Research on E-commerce Supply Chain Management HCI in International Trade Using Big Data and CAD Technology

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Abstract. This research investigates the role of Human-Computer Interaction (HCI) in enhancing e-commerce supply chain management within the context of international trade, leveraging big data analytics and Computer-Aided Design (CAD) technology. This paper presents a novel approach to enhancing cross-border e-commerce supply chain management by integrating mobile big data technology. We investigate the balance of 0 and 1 in the cross-commercial e-sports supply chain channel coding sequence, which decreases after channel encoding. The imbalance of the coding sequence is also linked to the degree of imbalance in the input sequence. Our findings suggest that the greater the input sequence's imbalance degree, the higher the imbalance degree of the coding output sequence. Importantly, our experimental analysis demonstrates that the proposed research on cross-border e-commerce supply chain management, based on mobile big data technology, can significantly enhance the efficiency of cross-border e-commerce supply chain management, thereby offering practical benefits to the industry.

Keywords: big data, cross-border e-commerce, supply chain, management model, Human-Computer Interaction
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1 INTRODUCTION

Cross-border e-commerce refers to the process in which transaction participants from different countries or regions transfer the traditional offline trade commodity display, transaction negotiation, commodity payment, and other processes online through the e-commerce platform to realize the value-added process of the supply chain. Cross-border e-commerce relies on Internet technology and has the characteristics of globality, intangibility, anonymity, and immediacy. However, although cross-border e-commerce has maintained a stable development, there are still many areas for improvement in the development process. These deficiencies are the bottleneck of the current development of cross-border e-commerce. From the supply chain perspective, we will discuss the problems and defects of production suppliers, international logistics providers, e-commerce service platforms, customs clearance, and tax refund processes in cross-border trade.

From the source, the stagnation of general innovation is mainly due to the need for moretage. Therefore, it is urgent to cultivate comprehensive e-commerce talents. Based on the current situation, the state actively promotes talent cultivation in international trade and e-commerce. Enterprises should also give play to their initiative, train and strengthen the comprehensive ability of internal personnel, and improve their comprehensive quality in terms of language, marketing, innovation, and other aspects. We can provide continuous impetus for category innovation by enhancing the comprehensive quality of talents in relevant fields. After having their own personalized and innovative products, enterprises should also pay attention to their own business management, brand building, and corporate culture construction, promote enterprises to face a broader market, and respond to possible risks and problems in cross-border trade with perfect internal management [1]. Business management involves making decisions, organizing and coordinating an enterprise's production and operation activities, and encouraging its members to achieve their tasks and objectives. Establishing a scientific management system should cover technology development management, marketing, business administration, and other aspects. An enterprise should determine its business management mode by enhancing its operational efficiency, improving its production efficiency, and giving full play to the potential of its employees in combination with its value characteristics [3]. As an intangible asset of an enterprise, brand building is also the top priority of enterprise development. Brand construction should focus on four main lines: brand identification, optimization, extension, and identification; only by taking integrity as the basis and product quality and product characteristics as the core can the image of the enterprise brand in consumers be improved. Corporate culture exists in all aspects of an enterprise, is the soul of its survival, operation, and development, and guides its business practice. Establishing a correct and positive corporate culture can form a strong cohesion and centripetal force among employees and influence and radiate to society through various media and public relations activities [18].

To reduce transportation costs, logistics providers can follow the current development trend and control the dynamic process of the whole commodity through overall coordination and planning of different logistics systems, such as social logistics, enterprise logistics, and international logistics, to achieve maximum benefits and minimum costs. Investment in the hardware of international logistics infrastructure can also significantly reduce the comprehensive logistics cost [19]. Logistics companies should strengthen the overall monitoring of the transport process and improve the after-sales service level. Timely clearing up the backlog of goods, using the Internet to present the transport link to customers, and realizing globalization, all-weather, and precision of international logistics. The logistics company can also trace the source of the goods during the transportation process, find the first person responsible for missing or damaged parts, and ensure the timeliness of delivery and the integrity of the goods. Only by integrating management, service, technology, and other elements into the logistics service can the overall progress and development of the logistics industry be guaranteed [11].

