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Retraction

Retracted: Predictive Analysis of User Behavior Processes in Cross-Border E-Commerce Enterprises Based on Deep Learning Models

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

References

[1] L. Yan, "Predictive Analysis of User Behavior Processes in Cross-Border E-Commerce Enterprises Based on Deep Learning Models," *Security and Communication Networks*, vol. 2022, Article ID 1560017, 6 pages, 2022.

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Research Article

Predictive Analysis of User Behavior Processes in Cross-Border E-Commerce Enterprises Based on Deep Learning Models

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Currently, the global consumer market is moving toward digitalization, and cross-border e-commerce enterprises are no exception and have to make adjustments in their operational strategies. Digitalization brings complexity, dynamism, and fragmentation in sales channels, media environment, and consumer behavior, requiring cross-border e-commerce enterprises to react more quickly and timely, and the need for intelligent operations is becoming more and more urgent. In this paper, through the problem of predicting the e-commerce user behavior process, the model usually needs to focus on both long-term preferences and short-term preferences of e-commerce users in the current behavior sequence; otherwise, the behavior prediction will be much less effective. Specifically, through a comprehensive analysis of typical cases, the strategies and problems in the intelligent operation process of China's cross-border e-commerce enterprises at the present stage are discussed, and corresponding suggestions are put forward, so as to promote the rapid development of China's cross-border e-commerce enterprises.

1. Introduction

According to data published by Internet World Stats, the number of Internet users now reaches 4.5 billion out of a global population of over 7 billion, with nearly 4.2 billion mobile Internet e-commerce users and 6.5 hours of Internet use per capita. There is no doubt that the global marketplace is virtually always in a digital environment. This is also true for cross-border e-commerce companies. How do Chinese cross-border e-commerce companies, which have grown rapidly in recent years, recognize the new environment brought about by digitalization? Digitalization implies an all-round complexity and fragmentation of consumer behavior, sales channels, and media environment [1]. The operation method relying on human resources alone can no longer adapt to the development of cross-border e-commerce but must adopt intelligent data-based operation strategies in appropriate operational aspects.

The global e-tailing market size exceeded USD 3 trillion in 2019, and the global e-tailing market consumption is expected to exceed USD 4.8 trillion in 2021, accounting for 17.5% of the global economic and trade market [2]. In order to seize the market and take the lead in developing the cross-border sector, many countries have launched e-commerce platforms for global or overseas specific markets, such as eBay, Amazon, Swift Commerce, and other e-commerce platforms with wider global coverage, to generate revenue in the international market [3]. In the scale of expansion, the current global cross-border e-commerce development system is becoming increasingly mature and has gone through the "wild growth" phase, facing a new development environment.

In the digital context, compared with the relatively single and static consumers, channels, and media in the past, cross-border e-commerce enterprises face consumers who are always online and have complex behaviors, as well as a large number of channels and media with different characteristics, and the operation mode is bound to shift from crude to refined to achieve the precise insight and timely satisfaction of consumer needs [4]. With the development of the technology and data industry, from the popularization and promotion of cloud services to the full commercialization of artificial intelligence technology, the new business intelligence that collects artificial intelligence, big data, cloud services, RPA, operations research, and other technologies begins to provide multidimensional decision-making intelligence services for cross-border e-commerce enterprises, and intelligent operation becomes possible [5].

For cross-border e-commerce enterprises, facing different sales channels from domestic ones, they must analyze the sales rhythm and algorithm mechanism of overseas channels in a targeted manner.

Smart pricing is to solve the problem of commodity pricing by continuously evaluating market dynamics through deep learning algorithms. When setting product prices, cross-border e-commerce enterprises will understand the prices of similar products on major platforms to determine a more competitive price dimension, but this process is dynamic and evolving, and large platforms such as Amazon and Sotheby's have already achieved dynamic pricing and timely adjustment strategies. For many smaller cross-border e-commerce operators, smart pricing includes changes in supply chain fronting and bargaining power of different supply vendors in addition to consumer-facing pricing dimensions [6].

