-border e-commerce enterprises are faced with two bottleneck problems. First, the traffic-type cross-border e-commerce enterprises lack good product accumulation and supply chain information, and cannot integrate the best supply chain resources. Second, the manufacturing-type cross-border e-commerce enterprises cannot accurately meet consumer demand in the international market, and it is difficult to plan and design according to the market preferences and key pain points. Therefore, it

is urgent to jointly build an open innovation system, use artificial intelligence technology to assist product innovation and development, promote the simultaneous upgrading of both the supply side and the demand side, and realize the intelligent evolution of cross-border e-commerce to a higher level.

Networking, digitalizing, and intelligence provide five driving forces for the development of cross-border e-commerce and even the upgrading of the whole industrial chain. First, it aims to achieve rapid growth by connecting supply and demand with cross-border e-commerce platforms, integrating international resources, exploring the global market, and driving the international development of common industrial clusters such as manufacturing, R&D, sales, logistics, and marketing, which have created huge space for global growth. Second, it is to gain high performance by implementing differentiated competition strategies for different countries, regions, and consumer markets, and those personalized marketing strategies such as products, brands, prices, channels, promotions, and services will bring more profit space to enterprises. Third, fully open will be achieved because the digital development of cross-border e-commerce enables more small and medium-sized enterprises to sell globally, facilitates the international cooperation of previously unrelated enterprises, promotes transnational, cross-border, and cross-industry supply chain cooperation, and makes the whole industrial operation more open, professional, transparent, and international. Fourth, experience will be optimized as cross-border e-commerce consumers can obtain first-class shopping experience from visual product display and experience system, intelligent product recommendation system, efficient customer service system, differentiated marketing communication system, and rich communication channels and means. Fourth, it is an excellent experience. Visual product display and experience system, intelligent product recommendation system, efficient customer service system, differentiated marketing communication system, and rich communication channels and means make cross-border e-commerce consumers obtain a first-class shopping experience. Fifth, it is a strong integration. The in-depth development and interwoven application of big data, blockchain, cloud computing, artificial intelligence, virtual reality, augmented reality, Internet of Things, and 5G technology have promoted data sharing and business integration, empowered all participants in the cross-border e-commerce ecosystem, provided rich application scenarios for cross-border e-commerce, and promoted supply chain coordination, cross scenario optimization, and industrial cluster upgrading.

Open innovation of technology networking, digitization, and intelligence has brought three benefits to cross-border e-commerce. One is to predict market demand. Cross-border e-commerce is characterized by globalization, complication, and dynamics. North America, Western Europe, and Japan are developed cross-border e-commerce markets, which grow steadily and step into maturity. The cross-border e-commerce market in emerging markets is rising rapidly, for instance, Malaysia and the Philippines in Southeast Asia, Russia in Eastern Europe, India in South

Asia, Brazil in South America, Mexico in Latin America, and the United Arab Emirates in the Middle East. The scale of cross-border e-commerce is growing rapidly and has huge potential. Therefore, it is necessary to accurately study and judge the local market demand with the help of digital technology. Second is the capacity to prepare supplies. Advance production, prestocking, and overseas warehouse configuration can avoid congestion and high freight rates during peak periods and losses caused by product shortage or unsalable. Epidemic situation abroad, which repeatedly hit the supply chain system of many countries, leads to the phenomenon appeared again and again, such as international logistics tight, soaring freight, warehouse explosion, and shortage of shipping containers, which are urgent to be optimized and solved with the help of information technology and has increased the dependence on cross-border e-commerce shopping and greatly promoted the development of overseas warehouses at the same time. Third is supply and demand prematching. Digital and intelligent technologies are rapidly spreading in the R&D and design, production and manufacturing, international marketing, website operation, and logistics distribution of cross-border e-commerce. The introduction of these technologies can effectively reduce redundant links in cross-border trade, clarify the rights and responsibilities of cross-border cooperation, break through the barriers of international trade cooperation, and improve the efficiency of supply and demand matching.

## 2. Literature Review

*2.1. Connotation and Role of Open Innovation.* With the help of information technology, open innovation can break the boundaries of enterprises, industries, and territories, thereby integrating and utilizing the internal and external innovation resources of organizations to the maximum extent and improving the efficiency of resource allocation and technological innovation. Chesbrough [1] believed that open innovation realizes the across organizational flow of innovation resources and can obtain and commercialize innovation resources from both inside and outside the enterprise, which greatly makes up for the lack of innovation resources within the enterprise and significantly enhances the innovation ability and innovation performance of the industrial chain [2, 3]. Fernandes et al. [4] combed the research achievements on open innovation and summarized the six research perspectives: open innovation concept, open innovation network, open innovation knowledge, open innovation spillover, open innovation management, and open innovation technology. Bereznoy et al. [5] did not regard knowledge sharing and open innovation as two independent processes and believed that with the help of digital platform ecosystem can realize the interwoven interaction between knowledge sharing and open innovation. Cross-border e-commerce does have a direct and positive impact on market innovation, and open innovation activities also have an important impact on the market value of e-commerce platform companies [6]. Advanced digital technologies and the acceleration of process digitization, as well as the

growing expectations of stakeholders, make it imperative for organizations to embrace open innovation [7].

The essence of open innovation is to open organizational boundaries, effectively integrate internal and external knowledge, information, technology, policies, and other resources, and integrate multiagent innovation to improve innovation performance. Open innovation in the context of cross-border e-commerce can involve a wider range of consumers and more types of enterprises around the world to promote the flow of innovation resources and the cooperation of innovation subjects in an all-round and multi-angle manner. The deep integration of open innovation with cross-border e-commerce, big data, and artificial intelligence can increase the depth and breadth of innovation opening, greatly extend the innovation chain, and improve the mode of innovation value chain, which promote the rapid flow of various important resource elements inside and outside the organization, effectively integrate global resources for innovation, and improve innovation ability. Through cross-border e-commerce networks, more consumers can participate in value cocreation and enhance their commercialization transformation capability.

