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PAPER

Integration of Mobile Interaction Technologies in Supply Chain Management for S2B2C E-Commerce Platforms

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ABSTRACT

With the rapid development of e-commerce, the supplier to business to consumer (S2B2C) model, as an emerging business model, has become an essential component of modern supply chain management. However, traditional supply chain management models are increasingly inadequate to meet the demands of the fast-changing market and complex supply chain collaboration, particularly in areas such as information sharing, real-time data updates, and demand forecasting. Existing research primarily focuses on the optimization of individual supply chain components, such as inventory management, order tracking, or logistics scheduling, with limited attention given to the collaboration between parties and the overall management of the supply chain under the S2B2C model. Additionally, while some studies have proposed information-sharing mechanisms and demand forecasting models based on mobile platforms, the practicality and accuracy of existing methods are still limited in practical applications due to factors such as data processing capabilities, algorithm accuracy, and the dynamic nature of consumer behavior. Therefore, this study proposes an integrated solution for supply chain management based on mobile interaction technology within the S2B2C e-commerce platform. The aim is to enhance the intelligence, flexibility, and transparency of the supply chain through technological innovation. The core research focuses on the implementation technologies for mobile terminals in supply chain management on the S2B2C e-commerce platform, along with the design and implementation of a demand forecasting model and algorithm based on mobile applications.

KEYWORDS

supplier to business to consumer (S2B2C) e-commerce platform, supply chain management, mobile interaction technology, demand forecasting, big data, intelligent algorithm

1 INTRODUCTION

With the rapid development of information technology, e-commerce has permeated various sectors of the global economy, particularly with the rise of the supplier to business to consumer (S2B2C) model, which has profoundly transformed traditional supply chain management. The S2B2C platform integrates suppliers,

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distributors, retailers, and consumers, thereby forming a complex supply chain network. However, a significant challenge remains in effectively coordinating the various components within this model, aiming to enhance the responsiveness, efficiency, and flexibility of the supply chain [1–5]. With the widespread adoption of mobile Internet and smart devices, mobile interaction technologies have provided new solutions for the S2B2C platform. These technologies enable the real-time transmission of supply chain information, thereby promoting efficient collaboration among supply chain stakeholders [6, 7]. Through mobile applications, the platform can not only track inventory, orders, and logistics in real time but also dynamically adjust supply chain management strategies based on consumer demand predictions, facilitating more precise optimization of the supply chain.

Despite existing studies focusing on the integration of mobile interaction technology with S2B2C e-commerce platform supply chain management, certain gaps remain in this area of research. Most studies primarily concentrate on optimizing individual components of the supply chain, such as inventory management or logistics scheduling, with limited exploration of overall supply chain collaboration [8–11]. Furthermore, although some studies have proposed mobile-based information-sharing mechanisms for the supply chain, the practical application of these models and systems remains limited due to issues such as data processing capabilities, accuracy of demand forecasting, and the complexity of algorithms [12–15]. Especially in the field of supply chain demand forecasting, current algorithms often fail to fully account for the dynamic nature of consumer behavior, leading to discrepancies between predicted and actual demand, which in turn impacts the flexibility and responsiveness of the supply chain [16–21]. Therefore, addressing these limitations and proposing more accurate and efficient mobile-based supply chain management solutions is a key challenge to be addressed by this study.

The main content of this study is divided into two parts: first, the implementation technologies for mobile terminals in supply chain management on the S2B2C e-commerce platform. This part investigates how mobile interaction technologies, the Internet of Things (IoT), big data, and other tools can be utilized to construct an efficient mobile platform for supply chain management, facilitating real-time data sharing, inventory management, and logistics tracking. The second part focuses on the implementation of a supply chain demand forecasting model and algorithm based on mobile applications. This aspect of the research aims to analyze consumer purchasing behaviors, order data, and other multidimensional information to develop an accurate demand forecasting model. The model would then be used to adjust supply chain strategies in real time via mobile applications, optimizing the supply chain's responsiveness and decision-making efficiency. Through these two research avenues, this study seeks to provide both theoretical support and technical solutions for the practical application of mobile-based supply chain management within S2B2C platforms, advancing the intelligent and integrated development of supply chain management in e-commerce.

2 IMPLEMENTATION TECHNOLOGIES FOR MOBILE TERMINALS IN SUPPLY CHAIN MANAGEMENT ON THE S2B2C E-COMMERCE PLATFORM

The application of mobile interaction technologies to supply chains provides the foundational infrastructure for real-time data sharing and information flow among the stakeholders in the S2B2C e-commerce platform. By integrating mobile technologies, the S2B2C platform enables suppliers, distributors, retailers, and consumers to access and update core supply chain information in real time via mobile devices.