2. Related Work

The research on big data by domestic and foreign scholars covers a wider range of fields, involving computer and automation technology, macroeconomic management and sustainable development, medicine, environmental sustainability and resource utilization, enterprise management, and business intelligence [7].

The authors of [8] introduced the application of big data in business intelligence for internal enterprise management. It is proposed that the dramatic decrease in the cost of data indexing and data storage has caused the need for big data applications for enterprises as a way to improve their competitive power. The need for the time between data collection and decision making to be reduced has stimulated innovation in business intelligence techniques [9]. The authors of [10] analyzed how Amazon, Wal-Mart, and Adidas used big data to gain a large amount of revenue and concluded that the application of big data in e-commerce has a broad prospect. However, there are definite barriers to the application of big data, which are challenged by the lack of employees' skills in big data analysis, in addition to the limitations of privacy protection [11]. Therefore, there is a need to define a framework for Big Data applications and to train employees with appropriate skills. The author of [12] analyzes both theoretically and empirically the issues of how companies can better apply the results of big data analytics and how to optimize the application of machine learning techniques in e-commerce. Currently, data-driven strategies can be applied to many aspects of e-commerce, including product recommendation and content marketing planning, and big data analytics and machine learning techniques are achievable in the future and have huge economic benefits [13, 14].

In China, the booming development of the big data industry makes the big data industry is shifting from information technology-driven to data-driven, and with the advancement of machine learning, human, and data mining technology, intelligence will benefit all walks of life [15]. The application of big data is developing from the Internet field to other fields, and the decision-making method of each industry is changing towards "data intelligence-driven" [16]. Taking advantage of the development of big data technology, cross-border e-commerce will practice the technology in all aspects of operation and management, thus promoting the further development of big data technology.

The author of [17] points out the uncertainty, emergence, and complexity of big data on the Web and summarizes the main problems in related applications while making an overall prediction of future development. The author of [18] points out that precision marketing is of great importance for e-commerce and suggests that the collection, storage, processing, and analysis of information play a decisive role in the realization of precision marketing. The emerging e-commerce service model proposed by [19] relies on the application of big data platforms, and its focus is on the new industrial chain driven by big data. Third-party network platforms and e-commerce enterprise platforms have all the interactive data of supply and demand sides and understand the full range of unique market information, and thus, it creates a new market opportunity for e-commerce model innovation. The author of [20] proposed three new models of e-commerce management based on big data, which are vertical segmentation of the field, personalized shopping guide, and data product service.

3. E-Commerce User Behavior Intention Extraction Method

In the e-commerce user behavior prediction problem, the model usually needs to focus on both long-term and short-term preferences of e-commerce users in the current behavior sequence; otherwise, the behavior prediction effect will be much worse; for example, in a continuous click browsing behavior, the e-commerce user who has been browsing swimsuit and swim cap suddenly clicked on eyeglasses and browsed. In this case, if the design of e-commerce user behavior prediction model is unreasonable, only considering the short-term preference of e-commerce users, that is, clicking on the browsing glasses, without fully considering the long-term preference of e-commerce users in the sequence, the model may need to understand the intention of e-commerce users through the behavior sequence. A good e-commerce user behavior prediction model should not only focus on the current interest points of e-commerce users but also on the behavioral intent of e-commerce users, because the two are complementary relationships.

(1) First is the lack of logistics advantages. Compared with Hangzhou, Yiwu, cross-border logistics in our city because of the small amount and scattered resulting in the distribution of time is not timely, and generally speaking, the time is about 1 day, and the cost is relatively high.

(2) Second is the lack of talent advantage. Zhuji is located in the middle of Hangzhou, Yiwu, cross-border talent "siphon" effect is obvious, e-commerce talent and enterprises are not willing to take root in the local, and it is difficult to form a cross-border development atmosphere. There are not

many local cross-border service providers, and the overall level is not high.