*2.2. Influencing Factors of Open Innovation.* Alassaf et al. [8] found that organizational culture, employee's knowledge and attitude, and employee incentives have a significant impact on open innovation. Wu and Ding [9] constructed an open innovation performance model including information technology capability, external knowledge integration, and search analysis strategy, and explored the internal mechanism of improving the performance of open innovation. The external knowledge search path is particularly important for the open innovation of small and medium-sized enterprises. When looking for external knowledge in the process of innovation research, it is suitable to adopt the combination of cognitive search and experiential search, while in the process of innovation development, it is suitable to adopt experiential search strategy [10]. Aiming at demand mining, process optimization, value cocreation, supply chain reconstruction, and ecosystem construction. Chen et al. [11] studied the strategy of optimizing consumption experience and enhancing customer value by taking advantage of digital technology. Yang and Liu [12] thought that open innovation generally goes through a process of "primary opening stage - mature opening stage - leading opening stage". Knowledge collaboration among users of open innovation communities is very important to increase the knowledge innovation activity of communities and strengthen the attractiveness of communities[13]. Shi et al. [14] analyzed the organization mode, development path, and innovation method of alliance blockchain in the context of open innovation.

*2.3. Realization Mode of Open Innovation.* Enterprise wishing to gain competitive advantages should focus on open innovation, actively utilize information technology and Internet platform to adjust business process management, and promote the implementation in their operating ecosystem and organizational network. It can manage and

coordinate open innovation decisions between strategy and operation to support the creation and acquisition of enterprise value[15]. The in-depth application of cloud computing, artificial intelligence, blockchain, and other technologies in enterprises ensures the efficiency, security, wisdom, and trust of cooperation, which lays a technical foundation for more openness and cooperation and opens a new era of achievable open innovation[16]. Allio [17] showed that open innovation should cooperate with experienced innovators, thus accelerating organizational learning and reduce internal inefficiency activities. Pera et al. [18] pointed out that the fundamental driving factors of multi-stakeholder value creation are trust, inclusiveness, and openness.

Based on customer experience and enterprise performance, workflow will be combined with powerful tools such as artificial intelligence technology, automation technology, and digital business platform to plan open innovation, improve the ability and efficiency of working mode information acquisition and organizational work, and be good at using innovative technology to build the core competitiveness of new business models [19]. Vincenzi and da Cunha [20] suggested that open innovation should consider operational innovation performance and commercial innovation performance, therefore determine the intensity, breadth, and depth of open innovation. Abbate et al. [21] proposed that open innovation requires digital platforms to provide collaborative process, tools, and services to support innovation interaction coupling and knowledge cocreation. As social media applications are widely used around the world, enterprises should actively utilize internal and external knowledge of social media to promote open innovation and development [22]. Papa et al. [23] demonstrated that in the context of complex collaborative networks, big data technology is used to promote the accumulation and exchange of data, continuously absorb new knowledge from the outside, and share the knowledge within the enterprise to the outside. This collaborative model has a strong impact on innovation performance.

Overall, artificial intelligence, which has gradually entered the field of cross-border e-commerce, promotes the automation and intelligent development of cross-border e-commerce. Existing applications include personalized recommendation, customer service robot, virtual experience, transaction risk identification, bogus deals, and false comment identification. However, the toughest question encountered in cross-border e-commerce operation is product development and selection. How to build an open innovation system by virtue of the international, digital, and intelligent advantages of cross-border e-commerce and maximize its proximity to market demand has become crucial. Cross-border e-commerce data is widely distributed among enterprises at each node of the supply chain. For the sake of data security, enterprises will not share private data for intelligent learning, which becomes a difficult problem for open innovation intelligent decision-making. However, existing relevant studies have not provided effective solutions. For example, Niu et al. [24] pointed out that the sharing of cross-border e-commerce sales data benefits all

parties in the supply chain, but there is no further analysis of how to share data. Markovict et al. [25] only pointed out that the open innovation of B2B enterprises should focus on the selection of business partners, innovation process, and innovation results. Yan et al. [26] believe that leading e-commerce platform companies should explore new markets through open innovation, integrate supply chains, and innovate products and services with the support of information technology. Zhang et al. [27] explored the use of tax rate uncertainty to implement cross-border e-commerce supply chain information sharing strategy.

To sum up, the existing open studies focus more on definition, influencing factors, and countermeasures and suggestions, while the specific intelligent optimization technologies and methods remain in the traditional index analysis and knowledge model. In the era of rapid development of artificial intelligence, it is necessary to use deep neural network to achieve a more comprehensive, more sensitive and deeper insight into the open innovation behavior of cross-border e-commerce, and realize intelligent innovation decisions.

Federated learning is a distributed machine learning approach in which clients learn global models in a privacy-preserving way, taking into account both information sharing and privacy protection [28]. The research on federal learning in cross-border e-commerce open innovation is very rare and still blank. This paper establishes the cross-border e-commerce sales data set, and constructs the cross-border e-commerce open innovation federated learning intelligent decision-making model with deep learning as the edge calculation, which can mine the innovation characteristics from more dimensions, more complex levels, and more platforms, and has higher applicability and accuracy. This study will help guide cross-border e-commerce enterprises to integrate the data resources of each node of the supply chain, identify the external path of internal innovation commercialization, and constantly broaden the development path.

