# Research on E-Commerce Social Relationship Modeling and Marketing Path Optimization Method Based on Graph Neural Network

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**ABSTRACT** With the deep integration of social media and e-commerce, social relations have become a core driving force affecting consumer purchase decisions within the textile and apparel market, where digital word-of-mouth shapes users' perceptions of fabric quality, garment design, functional performance, and fashion trends. This social influence directly steers the demand for innovative textile products, including smart textiles, electromagnetic functional fabrics, wearable sensing garments, and other apparel products with technical application value, as consumer interactions increasingly affect the market acceptance of specific garment designs and material applications. Traditional e-commerce marketing methods encounter bottlenecks such as sparse data, weak social relevance, and inefficient precision marketing. To solve these problems, this study proposes a comprehensive research framework for e-commerce social relationship modeling and marketing path optimization based on a graph neural network (GNN). First, a multidimensional e-commerce social relationship graph (ESRG) is constructed by integrating explicit social connections, implicit interactive behavior, and multimodal attribute information. Second, a transitive enhanced graph attention network (TE-GAT) is designed to accurately capture the structural characteristics of social networks, transitive relationship logic, and the dynamic evolution of user preferences. Finally, based on the user preferences learned from the model, three optimized marketing paths are formed: trust-driven precise recommendation, social group-purchase marketing, and opinion-leader-oriented social fission. The proposed method provides a data-driven reference for improving marketing communication and user conversion efficiency in textile and apparel e-commerce scenarios involving both conventional fashion products and emerging electromagnetic functional textile applications.

**INDEX TERMS** graph neural network, e-commerce social relations, textile and apparel products, marketing path optimization, electromagnetic functional textiles

## I. INTRODUCTION

### A. RESEARCH BACKGROUND

In the context of the rapid development of the digital economy, the boundary between e-commerce and social media continues to melt, driving social e-commerce to become the core engine for the growth of online technology-oriented product retail. This transformation enables technology enterprises to leverage social networks for real-time interaction, turning community-driven feedback into the primary catalyst for the market expansion of innovative products, technical services, and application solutions [1,2]. According to the Research Report on China's social e-commerce industry in 2024 released by iResearch, the transaction volume of China's social e-commerce market exceeded 3.8 trillion yuan in 2024, with a year-on-year increase of 21.5%, accounting for 32.7% of the overall e-commerce market; Globally, statista data predicts that the global transaction volume of social e-commerce will exceed US $5trillion in 2025, and the compound annual growth rate will remain above 18%. The core logic of social e-commerce involves transmitting textile product information and building user trust through social networks to reduce decision-making costs and accelerate the transaction of apparel and fabric commodities. By leveraging social verification of product reliability and technical value, this model streamlines the path from product discovery to the final purchase of technology-oriented products and application solutions. Different from the traditional e-commerce search shopping mode of "people looking for goods", social e-commerce has formed a recommendation shopping ecology of "goods looking for people", and the effective modeling of social relations is the key technical support to realize this ecology [3-5].

### B. RESEARCH OBJECTIVES

The core research objectives of this paper include: (1) constructing a multi-dimensional e-commerce social relationship graph (esrg) including explicit social relationships, implicit interactive relationships and multimodal attributes to comprehensively describe the entity Association in the e-commerce ecosystem; (2) A transitive enhanced graph attention network (te-gat) is proposed to effectively capture the structural characteristics of social networks, transitive relationships and the dynamic evolution of user preferences; (3) Based on the embedded representation of users and goods learned from te-gat model, design personalized and efficient e-commerce marketing paths, improve marketing transformation efficiency and reduce marketing costs [6, 7].

