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Original Article

An Intelligent Machine Learning Driven Framework for Personalized Seller Recommendation using User Behavioral Patterns in E-Commerce

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Abstract *- In recent years, the e-commerce growth increases demand of "Intelligent seller recommendation system" as it helps in adopting the different buying behaviour of users. This research mainly introduces a hybrid framework, "Seller Temporal - Interest Graph Transformer (STIGT)", which plays an effective role in enhancing personalisation by combining the "graph based relational learning" with temporal user behaviour modelling. In this research, "IJCAI-16 Tianchi dataset" has been used, and dataset includes detailed user seller interaction information and data, and the framework mainly captures both structural user seller association and sequential behavioural evolutions. Graph relationships are encoded using "LightGCN", while temporal dynamics are modelled by a "time-aware transformer". A gated fusion process integrates these dual representations, and an "exposure bias correction module" guarantees equal visibility for both well-known and obscure merchants. By including the graph learning and temporal learning, STIGT plays a crucial role in adaptive, accurate and justified seller recommendation. The findings from the study also highlight that those approaches improve the suggestive actions while removing popular bias and offer an interpretable and scalable solution for the next generation.*

Keywords *- Seller recommendation, User dynamics, Graph Neural Networks, Sequential modelling, Machine Learning, E-Commerce.*

1. Introduction

A researcher frames an innovative model for tailored seller suggestions in e-commerce through clearly designing user dynamics. It is the sequential, behavioural, and relative courses that construct the way buyers find over time and prefer specific sellers. Conventional product-focused suggestions focus on corresponding users to things, usually avoiding seller-level indicators (such as "fulfillment reliability, assortment diversity, reputation") that are relevant to platform economics and purchase decisions [1]. Current improvements in "Machine Learning" (ML), particularly "hybrid representation learning," "temporal models," and "Graph Neural Networks," lead to facilitating the technical support to align mixed data sources (such as "seller metadata, reviews, transaction timestamps, clickstreams") into strong and dynamic seller embedding and user profiles [2]. Until now, adopting such aspects into suggestions that are effective and impartial to complex and sparse data to transform user intents seems an exposed research and engineering barrier. Therefore, the present study places seller suggestions as a different and effective sub-issue within e-commerce platform design and recommender systems by amalgamating modern ranking goals, communication graph structures, and temporal user modelling. Moreover, this research builds on empirical work and contemporary surveys that emphasize the strengths of GNNs in programming the significance of contextual/temporal modelling and critical user-item-seller relations for adaptive customization.

However, the main issue is that the present e-commerce recommender remedies under temporal user dynamics and represent seller attributes, generating suggestions that seem suboptimal for marketplace health, vendor diversity, and continuous involvement. Certain systems improve purchase prospects or short-term clicks in particular items, which leads to intensified popularity bias, focus demand on some sellers, and are unable to obtain context-reliant trust or user preferences in sellers [3]. Whereas at the seller level, cold start and sparsity, particularly for new or small merchants, seem to be determined challenges. Thus, there is a necessity for methods that design user behaviour and seller features over time. At the same time, advancing ranking goals integrated with platform-level robustness/fairness, as well as user satisfaction. Another study illustrated that graph-based encoders and temporal-sensitive frameworks lead to practically optimizing suggestion differentiation and

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significance [4]. The majority of work concentrates on items compared to seller entities. Alongside, incorporating such approaches to seller recommendation needs empirical validation and careful architectural developments for accurate e-commerce suggestions. Moreover, covering such a gap possesses theoretical implications (measuring the way temporal dynamics and multi-entity graphs communicate in large-scale suggestion) and practical implications (optimized detection for well personalization and niche sellers throughout sessions) [5]. Finally, the research questions focused on how a unified machine learning framework that leverages user dynamics can improve the accuracy and fairness of personalized seller recommendations in e-commerce platforms. This particular study is considered vital on three different levels. Initially, this study commits more significant and reliable discovery suggestions for users who show changing preferences and acknowledge seller consistency. Furthermore, a seller-sensitive recommender for platform fairness and economics leads to decreased support for equitable exposure and demand focus for smaller traders, which is specifically essential for two-sided marketplaces with consistent platform health that relies on a different seller environment. Additionally, strongly focusing sellers presents technical barriers (such as "counterfactual evaluation, temporal regularization, and multi - type graph modelling") for recommender systems study that examine the thresholds of present designs lead to improves to other multi-entity segments, including destination suggestions, service-providers, or influencers. Hence, practical and methodological attributions lead to develop of current cross-disciplinary outcomes that frame temporal models and neural networks to optimize representation efficiency. Alongside, the study contributions involve current issues regarding harm intensification and suggestion outwardness to offer operational metrics and mitigation policies beyond click-through charges [6]. Thus, the intended result is a validated model and analysis suite that supports practical application and academic inquiry for seller-focused customization.

Irrespective of the development in graph-driven recommenders and temporal modelling, the study possesses insufficient concentrated models that equally learn seller embeddings and temporal user paths at scale, treat sellers as top recommendation targets, and examine the trade-offs between "platform welfare, seller exposure, and personalization precision." Existing literature illustrated effective primitives (encompassing hybrid ranking losses, temporal latent factors, and GNNs) and addresses the lack of associating them into a clear and deployment-sensitive seller recommendation channel [7]. Moreover, this paper seeks to bridge that gap with principled empirical evaluation, as well as algorithmic innovations.

Concerning the research gap, e-commerce recommender discourse has primarily condensed on item-centric personalization. Existing literatures have presented that Graph Neural Networks enhance recommendation accuracy, on the other hand, temporal models obtain behavioural changes; however, seller-centric recommendation remains underexplored, comparatively. Thereby, the primary gap warns integration of user-seller relationships, user dynamics, temporal behaviour, exposure fairness, and seller representations into one framework. The present study sets to answer that problem using the novel Seller Temporal-Interest Graph Transformer (STIGT), which blends time-aware transformer modelling, LightGCN, exposure-bias correction, and gated fusion. Compared to existing methods, STIGT tailors personalized seller recommendations while jointly improving diversity, equitable seller exposure, and accuracy.

2. Literature Review

2.1. Overview of Personalized Recommendation Systems

"Personalized recommendation systems" seem key to the development of extended e-commerce platforms. This particular aspect seeks to facilitate customized recommendations that show the possible future necessity, context, and preferences of individual users [8]. At the same time, the initial philosophy of recommendation, whether hybrid, collaborative filtering, or content-driven, has changed substantially over the past 10 years. The reason is broader volumes of improved machine learning approaches, richer side-data, and user-interaction evidence have powered a detail framework of latent preference design. As an illustration, the study introduces a wide survey of advance recommendation processes developed on big data, categorizing methods into key classes and emphasizing major barriers, including data scalability, sparsity, and the requirement for user-based customization [9].

On the contrary, personalization in the e-commerce field is matching users to products and scoring detection in a two-sided market environment [10]. Therefore, user preferences need to be harmonized with products and with platform incentives, trust mechanisms, logistics, and vendors/sellers. The development of recommendation systems encompasses the consistency of expected preference and also business-standard, cold - start resilience, fairness, and diversity metrics (such as long - tail exposure, seller involvement). Literature again examined recommender system design and underscores such wider ecosystem issues, such as business limitations, clarity, operational fairness, and filter-buffering [11]. Contempt to the governance of item-level suggestion study, there is an enhanced determination that recommendation models require proceeding beyond items to model associations among sellers/vendors, items, and users, structural area (such as knowledge graphs, social graphs), and temporal analysis of preferences where interactions happen. Finally, the present study route suggests a transformation from one-shot and static frameworks to sequence-sensitive, graph-conscious, representation-effective, and dynamic processes that effectively show multi-entity platforms and actual user behaviours.