### 3. Intelligent Optimization Model of Cross-Border e-Commerce Open Innovation Based on Federated Learning

*3.1. Federated Learning Type.* Big data is the “textbook” of intelligent learning. With the personal privacy protecting in the data security specification, it is more and more difficult to obtain large number of high-quality training data. As a result, federated learning is born from the application whose core idea is that data is available but invisible and the data does not move but model moves. Each data holder trains the model locally and the data will not flow out. The trained model with structure, parameters and gradient is exchanged, shared, and deployed among all participants, thus reducing the risk of data leakage. In 2016, Google scientist McMaha et al. first proposed the concept of federated learning [29]. Then, the deep learning framework PyTorch developed by Facebook began to adopt federated learning technology to protect users’ privacy, followed Google launched Tensorflow

Federated, Open Mined launched Pysyft, WeBank developed FATE, Baidu developed PaddlePaddle, showing broad research and application prospects. Federated learning can be divided into Horizontal Federated Learning, Vertical Federated Learning, and Federated Transfer Learning according to the different situations how holders own their data.

Federated learning, a distributed machine learning paradigm, allows training models of scattered data on large-scale edge or mobile devices without the need to collect raw data [30], which effectively mitigates unnecessary bandwidth loss, and enhances data privacy and legitimizing [31]. Palihawadana et al. [28] performed local clustering for customers with similar gradients, and then conducted further global aggregation. Lee and Lee[32] aggregated the strategies of each system into central strategies to speed up learning.

In horizontal federated learning, data characteristics  $X_1, X_2, \dots$  (some data sets also include label data  $Y$ ) of data sets of two data holders overlap largely, while the overlap of users  $U_1, U_2, \dots$  is small. In this way, data sets with the same data features of both parties but different users are extracted for training, as shown in Figure 1. Competitors of the same type of business or enterprises with the same business but distributed in different regions have different user groups or come from different regions and their intersection is very small. The joint training of this type of enterprises belongs to horizontal federated learning.

In longitudinal federated learning, users  $U_1, U_2, \dots$  in the data sets of the data holder have a large overlap, while the overlap part of data features  $X_1, X_2, \dots$  is small. Then the portion of data with the same users but different data characteristics is taken out for training, as shown in Figure 2. Users of enterprises in the same industrial chain and supply chain often have a large intersection, for example, banks and e-commerce enterprises. Banks record users’ income and expenditure and credit rating, while e-commerce enterprises record users’ browsing and purchasing information. Their intersection in data features is small, but the intersection of users is large. This type of joint training belongs to longitudinal federated learning. In the process of longitudinal federated learning, the user groups of both data holders cannot overlap completely. It is necessary to find the public ID sets of both sides without leaking data. This technology is called Private Set Intersection (PSI), that is, sample alignment.

In federated transfer learning, when the overlap between user  $U_1, U_2, \dots$  and data feature  $X_1, X_2, \dots$  of both data sets is relatively small, transfer learning is suitable to be utilized to overcome data or label deficiency. By relying on the similarity between data, tasks, or models, the model trained in the source domain is applied to the target domain, as shown in Figure 3. When the businesses of the two enterprises are different and the intersection of user groups is small, such as garment sales enterprises and book sales enterprises, garment sales enterprises have realized intelligent recommendation of clothes for customers, then, by transferring this intelligent recommendation ability to book sales enterprises through transfer learning, the effect of book intelligent recommendation for customers can be achieved. Joint

	ID	X1	X2	X3	Y
Data holder A	U1				
	U2				
	U3				
Data holder B	U4				
	U5				
	U6				

FIGURE 1: Horizontal federated learning.

	ID	X1	X2	X3	Y	X4	X5	ID
Sample alignment	U1							
	U2							U2
	U3							U3
	U4							U4
								U5
								U6

FIGURE 2: Longitudinal federated learning.

learning of the cross profession, cross-industry, interdepartmental and crossover marketing, and so on all belongs to federated transfer learning.

3.2. *Federated Learning Process.* The steps of federated learning process are as follows.

Step1: data holder A and B use their own data to train the local model.

Step2: local training model A and B encrypt gradient and then upload it to the server.

Step3: the server aggregates the gradient updating model parameters of each user to form a new aggregation model.

Step4: the server returns the updated aggregation model to both parties A and B.

Step5: each participant updates its own model and waits for the next round of training convened by the server.

If it is longitudinal federated learning, the technical means of encrypted text alignment (PSI) technology should be adopted before training to screen out common users among different enterprises in the system and then start training, as shown in Figure 4.

3.3. *Federated Learning Data.* Taking the dress category in the cross-border e-commerce market as an example, the sales records of 862 dresses in 2020 are collected, thus forming the dress sales data sets. The data set includes such characteristic variables as Dress ID, Style, Price, Rating, Size, Season, Neckline, Sleeve Length, Waistline, Material, Fabric Type (To simplify the in-store experience of clothing products Amazon merged the existing properties of Material and Fabric Type into Fabric Type properties starting from 8/20/2021.), Decoration, and Pattern Type. It also includes developing recommendation label variable. The attributes of this data set and their values are shown in Figure 5.

	ID	X1	X2	X3	Y	X4	X5	ID
Source domain	U1							
	U2							
	U3							
	U4							
								U5
								U6

FIGURE 3: Federated transfer learning.