Suppliers and distributors, for instance, can use mobile applications to monitor inventory levels, logistics status, and order progress in real time. This functionality not only aids in optimizing production, inventory, and distribution decisions but also allows for flexible responses to market demand and changes during actual operations. For example, when consumers place orders on the platform, the system can synchronize warehouse and logistics status instantly, thereby improving delivery efficiency and avoiding delays or inventory mismatches caused by information lag. Mobile interaction technologies enhance the transparency of every link in the supply chain, enable all parties to access key data in real time, and reduce information asymmetry and decision-making delays, thereby improving the overall efficiency and flexibility of the supply chain.

Given several practical and technical considerations, the Android platform was selected as the foundation for the mobile terminals of the S2B2C e-commerce platform's supply chain management. The Android operating system has a broad market penetration and user base, particularly in the global smartphone market, where Android devices dominate. This widespread adoption of Android-based mobile applications allows for broader engagement with supply chain participants, facilitating extensive data sharing and collaboration. Moreover, the open-source nature of the Android platform reduces development costs while offering high flexibility and customizability. As for the supply chain management on the S2B2C e-commerce platform, development teams can tailor functionalities and interfaces to meet specific business needs, adjusting system architecture as required. Additionally, the Android platform supports the integration of various third-party libraries and application programming interfaces (APIs), enabling the platform to effectively incorporate a range of supply chain-related technologies, such as the IoT, data analytics, and real-time communications, further enhancing its scalability and functionality.

In the supply chain management of the S2B2C e-commerce platform, the mobile terminal implementation technologies must possess substantial computational power and efficient multitasking capabilities. With current mainstream mobile terminal processors, such as ARM-based cores, the mobile terminals of the S2B2C platform are capable of handling complex supply chain management tasks, including real-time data sharing, order processing, logistics tracking, and inventory management. These tasks not only demand high computational performance but also require support for various external interfaces and sensors to ensure that supply chain stakeholders can interact with the system anytime and anywhere via mobile devices. For instance, Bluetooth, infrared, and USB interfaces can enable connections to IoT devices, allowing for real-time access to inventory data or logistics status; cameras can be used to scan barcodes or QR codes, enabling rapid identification of product information and facilitating automated warehouse management. Furthermore, interfaces such as SDRAM and MMC cards can expand storage capacity, ensuring rapid data read/write operations and providing more stable hardware support for supply chain management.

In the supply chain management of the S2B2C e-commerce platform, the hardware architecture of mobile terminals must possess robust processing power and sufficient storage capacity to support complex tasks such as real-time data sharing, order processing, logistics tracking, and inventory management. The single-core OMAP3430 processor, manufactured by Texas Instruments, was selected as the core processing unit for this platform. This processor, based on the ARM architecture, offers high computational efficiency and can handle multiple parallel tasks, meeting the supply chain management system's requirements for rapid response and multitasking capabilities. The high performance of the processor enables the platform to execute complex supply chain management algorithms on the mobile terminal, including inventory forecasting, demand analysis, and supply chain optimization, ensuring real-time synchronization of supply chain information across stakeholders. Additionally, the 512MB RAM and 2GB ROM configuration effectively supports multitasking and data storage needs, ensuring system smoothness and stability during data interaction and information processing. For the S2B2C platform, sufficient storage capacity allows for the accommodation of substantial amounts of supply chain data, including real-time order data, inventory status, and logistics information, thereby ensuring the smooth operation of supply chain management.

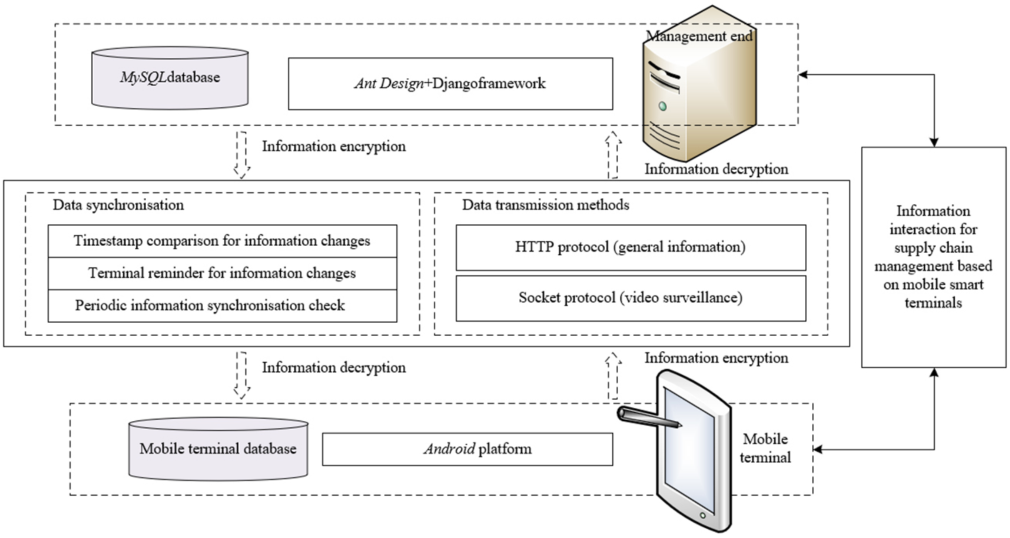

Fig. 1. Information interaction method for supply chain management based on mobile terminals