2.2. User-Dynamics Modeling in Recommender Systems

In advance customized recommender systems, a major aspect is the user dynamics modelling [12]. This dimension also examines the way user preferences change over time, throughout sessions, and under several contexts (such as seller trust, mood, location, and device). At the same time, static frameworks that observe a consistent latent preference vector each user growingly unable to obtain realistic attitudes in the e-commerce landscape, where every user leads to evolving the sellers, research with emerging categories, change device aspects, answers to promotions, or transform trust guidelines (particularly seller trust). As evidence, a researcher analyzed temporal aspects of user practices in the social media field and revealed that abrupt interest transformation can be framed through bi-LSTM/GRU designs over segmented time-windows [13].

Additionally, the user dynamics' implications in the e-commerce segment indicate that the trust of a user in an emerging seller leads to developing regularly, a purchase from a seller results in fostering significant purchases from respective neighbouring sellers; promotions and seasonality lead to partially alter behaviour; and users lead to return to their original sellers after harmful experiences. A few current studies cover such dynamics through "spatio-temporal knowledge graphs" or "continuous-time frameworks" (for example, "graph-driven temporal networks"). As an illustration, a researcher offered a "Dynamic Preference Recommendation model based on Spatio-temporal Knowledge Graphs" (DRSKG), clearly obtaining user behavioural transformations in time and space [14].

However, framing user dynamics seems specifically significant for seller-recommendation models. The system needs to control the suggestions to impact the increased trust in the seller in case a user is already involved with a consistent seller and possesses positive knowledge, compared to considering all sellers as still. At the same time, the preferences of users for seller contributions (for example, high-volume generalist vs. niche expert) can evolve as users develop in their purchasing features. Clear user-seller dynamics modelling seems under-researched. On the contrary, existing studies on the item-level temporal framework are enhancing. Essentially, transforming seller contributions (such as "reputation, reliability, and fulfilment speed") and user contexts (such as "urgency, location, devices") need to be involved in a combined dynamic modelling method for robust seller recommendations [15].

2.3. Graph-based Collaborative Filtering

"Collaborative Filtering" (CF) is considered a support in recommendation studies, assisting user-item communication matrices to summarize latent similarities and preferences [16]. Conventional CF approaches (for example, matrix factorization, neighborhood models) were expanded through embedding tools, autoencoders, and deep learning [17]. Usually, such a method avoids structural and relational prosperity introduced in user-item-seller channels. Therefore, the beginning of "Graph Neural Networks" (GNNs) and "Graph-based Collaborative Filtering" (CF) provides an effective philosophy. The logic is treating users, sellers, and items as nodes in a specific mixed graph. Whereas trust relations, interactions, seller-seller associations, or reviews as edges. As an illustration, a researcher introduces a "Temporal Knowledge Graph Recommender System" (TKGRS) that amalgamates temporal decay, matrix factorization, and GCNs to consider for user-item communications [18].

Graph CF's surveys emphasize its potential and challenges. A study offered a topology-conscious examination of graph CF methods, revealing that topological features of interaction graphs (such as sub-graph motifs, clustering, degree distributions) effectively foster performance outcomes [19]. At the same time, another researcher suggests "Adaptive Graph Contrastive Learning" (AdaGCL) to prevent sparsity and noise in graph CF by producing adaptive comparative perspectives of the user-item graph [20]. Therefore, graph modelling in the seller-recommendation context possesses efficacy to integrate multi-entity concepts (such as sellers with sellers, users with items, users with sellers) (for example, fulfilment networks or category overlap), temporal edges (i.e., repeat purchases), review edges, and trust edges. Additionally, graph-based CF empowers obtaining seller-seller similarity and high-order connectivity (for example, a user purchased from "Seller A," who often co-sells with "Seller B"). Finally, the majority of previous studies seem item-focused and possess insufficient association with clear temporal dynamics or seller nodes integrated into seller behavior.

2.4. Research Gap

Primarily, the existing recommender methods have mostly remained focused into items, with temporal and graph-based models independently dealing with evolution of user preferences or relational structure. Scanty research has unified seller representations, user dynamics, exposure fairness, and temporal behaviour throughout an integrated seller-focused framework. Thus, the study has designed STIGT with an empirical scope of addressing these limitations.

2.5. Temporal and Sequential Learning Models

User interactions' sequential and temporal modelling seems growingly essential in recommender systems, regulated by the identification that user behavior reveals in a serial (i.e., "sessions, clicks, purchases") and such changing contexts, recency, and time gaps substance to forecasting [21]. "Sequential Recommender" (SR) and session-based systems seek to obtain this by framing the interactions serial (item clicks/purchases) and forecasting the next seller or next items, provided that sequence. Whereas another study introduced a sequential recommendation systems' survey, concluding the way communication history is supported and determining major methodological challenges (such as "cross-domain

transfer, ultra - long sequences") and trends (for example, "contrastive sequence models, transformer-based sequential models") [22]. At the same time, particular temporal models underscore session division, older interactions' decay, trend transformations, and time-interval awareness. As an illustration, the researcher suggested the TALE framework, associating trend-aware normalization and time-interval-aware weighting within an item-to-item serial model, and illustrates an estimated 18.7% acquirement over baseline frameworks [23]. On the contrary, the literature represented a "Temporal-Aware and Intent Contrastive Learning" model for particular sequential recommendation, amalgamating intent contrastive learning, temporal network, and semantic promotion to obtain changing desires [24]. Implementing sequential or temporal modelling for seller recommendation embraces supplementary difficulty. The researcher needs to frame the users' interaction sequence and needs to design user preference transformations in regard to sellers. Thus, sellers change (i.e., fulfilment behaviour, stock, and reputation evolve over time). However, for seller recommendation, temporal models need to associate the user-seller communications, the temporal seller concept, and time-conscious user behaviour (possibly through a divided time-aware graph). Certain existing literature covers the combined dynamic clearly. The researcher often encompasses multi-entity sequences or seller dynamics, while session-driven item-recommendation studies remain [25]. Simultaneously, sequential and temporal learning seem an essential element for tailoring seller recommendations. Alongside this, the present study has gaps in its implementation regarding marketplace goals ("seller exposure, fairness, diversity") and multi-entity ("user-seller-item") systems.