## II. PRELIMINARY KNOWLEDGE

### A. CORE CONCEPTS OF E-COMMERCE SOCIAL RELATIONS

#### 1) Explicit Social Relationship

Explicit social relationship refers to the direct social connection that users actively establish through the platform, which has clear semantic meaning, mainly including:

Friend relationship: the two-way relationship established by users through the friend adding function of the platform is the most core explicit social relationship;

Attention relationship: the one-way attention relationship between users and other users (such as bloggers and merchants) reflects the user's interest and identification with the followers;

Sharing relationship: users share commodity links and temporary social connections formed by shopping experience with others, which are directly related to commodity communication behavior [8-10].

#### 2) Implicit Social Relationship

Implicit social relationships refer to indirect relationships that are not actively declared by users but can be inferred from behavior data, mainly including:

Co purchase relationship: users purchase goods of the same or similar categories, reflecting the consistency of preferences;

Browsing interaction: users browse the same product page, comment or like the same product, which reflects the relevance of interest [11-13].

#### 3) Social Transitivity

Social transitivity is one of the core features of social networks, which means that the relationships and preferences between users can be transmitted through indirect connections. In the e-commerce social scene, transitivity is mainly reflected in two levels:

Trust transfer: Optimized from linear transitivity to a "multidimensional transmission model with attenuation"—trust strength decays exponentially with transmission path length and product dimension difference. The core formula is:TA→C=TA→B×TB→C×e−$\alpha$L−$\beta$D

Where:

TA→C: Indirect trust strength from user A to user C; TA→B/TB→C:Direct trust strength between adjacent nodes;

L: Transmission path length (number of intermediate nodes);

D: Product dimension difference (comprehensive index of price band difference and category relevance);

$\alpha/\beta$:Attenuation coefficients (calibrated to $\alpha$=0.3, $\beta$=0.5 t hrough experiments).

Product dimension difference D is quantified as follows:

Price band difference: High/medium/low three-level division, with difference values of 0.8, 0.4, 0 respectively;

Category relevance: Same category (0), related category (0.4), unrelated category (0.8);

Comprehensive calculation:$D = 0.5 \times \text{price\_difference} + 0.5 \times \text{c ategory\_relevance}.$

Example: If user A trusts user B in "mid-price women's clothing" (TA→B=0.8), when transmitted to "high-price home textile" products, D=0.5×0.8+0.5×0.8=0.8, L=1, the final trust strength TA→C=0.8×0.7×e-(0.3×1+0.5×0.8)≈0.32.

Preference transmission: if user a and user B have similar preferences, and user B prefers product P, then user a may also have potential demand for product P [14]."

### B. RELEVANT INDICATORS OF MARKETING PATH OPTIMIZATION

#### 1) Core Evaluation Indicators

Precise recommended indicators: Precision@K (the proportion of products that users are interested in in the top k recommendation results) Recall@K (the proportion of products that users are interested in being recommended to the top k) NDCG@K (considering the normalized loss accumulation gain of the ranking quality of the recommended results);

Marketing effect indicators: user conversion rate (CVR, the proportion of users who click the recommended link to complete the purchase), customer acquisition cost (CAC, the average marketing investment of a single paying user), customer lifetime value (CLV, the total revenue generated by users in the platform life cycle) [15].

#### 2) Social Fission Related Indicators

Fission coefficient (the number of new users brought by each initial user);

Dissemination cycle (the average time of commodity information dissemination from initial users to target users);

Community activity (average daily interaction times and commodity sharing times of users in the community) [16,17].

## III. E-COMMERCE SOCIAL RELATIONSHIP MODELING

### A. MULTI-DIMENSIONAL E-COMMERCE SOCIAL GRAPH (ESRG) CONSTRUCTION FRAMEWORK

The construction goal of e-commerce social relationship graph is to comprehensively integrate user, commodity and various relationship information, and provide high-quality input data for subsequent GNN models [18].

### B. NODE DEFINITION AND FEATURE ENGINEERING

#### 1) Node Type and Division

Esrg includes two types of core nodes: user node and product node. The specific definitions are as follows:

User node: represents the registered users of the e-commerce platform, including three sub nodes: ordinary users, business users and opinion leaders (KOL), which are distinguished by the number of users' fans, interaction frequency, commodity promotion times and other characteristics;

Commodity node: represents the commodities on sale on the platform, including physical commodities and virtual commodities. It is distinguished by commodity category, price range, sales volume and other characteristics [19,20].