(3) Third is the lack of effective initiatives. Although the Shaoxing cross-border pilot area has been operating for nearly one year, but the proportion of enterprises taking the initiative to declare exports is still low, the market-oriented operation.

3.1. Principle of Extracting E-Commerce Users' Intention by Idea Power Mechanism. In the case of using recurrent neural networks as encoders, the encoded results usually originate from the last state of the input sequence, which can only express the current point of interest of e-commerce users to a certain extent and cannot provide a good characterization of the long-term preferences of e-commerce users, because long-term preferences need to be extracted from the whole sequence of behaviors. Moreover, regardless of the length of the input e-commerce user behavior sequence, the encoder encodes the input as a fixed-length representation vector, and there is more information loss, which is detrimental to the prediction of the model. In order to cope with this situation, the proposed method of e-commerce user behavior intention extraction allows the model to capture the e-commerce user behavior intention by introducing attention mechanism to self-learn the long-term preferences of e-commerce users in the behavior sequence. In recent years, in the task of machine translation, with the support of the attention mechanism, the deep model has been far more effective than other methods. In fact, there is a lot of redundant and unimportant information in the input data, and the role of the attention mechanism is to let the model automatically learn from the data, which information is relatively unimportant for the current task, and then ignore and forget this part of information, and which information is relatively important for the current task, and then keep and emphasize this part of information for a long time. This filtering process of the attention mechanism is also the process of capturing the main intention of e-commerce user behavior and learning the long-term preferences of e-commerce users in the current sequence.

Specifically, the attention module of the model filters each hidden state vector of the encoder part of the recurrent neural network, and the input h of the attention module is obtained by the $\overrightarrow{h}, \overleftarrow{h}$ splicing of the e-commerce user behavior sequence encoding method, and the attention module automatically learns the weight corresponding to each hidden state vector according to the data characteristics, and then, the model dynamically selects and linearly combines the input hidden state vectors at different moments based on the weights, so as to obtain the output c_t of the attention module.

$$c_{\mathbf{t}} = \sum_{i=1}^{t} \alpha_{ti} h_i, \tag{1}$$

where weight α determines which parts of the input sequence are to be retained or ignored under the current task, and weight α is calculated from the individual hidden state vectors.

$$\begin{aligned} \alpha_{ti} &= \operatorname{softmax}\left(q\left(h_t, h_i\right)\right), \\ q\left(h_t, h_i\right) &= V^T \sigma\left(W_1 h_t + W_2 h_i\right), \end{aligned} \tag{2}$$

where σ is the sigmoid activation function, a randomly initialized weight matrix W_1, W_2 is used to map h_t, h_i into the hidden vector space, and the computed results of the function q are fed into the softmax function for normalization to obtain the weights of each hidden state α. The last step of BiGRU, hidden state h_t, is calculated from the last input and the hidden state of the previous state, which can be abstractly understood as the current point of interest or short-term behavioral preferences of the e-commerce user, while the output $c_{\mathbf{t}}$ of the attention module is the information extraction for the whole sequence of behaviors, and since the module adaptively focuses on those e-commerce user behaviors that are more important, such as being able to learn that the sequence of e-commerce users clicking on swimming gear is more important, therefore, $c_{\mathbf{t}}$ contains the main intention of the e-commerce user during the current behavior, that is, the long-term behavioral preferences of the current sequence. By combining the short-term behavioral preferences h_t and long-term behavioral preferences $c_{\mathbf{t}}$ of e-commerce users in the current behavior sequence for learning and prediction, not only does it alleviate the problem of losing important information caused by encoding the input sequence as a fixed-length vector by the encoder and making full use of the sequence input information but also allows the model to focus on both the long-term and short-term preferences of e-commerce users in the current sequence, which can improve the prediction effect well [21–23].

