Analysis of Cross-Border E-commerce HCI Network Marketing Strategies Based on Social Media and AI-powered CAD

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Abstract. This study analyzes the Human-Computer Interaction (HCI) network marketing strategies employed in cross-border e-commerce, focusing on the integration of social media and AI-powered Computer-Aided Design (CAD) tools. It combines social media artificial intelligence technology to analyze cross-border e-commerce online marketing strategies. Moreover, the model reconstructs a weighted multi-granularity graph to make similar nodes closer in random walks to give greater weights between nodes with similar global structures and local neighborhood relationships. Therefore, parallelizing random walks on this graph can significantly reduce the time complexity of the model. In addition, this paper introduces the idea of the game to construct the income matrix to make it change dynamically during the walking process. The experimental analysis shows that the cross-border e-commerce network marketing system based on social media artificial intelligence has good strategy analysis and application effects.

Keywords: social media; AI-Powered CAD; cross-border e-commerce; E-commerce; Human-Computer Interaction
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1 INTRODUCTION

Today's world has entered the era of high-speed information, the Internet has become an indispensable part of people's lives, and convenience has become the central theme. With the continuous advancement of economic globalization, the traditional foreign trade model has been unable to keep up with the wave of the new era. Moreover, conventional foreign trade enterprises are gradually losing their competitive advantages in the market. In addition to the impact of the COVID-19 epidemic in the past two years, the economy has suffered a severe blow. In the sluggish situation of China's traditional economy, the cross-border e-commerce industry has sprung up, developed rapidly, and entered the public's field of vision extremely fast. At the same time, high sales on weekdays that only occur on large festivals have become the norm.

Moreover, it flourished in the domestic market and seized a large market in foreign countries. In addition, exporting many commodities abroad has brought infinite possibilities to the Chinese trade market, allowing people who love shopping to experience the fun of shopping without leaving home. A new trade model has emerged in cross-border e-commerce trade. This model is to conduct transactions through social media, which is similar to the domestic micro-business in China, called social cross-border e-commerce, and the novel trade form attracts many young people [14].

As people spend more and more time on social networks, social media commerce will be an essential way of retailing in the future. Social media converts massive traffic into sales, allows consumers to experience the fun of shopping, and allows users to communicate with like-minded friends and share the good things they have purchased. At the same time, social e-commerce sells not only the product itself but also a series of related services, which significantly improves the sales of target products and has strong customer loyalty [15].

Price setting is also essential for cross-border e-commerce trade, and preferential prices and high-quality products can attract overseas user groups more effectively. The price determination combines the market commodity price range with the psychological expectations of overseas buyers to ensure that it can attract a large number of user traffic and simultaneously ensure sufficient profits [8].

Suppose the first few items are preparations for the successful sale of products. In that case, improving the after-sales service of upgraded products is a service that must be implemented to increase customer stickiness, expand a broader market, and create a better brand reputation. Since cross-border e-commerce does not have offline physical stores and is relatively far away from most buyers, after-sales service has become the most worrying thing for many overseas buyers. Once the purchased products have quality problems and need to be repaired or returned, Cross-border transportation to the place of origin has caused the cost of product repair to skyrocket, and various issues have restricted the development of cross-border e-commerce in China. To break this barrier and upgrade after-sales service for this inconvenience, a maintenance service station can be established in the sales area, allowing buyers to repair products locally and improving the user shopping experience [10].

Because of the trend of social cross-border e-commerce, many brands without offline stores have appeared online. Many companies have tried their best to create a high-end image of their products in the competition but have yet to notice the development model of wireless offline services. Hidden dangers [9]. In the primary development stage of products, consumers may be blind and novel about cross-border shopping, but what follows is the mismatch between online products and offline supporting services, which seriously affects consumers' offline experience because of the lack of For entities, when conducting cross-border online transactions, consumers will be worried that the after-sales service is not in place. To avoid this concern for overseas users and improve the after-sales service to match the sales, it is possible to establish product maintenance in the corresponding area. The outlets focus on solving the problem of product return and maintenance for local users, thereby eliminating barriers caused by distance [1].

The marketing of cross-border e-commerce on social media largely relies on the dissemination of the network, that is, the user's forwarding and interaction of product information. Therefore, the most important thing for merchants is the content and quality of product publicity information and the publicity content to a large extent. It requires the cooperation of the marketing team and the art team. Still, many merchants need to study the shopping psychology of consumers specifically, but they should pursue the forwarding and viewing of information. The content is the same and has no new ideas, causing consumers' aesthetic fatigue [11]. As consumers watch more and more similar product information, products with no features will fail to catch consumers' attention. Marketing content is not an online joke but an essential part of the product marketing process. It is necessary to explore more potential Customers need to focus on building brand culture and value when developing a brand. It also needs to constantly innovate while updating products, combine its brand advantages with market demand, keep users fresh, and diversify products so consumers can think of them in different fields. Products expand the audience of the product brand to be more conducive to the promotion and development of the product [5].