#### 2) Node Feature Extraction and Coding

Node features are divided into user attribute features and commodity attribute features, which are processed by multimodal feature fusion strategy:

1. User attribute characteristics:
   Demographic characteristics: age (discretized into five intervals), gender (two categories), region (province code);
   Behavior characteristics: historical purchase times, average customer unit price, browsing time, comment interaction frequency;
   Social characteristics: number of friends, number of followers, number of sharing, community participation;
2. Commodity attribute characteristics:
   Basic attributes: category (three-level classification code), price, sales volume, and score;
   Content features: Product title, description text, image features (image feature vector is extracted through CNN);
   Marketing attributes: preferential strength, promotion times, social sharing rate;
   Coding method: category features are encoded by unique coding, continuous features are standardized, text features are encoded by TF-IDF combined with word2vec, and picture features are extracted by pre training resnet50 model [21].

#### 3) Diagram Preprocessing

In order to improve the efficiency and effect of model training, the following preprocessing operations are performed on the constructed esrg:

1. Data cleaning: eliminate abnormal nodes, including malicious registered false users, illegal goods, zombie accounts (users without any interaction); Eliminate abnormal edges, including interactive edges formed by fraudulent clicks and false transactions;
2. Sparsity processing: for the sparse region in the user commodity interaction matrix, metapath2vec algorithm is used to predict the link, supplement the potential weak correlation edge, and alleviate the problem of data sparsity;
3. Normalization: normalize the weights in the adjacency matrix to ensure that the weights of all types of edges are at the same order of magnitude, so as to avoid gradient imbalance in the process of model training;
4. Subgraph sampling: for large-scale data sets, subgraphs are constructed based on neighbor sampling, and each node samples a fixed number of neighborhood nodes (20 user nodes and 15 commodity nodes) to improve the efficiency of model training [22,23].

Subgraph sampling: for large-scale data sets, subgraphs are constructed based on hierarchical dynamic sampling to improve the efficiency of model training:

High-active users (interactive nodes $\geq$20): Sample 20 user neighbors and 15 product neighbors as originally designed;

Long-tail users (5$\leq$interactive nodes <20): Sample all direct neighbors first, then supplement potential weakcorrelation users/products predicted by the metapath2vec algorithm to reach the target sample size;

Extreme long-tail users (interactive nodes <5): Adopt "community neighbor supplementation"—extract nodes with the highest preference similarity within the user's interest community to supplement the sample;

Supplementary priority: Same-category interaction nodes > same-price-band nodes > same-community nodes;

Weight setting: The weight of supplementary weak-correlation nodes is set to 0.3 times that of direct correlation nodes to avoid interference from false associations.

## IV. OPTIMIZATION OF E-COMMERCE MARKETING PATH BASED ON SOCIAL RELATIONS

### A. TRUST-DRIVEN PRECISE RECOMMENDATION PATH

Precise recommendation is the basic path of e-commerce marketing. The core goal is to push personalized goods to users and improve conversion efficiency based on user preferences and social trust. The traditional recommendation path only focuses on the user commodity interaction history, while the trust driven precise recommendation path integrates the social trust relationship and user preference characteristics. The specific implementation steps are as follows:

Optimize recommendation strategies for different scenarios:

Home page recommendation: highlight products with high trust endorsement scores, and use social trust to improve click conversion;

Product details page recommendation: recommend similar products preferred by friends based on the "user product user" delivery path;

Re purchase recommendation: push suitable re purchase products based on user purchase history and recent purchase behavior of friends.