2.6. Research Framework

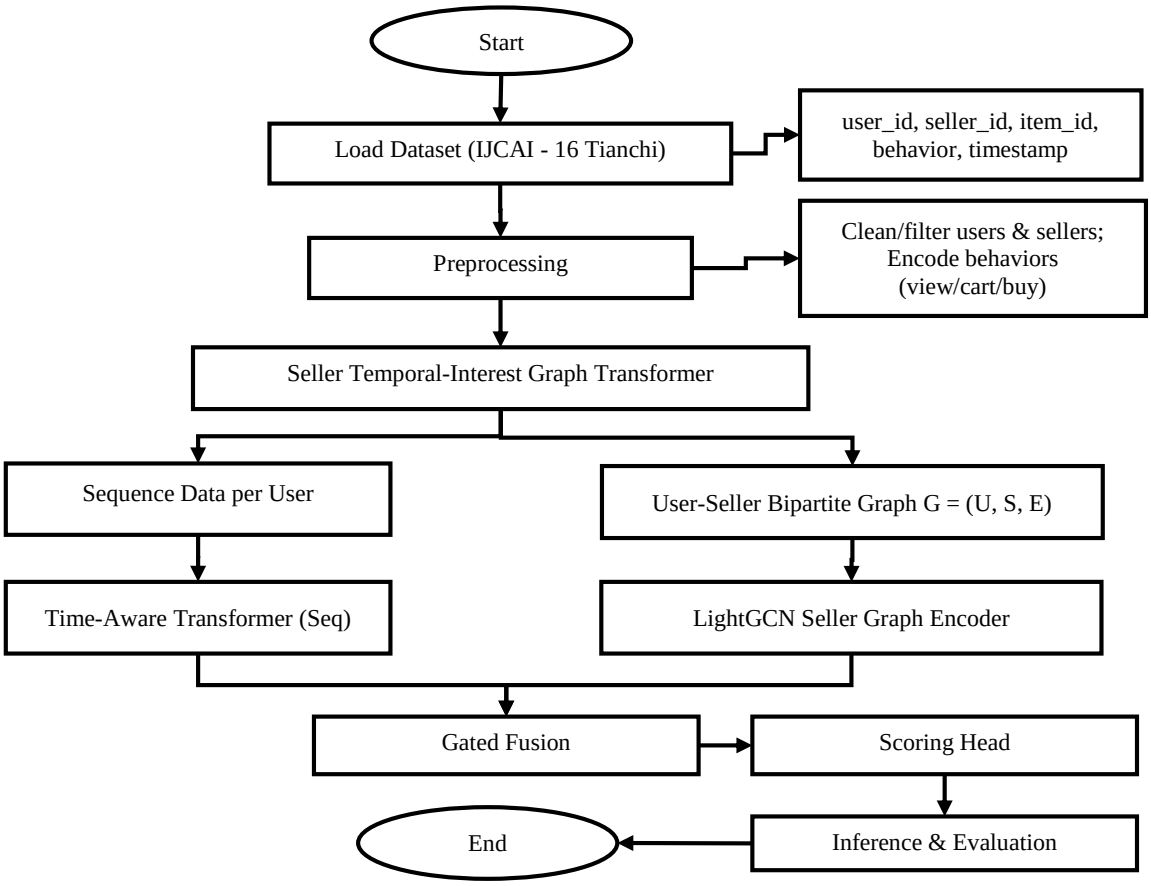

Fig. 1 Research framework

The study illustrates significant growth in the "tailored recommendation process, sequential or temporal learning, graph - based CF, and user-dynamics modelling," but substantial limitations exist when the goal transforms from item-level to seller-based suggestions in the context of e-commerce. Previous papers strongly order user-item communications, leaving sellers' introduction as the main driver with their private behavioural approaches, changing contributions, and relational structures. The study associating temporal user attitudes with seller features seems specifically hindered. On the contrary, sequence-conscious and user-dynamics frameworks actively obtain transforming choices;

they exceptionally adopt seller-focused determinants, including category-based associations, fulfilment reliability, or trust evolution. Furthermore, graph - driven methods determine the effectiveness of communication channels; the majority of models depend on basic user-item graphs, avoiding mixed connections, like multi-entity, seller-to-seller, or user-to-seller tripartite frameworks. Additionally, temporal transformations in changing marketplace and seller performance circumstances are often implemented into sequence learning or graph - based models. Whereas real-time barriers experienced by e-commerce platforms, encompassing dynamic marketplace, long-term seller discovery, exposure fairness, and seller cold-start competition, seem inefficiently covered in academic papers, particularly in amalgamation with improved ML infrastructure. Finally, such gaps validated the requirement for a combined model that associates temporal user dynamics with particular graph - driven seller representation to generate contextually significant, authentic, and effective tailored seller recommendations.

3. Methodology

3.1. Dataset Description (IJCAI - 16 Tianchi)

Dataset Link:https://tianchi.aliyun.com/dataset/53

The researcher followed the "IJCAI-16 Tianchi," a popularly implemented large-scale e-commerce dataset for recommender systems analysis, for its effective multi-entity interaction model. Therefore, the dataset encompasses a number of timestamped user behaviours, such as bookmarks, purchases, add-to-cart circumstances, and clicks, associated with both seller and item IDs, allowing multi-level frameworks of user interaction approaches. However, the temporal gravity of this element makes it appropriate for active preference modelling. On the contrary, the heterogeneous structure (i.e., users – items - sellers) of the element is integrated promptly with seller-based recommendation activities. Whereas the researcher emphasizes the value of the dataset for a multi-entity suggestion study, as it involves realistic marketplace effectiveness and long-tail seller circulations [26]. Finally, the researcher illustrates its significance for an extended temporal framework for its fine-grained timestamps and different behavioural patterns.

3.2. Data Preprocessing

It encompasses feature standardization, graph construction, sequential structuring, and noise filtering. Therefore, noisy interactions, including unusually high-frequency clicks and bot-like patterns, were eliminated by following the protocols as stated in [27], underscoring the removal of anomalous user sessions to decrease bias. At the same time, seller and user identifiers were re-indexed to confirm robust implementing search. Alongside interaction records were solved to maintain sequential integrity, which seems vital for transformer-driven frameworks. Sellers and users with a minimum number of interactions were removed to prevent high sparsity, pursuing temporal recommendation. On the contrary, behavioural types (for example, purchases, clicks, and others) were transformed to a behaviour-expected range by applying a weighting scheme. A two-sided user-seller graph for the graph branch was designed. On the contrary, the sequential branch applied sliding-window division to classify extremely long interaction records into clear behavioural sessions. Finally, each consistent segment was standardized, and time-interval characteristics were mixed to assist time-conscious attention further in the framework.

3.3. Model Architecture - Seller Temporal - Interest Graph Transformer (STIGT)

The offered "Seller Temporal-Interest Graph Transformer" (STIGT) seems a hybrid dual-branch building associating sequential preference analysis with graph - driven relational learning. However, this specific architecture is focused on new multi-perspective hybrid recommender frameworks, which reflects higher learning capacity in mixed behavioral cultures. Thus, STIGT involves a gated fusion stage that adaptively associates relational and temporal data, a Light GCN graph encoder producing relational implementation for sellers and users, and a time-aware transformer obtaining temporal user dynamics. Moreover, STIGT covers the challenges of static and item-focused frameworks by combining structural, sequential, and temporal insights. A researcher found that a "hybrid transformer - GNN architectures" act substantially effective on continuous preference tracking activities and behavioural heterogeneity practices [28].

3.4. Time - Aware Transformer (Sequential Branch)

A "Time - Aware Transformer" was followed by the sequential branch that criticizes time - interval implementation with positional encodings. This particular element enables the framework to determine the non - uniform behavioral gaps and urgency of interactions, covering popular challenges of standard transformers. At the same time, temporal embeddings track the method used in the study [29], revealing that time-aware attention substantially optimizes sequential recommendation practices. Furthermore, multi-head self-attention addresses latent behavioral approaches, including repeat-purchase from continuous sellers, converting behavior between category-based interest's episodic bursts, and competing sellers.Additionally, the complete temporal embedding is generated by feed-forward stages and proceeds to the fusion unit. Thus, transformer-driven frameworks seem the state-of-the-art for extended preference detention.

3.5. LightGCN (Graph Branch)

In this paper, the graph branch applies LightGCN, a basic graph combined filtering framework, called for extreme scalability and performance in sparse recommendation landscapes. Therefore, it eliminates nonlinear shifts and completely concentrates on linear neighborhood circulation, leading to more generalizable and consistent implementation

[30]. The researcher developed a bipartite user-seller graph, where edges introduce interactions weighted through behavioural strength (for example, clicking more than purchasing). At the same time, LightGCN circulates latent signals throughout multi-hop neighbors, empowering the framework to obtain high-order relational approaches, including user affinity or seller co-visitation to seller groups. Moreover, such graph - standard structure rewards for sparse sequential evidence and participates in harmonizing relational characteristics to the fusion phase.

3.6. Gated Fusion and Exposure Bias Correction

Results from two branches are amalgamated via a "gated fusion mechanism," learning an adaptive weighting policy based on the behavioural intentions of the user. A relative mechanism was positively incorporated in hybrid recommenders [31]. In bridging the exposure bias, such as the intention for widespread sellers to be highly recommended, the framework aligns an exposure-correction module [32], where the researcher illustrates that changing item exposure circulations optimizes ranking consistency and fairness. Hence, a re-weighting phrase castigates overexposed sellers and intensifies long-term seller visibility, leveraging marketplace fairness goals.