Cross-border e-commerce customs clearance and tax refunds involve complex, overwhelming procedures. To boost enthusiasm for e-commerce export tax rebates, we can start by reducing the cost of customs clearance and tax rebates. Applying Human-Computer Interaction (HCI) principles can help streamline these processes. We can simplify data entry, document submission, and routine tasks by designing user-friendly interfaces and implementing intelligent automation tools. This reduces errors, speeds up problem resolution, and lowers administrative burdens, encouraging more businesses to engage in e-commerce exports. Especially for small and medium-sized enterprises, some orders are small. For this situation, we can specify targeted phased tax policies, increase policy publicity and reasonable guidance, and reduce enterprise declaration costs. It is an inevitable requirement of the times to improve the coordination and cooperation mechanism between cross-border e-commerce regulatory departments, let all functional departments participate in building a cross-border e-commerce public data management platform, establish an organic and unified export tax rebate management mechanism with cross-departmental functions, and implement the integrated management of cross-border e-commerce enterprise tax collection and rebate [13]. Due to the large number of cross-border e-commerce products exported from different places, the tax collection place and tax refund place are separated, and the burden of export tax refund in various provinces and cities is unbalanced; the country should formulate a unified export tax refund indicator, reduce the vicious game of local governments in export tax refund, and create a fair and unified tax refund environment for the development of cross-border e-commerce. Enterprises should pay more attention to export tax rebates, keep close contact with upstream and downstream enterprises, and use information technology to ensure the timeliness of information. Enterprises can speed up their information construction, link their systems with the tax refund department’s online platform, improve export efficiency, and speed up the tax refund process [12]. Due to the frequent adjustment of the tax refund policy by the state, the complex and changeable international market, and the difference in tax rates in different countries, tax refund business personnel are required to improve their business capabilities constantly. Through irregular training, enterprises can enable employees to broaden their theoretical level, enhance their practical skills, and improve their adaptability to tax refund-related issues [2]

For the research on cross-border e-commerce dual-channel supply chain strategy, literature [15] mainly reviews the existing research results from the three aspects of dual-channel supply chain pricing, e-commerce dual-channel supply chain, product quality improvement, and recall order, The pricing problem of single traditional retail channel and online direct marketing channel is analyzed by using game theory. The coordination strategy of cooperative advertising between manufacturers and retailers in a dual-channel supply chain is studied[8]. Literature [9] believes that when manufacturers have online direct marketing channels, they can influence retailers’ pricing decisions by controlling the level of advertising investment. The impact of pricing and cooperative advertising strategies in a dual-channel supply chain under the Stackelberg game is analyzed; it is found that the design of direct sales channels and consideration of a compensation contract can improve the profits of supply chain members by Pareto. Literature [10] has studied government and supply chain decisions with or without carbon emission limits for dual channel sales and recycling closed-loop supply chains. The above studies pricing strategies, advertising decisions, and emission reduction strategies of traditional offline retail channels and online direct sales channels using game theory; however, it only analyzes the coordination effect under a single coordination mechanism（

In the e-commerce environment, the strategy of “compensation - franchise fee” proposed in the literature [4] can achieve the coordination of the dual channel supply chain and ensure the win-win situation of the dual channel supply chain members within a specific range. A transfer payment mechanism is designed to enable manufacturers and retailers to achieve a win-win situation. With the establishment of the white trade zone, cross-border offline retailers set up bonded warehouses in the free trade zone. Literature [6] has conducted a coordination study on the cross-border zero business dual-channel supply chain. By building a cross-border e-commerce dual-channel demand model, it has studied the pricing strategy of the cross-border e-commerce dual-channel retail model. Literature [17] has built a cross-border supply chain game model with retailers as the leaders of Stackelberg. By introducing tariffs, international transport costs, and other factors, This paper analyzes the impact of tariff changes on product pricing and the profits of each member of the transnational supply chain. The existing research on the e-commerce dual-channel supply chain mainly focuses on the pricing strategy of the supply chain. It does not consider cross-border product manufacturers’ product quality selection strategy in the cross-border e-commerce environment.

From a macro perspective, there have been a lot of studies on recall sequencing decision-making. Literature [16] has studied the recall decision-making of a single enterprise based on social welfare. Unlike Thomsen and others, this study is based on the equilibrium decision-making of supply chain members rather than a single enterprise. Product recall will affect the consumer experience, and it is also a nightmare for almost all enterprises in the supply chain. Literature [7] explains from the perspective of indirect punishment that the cost of product recall far exceeds the direct cost of replacing or repairing defective products. Based on the two consumer rights protection measures of product liability and ordering recall, literature [14] built a dynamic game model including consumer protection institutions, manufacturers, and retailers and studied the strategic interaction between the three. It also believed that under the situation of endogenous product quality and product quantity (order quantity), At the same time, achieving the coordination of its quality and quantity will become an essential issue of supply chain management, and corporate social responsibility will help improve the quality of products in the supply chain. Literature [5] considers product recall under the situation of uncertain market demand and studies the optimal ordering decision and optimal linear insurance contract decision under the supply chain linear insurance contract from the perspective of manufacturers

This paper combines mobile big data technology to analyze cross-border e-commerce supply chain management, improve operation efficiency, and promote stable development.

2 ANALYSIS OF CODEWORD PROPERTIES OF SUPPLY CHAIN CHANNEL CODING

2.1 Balance of Supply Chain Channel Coding Sequences

Different supply chain channel coding types have unique properties, such as the linear relationship in linear block codes and the constraint-based coding in convolutional codes. Integrating Human-Computer Interaction (HCI) principles can enhance the management of these coding systems. HCI can provide intuitive interfaces for configuring and monitoring codes, real-time feedback, and visualization tools to simplify complex tasks, quickly identify errors, and improve overall reliability and efficiency in supply chain operations. The parity check matrix of LDPC codes is sparse, while BCH codes and RS codes are cyclic. These features can be fully utilized during encoding and decoding.