Platform micro-businesses use unique platforms to carry out micro-business trading activities and rely on platform micro-businesses to propose a complete set of retail solutions; personal micro-businesses use personal circles of friends to carry out personal and purchasing commodity marketing business methods. Among these three micro-business business models, the entry threshold for individual micro-business is the lowest, and the lower the threshold, the more flooding it becomes, which leads to the out-of-control market and is used by criminals to become the cradle of marketing brainwashing[6]. The demand for cross-border commodities also provides fertile soil for the survival of individual micro-businesses. A large amount of consumer demand has fostered professional overseas purchasing agents. The low threshold has driven a large influx of testers, and the scale of overseas purchasing agents has accelerated. Relevant laws and regulations have yet to be standardized promptly. Various problems. Therefore, if social cross-border e-commerce wants to develop healthily, it is urgent to improve legal norms and use the law to punish illegal behaviours [7] severely.

Economic globalization has driven business and cultural exchanges around the world. However, cultural differences between countries and regions still exist, and different cultural backgrounds affect people's lives, thoughts, and behaviours. In cross-border e-commerce marketing communication, the display and interactive features of the Internet virtual environment not only bring convenience to online transactions but also challenge marketing communication. Consumers in different countries and regions demand product information content and expression methods. There are differences that, if not adopted, can negatively impact online marketing communication performance [2]. For example, the product display scene violates local cultural customs, or the marketing information content needs to be appropriately designed to avoid misunderstanding. The study found that Asians are accustomed to conveying information through physical and veiled means. At the same time, Americans are more detail-oriented and need more detailed background information, so they always try to find specific information. This shows that different cultural backgrounds and cultural differences profoundly affect consumers' communication habits and behaviours in other regions, and it also shows different needs for communication methods [3]. For cross-border e-commerce, its marketing display design and communication methods face the challenges of cultural differences, and it is necessary to explore adaptive strategies for cross-cultural online communication. Suppose there is a need for more evaluation and analysis of local cultural background and cultural differences. In that case, it will be easier to resonate with consumers, leading to resistance and disgust, aggravating marketing communication barriers [13]. The literature review briefly examines the evolution of cross-border e-commerce, emphasizing growth trends and Human-Computer Interaction (HCI) optimization in online transactions. It delves into communication theories pertinent to marketing strategies and the role of artificial intelligence analytics and social media in shaping consumer behaviour and network marketing, focusing on HCI principles. Moreover, it discusses cross-border communication strategies, including challenges and opportunities. It addresses emerging trends and recommendations for future research and business practices, highlighting the importance of integrating HCI principles in cross-border E-commerce environments.

Consumers increasingly turn from computers to smartphones for e-commerce transactions in the mobile Internet environment. The commodity information seen and heard through the e-commerce platform is the basis for consumption decisions [12]. Driven by virtual reality (VR) and artificial intelligence (AI) technologies, online product display forms are constantly enriched. Virtual reality scene-based displays and intelligent interaction are introduced based on traditional forms such as text, pictures, and videos. , which transmits commodity information in an all-around way and brings a new stage of consumer sensory cognition [4].

This paper combines social media artificial intelligence technology to analyze the cross-border e-commerce network marketing strategy, improve the effect of cross-border e-commerce network marketing, and promote the development effect of cross-border e-commerce network marketing.

2 MULTI-GRANULARITY NETWORK REPRESENTATION LEARNING BASED ON GAME THEORY

A multi-granularity network representation learning method is proposed based on game theory—MGNRL. The framework of the model is shown in Figure 1:

1. The first step is to calculate the importance of nodes in the network and divide the network nodes into multi-granularity graphs according to their importance.

2. The second step is constructing a weighted graph for each granularity layer. The node importance and neighborhood structure determine the edge weight between each node pair.

3. The third step is to generate a context for each node through a dynamic random walk.

4. The fourth step is to use the Skip-Gram model to train the node sequence and obtain the node's low-dimensional vector representation.

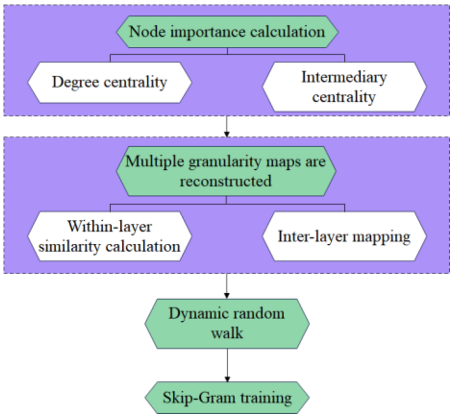

Figure 1: MGNRL framework diagram.