In terms of intelligent information interaction, the mobile terminal of the S2B2C e-commerce platform must facilitate data synchronization with the management system and ensure consistency through intelligent reminder mechanisms. Figure 1 illustrates the information interaction method for supply chain management based on mobile terminals. When data on the management system is changed, the system automatically sends a change notification to the terminal. Upon receiving the notification, the terminal prompts the user to update local data through a data change reminder module. This mechanism effectively prevents errors or mis-decisions caused by unsynchronized data, ensuring the accuracy and timeliness of data across all supply chain links. Unlike traditional terminals that only support information interaction via a single mode, the intelligent interaction method based on mobile smart terminals supports multiple interaction methods, optimizing information transmission efficiency and user experience. Additionally, by employing local data storage and periodic synchronization strategies, server load is significantly reduced, preventing bottlenecks in the information transmission process.

3 SUPPLY CHAIN DEMAND FORECASTING MODEL AND ALGORITHM IMPLEMENTATION BASED ON MOBILE APPLICATIONS

In the supply chain management of S2B2C e-commerce platforms, demand forecasting is a critical component for ensuring the efficiency of inventory management, order scheduling, and logistics operations. The demand forecasting model must possess strong time series modeling capabilities to address the complexity of demand fluctuations under varying market conditions. Additionally, within S2B2C e-commerce platforms, supply chain demand is influenced by multiple factors, including seasonal changes, promotional activities, and shifts in consumer behavior. These factors often exhibit complex non-linear relationships. Traditional linear forecasting methods may fail to fully capture these intricate demand patterns. Therefore, the Elman neural network was chosen in this study for supply chain demand forecasting. Figure 2 illustrates the architecture of the supply chain demand forecasting model based on mobile terminals.

The structure of the Elman network includes an input layer, a hidden layer, and a feedback layer, with the feedback layer capable of feeding back the output from the previous time step to the network, thereby forming a dynamic feedback mechanism, as shown in Figure 3. This feedback mechanism enables the network to retain the state information of historical data, providing a strong capability to model the temporal variations in demand within the S2B2C e-commerce platform. It can predict future demand based on factors such as historical sales data and market trends, ensuring that the platform can make accurate inventory predictions and order arrangements in a dynamic market environment. At the same time, the Elman neural network effectively captures the nonlinear relationships in supply chain demand and continuously optimizes the model through backpropagation algorithms, thereby improving the accuracy of the predictions.