3.2. Implementation of E-Commerce User Behavior Intention Extraction Method. To address the model parametric number problem, this paper innovatively proposes the embedding vector matching method, which is used to replace the traditional fully connected layer in the prediction stage. Figure 1 shows the decoding matching process, where the $|H|$-dimensional vector $\nu = [h_t, c_{\mathbf{t}}]$ from the BiGRU encoder fuses the behavioral sequence representation vector of e-commerce users' short-term preferences and long-term preferences. In the decoding and prediction stage, the prediction score of each candidate is generated by matching the embedding vector of m candidates, and usually, the representation vector from the encoder is decoded using the fully connected layer for multiclassification prediction, but if the fully connected layer is used, it can be calculated that the model needs to learn $|H| * |C|$ parameters, where $|H|$ is the dimensionality of the representation vector and $|C|$ is the number of candidates, and when the number of candidates is very large, the training is difficult and the resource consumption is also very large, for example, to predict the next product clicked by an e-commerce user, the number of candidates is very large. Therefore, this paper proposes the following matrix multiplication embedding vector matching method to compute the prediction score for the candidate items.

$$S_i = \nu\left(emb_i W\right)^T, \tag{3}$$

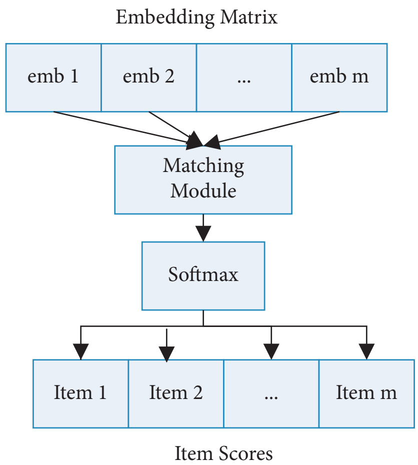

Figure 1: Decoder module of the model.

where emb_i is the $|D|$ dimensional embedding vector of the i th candidate, W is a $|D| * |H|$ dimensional weight matrix, S_i is the prediction score of the i th candidate, and usually, the size of $|D|$ and $|H|$ is tens to hundreds, while $|C|$ will be very huge, so using this matching method can greatly reduce the training parameters, and after getting the score of each candidate, it will be fed into the softmax function for normalization to get the final probability, and since in many scenarios, the model needs to give multiple predictions, such as predicting the k songs that e-commerce users are most likely to listen to next time, and the k products that e-commerce users are most likely to click next time, and the result of the e-commerce user behavior process prediction is a list of the k behaviors with the highest probability of prediction.

The loss function used for model training is the cross-entropy loss function that

$$L(p, q) = -\sum_{i=1}^{m} p_i \log(q_i), \tag{4}$$

where q is the predicted probability distribution and p is the true probability distribution, and the model is trained and optimized using the small-batch gradient descent algorithm or other variants until the loss converges [24, 25].

4. Performance Analysis

The proposed e-commerce user behavior process prediction model in this paper does not use the common prediction scheme of using the fully connected layer for classification in the decoding and prediction stage but uses the embedding vector matching method. Tables 1 and 2 show the performance comparison of using different decoding methods in the RecSys2015 dataset and Last FM dataset, respectively. It can be seen that the training time consumption performance of the embedding vector matching method on both RecSys2015 and Last FM datasets is better than that of the decoding method using the fully connected layer, thus indicating that the embedding vector matching method is effective for reducing model parameters and saving computational resources [26].

Table 1: Performance comparison of RecSys2015 experiments using different decoding methods (embedding dimension 200, number of neurons 100).

Decoding method	Training time (s)	Prediction time (s)
Embedding vector matching	2232	6.31
Fully connected layer	2425	6.22

Table 2: Performance comparison of last FM experiments using different decoding methods (embedding dimension 200, number of neurons 100).