G=(V, E) represents an undirected, unweighted network, |V| represents the number of nodes in the network, and |E| represents the number of edges. $IMP\ \ i$ represents the importance of node i in the network, which is defined as follows:

$$DC\ \ i\ = \sum_{j=1}^{|V|} x_{ij}\ \ i \neq j\ \ /\ \ |V| - 1 \tag{1}$$

$$BC\ \ i\ = \sum_{j<k} g_{jk}\ \ i\ \ /\ \ g_{ik} \tag{2}$$

$$IMP\ \ i\ = \lambda * DC\ \ i\ + \ 1 - \lambda\ * BC \tag{3}$$

Among them, DC(i) is the degree centrality of node i. If there is an edge between nodes i and j, then $x_{ij} = 1$; otherwise, $x_{ij} = 0$. BC(i) is the betweenness centrality of node i, g_{ik} represents the shortest paths between nodes j and k, and $g_{ik}\ i$ represents the shortest paths connecting nodes j, i, and k. First, we normalize DC and BC, define different weights open paren 0 less than lambda less than 1, and ts $0<\lambda<1$ for them for various network structures and tasks. Finally, the importance IMP() of node i can be obtained according to formula (3).

The network nodes are divided into four different granular layers, and for each layer, the structural similarity of node i and node j is given by:

$$S_k\ i,j\ = \frac{\min\ IMP\ i\ ,IMP\ j}{\max\ IMP\ i\ ,IMP\ j} \tag{4}$$

Among them, k represents the kth granular layer. In the kth layer, its adjacency matrix is defined as follows:

$$A_k\ i,j\ = \begin{cases} 1,\ i,j\ \in E \\ 0.\ i,j\ \notin E \end{cases} \tag{5}$$

Combining the structural similarity matrix S and the adjacency matrix A, the weight matrix of the kth layer is finally expressed as follows:

$$W_k\ i,j\ = \delta * S_k\ i,j\ +\ 1-\delta\ * A_k\ i,j \tag{6}$$

As shown in formula (6), W contains both the node's global structure and local edge information, where δ is used to adjust the weights occupied by S and A. This chapter has defined each granular layer and reconstructed the edge weights between nodes in the same layer. However, each granular layer is still independent of each other. Next, a mapping relationship needs to be established between each granular layer. The specific definitions are as follows:

$$W\ k,k+1\ = \sum\nolimits_{i,j} W_k\ i,k\ / \left|V_k\right|^2 \tag{7}$$

$$W\ k,k+1\ = 1-W_k\ k,k+1 \tag{8}$$

$W_k\ k,k+1$ represents the mapping relationship between the kth layer and the (k+1)th layer, and W(k,k-1) represents the mapping relationship between the kth layer and the (k-1)th layer. $\left|V_k\right|$ Represents the number of nodes in the kth layer. Each node of the intermediate granular layer adds two connections; one is used to connect the previous granular layer, and the other is used to connect the next granular layer. Finally, the reconstructed multi-granularity graph is defined as $G' = V_{mg},E_{mg},W()$, V_{mg} represents the set of reconstructed multi-granularity graph nodes, E_{mg} represents the set of edges, and W represents the weight matrix of each granular layer.

During the game process, nodes will adopt cooperation or betrayal strategies. For each granular layer, each node plays a game with other nodes. The whole game process can be divided into $\left|V_k\right|-1$ Sub-games.

Strategy C indicates that the node chooses a cooperative strategy, and strategy D indicates that the node selects a defection strategy. We assume that both nodes i and j are in the kth layer, $x = \alpha \sum W(i,k), k \in V_k \setminus j$ represents the payoff of edge (i, j) when the node chooses the cooperative strategy C, and node j is the successor of node i in the random walk process. $y = \beta W(i,j)$ represents the cost of the edge (i,j) itself when nodes i and j choose to cooperate. Vk represents the set of nodes in the kth granular layer, and α and β are hyperparameters that control the proportion of revenue and expenditure. For the model in this chapter, the nodes in the multi-granularity graph participate in the game, resulting in changes in the weights between nodes. Before participating in the game, the state of the edge weight is s_l; after the end of the game, the state becomes s_{l+1}, and the change of the weight before and after the game is given by the following formula:

$$W(i,j)_{s_{l+1}} = W(i,j)_{s_l} + \sum_{k \in V_k / j} \alpha W(i,k)_{s_l} - \beta W(i,j)_{s_l} \tag{9}$$

$$\forall k \in V_k \setminus j, W(i,k)_{s_{l+1}} = (1-\beta)W(i,k)_{s_l} \tag{10}$$

Among them, $alpha represents$ The income ratio obtained from other nodes, and β represents the payout ratio of each game. As shown in formulas (9) and (10), the nodes of each granular layer select the subsequent nodes of the random walk through a game.