If it is assumed that (n, k) is a linear block code and C is a codeword, the generator matrix is:

$$G=\begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_{k-1} \end{bmatrix}=\begin{bmatrix} g_{0,0} & g_{0,1} & \cdots & g_{0,n-1} \\ g_{1,0} & g_{1,1} & \cdots & g_{1,n-1} \\ \vdots & \vdots & \vdots & \vdots \\ g_{k-1,0} & g_{k-1,1} & \cdots & g_{k-1,n-1} \end{bmatrix} \tag{1}$$

If the information sequence is assumed to be $\boldsymbol{x}=(x_0 \quad x_1 \quad \cdots \quad x_{k-1})$, The generated codeword can be expressed as:

$$c=(c_0,c_1,\cdots,c_{n-1})=xG=(x_0,x_1,\cdots,x_{k-1})\begin{bmatrix} g_0 \\ g_1 \\ \vdots \\ g_{k-1} \end{bmatrix} \tag{2}$$

Any coded bit $c_i, i=0,1,\cdots,n-1$An be represented as:

$$c_i=g_{0,i}x_0 \oplus g_{1,i}x_1 \oplus \cdots \oplus g_{k-1,i}x_{k-1} \tag{3}$$

It is assumed that the information sequence to be encoded is memoryless and biased; the bias of 0 and 1 is ε, And the bias is the imbalance of 0 and 1. The weight of each column of G is $L_i, i=0,1,\cdots n-1$, then the probability of $c_i=1$Is:

$$Pr(c_i=1)=\sum_{l=1,3,\cdots}^{L_i}\binom{L_i}{l}\left(\frac{1}{2}-\varepsilon\right)^{l}\left(\frac{1}{2}+\varepsilon\right)^{L_i-l}=\frac{1}{2}[1-(2\varepsilon)^{L_l}] \tag{4}$$

The bias of the codeword bit c_i Is:

$$\varepsilon_{c_i} = \frac{1}{2}(2\varepsilon)^{L_i} \tag{5}$$

Because $\varepsilon \leq 1/2$ and $L_i \geq 1, L_i = 1, i = 0,1,\cdots,k-1$, $\varepsilon_{c_i} < \varepsilon$ The bias of the codeword is:

$$\varepsilon_c = \frac{1}{n}\sum_{i=0}^{n-1} \varepsilon_{c_i} = \frac{1}{n}\sum_{i=0}^{k-1}\frac{1}{2}(2\varepsilon)^1 + \frac{1}{n}\sum_{i=k}^{n-1}\frac{1}{2}(2\varepsilon)^{L_i} = \frac{k}{n}\cdot\varepsilon + \frac{1}{n}\sum_{i=k}^{n-1}\frac{1}{2}(2\varepsilon)^{L_i} \approx \frac{k}{n}\cdot\varepsilon \tag{6}$$

The primary generator matrix of the convolutional code (n,k,m) is:

$$G = (g_0 \quad g_1 \quad \cdots \quad g_{n-1}) = \begin{bmatrix} {g_0}^{(0)} & g_1^{(0)} & \cdots & {g_{n-1}}^{(0)} \\ {g_0}^{(1)} & g_1^{(1)} & \cdots & {g_{n-1}}^{(1)} \\ \vdots & \vdots & \vdots & \vdots \\ {g_0}^{(k-1)} & g_1^{(k-1)} & \cdots & {g_{n-1}}^{(k-1)} \end{bmatrix} \tag{7}$$

$$\boldsymbol{g}_j^{(i)} = \left[g_j^{(i)}(0) \quad g_j^{(i)}(1) \quad \cdots \quad g_j^{(i)}(m-1)\right] \tag{8}$$

Among them, i represents the i-th input, $0 \leq i \leq k; j$ represents the j-th output, $0 \leq j \leq n$; The information sequence of the ith input convolutional encoder is as follows:

$$\boldsymbol{x}_i = (x_{i,0} \quad x_{i,1} \quad \cdots) \tag{9}$$

Then, the bit sequence of the j-th output is:

$$c_j = x_0 * {g_j}^{(0)} \oplus x_1 * g_j^{(1)} \oplus \cdots \oplus x_{k-1} * g_j^{(k-1)} = \sum_{i=0}^{k-1} x_i * g_j^{(i)} \tag{10}$$

*represents convolution operation. If the non-zero bit in $\boldsymbol{g}_j^{(i)}$ is $\tilde{L}_{i,j}$, The bias of the whole codeword is:

$$\varepsilon_{cc} = \frac{1}{kn}\sum_{i=0}^{k-1}\sum_{j=0}^{n-1}\frac{1}{2}(2\varepsilon)^{\tilde{L}_{i,j}} \tag{11}$$