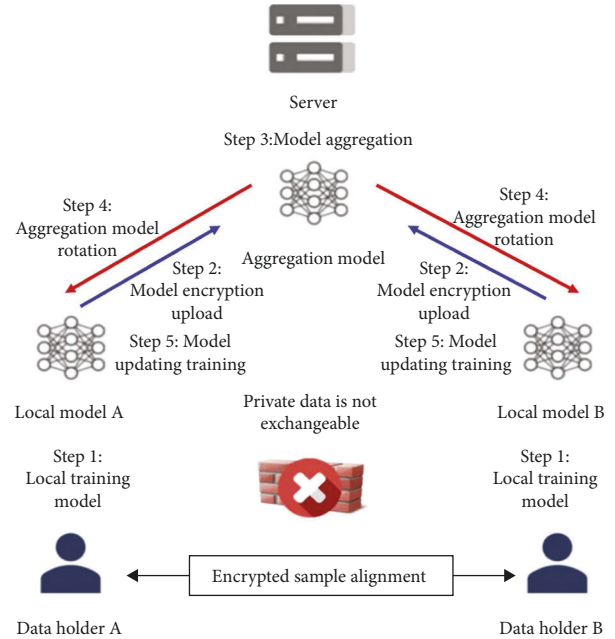


FIGURE 4: Federated learning process.

3.4. *Federated Learning Algorithm.* We use the federated averaging algorithm to optimize locally the participant client by reducing the local SGD (stochastic gradient descent) of the data holder participants and then aggregate the data at the central server. The objective function of Federated averaging is as follows:

$$f(\omega^*) = \min \left\{ f(\omega) = \frac{1}{M} \sum_{n=1}^M E[f(\omega; x; x \in n)] \right\}, \quad (1)$$

where  $M$  represents the number of data holders participating in joint modeling and  $\omega$  represents the current parameters of the model. The federal average algorithm is shown in Table 1.

## 4. Intelligent Optimization Analysis of Cross-Border e-Commerce Open Innovation Based on Federated Learning

4.1. *Data Preprocessing.* Before machine learning data need to be preprocessed to analyze the structure, characteristics, quality, attributes, and distribution of data, whether there are missing data, nonstandard data, uneven distributed data, and other situations such as, thereby laying a foundation for intelligent learning. The 862 data records in the data sets are allocated to Guest and Host for federated learning simulation, of which, the Guest holds 406 data and the Host holds

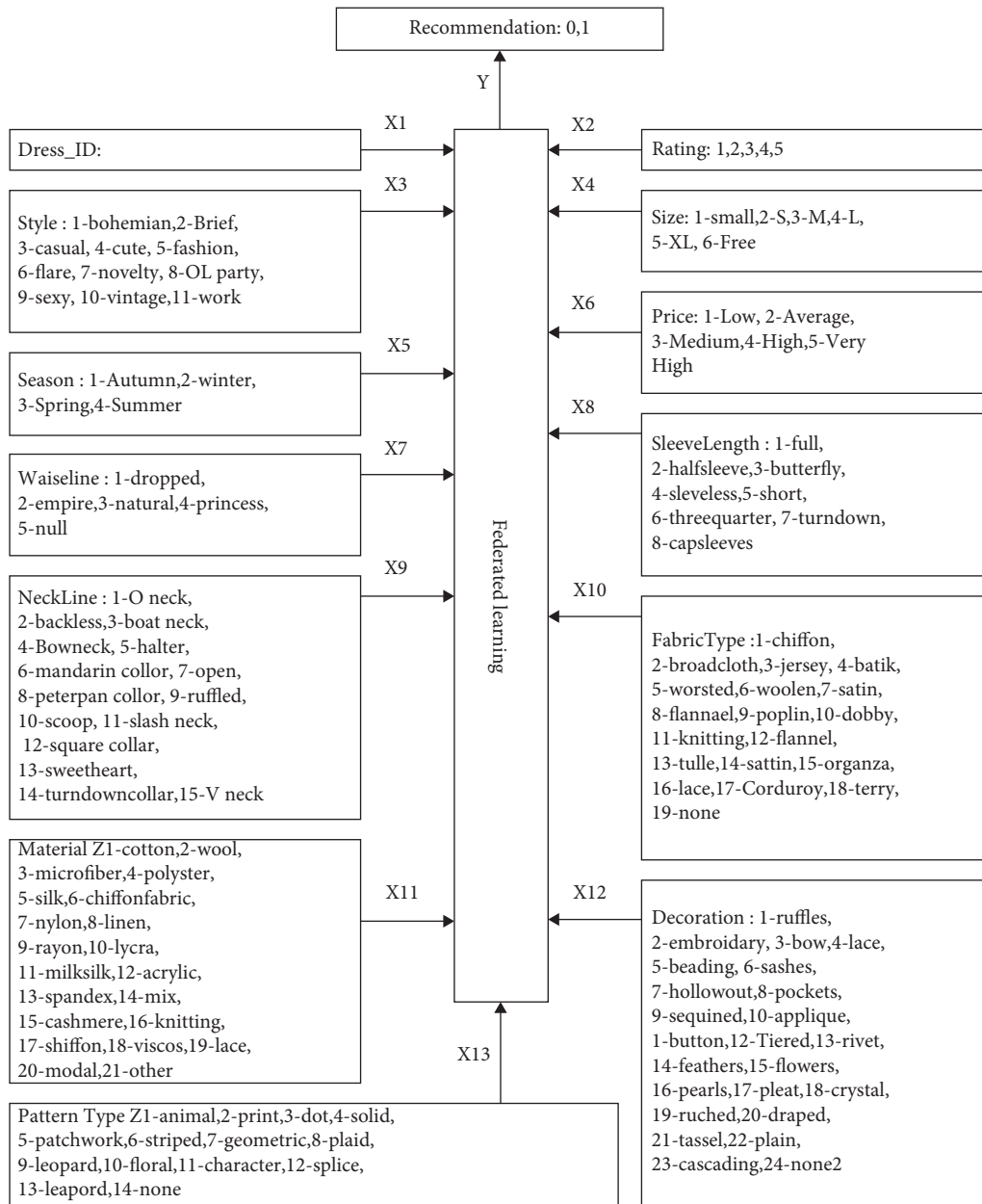


FIGURE 5: Sales data sets of dress category of cross-border e-commerce.