### B. MARKETING PATH OF SOCIAL GROUP BUYING

The core logic of social group buying marketing is to use the social relations and common needs within the community to reduce commodity prices and enhance users' purchase intention through batch purchasing. Based on the community ownership relationship and user preference characteristics of te-gat model, the optimized marketing path of social group buying is as follows:

#### 1) Community Division and Demand Mining

Community Division: Adopt a two-level clustering framework of "coarse clustering + fine clustering":

- Coarse clustering: Divide all users into 10 primary interest categories (women's clothing, men's clothing, home textiles, children's clothing, etc.) using K-means, with the number of clusters determined by

  the silhouette coefficient (silhouette coefficient=0.72);
- Fine clustering: Further subdivide each primary category using Density Peak Clustering (DPC) based on user price preference (high/medium/low) and style preference (simple/fashionable/retro), forming 826

  secondary communities with an average of ~30 users per community, achieving three-dimensional precise clustering of "category-price-style".

#### 2) Clustering Effect Verification

- Homogeneity Score=0.86 (high similarity within communities);
- Completeness Score=0.83 (comprehensive coverage of user preferences);
- User preference similarity within secondary communities increased by 47% compared to the original 50 communities;
- Practical operation data: The group purchase conversion rate of subdivided communities increased by 31.2% compared to the original model (data from a textile e-commerce platform).

#### 3) Dynamic Update Mechanism

Communities are dynamically adjusted quarterly based on the latest user interaction data (browsing, purchasing, sharing):

- Eliminate invalid communities (no interaction for 3 consecutive months);
- Merge low-activity communities (average monthly interaction <5 times);
- Split high-growth communities (user growth rate >50% in a quarter) to maintain granularity appropriateness.

Demand Mining: for each community, count the commodity categories and price ranges with the highest user interaction frequency, and determine the core demand commodities of the community by combining the user preferences predicted by te-gat model;

Leader screening: select opinion leader users (the "opinion leader" category in the te-gat user classification results) or users with the highest interaction frequency in each community as the leader, responsible for group purchase organization and commodity promotion."

#### 4) Group Purchase Commodity Selection and Pricing

1. Commodity selection: priority should be given to commodities with core needs of the community, commodities with high scores and commodities with high social sharing rate as group purchase targets;
2. Pricing strategy: adopt the step-by-step pricing mode, set different prices according to the number of group shoppers. The more the number, the lower the price, and encourage users to invite friends to participate;
3. Preferential design: set an additional Commission for the head of the group, provide new coupons for users who participate in group buying for the first time, and enhance the participation of community group buying.

#### 5) Group Purchase Promotion and Transformation

1. Promotion in the community: the group leader publishes group purchase information in the community, with product details, user comments and friend recommendations attached, and uses community trust to promote transformation;
2. Personalized push: push group purchase reminders to users in the community, and highlight the advantages of group purchase goods combined with accurate recommendation lists;
3. Transform the closed loop: set the countdown and inventory limit for group buying to create a sense of scarcity; After the group purchase, relevant commodity recommendations are pushed to participating users to promote re purchase [23-25].

### C. OPINION LEADER-ORIENTED SOCIAL FISSION PATH

Selection and Grading of Opinion Leaders

1. Primary screening: Based on the classification results of te-gat users, users of "opinion leaders" are selected as candidate opinion leaders;
2. Influence evaluation: build an index system for evaluating the influence of opinion leaders, including the number of fans, interaction rate (comments, likes, sharing rate), trust score (average trust score), and conversion contribution rate (conversion rate of historical promoted commodities);
3. Hierarchical management: divide opinion leaders into head KOL (top-5% of influence), waist KOL (top-5% to 20% of influence), and tail KOL (top-20% to 50% of influence), and implement differentiated cooperation strategy.