2.2 XOR Codeword Properties Between Codewords in Supply Chain Channel Coding

For linear block codes, the parameter is (n,k), k is the information bit, n is the codeword, the information code space is O, the number of information elements is 2^k, The codeword space is C, and the number of codewords is 2^k. The codeword in the codeword space is:

$$\boldsymbol{C}_1 = [c_{11} \quad c_{12} \quad \cdots \quad c_{1n}]\boldsymbol{C}_2 = [c_{21} \quad c_{22} \quad \cdots \quad c_{2n}] : \boldsymbol{C}_{2^k} = [c_{2^{k_1}} \quad c_{2^{k_2}} \quad \cdots \quad c_{2^k n}] \tag{12}$$

The G matrix represents the generator matrix:

$$G = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ g_{k1} & g_{k2} & \cdots & g_{kn} \end{bmatrix} \tag{13}$$

M represents information code:

$$M_1 = [m_{11} \quad m_{12} \quad \cdots \quad m_{1k}]M_2 = [m_{21} \quad m_{22} \quad \cdots \quad m_{2k}] : M_{2^t} = [m_{2^{t_1}} \quad m_{2^{t_2}} \quad \cdots \quad m_{2^t k}] \tag{14}$$

Because of $\boldsymbol{C} = \boldsymbol{MG}, \boldsymbol{C}^T = \boldsymbol{G}^T\boldsymbol{M}^T$, The codeword can be expressed as:

$$\begin{bmatrix} c_{1k+1} \\ c_{1k+2} \\ \vdots \\ c_{1n} \end{bmatrix} = \begin{bmatrix} g_{11} & g_{21} & \cdots & g_{k1} \\ g_{12} & g_{22} & \cdots & g_{k2} \\ \vdots & \vdots & \vdots & \vdots \\ g_{1n} & g_{2n} & \cdots & g_{kn} \end{bmatrix} \begin{bmatrix} m_{11} \\ m_{12} \\ \vdots \\ m_{1k} \end{bmatrix} \begin{bmatrix} c_{2^k k+1} \\ c_{2^k k+2} \\ \vdots \\ c_{2^k n} \end{bmatrix} = \begin{bmatrix} g_{11} & g_{21} & \cdots & g_{k1} \\ g_{12} & g_{22} & \cdots & g_{k2} \\ \vdots & \vdots & \vdots & \vdots \\ g_{1n} & g_{2n} & \cdots & g_{kn} \end{bmatrix} \begin{bmatrix} m_{2^k 1} \\ m_{2^k 2} \\ \vdots \\ m_{2^k k} \end{bmatrix} \tag{15}$$

We assume that $1 \leq p < q \leq 2^k, S$ is a $1 \times n$-dimensional matrix, take two codewords C_p and C_qIn the codeword space, and set:

$$\boldsymbol{S} = \boldsymbol{C}_p \oplus \boldsymbol{C}_q \tag{16}$$

Then, there is:

$$S = C_p \oplus C_q = (M_p G) \oplus (M_q G) = G(M_p \oplus M_q) \tag{17}$$

Certification: Because $a \oplus b = \bar{a}b + a\bar{b}$ and $\overline{ab} = \bar{a} + \bar{b}$, Then there is:

$$(ab) \oplus (ac) = \overline{ab}ac + ab\overline{ac} = (\bar{a} + \bar{b})ac + ab(\bar{a} + \bar{c}) = \bar{a}ac + \bar{b}ac + \bar{a}ab + ab\bar{c} = a\bar{b}c + ab\bar{c} = a(\bar{b}c + b\bar{c}) = a(b \oplus c) \tag{18}$$

Therefore, formula (17) holds.

Because the XOR sequence of the two information sequences is still in the information space, the obtained S codeword still belongs to the codeword in the codeword space.

Simulation condition settings: The supply chain channel coding adopts (7,4) Hamming code, and the data length is 3500. After the Hamming code encoding of (7,4) parameters is performed on the two sequences simultaneously, the codewords are aligned, and the two encoded sequences are directly XORed. The obtained codewords are identified by supply chain channel coding, 100 Monte Carlo experiments are performed, and the identification results are shown in Figure 1. The bit error rate of the horizontal axis in the figure represents the sum of the two Hamming code sequences' bit error rates, and the two Hamming code sequences and the bit error rates of the two Hamming code sequences are equal.

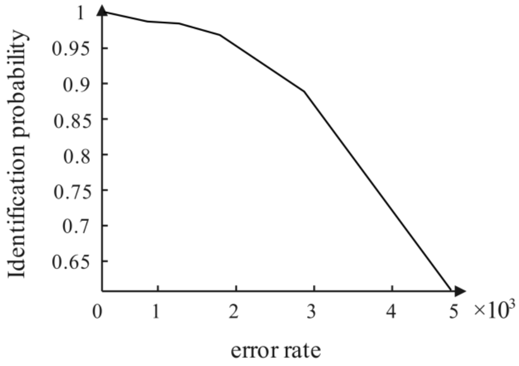


Figure 1: The relationship between Hamming code recognition probability and bit error rate.