The core idea of Skip-Gram is to maximize the likelihood of context in the sequence, which is defined as follows:

$$\Pr(\{i-w,\ldots,i+w\} \setminus i \mid \Phi(i)) = \prod_{\substack{j=i-w \\ j \neq i}}^{i+w} \Pr(j \mid \Phi(i)) \tag{11}$$

Where w is the size of the window? For each node $j \in V$, A hierarchical Softmax assigns a specific path in the classification tree consisting of tree nodes $T_0, T_1, T_2, \ldots, T_h$. In this case, its conditional probability can be defined as follows:

$$\Pr(j \mid \Phi(i)) = \sum_{u=1}^{h=\log|V|} \Pr(T_u \mid \Phi(i)) \tag{12}$$

Among them, the vector of node i is denoted as $\Phi(i) \in R^d$. $\Pr(T_u \mid \Phi(i))$ can be computed by a binary classifier assigned to T_u, and T_u Is is the parent of node j. Two cases from the root node to the leaf node, the left or right branches, correspond to the logistic regression problem. Therefore, $\Pr(T_u \mid \Phi(i))$ can be defined as follows:

$$\Pr(T_u \mid \Phi(i)) = \begin{cases} \sigma(\psi(T_u) \cdot \Phi(i)), T_u = 0 \cdot \\ 1 - \sigma(\psi(T_u) \cdot \Phi(i)), T_u = 1 \end{cases} \tag{13}$$

Among them, $\sigma(\psi(T_u) \cdot \Phi(i)) = 1 / \left(1 + e^{-\psi(T_u) \cdot \Phi(i)}\right)$, $\psi(T_u)$ Is the vector representation of T_u. Since T_u can only take two values, 0 and 1, formula (13) can be rewritten as:

$$\Pr\ T_u \mid \Phi\ i\ \ = \left[\sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ \right]^{1-T_u} \cdot \left[1-\sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ \right]^{T_u} \tag{14}$$

The objective function is to maximize the conditional probability according to its feature representation, which can be expressed as:

$$\Pr\ T_u \mid \Phi\ i\ \ \underset{\Phi}{max} \prod_{i \in V} \prod_{u=1}^{\log|V|} \Pr\ T_u \mid \Phi\ i \tag{15}$$

Correspondingly, the loss function can be defined as minimizing the inverse of its logarithmic function:

$$\begin{aligned} EqualsL &= \underset{\Phi}{min}\ -\sum_{i \in V} logPr\ \ j \mid \Phi\ i \\ &= \underset{\Phi}{min}\left(-\sum_{i \in V} \log \prod_{u=1}^{\log|V|} \left\{ \begin{matrix} \sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ ^{1-T_u} \cdot \\ 1-\sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ ^{T_u} \end{matrix} \right\}\right) \\ &= \underset{\Phi}{min}\left(-\sum_{i \in V} \sum_{u=1}^{\log|V|} \left\{ \begin{matrix} \sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ ^{1-T_u} + \\ 1-\sigma\ \ \psi\ \ T_u\ \ \cdot \Phi\ \ i\ ^{T_u} \end{matrix} \right\}\right) \end{aligned} \tag{16}$$

3 ANALYSIS AND APPLICATION OF CROSS-BORDER E-COMMERCE ONLINE MARKETING STRATEGY BASED ON SOCIAL MEDIA ARTIFICIAL INTELLIGENCE

Based on the business ecosystem theory and scholars' research, this paper summarizes the definition of cross-border e-commerce ecosystem: the core enterprises of cross-border e-commerce rely on Internet technology to build cross-border e-commerce platforms, gather consumers, suppliers, other service providers (payment service providers, logistics service providers, media and advertising service providers) and other subjects, interact with the external environment, play their respective advantages around the core enterprises, exchange resources and materially complement each other, and form a complex ecological network system, as shown in Figure 2.

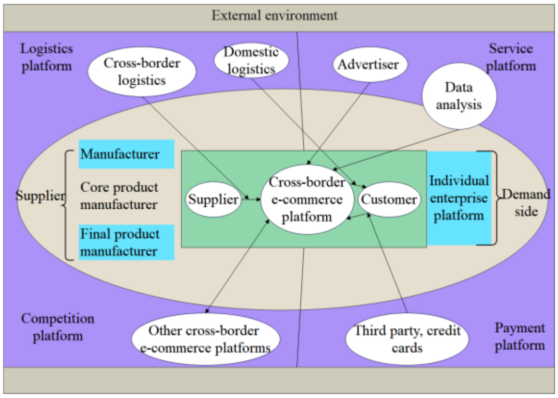

Figure 2: Cross-border E-Commerce platform ecosystem.