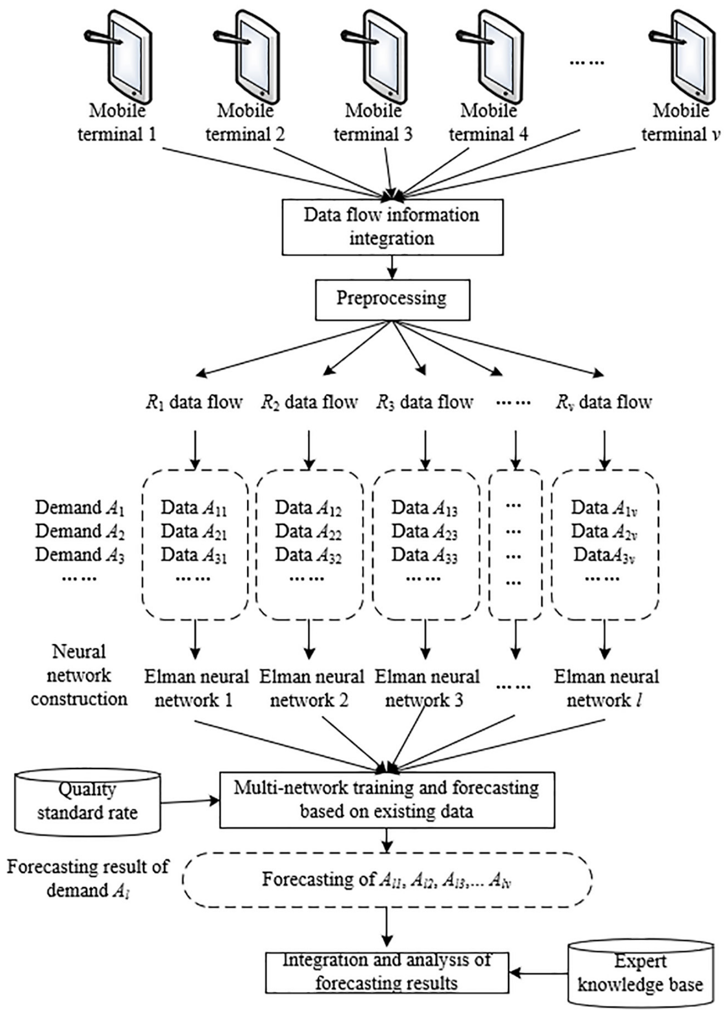

Fig. 2. Supply chain demand forecasting model based on mobile terminals

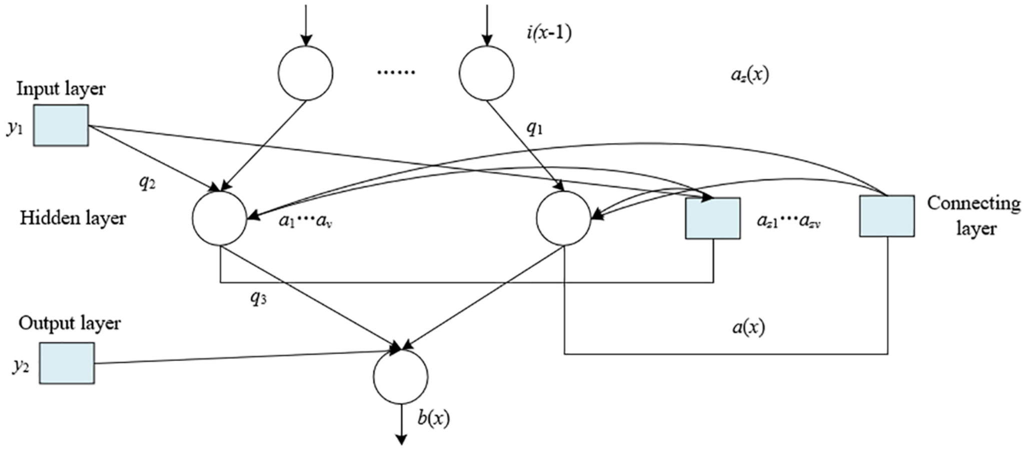

Fig. 3. Elman neural network structure

During the algorithm implementation phase, the management end must first integrate and preprocess the supply chain demand data collected by each mobile terminal from the e-commerce platform. Let the demand data of the k-th supply chain, reported by the u-th mobile terminal, be denoted as A_{uk}, forming a two-dimensional matrix of demand data as shown in Eq. (1).

$$DA = \begin{bmatrix} A_{11} & A_{12} & A_{12} & \cdots & A_{1v} \\ A_{21} & A_{22} & A_{23} & \cdots & A_{2v} \\ A_{31} & A_{32} & A_{33} & \cdots & A_{3v} \\ \cdots & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \tag{1}$$

Assuming that the demand data known for each mobile terminal is represented as $A_{1(u+1)}$, $A_{2(u+1)}$, $A_{3(u+1)}$, and so on, further determination can be made to check whether each set of forecasting results falls within the suppliable range of the supply chain, as shown in Eq. (2).

$$A = \begin{bmatrix} A_{1(u+1)} \\ A_{2(u+1)} \\ A_{3(u+1)} \\ \cdots\cdots \end{bmatrix} = \begin{bmatrix} EL\left(a_{11} \quad a_{12} \quad a_{13} \cdots\cdots a_{1u}\right) \\ EL\left(a_{21} \quad a_{22} \quad a_{21} \cdots\cdots a_{2u}\right) \\ EL\left(a_{31} \quad a_{32} \quad a_{33} \cdots\cdots a_{3u}\right) \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \end{bmatrix} NT \quad \bar{L} \qquad \bar{L} = \begin{bmatrix} L_1^- \\ L_2^- \\ L_3^- \\ \cdots \end{bmatrix} \tag{2}$$

Let the standard intervals corresponding to each mobile terminal be denoted as L_1^-, L_2^-, L_3^-, etc. The lower bound of the suppliable quantity range for each mobile terminal's supply chain is denoted as l_{1m}, l_{2m}, l_{3m}, etc., while the upper bound of the suppliable quantity range is denoted as l_{1l}, l_{2l}, l_{3l}, etc. Then, the following holds:

$$L^- = \begin{bmatrix} L_1^- = \left[l_{1m}, l_{1l}\right] \\ L_2^- = \left[l_{2m}, l_{2l}\right] \\ L_3^- = \left[l_{3m}, l_{3l}\right] \\ \cdots\cdots = \left[\cdots\cdots, \cdots\cdots\right] \end{bmatrix} \tag{3}$$

If $A_{1(u+1)} \in L_1^-$, this indicates that, in the future, the mobile terminal can obtain the required supply chain products or materials. The same logic applies to other intervals.