Convolutional code is a finite memory system; this group's check element is related to the information element of this group and the previous grouping. If the convolutional code parameter is assumed to be $(n, k, m), sl = n \cdot m$, The generator matrix is $\boldsymbol{G}_\infty$:

$$G_w = \begin{bmatrix} g_0 & g_1 & \cdots & g_m & 0 & \cdots & \cdots & \cdots \\ 0 & g_0 & g_1 & \cdots & g_m & 0 & \cdots & \cdots \\ 0 & 0 & g_0 & g_1 & \cdots & g_m & 0 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \tag{19}$$

The check matrix $\boldsymbol{H}_\infty$ is:

$$H_\infty = \begin{bmatrix} h_0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \square \\ h_1 & h_0 & 0 & \cdots & \cdots & \cdots & \cdots & \square \\ h_2 & h_1 & h_0 & 0 & \cdots & \cdots & \cdots & \square \\ \square & \square & \square & \square & \cdots & \square & \square & \square \\ h_m & h_{m-1} & \cdots & h_0 & 0 & \cdots & \square & \square \\ 0 & h_m & h_{m-1} & \cdots & h_0 & 0 & \cdots & \square \\ 0 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{20}$$

From $\boldsymbol{C}_\infty \boldsymbol{H}_\infty^T = 0$, The relationship between the convolutional code word and the dual code word is obtained: the code word is $\boldsymbol{C} = (c_1, c_2, \cdots, c_{sl})$, The dual code word is $\boldsymbol{h}_\infty = (h_1,\ h_2, \cdots,\ h_{sl})^T$, $\boldsymbol{C}\boldsymbol{h}_\infty = c_1 h_1 + c_2 h_2 + \cdots + c_{sl} h_{sl} = 0$.We set the convolutional code word to be $\boldsymbol{C}_1 = (c_{11}, c_{12}, \cdots c_{1,sl})$, $\boldsymbol{C}_2 = (c_{21}, c_{22}, \cdots c_{2,sl})$, And set:

$$R = C_1 \oplus C_2 \tag{21}$$

Then,

$$Rh_\infty = (C_1 \oplus C_2)h_\infty = (C_1 h_\infty) \oplus (C_2 h_\infty) = 0 \tag{22}$$

The simulation conditions are set: 1/2 code rate, the constraint degree is 7, the generator matrix is a convolutional code of [133171], and the data adopts 3500, 100 Monte Carlo experiments. The recognition result is shown in Figure 2. The bit error rate of the horizontal axis in the figure represents the sum of the two convolutional code sequences' bit error rates; the two convolutional code sequences and the bit error rates of the two convolutional code sequences are equal.

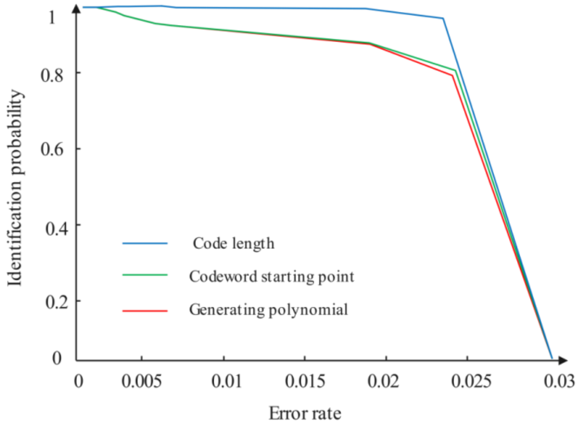


Figure 2: The relationship between the recognition probability of convolutional codes and the bit error rate.

If it is assumed that the deletion matrix is D and other parameters such as convolutional codes, the deleted convolutional code word $\tilde{C}$ obtained through the deletion matrix can be expressed as:

$$\tilde{C} = CD \tag{23}$$

Then, the XOR codeword between the codewords of the deletion convolutional code can be expressed as:

$$\tilde{R} = (\tilde{C}_1 \oplus \tilde{C}_2)h_\infty = (C_1 \oplus C_2)Dh_\infty = ((C_1 \oplus C_2)h_\infty)D = ((C_1 h_\infty) \oplus (C_2 h_\infty))D = \mathbf{0} \tag{24}$$

The simulation conditions are set: 2/3 code rate, constraint degree 7, generator matrix is [133171], and deletion mode is deletion convolutional code of [001110]. Since the deletion convolutional code requires more data than the convolutional code, the amount of data is 7000, 100 Monte Carlo experiments. The recognition results are shown in Figure 3.

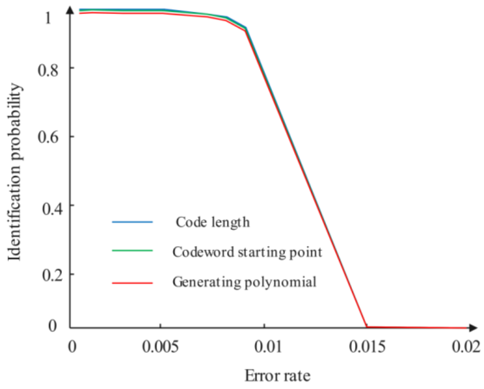


Figure 3: The relationship between the recognition probability of deletion convolutional code and the bit error rate.