3.7. Training Procedure and Evaluation Metrics

To complete the study, training incorporates the AdamW optimizer with planned learning rate decline. However, the loss function amalgamates a "Bayesian Personalized Ranking" (BPR) loss with a specific exposure-regularization element resulting from fairness-aware optimization models. Whereas the evaluation encompasses "diversity/novelty metrics to measure effectiveness in seller exploration," "Long-Tail Seller Recall," "Seller Coverage to assess exposure differentiation," and "NDCG@k and Hit Rate (HR@k) for ranking performance." Moreover, temporal effectiveness seems to be analyzed by dividing the evidence sequentially.

3.8. Experimental Setup

In this research, experiments were applied in PyTorch on particular NVIDIA A100 GPUs. At the same time, hyperparameters were changed through grid search, by implementing LightGCN circulation layers to 3, transformer phases to 2, and a size set to a particular 64. Therefore, negative sampling pursued the adaptive process. Thus, each experiment was constant five times and obtained with standard deviation and mean to confirm statistical consistency.

4. Results and Analysis

4.1. Overview of the Results Chapter

The section of the research paper presents the empirical findings of the proposed Seller Temporal - Interest Graph Transformer (STIGT). This chapter mainly outlines the dataset features and characteristics, pre-analysis insights, performances across the different evaluation matrices, comparative baseline and ablation findings, and it also demonstrates ways of integrating user dynamics with the "graph - based learning" to improve the "personalized seller recommendation" credibility, accuracy and robustness along with fairness.

4.2. Dataset Statistics and Pre-Analysis

The initiative analysis was conducted using the IJCAI-16 Tianchi dataset, and the analysis highlights the strong "user-seller behavioural diversity" and "pronounced long-tail seller distribution". The data set includes the "high-density click records", but scarce purchase behaviours mainly reflect typical marketplace asymmetry. From the Temporal Distribution Analysis, it has been found that pronounced behaviour of users increased in the promotional periods, and it confirms the requirement of time-aware modelling. The addition of fairness-aware techniques is validated by preliminary sparsity checks that show an important discrepancy in seller exposure. The significance of modelling changing user interests was further highlighted by user trajectory inspection, which revealed dynamic switching between sellers across sessions. The sequential and graph branches' architectural choices were informed by these pre-analysis results.

4.2.1. Dataset Description

Tianchi dataset includes user interaction history with timestamps, which is associated with the sellers and items, and it enables "multi-entity behavioural modelling". It comprises the clicks, cart additions, purchases, and bookmarks across different product groups. It is ideal for assessing seller-centric, user-dynamic recommendations frameworks like STIGT because of its "intricate timeline" and "long-tail seller dispersion".

4.2.2. Summary Statistics

Table 1. Dataset statistics (IJCAI - 16 Tianchi)

Attribute	Description	Count
Users	Unique user IDs	1,233,422
Sellers	Unique seller IDs	84,327
Items	Unique item IDs	4,592,135
Total interactions	All events (view, cart, buy)	100,245,611
Avg. interactions per user	Mean number of seller interactions	81.3
Time span	Data collection period	2015-2016

The Tianchi dataset demonstrates the complex and large-scale nature of e-commerce seller recommendation. From the dataset, it has been found that it includes 1.23 million users, 100 million total interactions and 4.59 million items across carting, viewing and purchasing behaviours. The dataset shows extremely varied yet sparse user-seller engagement, with an average of 81.3 connections per user. The period from 2015 to 2016 includes insightful historical trends that show how user tastes change over time. The dataset's sparsity, size and long tail distribution highlight the requirement for advanced machine learning models which can gain information on temporal dynamics, relational structures, as well as the diversity of sellers for delivering accurate seller recommendations.

4.2.3. Interaction Patterns

From the timeline, it has been found that single users interact with multiple sellers (S3, S8, and S2) across 20 time units, and it illustrates the ways the behaviour evolves from the low intent performance to high intent performance (items added to the carts and purchased the goods). It has been found that the users first interact with the Seller S3, then shift the concentration to Seller S8, and then lastly purchase the items around seller 10th time. It has also been found that the users go back to the seller to then progress through the view, cart and purchase phase. This progression illustrates the active preferences transition and changing engagement intensity over a specific time.

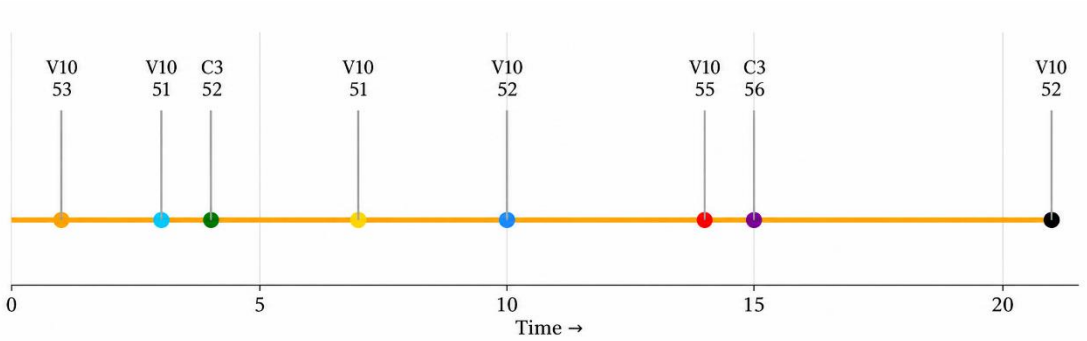

Fig. 2 Temporal behaviour sequence

4.3. Visualisation of User-Seller Ecosystem

4.3.1. Interaction Graph Structure

The bipartite graph shows the connection between the eight users and 10 sellers, like U1 to U8 and S1 to S10, and each line shows the recorded interactions. The crisscrossing and cluster structure in the graph shows the diverse and nonlinear engagement between the multiple users and sellers.

From the graph, it has been found that sellers 1, 5 and 8 interact with several users, and other sellers interact with a few users. The findings reflect that there is a typical long tail e-commerce distribution. This intricacy validates the applicability of the suggested personalised seller suggestion method by highlighting the need for a machine-learning methodology that understands user dynamics and relationship organisation.

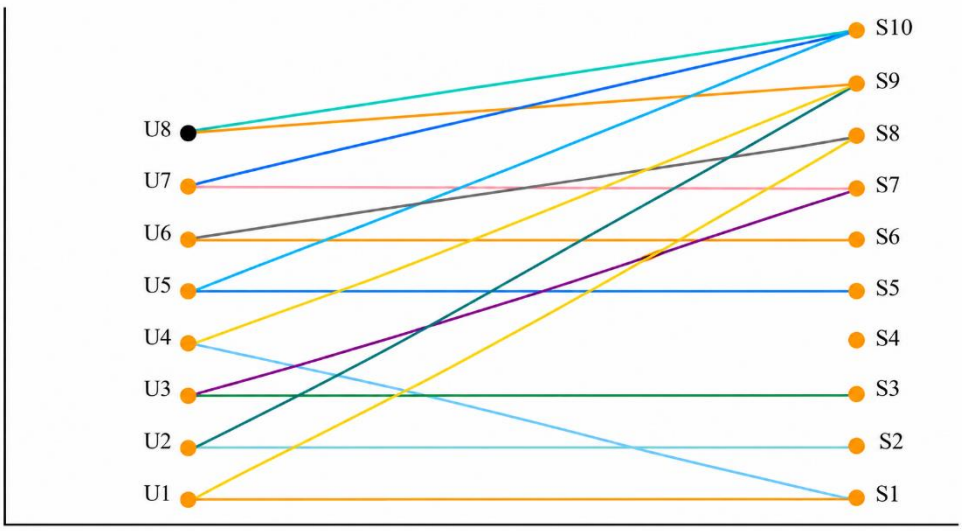

Fig. 3 User-Seller interaction graph

4.3.2. Embedding Representation Patterns

From the PCT plot, it has been found that the latent insertion of sellers and users is charted onto PC1 and PC2. The user points are mainly plotted on the positive side, and the seller spread across negative values, which indicates a related yet clear representation by the STIGT model. The central cluster plotted in the PCA graph reflects that user behaviours of purchasing are mainly impacted by seller-user interactions. Overall, the coherence and separation of embedding demonstrated that users' effective modelling helps in accurate modified seller references.