The e-commerce platform marketing system cooperates with the mobile mall to provide services for customers, micro-tweeters, and system administrators. It involves a mixed-methods approach, combining quantitative analysis of social media artificial intelligence with qualitative examination of communication strategies. Data collection includes sourcing social media data and secondary sources supplemented by surveys. Analysis techniques encompass statistical analysis, sentiment analysis, and thematic coding, with consideration for Human-Computer Interaction (HCI) principles. By integrating HCI into data collection and analysis processes, researchers can ensure that the methods are user-friendly and accessible, enhancing the overall research quality and usability of findings in E-commerce and digital communication strategies. According to the demand analysis and role division, the marketing system is designed to consist of four functional modules, as shown in Figure 3.

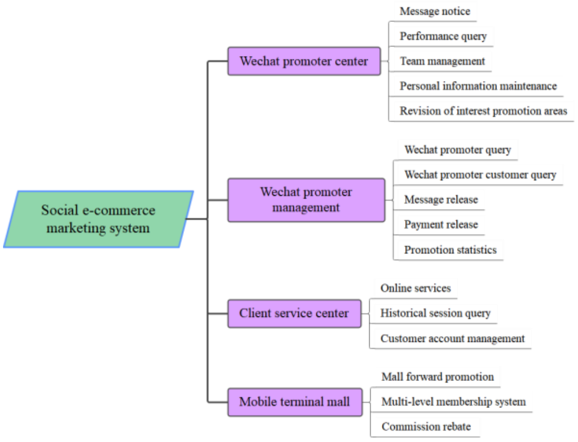

Figure 3: System function block diagram.

Software development technology stack generally refers to combining N technologies (N>1) to achieve a particular purpose as an organic whole. This system's development technology stack is shown in Figure 4.

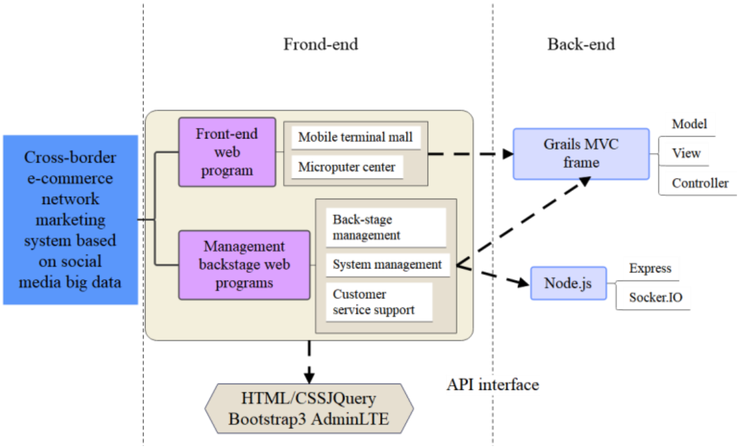

Figure 4: System development technology stack.

The cross-border e-commerce marketing system based on socialization is divided into a PC-side Web management background and a Web front-end platform. The system architecture is shown in Figure 5.

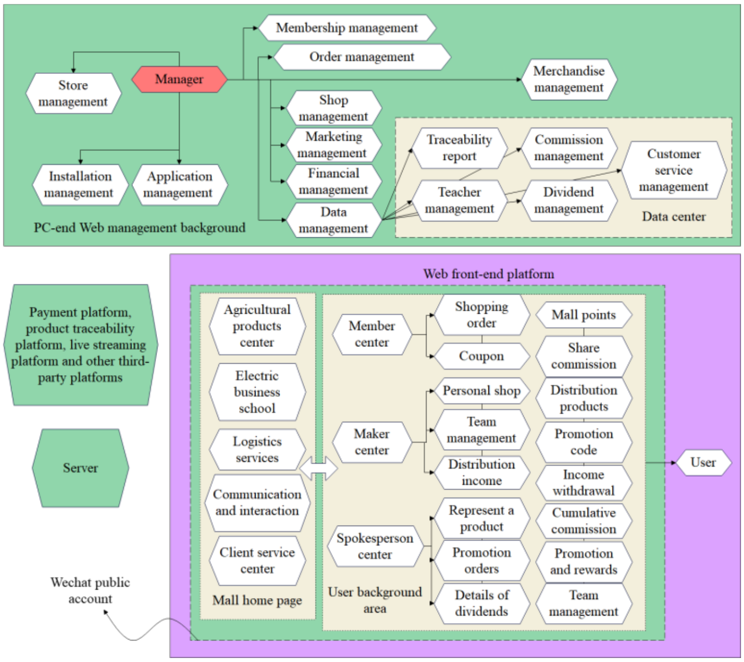

Figure 5: Cross-border E-Commerce marketing system based on socialization.

4 ANALYSIS OF RESULTS

This paper selects the more advanced network representation learning algorithms in recent years for comparison, and the algorithms based on random walks include DeepWalk, node2vec, and struc2vec, as well as the LINE algorithm for modelling the network structure. Its specific introduction is as follows:

DeepWalk: The DeepWalk algorithm first introduces deep learning into network embeddings, applies the word training model to random walk sequences, and finally obtains a low-dimensional vector representation of nodes.