The bit error rate of the horizontal axis in the figure represents the sum of the bit error rates of the two deletion mode convolutional code sequences, and the bit error rates of the two deletion mode convolutional code sequences are equal. It can be seen from the simulation results that the sequence obtained by removing the deletion and the XOR of the convolutional coding sequence is still recognized as the deletion convolutional code. The identification probability of the starting point of the codeword and the generator polynomial is equal, and the error resistance is lower than the identification of the code length. When the bit error rate is lower than 0.01, the recognition probability is close to 1. The performance drops sharply when the bit error rate is higher than 0.01. When the bit error rate reaches 0.015, it cannot be correctly identified.

3 RESEARCH ON CROSS-BORDER E-COMMERCE SUPPLY CHAIN MANAGEMENT BASED ON MOBILE BIG DATA TECHNOLOGY

In the context of cross-border e-commerce, a cross-border e-commerce dual-channel supply chain model consisting of a single overseas supplier (leader) and a single bonded domestic retailer (subordinate) is constructed (Figure 4). This paper explores how foreign suppliers and domestic retailers determine direct sales channels, sales prices in domestic retail channels, and quality choices. Moreover, this paper extends product quality improvement to product recall, analyzes the impact of product recall cost and quality improvement efficiency on the balanced decision-making of supply chain members, and provides an effective guarantee for overseas suppliers and domestic retailers to determine reasonable decisions.

The primary operation mode of cross-border e-commerce is summarized as shown in Figure 5, and its end users are divided into two categories: individuals (C) and enterprises (B). This constitutes the three basic transaction modes of B2B, B2C (C2B) and C2C. Cross-border e-commerce enterprises are divided into two categories: platform enterprises and self-operated enterprises. The former only provides platform intermediary services for merchants and charges service fees. The latter deals directly with end-users and makes profits through distribution or consignment. The cross-border e-commerce business involves import and export activities across borders and customs.

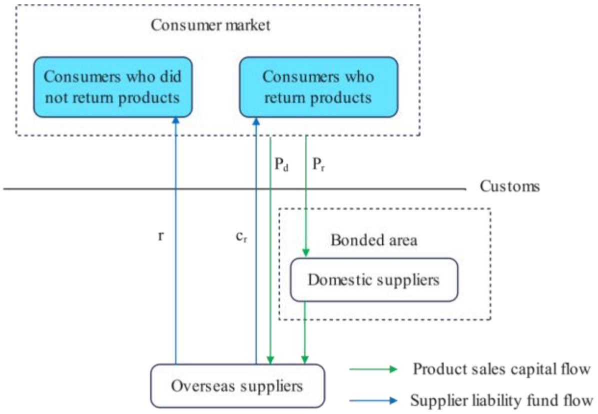


Figure 4: Cross-border e-commerce dual-channel supply chain structure.

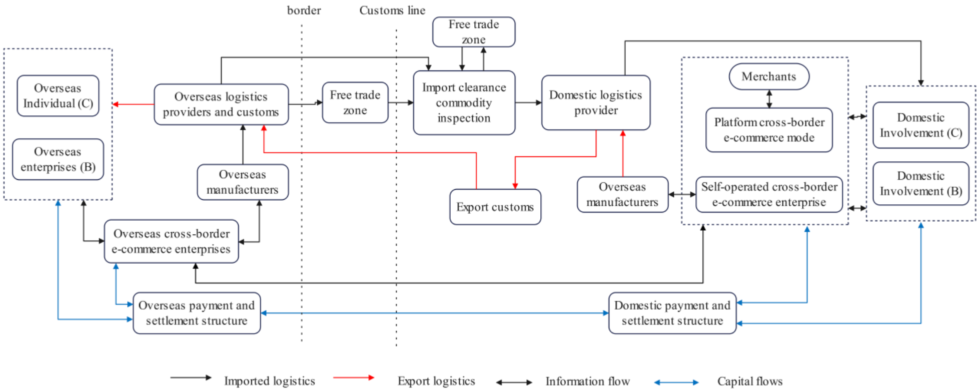


Figure 5: The fundamental operating model of cross-border e-commerce.

From the overall perspective of the cross-border e-commerce ecological community, the key groups that impact its soft supply chain are consumer users, e-commerce platforms, and supplier groups. In general, as an integrator of supply and demand resources, cross-border e-commerce platforms, their selection of suppliers, and the organization of a soft supply chain are determined by the factors mentioned above, which are flexible and diverse. Therefore, by simulating the ecological relationship reflected by the above factors, we can better grasp the key influencing factors and characteristics of the cross-border e-commerce soft supply chain to formulate operational strategies in a targeted manner. The observable indicators of the main influencing factors of cross-border e-commerce platforms can be summarized as shown in Figure 6.

The number of commodity categories, the shelf time of commodity categories, the number of new users per unit time, the length of user retention, and the conversion rate of commodity purchases are obtained as simulation analysis. The relationship between parameter variables is shown in Figure 7. Figure 7 shows the relationship between 5 indicators (indicators in the grey background box in Figure 3) and 11 parameter variables that affect the critical indicators of the supply chain. It can be seen from the figure that the number of commodity categories in the five indicators is related to the set of all users, the conversion rate of commodity purchases, the number of new commodity categories per unit of time, and the average time of commodity category loss.