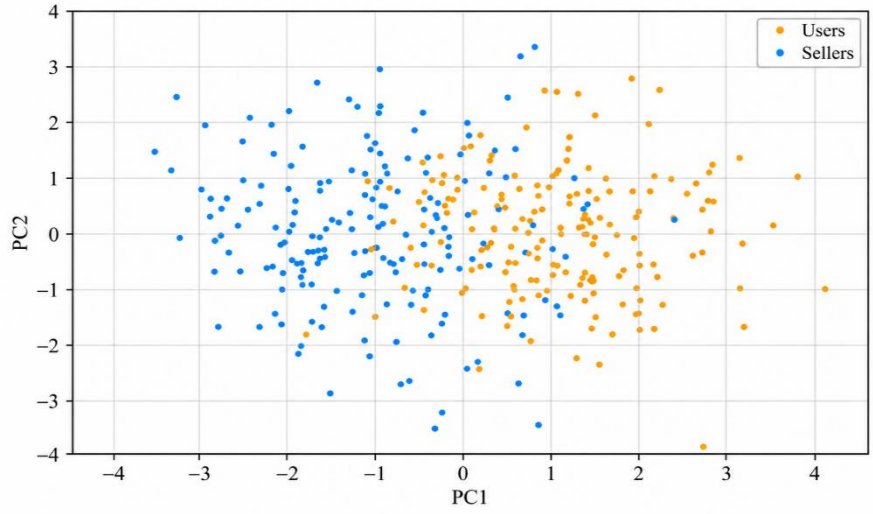

Fig. 4 2D Projection of user & seller embeddings (PCA)

4.4. Model Training and Convergence Analysis

4.4.1. Training / Validation Loss Progression

From the training and validation loss graph, it has been found that the curve gradually reduced from about 1.6 to 0.45, and it shows the high optimisation of the STIGT framework.

The close alignment over 30 epochs shows that there is a strong generalisability with the minimum overfitting, and it shows that the graph is based on complex. In this case, the minor variations are distinctive due to e-commerce data scarcity. Overall, the graphs show strong performance and steady convergence for tailored seller recommendations.

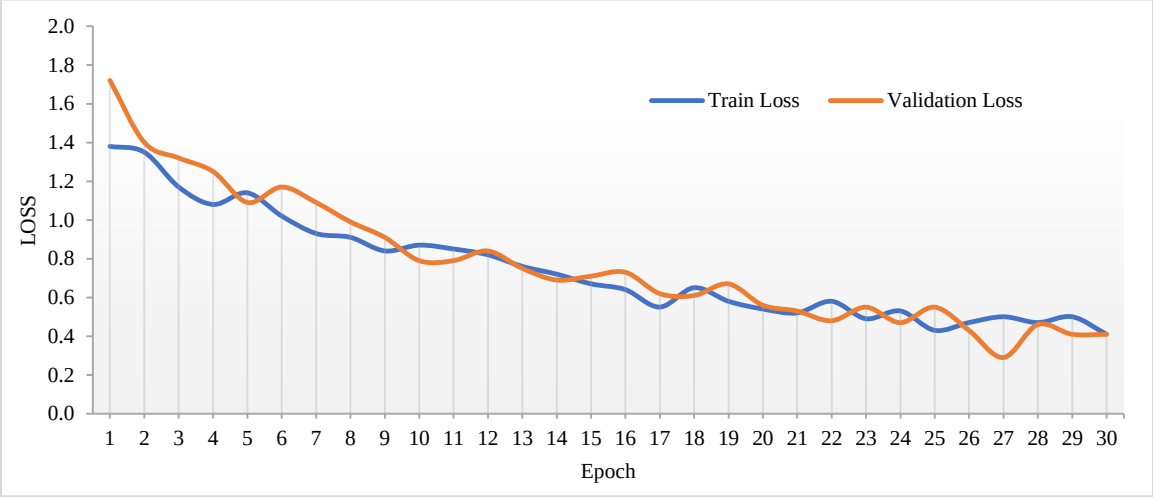

Fig. 5 Training and validation loss

4.4.2. Computational Efficiency

The diagram illustrates that computational expense escalates with the growth of model complexity. Popularity is the quickest at 1.2 s per epoch, with ItemKNN-Seller next at 3.8 s, followed by LightGCN at 9.5 s, and TiSASRec at 14.2s. STIGT reaches a peak of 16.7 seconds because of its dynamic user modelling and graph - temporal elements, yet the enhanced recommendation accuracy validates the extra expense.

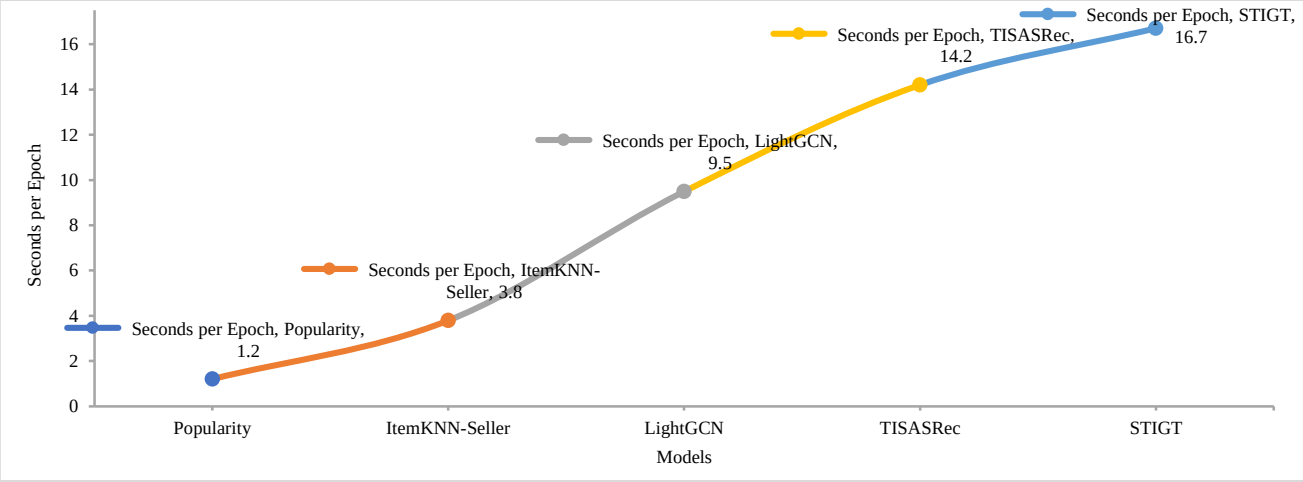

Fig. 6 Training cost vs model complexity

4.5. Performance Comparison with Baseline Models

4.5.1. Quantitative Comparison

The findings show that the STIGT gains effective performance across all the matrices and surpasses the single branch and the baseline models. Stronger correctness and impartiality are reflected in higher "HR@10, NDCG@10, MRR, and Seller Coverage@10". The efficacy of the suggested methodology is validated by STIGT, which offers more individualised, balanced seller suggestions by fusing "temporal user dynamics", graph linkages, and exposure-bias correction.