456 data, as shown in Figure 6 and the figure shows the first five records in the data of both parties. It could be seen that the attribute values in the data set are all English characters, and these unprocessed data cannot be used for machine learning. Therefore, the text of the attribute value is converted according to the corresponding numbers in Figure 5. After conversion, the first five records in the data sets of both Guest and Host are shown in Figure 7. Meanwhile, the attribute value Dress\_ID does not affect intelligent development decisions, so delete Dress\_ID attribute. Finally, the data is segmented, where 80% is used as training data that the Guest side includes 324 training data and the Host side includes 364 training data, and 20% as test data that the Guest party includes 84 test data and the Host party includes 92 test data.

**4.2. Local Deep Learning.** The data holders Guest and Host utilize their own data to train the local model and use the deep neural network to complete the local training. First, a fully connected layer called dense\_1 is constructed as the input layer, and ReLU activation function is used to transform the 12-dimensional input into 128-dimensional output, the layer thus generating 1664 estimated parameters  $w$ . In order to avoid overfitting phenomenon in machine learning process, a random disconnection layer dropout\_1 is added and 20% of input neurons are disconnected when updating parameters each time during training. Subsequently, a fully connected layer dense\_2 is established and ReLU activation function is used to transform 128-dimensional inputs into 32-dimensional outputs, at which time 4218 estimated parameters  $w$  are generated. Finally, the

TABLE 1: Federated learning averaging algorithm.

Federated averaging algorithm	
	Randomly select $M(n = 1, \dots, M)$ participants from $N$ participants; $I$ is the time of cycle; $\omega_0$ is The initial gradient provided for the server; $E$ is the number of time periods on the local SGD (stochastic gradient descent); Server: To initialize $\omega_0$ From $\tau = 1, \dots, T$ : The server sends $\omega_\tau$ to $M_\tau$ : Each client $n \in M_\tau$ : $\omega_{\tau+1}^n \leftarrow \text{Local Update}(n, \omega_\tau)$ $\omega_{\tau+1} \leftarrow 1/N \sum_{n=1}^{M_\tau} \omega_{\tau+1}^n$ Local Update $(n, \omega)$ : Number of local device sessions for each participant 1 to $E$ : Update $\omega_{\tau+1}^n$ according to the learning rate $\eta$ and $\omega_\tau^n$ Feedback $\omega_{\tau+1}^n$ to the server
Input:	
Output:	Optimized global gradient $\omega$

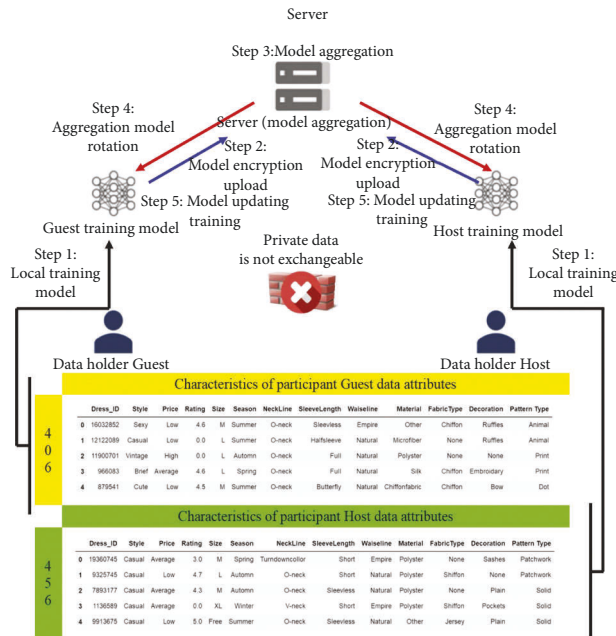


FIGURE 6: Federated learning process of open innovation in cross-border e-commerce.

fully connected layer dense\_3 is established, and the sigmoid function is used to transform the 32-dimensional inputs into the 2-dimensional outputs  $Y'$ , as shown in Figure 8.

The data holder Guest uses Keras learning framework and Adam optimizer to train the model for 500 rounds with its own data and the results are shown in Table 2. Training loss decreases from 0.7694 to 0.1123 and training accuracy increases from 0.5386 to 0.9645. The testing loss is 1.7040 and the testing accuracy is 0.5915. The effect is not ideal.

The Keras learning framework and Adam optimizer are used to train the data holder Host for 500 rounds and the results are shown in Table 3. The training loss decreases from 0.8093 to 0.0710 and the training accuracy increases from 0.4986 to 0.9780. The testing loss is 1.3690 and the testing accuracy is 0.6254. The effect is also poor.

**4.3. Federated Learning Training.** The local trained models of Guest and Host are encrypted with gradients and uploaded to the server. The server end aggregates the gradients of both sides and updates the model parameters with the average algorithm to form a new aggregation model. The server end returns the updated aggregation model to Guest and Host participants. Guest and Host update their models and participate in the next round of training summoned by the server end. The process is shown in Figure 6.

The Pysyft framework is used to conduct federated training for Guest and Host and the training results are shown in Table 4. It is seen that the training loss is reduced from 0.7427 to 0.0748, and the training accuracy is improved from 0.5327 to 0.9798. The testing loss is 0.9476 and the testing accuracy is 0.7880. The effect is greatly improved.