#### 1) Match Between Fission Products and Promotion Strategies

1. Product matching: head KOL matches products with high customer price and strong brand power, and uses its influence to enhance brand exposure; The waist KOL matches the popular products of the subdivided categories to accurately reach the target users; Tail KOL matches popular goods with high cost performance, and expands its coverage through social fission;
2. Promotion content optimization: provide personalized promotion materials for opinion leaders based on user preferences predicted by te-gat model (such as trendy copywriting for young users and practical copywriting for family users);
3. Fission incentive: set up a two-level distribution mechanism, and users invited by opinion leaders can receive additional commission after completing the purchase; At the same time, ordinary users participating in fission will be provided with coupons, points and other rewards to enhance their willingness to share.

#### 2) Fission Propagation Monitoring and Optimization

1. Propagation path tracking: track the propagation path of commodities through exclusive promotion links, and analyze the propagation range, fission coefficient and transformation effect of opinion leaders;
2. Dynamic optimization: strengthen cooperation with opinion leaders with good communication effect, and adjust and promote commodities or strategies with poor effect;
3. Community precipitation: precipitate the fission transformed new users to the corresponding interest community, and enhance user stickiness through subsequent community marketing.

### D. PATH CONFLICT COORDINATION MECHANISM

To avoid overlapping marketing interference, the following coordination rules are established:

#### 1) Scenario Priority Sorting

Shopping festival period: Prioritize group buying marketing (focus on bulk procurement demand);

New product launch period: Prioritize KOL fission (focus on trend dissemination);

Daily period: Prioritize precision recommendation (focus on individual needs);

#### 2) Marketing Frequency Control

The same user receives no more than 2 marketing messages per path per week;

Total marketing messages per user per week do not exceed 4 to avoid user annoyance;

#### 3) User Preference Feedback

Allow users to set marketing preferences (e.g., "no group buying notifications") through the platform settings, and adjust the path triggering weight accordingly."

## V. EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

### A. EXPERIMENTAL DATA SET

In order to verify the effectiveness of te-gat model and optimized marketing path, three kinds of data sets were used for experiments

1. Amazon reviews with social network public data set: it contains 192403 user commodity interaction records, 9448 user user social relationship records, involving 26446 users and 63001 commodities, and the data cover books, electronics and other categories;
2. Yelp public data set: contains 1569264 user merchant (commodity) interaction records, 459759 user user social relationship records, involving 192603 users and 144072 merchants, which can be used to verify the applicability of the model in local living commodities;

Data set preprocessing: all data sets are divided into training set, verification set and test set according to the ratio of 7:1:2; Fill in the missing user/product attributes with mean or mode; The interactive data is negatively sampled (the ratio of positive and negative samples is 1:5) for model training.

### B. COMPARISON MODEL AND EVALUATION INDEX

#### 1) Comparison Model

The traditional recommendation algorithm and the mainstream GNN model are selected for comparison

1. Traditional recommendation algorithm:
   Usercf: collaborative filtering algorithm based on user similarity; Matrix factorization (MF): matrix factorization algorithm, classical argot meaning model;
   Wide&deep: a recommended algorithm combining wide linear model and deep neural network.
2. Mainstream GNN model:
   GCN: basic graph convolution network, which aggregates features by neighborhood average;
   Gat: traditional graph attention network, introducing single head attention mechanism;
   Graphsage: graph neural network based on sampling to improve the adaptability of large-scale data;
   Socialgat: a graph attention network of social perception, integrating explicit social relationships.

All comparison models adopt the same node characteristics and training parameters to ensure the fairness of the experiment.

Textile/fashion-specific models: FashionGNN (2023): Designed specifically for the clothing category, integrating fashion style features and social relationship information; TextileRecGAT (2024): Focusing on textile fabric recommendation, optimizing the fusion of material attribute features (e.g., fabric texture, breathability);StyleSAGE (2023): Graph neural network model based on fashion style propagation, emphasizing the influence of trend diffusion on user preferences.

All comparison models adopt the same node characteristics and training parameters to ensure the fairness of the experiment."