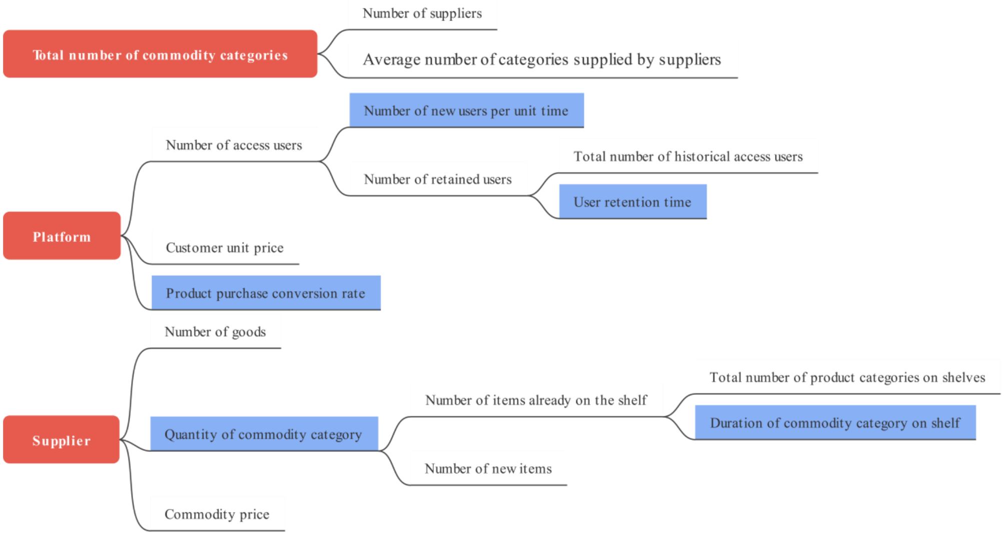


Figure 6: Observable indicators of impact on the ecological community of cross-border e-commerce soft supply chain.

The shelf time of a commodity category is related to the number of new commodity categories per unit of time and the average time for the loss of commodity categories. The user retention time is associated with the number of new users per unit and the average time of user churn. The number of new users per unit of time and the conversion rate of product category purchases are directly collected and calculated.

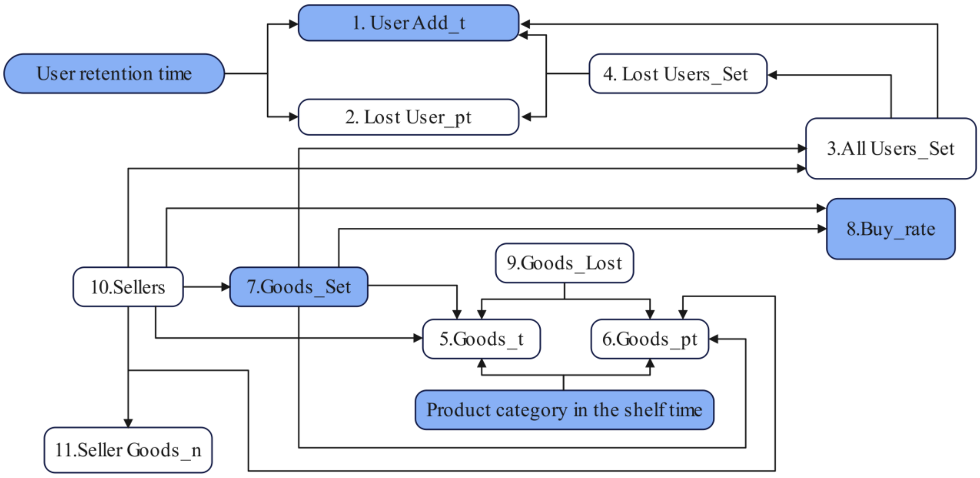


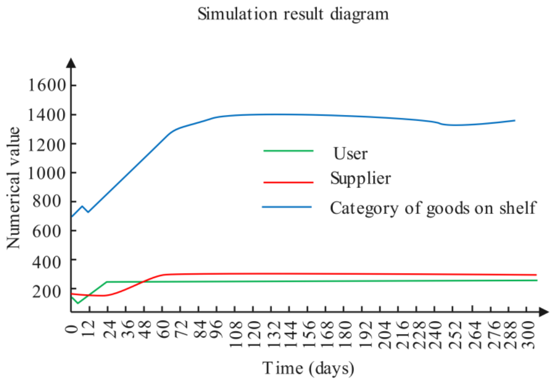
Figure 7: The relationship diagram between parameters and variables.

The operating mechanism of the cross-border e-commerce platform and its characteristics are complex, and it is challenging to use a general mathematical model to describe and analyze it well. The article takes the "wolves eat sheep" ecosystem model as a modeling design paradigm. According to the above ecological mechanism of the cross-border e-commerce platform, a dynamic simulation model is designed, and relevant parameters are set through the collected platform business data.