Dress_ID	Style	Price	Rating	Size	Season	Neck Line	SleeveLength	Waive line	Material	Fabric Type	Decoration	Pattern Type
0 16032852	9	1	4.6	3	4	1	4	2	21	1	1	1
1 12122089	3	1	0.0	4	4	1	2	3	3	19	1	1
2 11900701	10	4	0.0	4	1	1	1	3	4	19	24	2
3 966083	2	2	4.6	4	3	1	1	3	5	1	2	2
4 879541	4	1	4.5	3	4	1	3	3	6	1	3	3

Data processed by data holder Guest

Dress_ID	Style	Price	Rating	Size	Season	Neck Line	SleeveLength	Waive line	Material	Fabric Type	Decoration	Pattern Type
D9360745	3	2	3.0	3	3	14	5	2	4	19	6	5
I9325745	3	1	4.7	4	1	1	5	3	4	1	24	5
Z7893177	3	2	4.3	3	1	1	4	3	4	19	22	4
3I136589	3	2	0.0	5	2	15	5	2	4	1	8	4
49913675	3	1	5.0	6	4	1	4	3	21	3	22	4

Data processed by data holder Host

FIGURE 7: The first 5 records of the data sets processed by both data holders.

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 128)	1664
activation_1 (Activation)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 32)	4128
activation_2 (Activation)	(None, 32)	0
dense_3 (Dense)	(None, 2)	66
activation_3 (Activation)	(None, 2)	0
Total params: 5,858		
Trainable params: 5,858		
Non-trainable params: 0		

FIGURE 8: Deep neural network structure of open innovation of cross-border e-commerce open innovation.

**4.4. Analysis of Federated Learning Results.** The fully transparent situation is selected for comparison, that is, all the Guest and Host data are open and shared, and 862 pieces of data from both are used for overall training. The learning framework Keras is also used, and Adam optimizer is selected for deep learning of all the data, where 80% of the data is used as training data (including 689 pieces of data) and 20% of the data is used as testing data (including 173 pieces of data). The learning results are shown in Table 5. It is seen that the training loss decreases from 0.2538 to 0.0442, and the training accuracy increases from 0.9020 to 0.9826. The testing loss is 0.8188 and the test accuracy is 0.8092 with the effect reaching a good level.

By comparing overall learning, Guest local learning, Host local learning, and federated learning (Figure 9), it

could be found that overall learning is optimal in terms of indicators such as training accuracy, training loss, testing accuracy and testing loss, followed by federated learning, and local learning at the last. In the increasingly demanding environment of data protection, federated learning is the best choice and can achieve better learning results.

In this paper, 13 characteristic attributes and 1 label attribute are applied to construct a deep neural network, which is rich in variables and delicate in description, and can better identify the key features in open innovation system. With the continuous accumulation and improvement of data, more abundant characteristic variables and label variables of cross-border e-commerce can be developed, and more in-depth open auxiliary decisions such as product, quantity, price, channel, and promotion can be made. Then,



TABLE 2: Local learning results of data holder Guest.

	Training rounds	Training time	Training loss	Training accuracy
Epoch 1/500	324/324 [=====]	-0s 462us/step	- Loss: 0.7697	- Accuracy: 0.5386
Epoch 2/500	324/324 [=====]	- 0s 58us/step	- Loss: 0.7236	- Accuracy: 0.5556
Epoch 3/500	324/324 [=====]	- 0s 52us/step	- Loss: 0.6956	- Accuracy: 0.5818
.....				
Epoch 498/500	324/324 [=====]	- 0s 58us/step	- Loss: 0.1102	- Accuracy: 0.9545
Epoch 499/500	324/324 [=====]	- 0s 58us/step	- Loss: 0.1215	- Accuracy: 0.9506
Epoch 500/500	324/324 [=====]	- 0s 49us/step	- Loss: 0.1123	- Accuracy: 0.9645
Test sample		Test application time	Testing loss	Testing accuracy
82/82	[=====]	-0s 438us/step	- Loss: 1.7040	- Accuracy: 0.5915

TABLE 3: Local learning results of data holder Host.

	Training rounds	Training time	Training loss	Training accuracy
Epoch 1/500	364/364 [=====]	-0s 614us/step	- Loss: 0.8093	- Accuracy: 0.4986
Epoch 2/500	364/364 [=====]	- 0s 74us/step	- Loss: 0.6864	- Accuracy: 0.6003
Epoch 3/500	364/364 [=====]	- 0s 71us/step	- Loss: 0.6686	- Accuracy: 0.6058
.....				
Epoch 498/500	364/364 [=====]	- 0s 55us/step	- Loss: 0.0714	- Accuracy: 0.9753
Epoch 499/500	364/364 [=====]	- 0s 49us/step	- Loss: 0.0728	- Accuracy: 0.9778
Epoch 500/500	364/364 [=====]	- 0s 52us/step	- Loss: 0.0710	- Accuracy: 0.9780
Test sample		Test application time	Testing loss	Testing accuracy
92/92	[=====]	-0s 531us/step	- Loss: 1.3690	- Accuracy: 0.6254

TABLE 4: Federated training results.

	Training rounds	Training time	Training loss	Training accuracy
Epoch 1/500	(Guest, host) [=====]	-0s 326us/step	- Loss: 0.7427	- Accuracy: 0.5327
Epoch 2/500	(Guest, host) [=====]	- 0s 54us/step	- Loss: 0.6838	- Accuracy: 0.5672
Epoch 3/500	(Guest, host) [=====]	- 0s 67us/step	- Loss: 0.6878	- Accuracy: 0.5726
.....				
Epoch 498/500	(Guest, host) [=====]	- 0s 54us/step	- Loss: 0.0728	- Accuracy: 0.9791
Epoch 499/500	(Guest, host) [=====]	- 0s 47us/step	- Loss: 0.0695	- Accuracy: 0.9773
Epoch 500/500	(Guest, host) [=====]	- 0s 51us/step	- Loss: 0.0748	- Accuracy: 0.9798
Testing samples		Testing time	Testing loss	Testing accuracy
(Guest, host) [=====]		-0s 447us/step	- Loss: 0.9476	- Accuracy: 0.7880

TABLE 5: Overall learning results.