Decoding method	Training time (s)	Prediction time (s)
Embedding vector matching	88	1.65
Fully connected layer	92	1.71

In order to make full use of the temporality of the solution data, this paper proposes a temporal migration learning training method borrowing the idea of migration learning, which has significant improvement in the prediction effect on two datasets with different domains. The main focus here is on the training time consumption difference between the temporal migration learning method and the full set learning method. Tables 3 and 4 show the time of using different training methods in RecSyS2015 dataset and the last FM dataset, respectively. It can be known that the training time consumption of migration learning is divided into two parts: pretraining and fine-tuning. The pretraining phase uses early data training, the fine-tuning phase uses early data training, and the fine-tuning phase uses the latest data training. From the table, we can see that although the temporal transfer learning training method is divided into two phases and requires two training sessions, the total training time is greatly reduced compared with the full set training method. The time consumption is reduced by about ten to twenty percent.

Table 5 shows the comparison of the training and prediction time of the proposed e-commerce user behavior prediction model with and without the introduction of dynamic attributes, and it is obvious that the method without the introduction of dynamic attributes has obvious advantages in both training and prediction time. However, the improvement is insignificant compared to the improvement brought by the introduction of dynamic attributes.

Relying on the intelligent and automated supply chain management of big data, the system data will automatically generate procurement time, procurement quantity, and other plans and arrange distribution, allocation, and reverse logistics tasks in conjunction with the warehouse storage situation. In addition, the intelligent management system can realize continuous dynamic inventory, as shown in Figure 2. Our method can be used in the whole process of receipt, delivery, and return in the whole warehouse, making the inventory accuracy, on-time delivery rate, and on-time delivery rate of e-commerce reach 99.9%, 100% and 98%, respectively. The algorithm in this paper has a powerful data algorithm in the backend of the operations center, allowing

Table 3: Performance comparison of different training methods for RecSys2015 experiments (embedding dimension 200, number of neurons 100).

Training method	Pretraining time (s)	Fine-tuning time (s)	Training time (s)
Full set training	No	No	2221
Time transfer learning	1521	553	1978

Table 4: Performance comparison of different training methods for last FM experiments (embedding dimension 200, number of neurons 100).

Training method	Pretraining time (s)	Fine-tuning time (s)	Training time (s)
Full set training	No	No	88
Time transfer learning	38	29	68

Table 5: Performance comparison of last FM experiments with and without dynamic attributes (embedding dimension 200, number of neurons 100).

Whether to introduce dynamic attributes	Training time (s)	Prediction time (s)
Yes	88	1.59
No	72	1.65

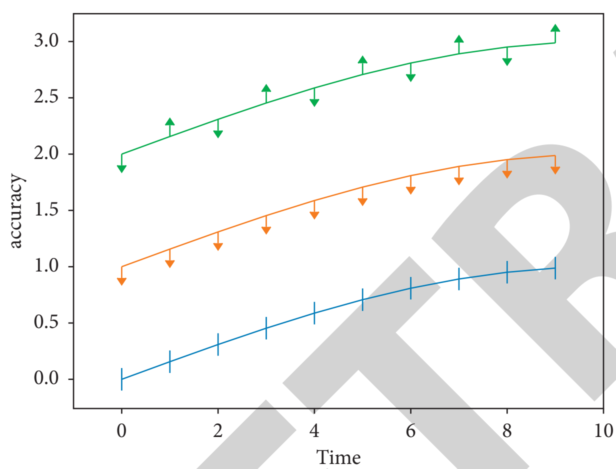

Figure 2: Different methods of logistics optimization.

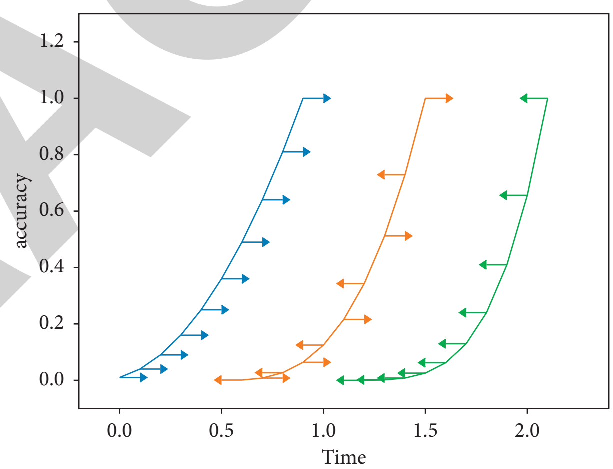

Figure 3: Item conversion rate.

logistics pickers to randomly optimize the path of picking, with the moment mechanism of the optimal path being nearly 60% less than the picking walking path under traditional operational processes.