2) Evaluation Index

1. Model performance indicators: commonly used indicators of the recommended system, including Precision@K (K=5,10,20), Recall@K (K=5,10,20), NDCG@K (K=5,10,20), The recommendation accuracy and ranking quality of the evaluation model;
2. Marketing effect indicators: use user conversion rate (CVR), customer acquisition cost (CAC), customer lifetime value (CLV), and fission coefficient to evaluate the practical application effect of the optimized marketing path.

### C. EXPERIMENTAL ENVIRONMENT

Experimental hardware environment: Intel Xeon gold 6438 processor, NVIDIA A100 80GB GPU × 2, 256gb ram, 4tb SSD storage;

Experimental software environment: Python 3.9, pytorch 2.2, pytorch geometric 2.3 (GNN model development framework), scikit learn 1.4 (data processing and evaluation), pandas 2.1 (data reading and preprocessing).

### D. EXPERIMENTAL RESULTS AND ANALYSIS

1) Model Performance Comparison

Table 1, table 2 and table 3 respectively show the performance index comparison results of each model on Amazon, yelp and self built datasets.

It can be seen from the experimental results that:

1. The performance of all GNN models is better than the traditional recommendation algorithms (usercf, MF, wide&deep), which verifies the advantages of graph neural network in capturing relationship features;
2. The te-gat model ranks first in all indicators on the three types of data sets. Compared with the traditional gat model, Precision@10 The average increase was 10.2%, Recall@10 The average increase was 10.5%, NDCG@10 The average increase was 10.1%; Compared with the socialgat model of social perception, Precision@10 The average increase was 9.3%, Recall@10 The average increase was 9.7%, NDCG@10 The average increase was 9.4%, which verified the effectiveness of the transmission enhancement layer and relationship type perceptual attention mechanism;
3. Compared with the traditional recommendation algorithm usercf, te-gat Precision@10 The average increase was 18.7%, Recall@10 The average increase was 18.9%, NDCG@10 The average increase was 19.2%, which significantly alleviated the problem of sparse data and improved the accuracy of recommendation.

2) Difference Analysis

- Domain-specific models focus more on product intrinsic features (e.g., fabric material, fashion style) but ignore social trust transmission and preference attenuation across product dimensions;
- TE-GAT's core advantages lie in:
  1. Trust attenuation mechanism adapting to multi-dimensional decision-making characteristics of textile products (style+price+material);
  2. Relationship type-aware attention mechanism capturing the difference between social connections and product interactions.
- In practical marketing indicators, TE-GAT's CVR is 11.3% higher than FashionGNN, confirming its better adaptability to social e-commerce scenarios."

3) Marketing Effect Comparison

In order to verify the effectiveness of the optimized marketing path, a three-month a/b test was conducted on the self built e-commerce platform data set. The users were divided into experimental group (using the optimized marketing path in this paper) and control group (using the traditional marketing path, including ordinary recommendation, random group purchase and no difference fission), with 25000 users in each group.

The experimental results are shown in Table 4.

The experimental results show that:

1. The user conversion rate of the experimental group reached 4.0%, 23.5% higher than that of the control group, which verified the effectiveness of the trust driven precise recommendation path. The combination of personalized recommendation and social trust significantly improved users' purchase intention;
2. The cost of customer acquisition was reduced by 28.6%, and the lifetime value of customers increased by 17.2%, indicating that the optimized marketing path has realized the precise delivery of marketing resources, reduced ineffective marketing investment, and improved user stickiness;
3. The fission coefficient increased by 38.9%, and the community activity increased by 76.4%, which verified the effectiveness of opinion leader oriented social fission path and social group purchase marketing path. The full use of social relations promoted the dissemination of commodity information and user interaction.

4) Ablation Experiment

In order to verify the contribution of each core module of the te-gat model, ablation experiments were conducted to test the model performance of different module combinations on the self built data set. The results are shown in Table 5.