The structure configuration of the Elman neural network in supply chain demand forecasting typically includes an input layer, a hidden layer, and an output layer. In the S2B2C e-commerce platform, the input layer generally includes several key factors influencing demand, such as historical sales data, promotional activities, seasonal variations, inventory levels, and other relevant information. These data can be used as input vectors to the network. Through the recursive mechanism of the hidden layer, the Elman network can effectively capture the temporal features and nonlinear relationships in the input data, subsequently predicting future demand quantities through the output layer. Let the l-dimensional output node vector be denoted by b, the e-dimensional input vector by i, and the feedback state vector of v by A_z. The v-dimensional intermediate layer node vector is denoted by a, the connection weights from the intermediate layer to the output layer by q^3, the connection weights from the input layer to the intermediate layer by q^2, and the connection weights from the connecting layer to the intermediate layer by q^3. The nonlinear state-space expressions of the Elman network are given by:

$$a(x) = d\left(q^1 a_z(x) + q^2(i(x-1))\right) \tag{4}$$

$$a_z(x) = a(x-1) \tag{5}$$

$$b(x) = h\left(w^3 a(x)\right) \tag{6}$$

Let the transfer function of the output neurons be denoted by $h(*)$, and the transfer function of the intermediate layer neurons by $d(*)$, i.e.:

$$d(a) = \frac{1}{1+e^{-a}} \tag{7}$$

Let the target input vector be denoted by $b_j^*(x)$, the actual output vector by $b_j(x)$, and the learning objective function be the sum of squared error's function:

$$R(x) = \sum_{j=1}^{v} \left(b_j(x) - b_j^*(x)\right)^2 \tag{8}$$

The implementation steps for demand forecasting in the S2B2C e-commerce platform based on the Elman neural network can be divided into several key stages to ensure that the model can effectively capture the dynamic demand patterns within the supply chain and provide accurate predictions. The following outlines the six complete steps involved in achieving this objective:

Step 1: Elman neural network initialization and input vector construction: After data normalization, the next step is the initialization phase of the Elman neural network. By synthesizing the multi-dimensional input data, a complete input vector was constructed. This input vector was then passed from the input neurons into the network, where it was processed by the hidden layer. In the hidden layer, the Elman network captured the temporal relationships and dynamic dependencies in the input data through its recursive structure, providing the foundation for subsequent demand forecasting. Let WL_u represent the output matrix of the hidden layer after a_u is input into the network, and $WL_{z(u)}$ represent the information matrix transmitted to the connecting layer after a_u passes the hidden layer, as shown by the following equation:

$$WL_u = \frac{1}{1+e^{-\left[\mu^1 WL_{z_{(u-1)}} + \mu^2 a_{(u)}\right]}} \tag{9}$$

Step 2: Output propagation and error calculation: After the input vector was computed through the hidden layer, the Elman neural network generated an output value, representing the forecast of future demand. The output layer then propagated the neural network's predicted value to the external system for comparison with the actual demand data, thus enabling the calculation of error. In the S2B2C platform, large forecasting errors may affect decisions related to inventory management and order scheduling. The magnitude of the error directly reflects the performance of the network. If the error is large, it indicates a significant discrepancy between the model's predicted values and actual demand, suggesting the need for further model adjustment. The error calculation formula is as follows:

$$R(x) = \frac{1}{2}\left(b_f(x) - b(x)\right)^T \left(b_f(x) - b(x)\right) \tag{10}$$

Step 3: Weight adjustment and error backpropagation: Accurate demand forecasting is critical for the S2B2C e-commerce platform, as large errors can lead to inventory shortages or surpluses, thereby impacting supply chain efficiency and customer satisfaction. When the error exceeds the predefined quality threshold, the error backpropagation algorithm was employed in this study to adjust the weight matrix. The weight adjustment formula is given as follows:

$$\Delta\mu = \frac{\partial R}{\partial \mu} = -\lambda \sigma a_u \tag{11}$$

The weight adjustment formula for each layer is as follows:

$$\mu(s+1) = \mu(s) + \beta\mu(s) \tag{12}$$

Step 4: Data upload and construction of new input vectors: As time progresses, demand data on the S2B2C e-commerce platform continuously evolves, with new sales data, product information, and other relevant factors being uploaded through mobile terminals on the platform. In this process, several sets of the latest product data uploaded from each terminal were used as new input vectors. To ensure that the Elman neural network can adapt to the latest market changes, these newly uploaded data need to be integrated into the existing input vectors and used for subsequent model training. The most recent sets of demand data uploaded by each mobile terminal were incorporated into the corresponding trained Elman neural network as input vectors in this study, thereby yielding the corresponding demand prediction values for the respective mobile terminals.