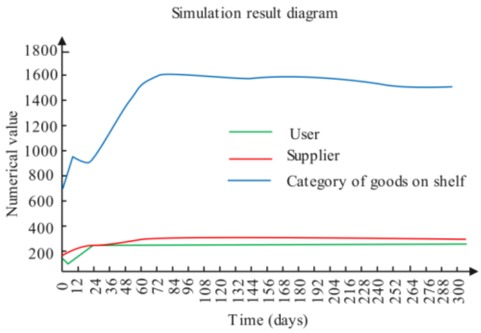
On this basis, this paper sets five principal component factor indicators: a 300-day window period, simulates an analysis of the number of commodity categories, the shelf life of commodity categories, the number of new users, the user retention time, and the purchase conversion rate to perform simulation analysis to observe their impact on the cross-border e-commerce supply chain.

Figure 8(a) shows the changes over time in the number of active users of the cross-border e-commerce platform (users), the number of suppliers maintained in the platform (sellers), and the number of goods on the shelf (goods) when the initial parameters remain unchanged, that is when no control measures are taken. If the number of newly released commodity categories per unit time is increased from 500 to 1000, the simulation results are shown in Figure 8(b). Suppose the number of newly released commodity categories is increased from 500 to 1,000 in a unit of time. In that case, the number of suppliers required to provide the above different commodity categories will also increase accordingly, and the total number of commodity categories on the shelf will also increase. Therefore, the number of suppliers mentioned above and the total number of product categories that can be maintained on the platform does not grow linearly with the number of newly released product categories.

The simulation results also show that through the above measures, increasing the number of newly released commodity categories, the number of suppliers on the platform, the retention time of users, and the total number of commodity categories can reach the peak faster.



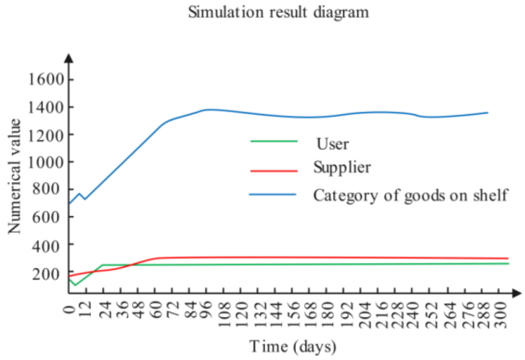
(a) The result diagram when the initial parameters are unchanged



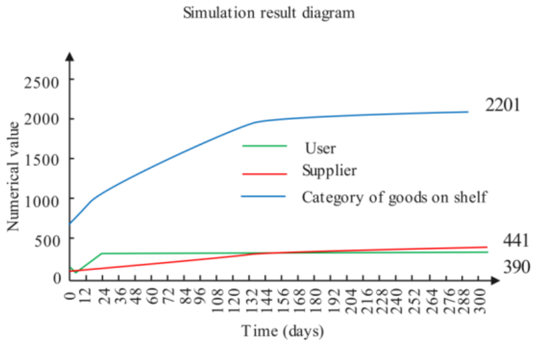
(b) The resulting diagram of the increase in the number of newly released product categories

Figure 8: Data processing experiment 1 of cross-border e-commerce supply chain.

Figure 9 (a) shows the simulation results if the shelf time of the commodity category is increased from 10 to 20 units. The simulation results are also shown in Figure 9(b) if the number of new users per unit time is increased from 100,000 to 200,000.



(a) The resulting diagram of the increase in the number of new users



(b) The resulting diagram of the increase in the number of new users

Figure 9: Data processing experiment 2 of cross-border e-commerce supply chain.

From the above analysis, the cross-border e-commerce supply chain management system based on mobile big data technology proposed in this paper can effectively improve its efficiency.

4 CONCLUSIONS

The supply chain organization of cross-border e-commerce is an on-demand supply model formed by the changes in the international market and according to the characteristics and requirements of specific orders. Its supply chain has flexible and diverse soft structure characteristics, and traditional supply chain modeling and simulation methods are challenging to describe and analyze its complex changes effectively. This paper integrates Human-Computer Interaction (HCI) principles with mobile big data technology to analyze cross-border e-commerce supply chain management, aiming to enhance operational efficiency and promote the stable development of cross-border e-commerce. By incorporating HCI, the user interface and experience of interacting with mobile big data technology are optimized, ensuring the analysis process is intuitive and user-friendly. The experimental analysis demonstrates that the research on cross-border e-commerce supply chain management based on mobile big data technology, enriched with HCI, significantly improves the efficiency of cross-border e-commerce supply chain management. This integration fosters better user engagement and decision-making within the cross-border e-commerce domain. In future research, the systematic internal mechanism of the ecological community of the cross-border e-commerce supply chain will be further explored, and a more perfect dynamic process mechanism model will be constructed. It was combined with the policy environment and changes in international trade, extensive data analysis was carried out, and a more in-depth systematic study was carried out from the perspective of combining internal mechanism modeling with macroscopic extensive data analysis.

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