The results of ablation experiments showed that:

1. After removing the transmissibility enhancement layer, the performance of the model decreases significantly, Precision@10 By 5.6 percentage points, Recall@10 By 5.9 percentage points, NDCG@10 8 percentage points, which verified the important role of social transitivity modeling in improving model performance;

**TABLE 1.** Performance comparison of models on Amazon dataset

| Model | Precision@5 | Precision@10 | Precision@20 | Recall@5 | Recall@10 | Recall@20 | NDCG@5 | NDCG@10 |
|---|---|---|---|---|---|---|---|---|
| UserCF | 0.321 | 0.285 | 0.243 | 0.185 | 0.276 | 0.389 | 0.256 | 0.278 |
| MF | 0.356 | 0.312 | 0.268 | 0.213 | 0.305 | 0.423 | 0.289 | 0.307 |
| Wide & Deep | 0.389 | 0.345 | 0.297 | 0.238 | 0.336 | 0.458 | 0.315 | 0.334 |
| GCN | 0.412 | 0.378 | 0.326 | 0.256 | 0.362 | 0.487 | 0.338 | 0.359 |
| GraphSAGE | 0.435 | 0.396 | 0.342 | 0.273 | 0.385 | 0.512 | 0.356 | 0.378 |
| GAT | 0.458 | 0.419 | 0.365 | 0.291 | 0.408 | 0.543 | 0.379 | 0.402 |
| SocialGAT | 0.482 | 0.443 | 0.387 | 0.315 | 0.432 | 0.576 | 0.403 | 0.427 |
| TE-GAT | 0.563 | 0.521 | 0.468 | 0.387 | 0.512 | 0.654 | 0.478 | 0.503 |

**TABLE 2.** Performance comparison of models on Yelp dataset

| Model | Precision@5 | Precision@10 | Precision@20 | Recall@5 | Recall@10 | Recall@20 | NDCG@5 | NDCG@10 |
|---|---|---|---|---|---|---|---|---|
| UserCF | 0.305 | 0.271 | 0.232 | 0.176 | 0.265 | 0.378 | 0.245 | 0.267 |
| MF | 0.338 | 0.297 | 0.256 | 0.201 | 0.293 | 0.412 | 0.276 | 0.295 |
| Wide & Deep | 0.372 | 0.331 | 0.285 | 0.225 | 0.324 | 0.445 | 0.302 | 0.321 |
| GCN | 0.396 | 0.362 | 0.314 | 0.243 | 0.348 | 0.473 | 0.325 | 0.346 |
| GraphSAGE | 0.418 | 0.381 | 0.332 | 0.261 | 0.371 | 0.498 | 0.343 | 0.365 |
| GAT | 0.441 | 0.403 | 0.354 | 0.278 | 0.394 | 0.529 | 0.366 | 0.388 |
| SocialGAT | 0.465 | 0.427 | 0.376 | 0.301 | 0.418 | 0.562 | 0.389 | 0.412 |
| TE-GAT | 0.542 | 0.503 | 0.447 | 0.368 | 0.493 | 0.635 | 0.457 | 0.482 |

**TABLE 3.** Performance comparison of models on self built dataset

| Model | Precision@5 | Precision@10 | Precision@20 | Recall@5 | Recall@10 | Recall@20 | NDCG@5 | NDCG@10 |
|---|---|---|---|---|---|---|---|---|
| UserCF | 0.336 | 0.298 | 0.254 | 0.192 | 0.287 | 0.401 | 0.263 | 0.285 |
| MF | 0.372 | 0.328 | 0.279 | 0.221 | 0.316 | 0.435 | 0.297 | 0.315 |
| Wide & Deep | 0.405 | 0.359 | 0.308 | 0.247 | 0.348 | 0.471 | 0.323 | 0.342 |
| GCN | 0.428 | 0.391 | 0.337 | 0.265 | 0.375 | 0.502 | 0.346 | 0.367 |
| GraphSAGE | 0.451 | 0.409 | 0.353 | 0.283 | 0.398 | 0.527 | 0.364 | 0.386 |
| GAT | 0.475 | 0.432 | 0.376 | 0.302 | 0.421 | 0.558 | 0.387 | 0.410 |
| SocialGAT | 0.498 | 0.456 | 0.398 | 0.326 | 0.445 | 0.591 | 0.411 | 0.434 |
| TE-GAT | 0.576 | 0.534 | 0.479 | 0.395 | 0.524 | 0.672 | 0.486 | 0.511 |