	Training rounds	Training time	Training loss	Training accuracy
Epoch 1/500	689/689 [=====]	- 0s 43us/step	- Loss: 0.2538	- Accuracy: 0.9020
Epoch 2/500	689/689 [=====]	- 0s 55us/step	- Loss: 0.2176	- Accuracy: 0.9115
Epoch 3/500	689/689 [=====]	- 0s 49us/step	- Loss: 0.2860	- Accuracy: 0.8781
.....				
Epoch 498/500	689/689 [=====]	- 0s 43us/step	- Loss: 0.0592	- Accuracy: 0.9746
Epoch 499/500	689/689 [=====]	- 0s 46us/step	- Loss: 0.0330	- Accuracy: 0.9813
Epoch 500/500	689/689 [=====]	- 0s 42us/step	- Loss: 0.0442	- Accuracy: 0.9826
Testing samples		Testing time	Testing loss	Testing accuracy
173/173 [=====]		-0s 202us/step	- Loss: 0.8188	- Accuracy: 0.8092

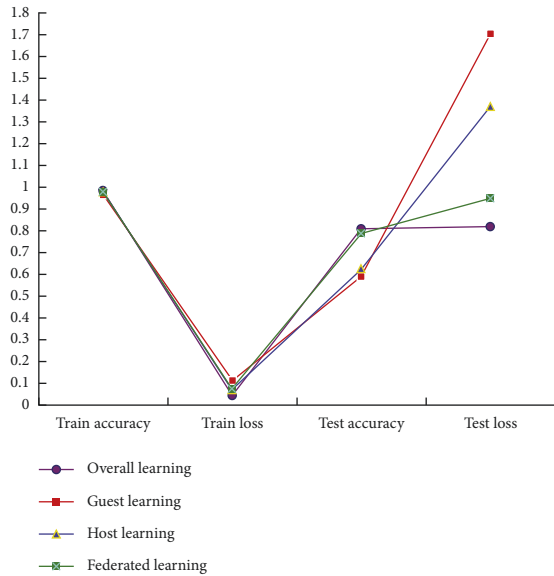


FIGURE 9: Comparison of overall learning, local learning, and federated learning.

the trained model can be applied to other target areas of cross-border e-commerce market, and the open innovation decision-making ability can be transferred to cross-border e-commerce enterprises selling other categories by increasing industry data of target categories. A good result was achieved by dividing 862 data records between Guest (holding 406 data records) and Host (holding 456 data records) for federated learning simulation. Further research will achieve cross-market, cross-platform, cross-industry, cross-category, and cross-department application of intelligent customization through collaborative promotion of open innovation and intelligent optimization of cross-border e-commerce.

## 5. Collaborative Promotion Strategy of Open Innovation and Intelligent Optimization of Cross-Border e-Commerce Based on Federated Learning

**5.1. Creating Intelligent Application Scenarios.** In the deployment and application of artificial intelligence in cross-border e-commerce enterprises, it is very important to know what the pointcut is and application-oriented solution to practical problems is a better choice. The cross-border e-commerce sector has already used some AI technologies to improve business efficiency and optimize customer experience. The current applications include personalized recommendation, customer service robots, virtual experience, transaction risk identification, bogus deals, and comment identification. However, the thorniest problem encountered in cross-border e-commerce operation is product development and selection. How to build an open innovation system by virtue of the international, digital, and intelligent advantages of cross-border e-commerce and maximize its proximity to market demand has become crucial. We should

build application scenarios, big data platforms, and analysis models around the demands for open product innovation intelligent decision making and accumulate AI analysis foundation, such as market environment data, consumer behavior data, product development data, supply chain collaboration data centering on enterprise brand strategy, competitive strategy, and value chain promotion strategy.

**5.2. Consolidate the Foundation of Internal Coordination.** Both federal learning and open innovation require a better collaborative foundation within cross-border e-commerce enterprises. From the perspective of process, it includes a series of processes, such as organization and production of products, selection of goods on the shelves, consultation and ordering of buyers, payment transaction, logistics distribution, evaluation and feedback, after-sales service, customer sentiment maintenance, and so on. These processes are interlocked, and the information flow is inextricable, which contains valuable big data.

From the perspective of management, the management businesses include organizational structure, automatic operation, information integration, and resource sharing, which are extremely important for power and responsibility division, rapid response, accurate and timely data turnover, standardized and efficient operation. From the perspective of scene, most cross-border e-commerce sellers sell products on multiple mainstream cross-border e-commerce platforms at the same time, such as Amazon, AliExpress, eBay, Wish, and Shopee. Some big brand sellers even build their own independent cross-border e-commerce sites, such as Anker and Aukey. Some cross-border e-commerce sellers have established overseas experience stores and customer service centers, thus forming a multiscene mode of multi-platform online and offline integration, which needs to connect online and offline data on multiple platforms. In the process of consolidating the foundation of internal coordination, cross-border e-commerce enterprises should do a good job in three aspects. First, they should build a unified system of information and integrate the cross-border e-commerce sales data of all platforms. Second, to promote the standardization of data, develop a unified business caliber for the structured and unstructured data used in the business process, and break through the application barrier of multisource heterogeneous data. Third, they should continue to accumulate data to lay a big data foundation for open innovation decisions.