LINE proposes first- and second-order proximity to preserve the network's local and global structure.

node2vec: This algorithm is an improved algorithm of DeepWalk, which takes more information into account and controls the walk mode by setting two parameters. The parameter selection range for different experiments is $p,q\in\{0.25,0.5,1,2\}$, and the best effect is selected as the final result.

struc2vecl3: This algorithm can capture a vector representation of a node's structural identity, use a hierarchy to measure the similarity of nodes at different levels, encode the structural similarity, and generate a node's structural context by building a multi-layer graph.

MGNRL: The algorithm proposed in this chapter processes nodes hierarchically according to the network structure and dynamically adjusts edge weights by designing a revenue matrix.

In addition to the mirrored karate network dataset, the experimental algorithm has some standard parameters in all experiments, and the specific settings are as follows:

1. The vector dimension obtained by training (a=128):
2. The number of walks for each node (r=10):
3. Sequence length of each walk (t=80):
4. Window size for Skip-Gram training (w=10):
5. The number of samples for negative sampling (neg=5).

The mirrored cross-border e-commerce network marketing network is shown in Figure 6, where a colour represents nodes with the same label. The parameters of the experiment in this section are set as follows: d=2, r=5, 1=15, w=5, neg=3. The above algorithms are used to learn the 2-dimensional representation of the mirror karate network, respectively, and the vector distribution is shown in Figure 7. As can be seen from Figures 7(a), 7(b), and 7(c), DeepWalk, LINE, and node2vec cannot capture the isomorphism of nodes. MGNRL and struc2vec can capture information on the node's global structure well. For the struc2vec algorithm, in Figure 7(d), the nodes in the upper left cluster have a good distribution, and the vector distances of some similar nodes are relatively close. However, lighter-coloured nodes show poor results and intersect with nodes of other types of nodes.MGNRL can capture the isomorphism and homogeneity of the network. It can be seen from Figure 7 that node 67 is a mirror node of node 12; that is, they have the same structure (degree 1 and the same neighbourhood structure). Therefore, there is almost the exact vector representation in Figure 5(e). The top of Figure 7(e) gathers a bunch of light blue nodes, which are nodes of the same label in the original karate network, so they have similar representations. At the same time, there are the same bunch of light blue nodes in the lower part of the graph, which are the same kind of nodes in the mirror network.

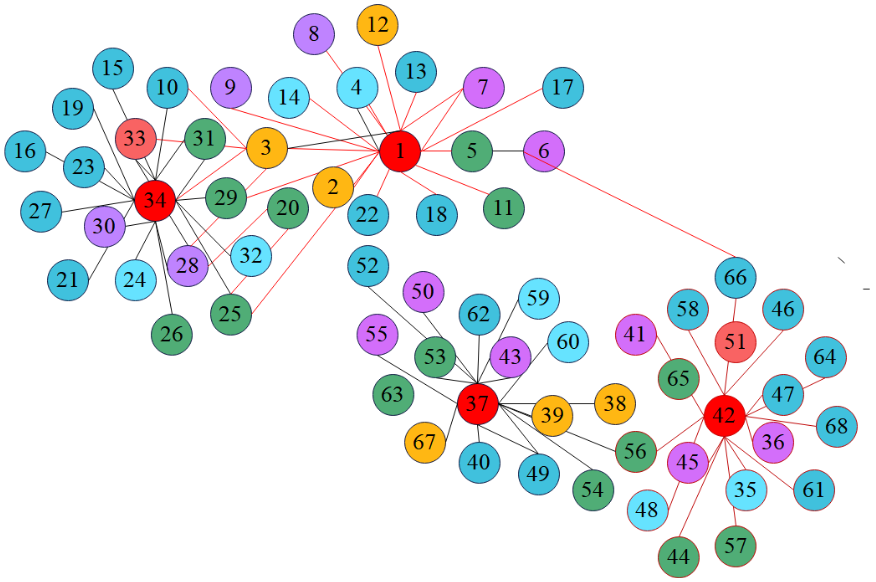

Figure 6: Mirror network.

The above experiments have verified that the cross-border e-commerce network marketing system based on prominent social media data can play a specific role in the data analysis of cross-border e-commerce marketing network marketing. After that, the effect of cross-border e-commerce network marketing strategy formulation based on social media artificial intelligence proposed in this paper is analyzed, and the results shown in Table 1 are obtained.