$$A_l = \left(a_{l1}, a_{l2}, \ldots, a_{l(u-1)}\right)^T \tag{13}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the data provided in Figure 4, which compares the number of experiments with the connection establishment time for both without and with historical data, the experiments recorded the time required to establish a mobile interaction connection under both conditions. The data indicate that, in the case of no historical data, the time required for the connection fluctuated significantly as the number of experiments increased, showing notable variability. For example, when the number of experiments was 0, the connection time was 2940 ms, and at experiment number 90, the time was 2990 ms, demonstrating a certain range of fluctuation throughout the process. In contrast, when historical data were available, the connection time exhibited a more stable trend, and as the number of experiments increased, the time tended to stabilize. For instance, at experiment number 0, the time was 2540 ms, and at experiment number 90, the time was 2590 ms, with a much smaller overall fluctuation. Furthermore, the connection time was significantly shorter compared to the scenario without historical data. From the data, it can be concluded that, on the S2B2C e-commerce platform, as historical data accumulate, the response speed and data flow efficiency of the platform's supply chain management system gradually improve, enabling better support for real-time data sharing and logistics tracking functionalities, thus enhancing the overall operational efficiency of the platform.

Based on the data provided in Figure 5, the performance of platform throughput under three different information update strategies, namely, normal communication, occasional updates, and periodic updates, was observed across different experimental trials. The experimental results indicate that under normal communication, throughput remained relatively stable, fluctuating between 1.8 and 2.5 for most of the experimental trials, with minimal variation. However, occasional lower throughput values were recorded (e.g., at trial numbers 40 and 90, throughput was 1.7 and 1.8, respectively). In the case of occasional updates, throughput was generally higher, fluctuating between 2.0 and 2.5 for the majority of the trials, though lower throughput was also observed in some experiments (e.g., trial numbers 10 and 50, with throughput values of 2.2 and 2.1, respectively). Under the periodic update strategy, throughput was generally lower, particularly at higher experimental trial numbers (e.g., at trial numbers 50 and 60, throughput was 0.8 and 0.4, respectively). For most of the experiments, throughput ranged from 0.2 to 1.2, with some extreme cases recording as low as 0.23. These results suggest that the periodic update method significantly impacted platform throughput, with throughput consistently lower than that observed under both normal communication and occasional update strategies.

Based on the platform test results presented in Table 1, the response time data and execution outcomes for various tests can be observed. The startup time is recorded at 665 milliseconds, indicating that the platform is able to complete initialization and successfully launch within a relatively short time. The response time for determining whether the homepage has been entered is 248 milliseconds, demonstrating the platform's ability to quickly ascertain if the user has successfully accessed the homepage and provide real-time feedback. The time for tag recognition is 2125 milliseconds, which is relatively long and may be attributed to the platform's need to identify and load multiple tags, involving a more complex data processing procedure. The list information display time is 1325 milliseconds, showing the efficiency of loading and presenting list data. This response time is moderately long compared to the other tests. The warehouse entry response time is 1254 milliseconds, indicating that the system is able to quickly respond and complete the data entry process. Overall, the data demonstrates the platform's performance across various stages, including startup, homepage determination, tag recognition, information display, and data storage. The response time is deemed reasonable, indicating that the platform exhibits strong performance in mobile supply chain management applications.