The dimension is the intelligent recommendation, which is a personalized recommendation based on search, purchase, and browsing history, in order to improve the sales conversion rate. The ZAFUL platform of global e-shop has the function of "thousand people, thousand faces" intelligent recommendation, and it will apply the algorithm to the category page and personal center page, so that the traffic will not be limited to the head products but recommend more SKU for consumers, and if the consumer does not click the page more than three times, it will recommend another product for the consumer. If a consumer does not click on the page more than three times, another product will be recommended for the consumer. Through this form, the conversion rate of the sales channel is effectively improved, as shown in Figure 3.

5. Conclusion

Faster and more timely responses from cross-border e-commerce companies bring great benefits to intelligent operations. In this paper, through the e-commerce user behavior process prediction problem, the model usually needs to focus on both long-term preferences and short-term preferences of e-commerce users in the current behavior sequence; otherwise, the effect of behavior prediction will be much worse. The corresponding suggestions are put forward so as to promote the rapid development of cross-border e-commerce enterprises in China. In particular, through a comprehensive analysis of typical cases, the strategies and problems in the intelligent operation process of Chinese cross-border e-commerce enterprises at this stage are discussed, and corresponding suggestions are put forward to promote the rapid development of China's cross-border e-commerce enterprises.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] F. Zhang and Y. Yang, "Trust model simulation of cross border e-commerce based on machine learning and Bayesian network," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–11, 2021.

[2] L. Guo, "Cross-border e-commerce platform for commodity automatic pricing model based on deep learning," *Electronic Commerce Research*, vol. 22, no. 1, pp. 1–20, 2020.

[3] Y. Yang, "Research on the optimization of the supplier intelligent management system for cross-border e-commerce platforms based on machine learning," *Information Systems and E-Business Management*, vol. 18, no. 4, pp. 851–870, 2020.

[4] G. Li and N. Li, "Customs classification for cross-border e-commerce based on text-image adaptive convolutional neural network," *Electronic Commerce Research*, vol. 19, no. 4, pp. 779–800, 2019.

[5] W. Mu, "A big data-based prediction model for purchase decisions of consumers on cross-border e-commerce platforms," *Journal Européen des Systèmes Automatisés*, vol. 52, no. 4, pp. 363–368, 2019.

[6] Y. Luo, J. Ma, and C. Li, "Entity name recognition of cross-border e-commerce commodity titles based on TWs-LSTM," *Electronic Commerce Research*, vol. 20, no. 2, pp. 405–426, 2020.

[7] F. B. Saghezchi, A. Radwan, J. Rodriguez, and T. Dagiuklas, "Coalition formation game toward green mobile terminals in heterogeneous wireless networks," *IEEE Wireless Communications*, vol. 20, no. 5, pp. 85–91, 2013.

[8] S. S. Alrumiah and M. Hadwan, "Implementing big data analytics in e-commerce: vendor and customer view," *IEEE Access*, vol. 9, Article ID 37281, 2021.

[9] L. Wen, "Development analysis of cross-border E-commerce logistics based on big data technology under safety law protection," *International Journal of Information Systems in the Service Sector*, vol. 14, no. 2, pp. 1–14, 2022.

[10] C. Zhang, T. Xie, K. Yang et al., "Positioning optimisation based on particle quality prediction in wireless sensor networks," *IET Networks*, vol. 8, no. 2, pp. 107–113, 2019.

[11] S. Guan, "Smart E-commerce logistics construction model based on big data analytics," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 3015–3023, 2021.