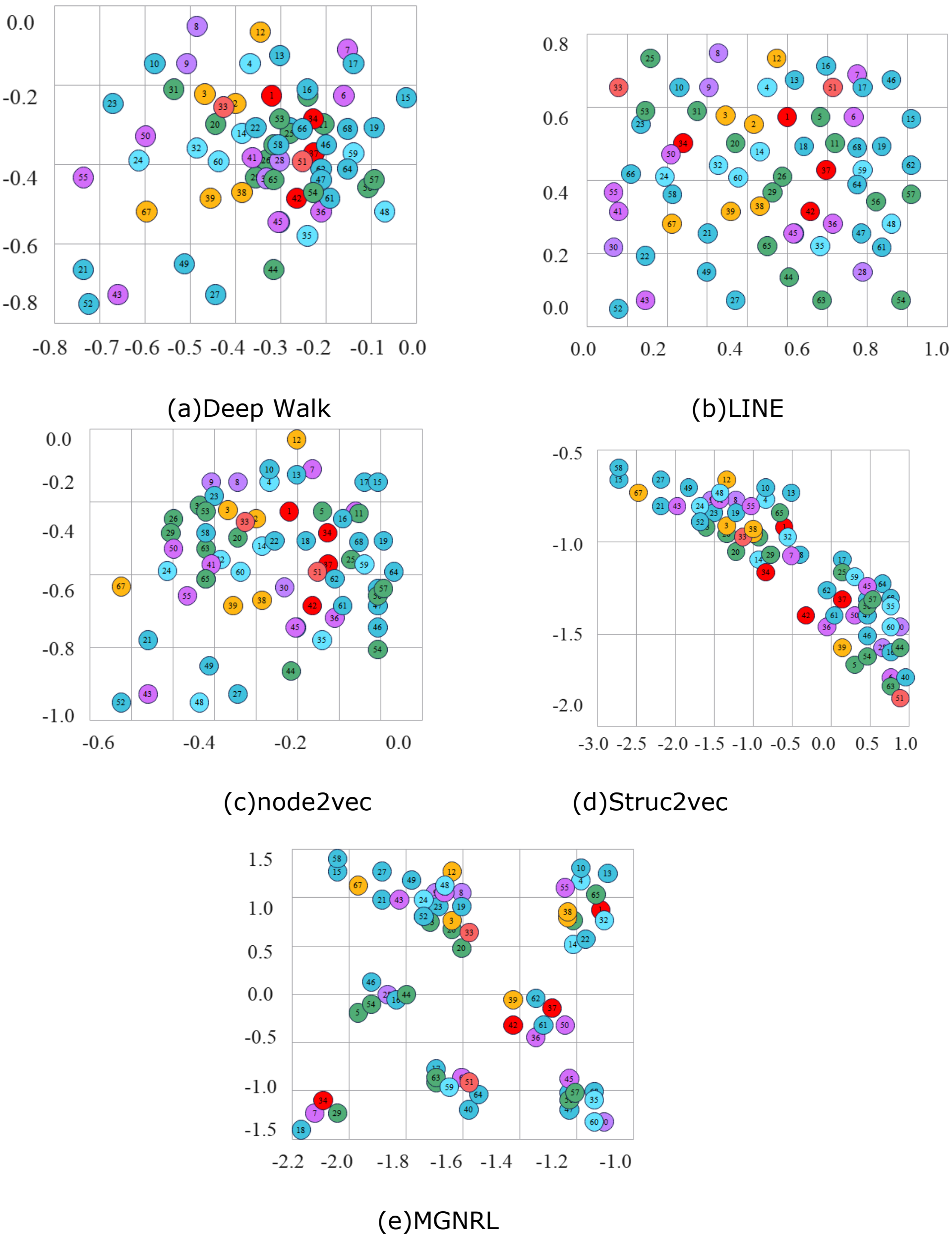

Figure 7: 2D vector representation of mirrored cross-border E-commerce marketing network nodes.

Num	*Strategic Analysis*	*Num*	*Strategic Analysis*	*Num*	*Strategic Analysis*
1	*84.267*	*16*	*88.619*	*31*	*88.475*
2	*86.852*	*17*	*85.376*	*32*	*88.928*
3	*83.981*	*18*	*89.641*	*33*	*83.664*
4	*82.229*	*19*	*87.549*	*34*	*83.231*

5	*85.680*	*20*	*85.554*	*35*	*84.453*
6	*87.730*	*21*	*89.115*	*36*	*82.092*
7	*82.195*	*22*	*87.283*	*37*	*84.894*
8	*82.405*	*23*	*87.043*	*38*	*88.965*
9	*82.191*	*24*	*89.384*	*39*	*86.498*
10	*89.047*	*25*	*85.530*	*40*	*82.316*
11	*89.940*	*26*	*89.705*	*41*	*87.622*
12	*88.807*	*27*	*86.376*	*42*	*83.327*
13	*89.070*	*28*	*86.612*	*43*	*87.307*
14	*83.333*	*29*	*89.834*	*44*	*84.308*
15	*84.785*	*30*	*85.683*	*45*	*86.590*

Table 1: The effect of formulating a cross-border E-commerce online marketing strategy based on social media artificial intelligence.

The above experimental analysis shows that the cross-border e-commerce network marketing system based on prominent social media data has good strategy analysis and application effects.