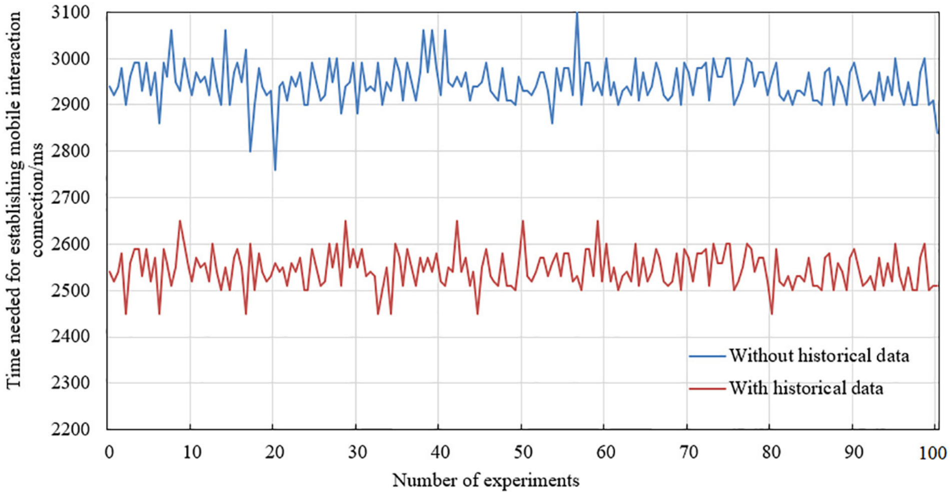

Fig. 4. Comparison of time needed for establishing mobile interaction connection

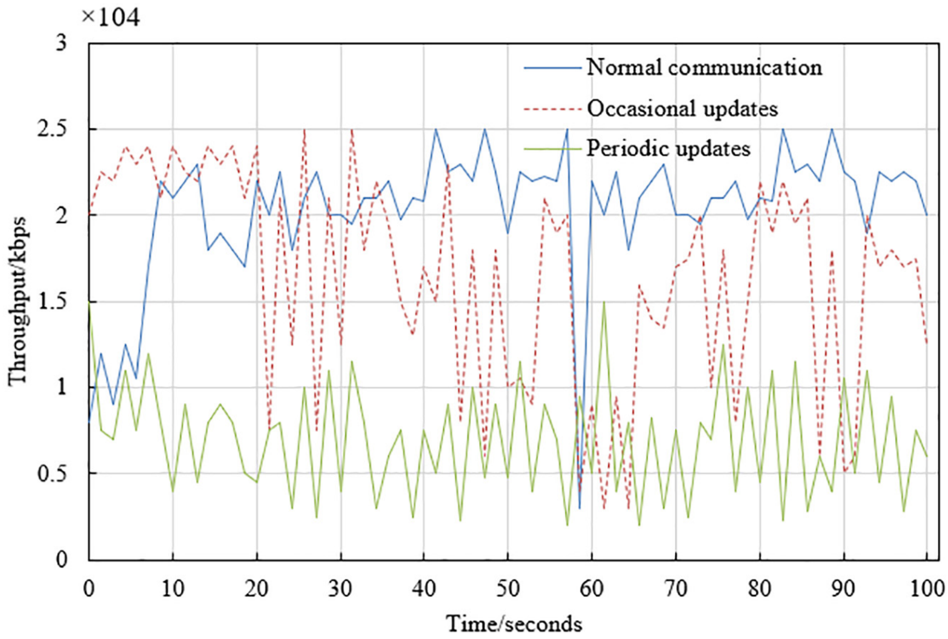

Fig. 5. Impact of information updates on platform throughput

Table 1. Platform test results

No.	Test Item	Response Time	Execution Result
1	Startup time	665 ms	Success
2	Determination of homepage entry	248 ms	Success
3	Tag recognition time	2125 ms	Success
4	List information display time	1325 ms	Success
5	Warehouse entry response time	1254 ms	Success

Based on the data presented in Figure 6, the demands A, B, C, and D (representing conventional demand, seasonal demand, emergency demand, and promotional demand, respectively) show some fluctuation as the number of experimental trials increases. These demand data represent the system's feedback at different time points. For demand A, in the initial trials, the values fluctuated between 120 and 124, but a significant increase was observed between trial numbers 30 and 40, reaching 164. Afterward, the demand decreased back to around 120 and stabilized. Demand B remained at approximately 90 during the first few trials with slight fluctuations, but a clear increase was noted in subsequent trials, especially between trials 30 and 40, where it reached 134 and stabilized. Demand C remained relatively low, fluctuating around 70 initially, but a noticeable increase in demand occurred between trial numbers 30 and 40, especially after trial 40, when it reached 120 and showed a degree of stability. Lastly, demand D remained relatively low, initially fluctuating around 40, with a slight increase observed between trial numbers 30 and 40 (rising to 84), but the overall fluctuation was minimal and remains stable. From these demand data, it can be concluded that as the number of trials increases, the fluctuations and growth trends of different demands reflect the system's load variations at different time points. This is likely closely related to the system's response time and resource scheduling strategies. The higher fluctuation of demand A could be attributed to the system's handling of large-scale data, where fluctuations in demand result in changes in system load, thus affecting the response time. During peak demand periods (such as trials 30 to 40), the platform may face an increased number of data processing tasks and greater pressure on resource allocation, leading to longer response times. In contrast, the smaller fluctuation observed in demand B and demand C suggests that these demand types may involve lower data processing requirements, allowing the system to respond more efficiently. The higher stability of demand D indicates that in certain stages of the supply chain, demand is infrequent, enabling the platform to maintain a low load and ensuring a faster response time.

The data in Table 2 presents the feedback data from three mobile terminals when processing different demands, reflecting the distribution of quantities for each demand across the different terminals. For demands 1 to 6 (representing daily demand, promotional demand, holiday demand, seasonal demand, pre-order demand, and inventory replenishment demand, respectively), the variation in feedback across different terminals is relatively small. The demand values for Mobile Terminal 1 are slightly higher than those for the other two terminals, with the overall range fluctuating between 22.14 and 24.63 thousand units. This suggests that when the demand is relatively balanced, the responsiveness of each terminal to the demand is consistent. For demands 7 to 12 (representing urgent demand, long-term planning demand, customized demand, return demand, order-based production demand, and standby demand), similar trends are observed. The demand values for Mobile Terminal 1 are generally slightly higher than those for Mobile Terminals 2 and 3, especially for demand 8 (246,300 units), demand 10 (245,800 units), and demand 12 (unknown). By analyzing the data, it is apparent that the feedback data from the three terminals follow a certain pattern, indicating that the load and responsiveness across different devices are generally well-balanced. Each terminal is able to maintain stable data processing when responding to various demands.