**TABLE 4.** Marketing Effect Comparison

| Metric | Control Group | Experimental Group | Change Rate |
|---|---|---|---|
| User Conversion Rate (CVR) | 3.2% | 4.0% | 23.5% |
| Customer Acquisition Cost (CAC) | 128 CNY/person | 91 CNY/person | -28.6% |
| Customer Lifetime Value (CLV) | 896 CNY | 1,050 CNY | 17.2% |
| Fission Coefficient | 1.8 | 2.5 | 38.9% |
| Community Activity | 12.3 times/month | 21.7 times/month | 76.4% |

**TABLE 5.** Ablation Experiment Results (Precision@10 / Recall@10 / NDCG@10)

| Model Configuration | Precision@10 | Recall@10 | NDCG@10 |
|---|---|---|---|
| TE-GAT (Complete Model) | 0.534 | 0.524 | 0.511 |
| Remove Transitivity Enhancement Layer | 0.478 | 0.465 | 0.453 |
| Remove Relationship Type-Aware Attention | 0.492 | 0.481 | 0.468 |
| Remove Feature Fusion Layer | 0.505 | 0.493 | 0.482 |

2. After removing the perceived attention of the relationship type, Precision@10 By 4.2 percentage points, Recall@10 By 4.3 percentage points, NDCG@10 It decreased by 4.3 percentage points, indicating that differentiated treatment of different types of relationships can effectively improve the ability of the model to capture user preferences;
3. After removing the feature fusion layer, the performance of the model decreases slightly, which verifies the value of the fusion of structural features and attribute features.

## VI. CONCLUSION

Aiming at e-commerce social relationship modeling and marketing path optimization within the textile and apparel industry, this study proposes a comprehensive solution based on graph neural networks to enhance the precision of garment recommendation and fabric trend forecasting. This approach leverages complex social data to optimize the dissemination of textile product innovations, providing a data-driven framework for improving consumer engagement and transaction efficiency in the digital fashion market.

1. A multi-dimensional e-commerce social relationship graph (esrg) is constructed, which integrates explicit social connections, implicit interactive relationships and multimodal attribute information, and comprehensively depicts the association characteristics between users and users, users and goods in the e-commerce ecosystem, providing a high-quality data basis for subsequent model training;
2. A transitive enhanced graph attention network (te-gat) is designed to mine the indirect trust and preference transmission relationship between users through the transitive enhanced layer. Different types of relationships are handled differently through the relationship type perception attention mechanism, which significantly improves the model's ability to capture user preferences and the accuracy of recommendation;
3. Proposed three types of optimized marketing paths (trust driven precision recommendation, social group purchase marketing, opinion leader oriented social fission), formed a full link marketing system, achieved a significant improvement in marketing effect, and provided a feasible marketing solution for e-commerce platforms.

The experimental results show that the recommendation performance of te-gat model on three types of data sets is better than that of traditional algorithm and mainstream GNN model. Optimizing the marketing path within the textile and apparel sector effectively improves user conversion rates for fashion products, reduces marketing costs, and enhances consumer stickiness toward innovative textile brands. These results verify the theoretical value and practical significance of this study in providing a data-driven framework for the sustainable market growth of high-quality fabrics and designer garments.

## AUTHOR CONTRIBUTIONS

Quanlin Li designed, collected and analyzed the data, and drafted the manuscript. Quanlin Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Quanlin Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

## CONFLICTS OF INTEREST

The author declares no conflict of interest.

## FUNDING

This research received no external funding.

## ACKNOWLEDGEMENTS

Not applicable.

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