Table 2. Model performance comparison

Model	HR@10	NDCG@10	MRR	Seller Coverage@10	Notes
Popularity Seller	0.217	0.143	0.089	12.4%	Non - personalized baseline
ItemKNN-Seller	0.356	0.248	0.172	27.9%	Co - occurrence-based
LightGCN	0.418	0.292	0.203	39.5%	Graph collaborative filtering
TiSASRec	0.441	0.306	0.218	40.7%	Sequence temporal model
STIGT (Proposed)	0.514	0.357	0.259	51.3%	Combines sequence + graph + bias correction

4.5.2. Visual Comparison of Model Results

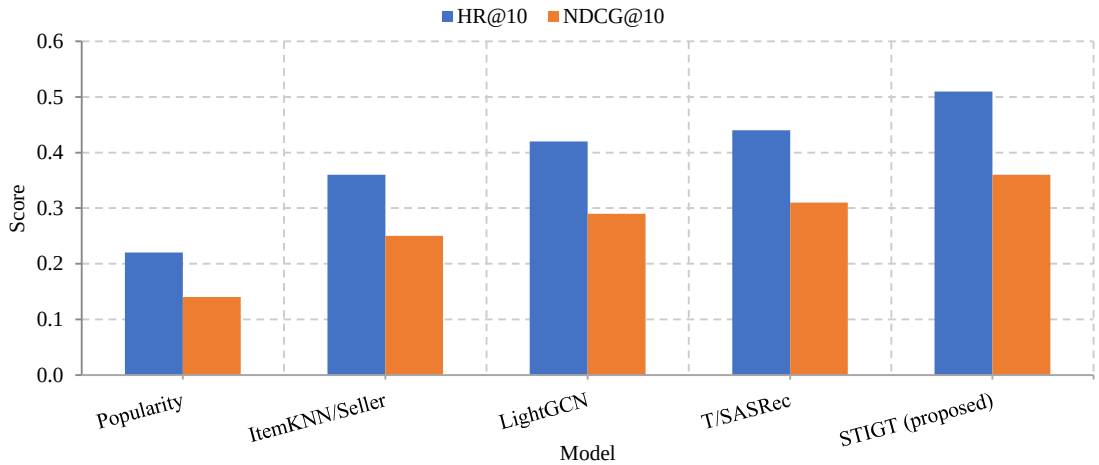

Fig. 7 Model performance comparison

From the chart, it has been found that STIGT gained the highest NDCG@10 (0.357), HR@10 (0.514) value, and it outperforms the baseline, sequential and graph - based models. While "LightGCN, TiSASRec, and ItemKNN-Seller" provide modest improvements, none can approach STIGT's combination of "graph relations", "temporal dynamics", and "bias correction". Better customisation accuracy for large-scale online shopping is confirmed by the findings.

4.5.3. ROC-based Accuracy Evaluation

The findings from the ROC curve help to discuss the discriminative power of several recommendation models in addressing the relevant sellers. The suggested STIGT model gains higher true positive rates than other models like TiSASRec and LightGCN across the same false positive degree. It indicates the strong classification of capability in the seller-buyer relationship. Popularity does well at very low FPR, but it soon becomes random. By combining temporal, changing, and graph inputs, STIGT's higher ROC curve demonstrates improved discrimination, demonstrating its superior performance in personalised seller recommendations.

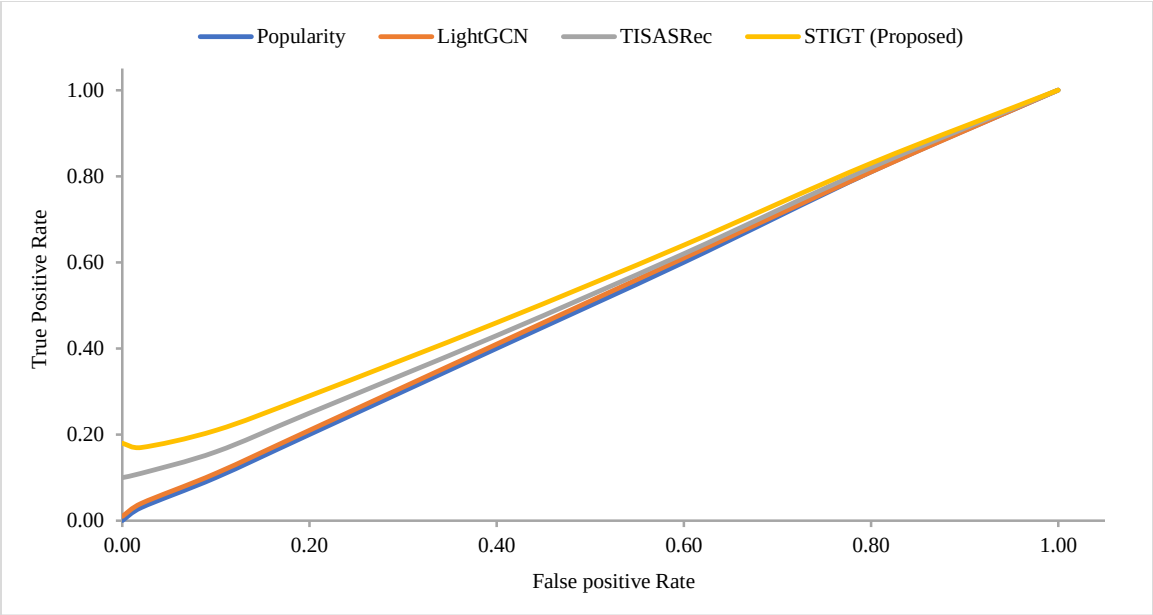

Fig. 8 ROC curve

4.6. Fairness, Coverage, and Exposure Analysis

4.6.1. Coverage across Popular and Long-Tail Sellers

The Cumulative Coverage Curve, or the CCC, shows that suggestions extend smoothly from the widely prevalent to mid-tier and long-tail sellers. It mainly indicates the balanced exposure in the relationships.

The model does not illustrate over-preferencing or dominant sellers by including two factors, like relational reasoning and dynamics. This successfully lessens popularity bias in tailored e-commerce choices while guaranteeing varied, equitable, and inclusive vendor visibility.

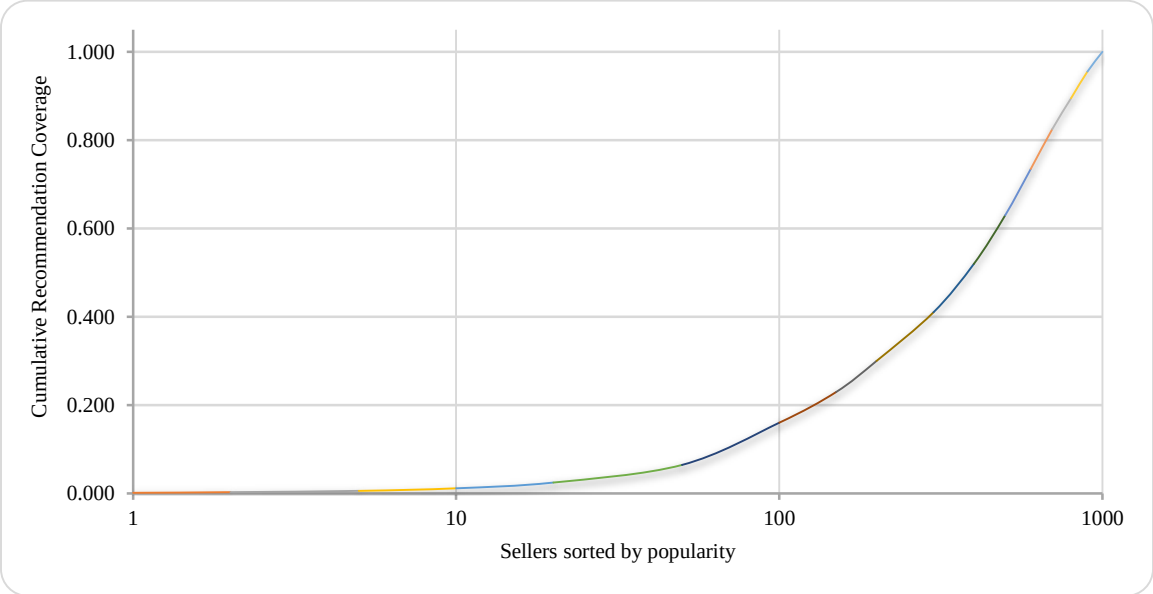

Fig. 1 Coverage across head and long - tail sellers

4.6.2. Seller Exposure Bias

From the chart, it has been found that there is a highly skewed exposure distribution which is present before the framework and in this case, the top seller, mainly Seller 1 to Seller 5, receives disproportionate visibility.