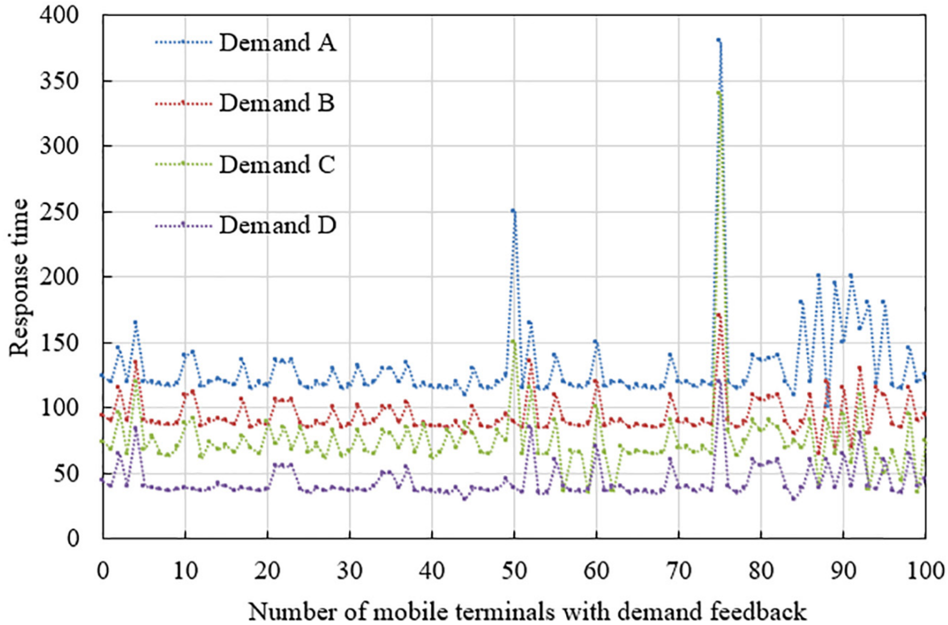

Fig. 6. Correlation between the number of mobile terminals with demand feedback and system response time

Table 2. Feedback data from three mobile terminals

Demand	Mobile Terminal 1 (10,000 Units)	Mobile Terminal 2 (10,000 Units)	Mobile Terminal 3 (10,000 Units)	Demand	Mobile Terminal 1 (10,000 Units)	Mobile Terminal 2 (10,000 Units)	Mobile Terminal 3 (10,000 Units)
Demand 1	24.26	22.89	22.56	Demand 7	24.51	23.25	22.35
Demand 2	24.23	22.79	22.44	Demand 8	24.63	24.21	22.32
Demand 3	24.58	22.56	22.74	Demand 9	24.36	22.26	22.14
Demand 4	24.16	22.89	22.36	Demand 10	24.58	23.26	22.56
Demand 5	24.59	22.76	22.85	Demand 11	24.31	23.26	22.14
Demand 6	24.26	22.85	22.56	Demand 12	Unknown	Unknown	Unknown

5 CONCLUSION

Based on the study framework of the integration of mobile interaction technologies in supply chain management for S2B2C e-commerce platforms, combined with multiple experimental results, this study systematically explores how the integration of mobile technology, the IoT, and big data can optimize various components of supply chain management. The research demonstrates that integrating mobile interaction technology on the S2B2C platform can significantly enhance real-time data sharing and information flow among all parties within the supply chain, thereby improving overall supply chain transparency and responsiveness. For instance, the demand forecasting model based on the Elman neural network can not only accurately predict consumer demand but also adjust supply chain strategies in real time according to demand fluctuations, aiding the platform in optimizing inventory management and logistics scheduling, thus enhancing decision-making efficiency and supply chain flexibility. Experimental results indicate that the relationships between platform throughput, information updates, and response time are of significant importance, particularly in situations with large demand fluctuations. Optimizing these parameters is crucial for enhancing system efficiency. Moreover, the analysis of feedback data from the three terminals further verifies the consistency and stability of demand response across different terminals, proving the value of mobile interaction technology in supply chain management.

However, several limitations exist within this study. First, although the Elman neural network effectively forecasts demand fluctuations, the model may be constrained by computational resources and real-time updates when dealing with large-scale complex data. Future research could consider integrating more sophisticated deep learning algorithms or other efficient prediction models to improve accuracy. Second, the study primarily focuses on demand forecasting and response efficiency optimization. Future work could explore how IoT devices and big data technologies can be more comprehensively integrated in practical applications, driving the intelligent upgrading of the entire supply chain. Additionally, this study does not address the diverse demands in different supply chain scenarios. Future research could extend to more industry application scenarios, verifying the feasibility and effectiveness of the integration of mobile interaction technology and supply chain management.

6 ACKNOWLEDGEMENT

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