[12] F. Wang, Y. Yang, G. K. F. Tso, and Y. Li, "Analysis of launch strategy in cross-border e-Commerce market via topic modeling of consumer reviews," *Electronic Commerce Research*, vol. 19, no. 4, pp. 863–884, 2019.

[13] Y.-H. Hsiao, M.-C. Chen, and W.-C. Liao, "Logistics service design for cross-border E-commerce using Kansei engineering with text-mining-based online content analysis," *Telematics and Informatics*, vol. 34, no. 4, pp. 284–302, 2017.

[14] H. Zhao, P.-L. Chen, S. Khan, and O. I. Khalafe, "Research on the optimization of the management process on internet of things (Iot) for electronic market," *The Electronic Library*, vol. 39, no. 4, pp. 526–538, 2021.

[15] S. Palanisamy, B. Thangaraju, O. I. Khalaf, Y. Alotaibi, and S. Alghamdi, "Design and synthesis of multi-mode bandpass filter for wireless applications," *Electronics*, vol. 10, no. 22, p. 2853, 2021.

[16] Y. Zhang, "Sales forecasting of promotion activities based on the cross-industry standard process for data mining of E-commerce promotional information and support vector regression," *Journal of Computers*, vol. 32, no. 1, pp. 212–225, 2021.

[17] P. Lakshmi, D. StalinDavid, I. Kalaria, S. Jayadatta, A. Sharma, and D. Saravanan, "Research on collaborative innovation of E-commerce business model for commercial transactions," *Turkish Journal of Physiotherapy and Rehabilitation*, vol. 32, no. 3, pp. 787–794, 2020.

[18] C. Wu, B. Yan, R. Yu et al., "Retracted article: digital forensics system based on dynamic path prediction and the competitiveness of cross-border e-commerce SMEs," *Personal and Ubiquitous Computing*, vol. 25, no. S1, p. 11, 2021.

[19] F. A. Al-Mekhlafi, R. A. Alajmi, Z. Almusawi et al., "A study of insect succession of forensic importance: Dipteran flies (diptera) in two different habitats of small rodents in Riyadh City, Saudi Arabia," *Journal of King Saud University-Science*, vol. 32, no. 7, pp. 3111–3118, 2020.

[20] G. Cai, Y. Fang, J. Wen, S. Mumtaz, Y. Song, and V. Frascolla, "Multi-carrier M-ary DCSK system with code index modulation: an efficient solution for chaotic communications," *IEEE Journal of Selected Topics in Signal Processing*, vol. 13, no. 6, pp. 1375–1386, 2019.

[21] L. Li and J. Zhang, "Research and analysis of an enterprise E-commerce marketing system under the big data environment," *Journal of Organizational and End User Computing*, vol. 33, no. 6, pp. 1–19, 2021.

[22] C. I. Cucu Ika Agustyaningrum, M. Haris, R. Aryanti, and T. Misriati, "Online shopper intention analysis using conventional machine learning and deep neural network classification algorithm," *Jurnal Penelitian Pos dan Informatika*, vol. 11, no. 1, pp. 89–100, 2021.

[23] A. Rahman, M. Hameed Siddiqi, and S. Lee, "Rough set-based approaches for discretization: a compact review," *Artificial Intelligence Review*, vol. 44, no. 2, pp. 235–263, 2015.

[24] Y. Li, Y. Zhang, F. Luo, W. Zou, Y. Zhang, and K. Zhou, "Customer tiered purchase forecast by mobile edge computing based on Pareto/NBD and SVR," *China Communications*, vol. 18, no. 11, pp. 1–10, 2021.

[25] A. Malakauskas and A. Lakštutienė, "Financial distress prediction for small and medium enterprises using machine learning techniques," *Engineering Economics*, vol. 32, no. 1, pp. 4–14, 2021.

[26] B. B. Hazarika and R. Mousavi, "Review of cross-border E-commerce and directions for future research," *Journal of Global Information Management*, vol. 30, no. 2, pp. 1–18, 2021.