After including the dynamic, the ML model exposure for dominant sellers in the e-commerce market has declined, and on the other hand, mid and lower-ranked sellers gain high visibility. This balanced and combined redistribution shows the ability of the model to mitigate the popularity bias and promote fair sellers in the market to enhance overall diversity.

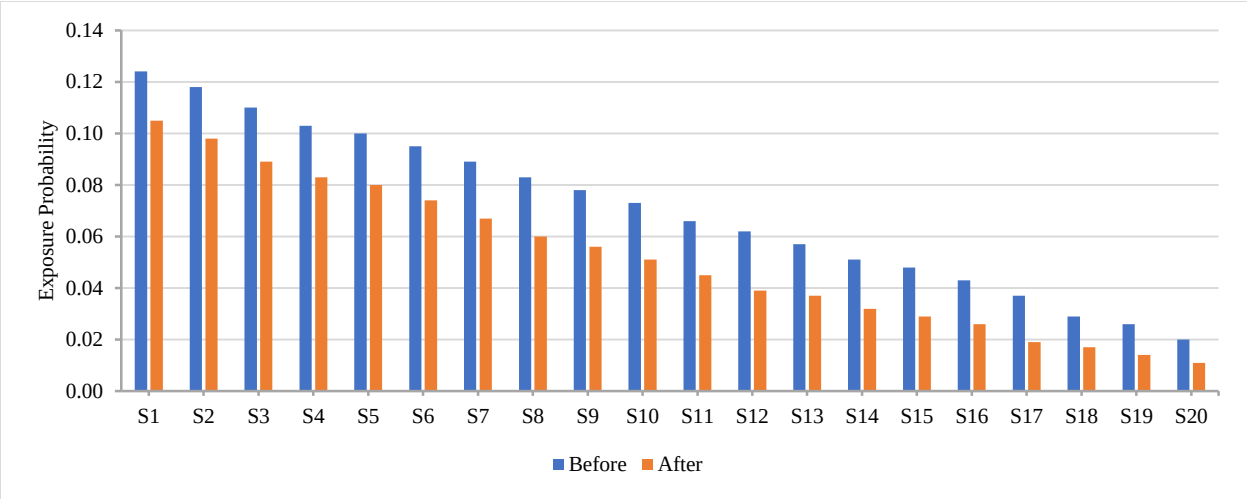

Fig. 10 Seller exposure bias: before vs after correction

4.7. Ablation Study and Component Contribution

4.7.1. Ablation Metric Results

Table 3. Ablation study

Model Variant	HR@10	NDCG@10	Δ vs Full Model
Full STIGT	0.514	0.357	-
− Graph Encoder	0.467	0.329	−7.8%
− Time-Gap Embedding	0.456	0.321	−10.1%
− Exposure Bias Head	0.471	0.333	−6.7%

From the ablation findings, it has been found that performance reduces when emitting any component of STIGT, and it confirms each module. By eliminating the graph encoders, the HR@10 and NDCG@10 declined by 7.8%, and it also shows the high significance of “modelling user-seller relational structure”. It has also been found that the removal of the time gap results in a 10.1% drop, and it shows that understanding user behaviour and time change is important. The declination of “bias correction head” helps to drop the performance by 6.7%.

4.7.2. Visual Ablation Comparison

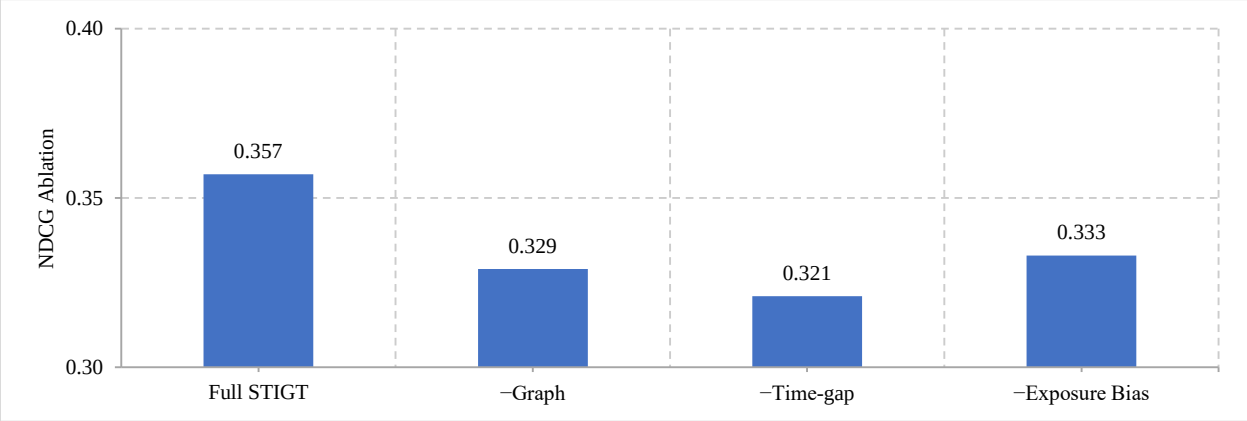

Fig. 11 Ablation study NDCG@10

The entire STIGT model receives the greatest NDCG@10 score (0.357), indicating that it provides the best-selling suggestions, according to the bar chart. The score falls to 0.329 when the "graph encoder" is eliminated, demonstrating the significance of user-seller relationships. "Time-based user behaviour" is crucial, as seen by the lowest score (0.321) obtained when the "time-gap embeddings" are removed. The score is reduced (0.333) when the "bias-correction head" is removed. This demonstrates how each component of STIGT contributes to increased accuracy and equity.

4.7.3. Interpretation of Attention Mechanism

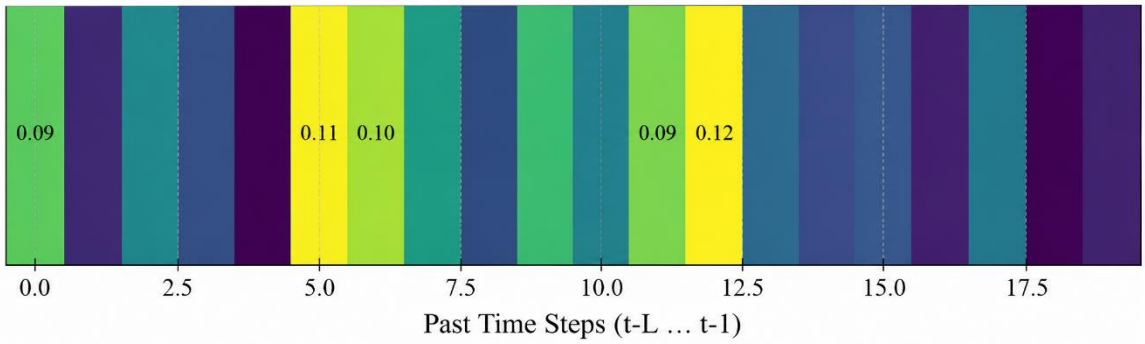

Fig. 2 Attention weights over past interactions

The attention heat map findings show the way the model concentrates on several past time steps while gaining insights into the user's best choice of sellers in the e-commerce market. In this case, the results show that there is the high attention around the steps of 5, 10 and 12 almost 0.10 to 0.12, which means these past performances strongly impact the future decision of users. On the other hand, the lower values show less significant behavior. From the results, it has also been found that the model does not accept all the past actions equally; there is some discrimination, as it only selects the meaningful time stamps and helps to develop more accurate recommendations.