5 CONCLUSIONS

As people spend more and more time on social networks, social media commerce will be an essential way of retailing in the future. Social media transforms massive traffic into sales and allows consumers to communicate with their like-minded friends and share the good things they bought while enjoying the fun of shopping. Moreover, social e-commerce sells not only the product itself but also a series of related services, which significantly improves the sales of target products and has strong customer loyalty. This article combines social media artificial intelligence technology with Human-Computer Interaction (HCI) principles to analyze cross-border e-commerce online marketing strategies to enhance effectiveness. The experimental analysis demonstrates that integrating HCI into the cross-border e-commerce network marketing system based on prominent social media data yields positive strategy analysis and application effects, improving user engagement and overall marketing performance.

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REFERENCES

[1] Chang, D.; Gui, H. Y.; Fan, R.; Fan, Z. Z.; Tian, J.: Application of Improved Collaborative Filtering in the Recommendation of E-Commerce Commodities, International Journal of Computers Communications & Control, 14(4), 2019, 489-502. https://doi.org/10.15837/ijccc.2019.4.3594

[2] Chen, J.: The Application of Commodity Recommendation in Cross-border E-commerce: Current Situation and Prospect, Frontiers in Economics and Management, 2(1), 2021, 266-274.

[3] He, G.: Enterprise E-Commerce Marketing System Based on Big Data Methods of Maintaining Social Relations in the Process of E-Commerce Environmental Commodity, Journal of Organizational and End User Computing (JOEUC), 33(6), 2021, 1-16. https://doi.org/10.4018/JOEUC.20211101.oa16

[4] Hosseini, F.; Sadighi, H.; Mortazavi, S. A.; Farhadian, H.: An E-Commerce SWOT Analysis for Export of Agricultural Commodities in Iran, Journal of Agricultural Science and Technology,

21(7), 2019, 1641-1656.
[5] Huang, Y.; Chai, Y.; Liu, Y.; Shen, J.: Architecture of Next-Generation E-Commerce Platform, Tsinghua Science and Technology, 24(1), 2018, 18-29. https://doi.org/10.26599/TST.2018.9010067
[6] Liang, L.; Qin, X.: Research on Consumers Online Shopping Decision-Making and Recommendation of Commodity Based on Social Media Network, Cluster Computing, 22(3), 2019, 6529-6539. https://doi.org/10.1007/s10586-018-2296-7
[7] Liu, D.; Huo, C.; Yan, H.: Research of Commodity Recommendation Workflow Based on LSH Algorithm, Multimedia Tools and Applications, 78(4), 2019, 4327-4345. https://doi.org/10.1007/s11042-018-5716-z
[8] Pan, H.; Zhang, Z.: Research on Context-Awareness Mobile Tourism E-Commerce Personalized Recommendation Model, Journal of Signal Processing Systems, 93(2), 2021, 147-154. https://doi.org/10.1007/s11265-019-01504-2
[9] Shen, J.; Zhou, T.; Chen, L.: Collaborative Filtering-Based Recommendation System for Big Data, International Journal of Computational Science and Engineering, 21(2), 2020, 219-225. https://doi.org/10.1504/IJCSE.2020.105727
[10] Subramaniyaswamy, V.; Logesh, R.; Chandrashekhar, M.; Challa, A.; Vijayakumar, V.: A Personalised Movie Recommendation System Based on Collaborative Filtering, International Journal of High Performance Computing and Networking, 10(1-2), 2017, 54-63. https://doi.org/10.1504/IJHPCN.2017.083199
[11] Wang, Z.; Wan, M.; Cui, X.; Liu, L.; Liu, Z.; Xu, W.; He, L.: Personalized Recommendation Algorithm Based on Product Reviews, Journal of Electronic Commerce in Organizations (JECO), 16(3), 2018, 22-38. https://doi.org/10.4018/JECO.2018070103
[12] Wei, C.; Niu, J.; Guo, Y.: DLGNN: A Double-Layer Graph Neural Network Model Incorporating Shopping Sequence Information for Commodity Recommendation, Sensors and Materials, 32(12), 2020, 4379-4392. https://doi.org/10.18494/SAM.2020.3056
[13] Xu, J.; Hu, Z.; Zou, J.: Personalized Product Recommendation Method for Analyzing User Behavior Using DeepFM, Journal of Information Processing Systems, 17(2), 2021, 369-384.
[14] Yang, F.: A Hybrid Recommendation Algorithm–Based Intelligent Business Recommendation System, Journal of Discrete Mathematical Sciences and Cryptography, 21(6), 2018, 1317-1322. https://doi.org/10.1080/09720529.2018.1526408
[15] Zhou, L.: Product Advertising Recommendation in E-Commerce Based on Deep Learning and Distributed Expression, Electronic Commerce Research, 20(2), 2020, 321-342. https://doi.org/10.1007/s10660-020-09411-6