**5.3. Promoting External Openness and Cooperation.** Intelligent innovation decisions of open products of cross-border e-commerce need the support of big data sets but the data accumulated by each cross-border e-commerce enterprise is very limited. Therefore, it is necessary to promote the open cooperation between cross-border e-commerce enterprises and the outside world and boost the sharing and circulation of data resources. There are many cooperation agents in cross-border e-commerce, which can be divided into four categories. The first category is cross-border e-commerce sellers, including small sellers based on traffic,

professional sellers on e-commerce platforms, independent website sellers, factory direct sellers, and B2B wholesale sellers from cross-border e-commerce. The second category is cross-border e-commerce operation service providers, which provide the services such as store agent operation, digital operation, customer management, search engine optimization, model photography, advertising alliance, and international marketing. The third category is cross-border e-commerce warehousing and logistics providers and the services offered are domestic transportation, international transportation, SaaS logistics services, overseas warehouses, comprehensive foreign trade services, customs declaration and inspection, and international freight forwarders and so forth. The fourth category is cross-border e-commerce financial payment providers, which provide services including third-party payment, credit financing, foreign exchange settlement, tax treatment, and insurance claims. It is needed to put through multiple data ports, integrate heterogeneous data, solve data islands in supply chain, and promote data sharing and parallel cooperation among node enterprises.

*5.4. Bilateral Sides Driven Open Innovation.* The open innovation of cross-border e-commerce is an integrated innovation of frontend sales and backend supply chain, which needs to be coordinated from both the consumer side and the supply side. On the one hand, e-commerce and social media develop intertwined on the consumption side of cross-border e-commerce. Social media brings flow for e-commerce, and e-commerce monetizes social media. The socialized attribute of cross-border e-commerce is becoming more and more obvious. Consumers communicate constantly with others in the process of cross-border e-commerce shopping: publish shopping comments or consult other consumer evaluations. More and more cross-border e-commerce products are promoted through social media, especially live broadcast and short video, and consumers of cross-border e-commerce are very receptive to these new media advertisements. Consumers around the world are enthusiastic about shopping through cross-border e-commerce platforms and have an increasing demand for “shopping anytime and anywhere”. They can obtain interesting, novel, and cheap goods from all over the world, and the “online” and “globalization” of consumption continue to advance. Therefore, on the consumption side, open product innovation should focus on providing consumers with seamless and integrated omnichannel shopping experience, using digital technology to break through consumption bottlenecks and optimize customer experience. On the other hand, on the supply side, the focus of product innovation has expanded from a single cross-border e-commerce enterprise to the entire supply chain of cross-border e-commerce. With the deepening of economic globalization, enterprises need to acquire and integrate innovation resources on a global scale. Therefore, cross-border e-commerce and digital operation must be used to carry out supply chain cooperation on a global scale, coordinate the operation process, and change the open innovation form from “enterprise-enterprise” mode to “consumer-supply chain” mode.

*5.5. Building an Open Sharing Mechanism.* Big data training test set business of cross-border e-commerce open innovation involves numerous data, including product characteristics, customer assets, customer preferences, customer behavior, transaction services, operation management, production and manufacturing, and collaborative operation. These data are widely generated and distributed among cross-border e-commerce sellers, operation service providers, warehousing and logistics providers, manufacturers, financial payment providers, government management departments, and other entities. The data exist in the form of fragmentation and each department will not share their own data for the sake of data security. In order to guarantee the big data support of open intelligent innovation, five mechanisms need to be constructed. First, to establish a data security mechanism. The data owner of cross-border e-commerce can clean, analyze, model, visualize, align, and encrypt the original data according to the requirements of intelligent model, and the preprocessed data shall be integrated, edited, and desensitized to form data products. Desensitized data after processing is no longer the original data, which can well solve the problems of data privacy protection and data ownership, and enterprises need not worry about the leakage of their business data. Second, to optimize the supply chain coordination mechanism. Cross-border e-commerce supply chain managers should strengthen the strategic collaboration of node enterprises and develop common agreed agreements to realize the sharing of models and data. The third is to enhance the value chain through digitization. Make full use of intelligent analysis technology, closely watch the demand dynamics of domestic and foreign markets, closely follow the development trend of cross-border e-commerce industry, establish a sound virtuous cycle ecosystem of investment and financing, R&D and design, cultural creativity, processing and manufacturing, after-sales service, logistics and distribution, and international marketing, and promote the clustering development of cross-border e-commerce industry. Fourth, to guide the ecosphere development through open innovation. We should achieve the development of international network marketing and brand management, cross-border e-commerce business translation, cross-border business model, cross-border e-commerce live broadcast, cross-border e-commerce short video production, creative design, international supply chain management, supply chain finance, intelligent recommendation system, intelligent customization system and other cross-border e-commerce brand construction supporting industry, boost cross-border e-commerce brand to the international high-end development, and realize the integrated operation of cross-border e-commerce industry from digital recognition, global interconnection, prematching to global empowerment. Fifth, to improve the mechanism for distributing benefits. These desensitized data products form a federated learning network for learning and carry out joint training on the premise that the data of each participant is not released locally. The federated learning model and federal intelligent analysis tools thus constructed can not only be used by cross-border e-commerce federated learning participating enterprises but

also be sold in the market in the form of intelligent products. The gains obtained are shared between data providers and trainers, which enhances the motivation for sharing data among enterprises and federated learning.

### Data Availability

The datasets used to support the findings of this study are available from the authors upon reasonable request because they are from cross-border e-commerce enterprises and have certain commercial privacy.

### Ethical Approval

This article does not contain any studies with human participants and animal studies.

### Conflicts of Interest

The authors declare that they have no conflicts of interest.

### Authors' Contributions

All authors contributed equally to this work. In addition, all authors have read and approved the final manuscript and gave their consent to publish the article.

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