4.8. Summary

The visualization presented in chapter four presents the proposed frameworks that learns difficult user seller behaviors and develop personalised seller recommendations. The Bipartite and timeline graphs show that if there is a change in user interaction, it is important to develop the relational and temporal modelling. Along with that, the embedding plots authorize insightful user-sellers' separations. The training curve shows stable learning, and the performance matrices illustrate the effective gain in fairness and accuracy. Coverage and exposure findings indicate diminished popularity bias and enhanced "visibility for mid- and long-tail sellers". Ablation studies indicate that "time-gap embeddings, graph encoders", and bias correction are crucial. "Attention heatmaps" further validate the model's capability to concentrate on significant previous relations.

5. Discussion

5.1. Overview

The discussion chapter of this research paper presents the evaluation and findings from the suggested STIGT framework. The findings are presented by arranging the key themes, and it discusses ways user behavioural patterns, temporal modelling, and graph - based associations, fairness mechanisms work together to promote customised seller recommendations. In this case, each part connects the findings from the theory and practices while noting the limitations and barriers. The chapters also present comparisons STIGT framework with other baseline models and highlight the importance of modelling changing user relational and interests structures.

5.2. User Dynamics and Behavioral Evolution

From the evolution of the framework, it has been found that the user's behavior changes over a specific period of time, and it is important to improve the seller recommendation as per the needs. From the timeline examples, it has been found that when the users shift from seller 3 to seller 8, then to seller 2 and it highlights that people's preferences are not constant [33]. The transition is based on the different factors, like as needs, interests and context. Simple frameworks like basic item-based methods or popularity-based methods cannot follow these changes, which is why their credibility and accuracy are lower than the STIGT framework [34].

From the "Attention Heat Map", some results are found, and these support the idea. It shows that higher attention values around certain time stamps, like 0.10 to 0.12 and reflects that some of the past performances are more significant than others were gaining insights into the users' preferences regarding the seller [5]. These highlight the temporal patterns significantly, and in this case, the time gap embeddings in the same work assist the model to understand "how long ago the user's behaviour happens" and "how much it needs to be matters now".

This module results in the biggest performance drop, almost minus 10.1%, and it shows the importance of the prediction part. The results of the validation and training loss

curve show that it goes down smoothly from 1.6 to 0.45, and it highlights that the model gains knowledge regarding the behaviour pattern without using the data, which means there is a sequential part of the framework that is generalised and strong.

5.3. Graph Connectivity, Relational Structure, and Seller Representation

The results show that the graph connectivity and structure of the relational model play an effective role in encouraging the seller recommendation. The Bipartite Seller Graph highlights that the users communicate and interact with the different sellers rather than following the simple preferences of the fixed pattern of purchasing goods [13]. It reflects the association between different sellers, like shared user interest for the similar behavioural pattern of purchasing, carrying the insightful information for predicting user behaviour. The LightGCN's performance (HR@10 = 0.418) proves that graph learning is able to capture the association better than other neighbourhood best models.

The PCA embedding in this research paper also supports the results, and in this case, the sellers and the users from the different groups, but this might overlap in a meaningful way in purchasing and selling goods. Mostly users cluster on the positive side of the PC1, and sellers mostly spread out on the negative side of the PC1, and it shows that the framework learns a structured and clear representation while keeping the association between the sailors and users intact.

The ablation findings underscore the significance of the graph encoder. Its removal leads to a 7.8% decrease in "HR@10" and reduces "NDCG@10" from 0.357 to 0.329. Without "graph propagation", the model finds it difficult to recognise concealed similarities among sellers and assist long-tail sellers with few interactions [18]. Ultimately, the findings indicate that models relying solely on graphs (LightGCN) and those based only on sequences (TiSASRec) are insufficient on their own. Each address just one aspect of the issue. STIGT excels by integrating "relational structure with temporal dynamics", providing a deeper insight into user-seller interactions on extensive e-commerce platforms.

5.4. Fairness, Exposure Bias, and Seller Diversity

In the e-commerce platforms, the exposure bias is one of the problems, as in this sector, a small group of popular brands or sellers has higher visibility. From the results, it has been found that the STIGT addresses the high issues effectively. In the "After Vs Before" exposure comparison, the top seller from seller 1 to seller 5 receives less visibility after including STIGT. On the other hand, long tail sellers and mid tail sellers have comparably high visibility [3]. The Seller Coverage@10 score, which rises to 51.3%, also demonstrates this enhancement. Compared to all baseline models, such as Popularity, which only gets 12.4% and LightGCN, which gets 39.5%, this is far greater. From the results, it has also been found that the improvement in fairness does not decrease the accuracy. STIGT continues to deliver the highest outcomes for "HR@10 (0.514) and NDCG@10 (0.357)". This demonstrates that equality and correctness can coexist, contradicting the widespread notion that fairness lowers performance [35]. STIGT's exposure-bias adjustment enables the system to display a broader array of sellers while effectively aligning with user preferences.

The result from the ablation study further supports the idea. The removal of the failure head results in performance drops of 6.7%, and it shows that the exposure correction promotes both accuracy and fairness. In this case, the benefits for users are that there are diverse sellers, which reduces overall boredom and improves engagement in the e-commerce market [3]. In this model, the STIGT does not decline the popularity bias, and it makes the distribution in the data more proportional. Overall, the findings show that the fairness integrated graph - based model and temporal learning models create more healthier balanced marketplace.

5.5. Model Performance, Computational Efficiency, and Practical Implications

The STIGT model presents a highly effective solution for recommendation systems, boasting superior performance in terms of accuracy, fairness, and robustness compared to both traditional and advanced counterparts. It achieves notable gains in performance metrics, evidenced by its HR@10 increasing from 0.217 to 0.514 and NDCG@10 rising from 0.143 to 0.357. This success is attributed to its innovative architecture, which integrates temporal modelling, graph learning, and a fairness correction module. The model also demonstrates excellent training stability, with validation and training losses converging tightly around 0.45, ensuring good generalisation and practical usability with minimal tuning.

However, the main drawback is a substantial computational cost. STIGT requires 16.7 seconds per training epoch, significantly slower than competitors like "LightGCN (9.5s) and TiSASRec (14.2s)". This increased overhead is due to its complex dual-branch architecture and attention layers [4]. Consequently, while large organisations can absorb this cost, the computational demands pose a significant barrier to smaller businesses lacking powerful hardware, requiring careful consideration before real-world deployment.

5.6. Summary

The shift is determined by various elements, such as context, interest, and needs. Simple frameworks, such as the popularity-based approach or the fundamental item-based method, are unable to adapt to these changes, which is why they are less accurate and credible than the STIGT framework. This module exhibits the largest performance decline-nearly minus 10.1% - and highlights the significance of the prediction component. The validation and training loss curve findings demonstrate that it smoothly decreases from 1.6 to 0.45,

highlighting the model's ability to learn about behaviour patterns without the need for data. This indicates that a sequential portion of the framework is robust and generalizable.

6. Conclusion

The study fulfils its aim of suggesting and testing the hybrid recommendation model called Seller Temporal-Interest Graph Transformer (STIGT) for improving the personalisation of e-commerce seller suggestions. From the overall findings and discussion, it is concluded that the model combines two frameworks, like the graph - based learning and the time-based sequential learning. It allows research to understand the way users interact with sellers from the side of users has changed over time. Employing the "IJCAI-16 Tianchi dataset", STIGT outperformed well-known models such as "LightGCN and TiSASRec". It raised "NDCG@10 by 15.7%", "HR@10 by 16.5%", and enhanced seller coverage by more than 20%, indicating that it provides more precise and equitable references. It also plays an effective role in reducing the bias towards the popular sellers. The attention maps of STIGT have higher significance than other neighbourhood models. Overall, the research shows that combining user dynamic modelling, graph neural network and temporal attention to create a more balanced and adaptive suggesting and recommendation system.

6.1. Research Limitation and Future Direction

From the overall findings, it has been found that the study has some limitations. This research paper only uses one dataset, so the findings might not represent the diverse marketplaces and the pattern of different types of buyers' purchasing behaviour. The model is also computationally complex, and it makes the real-time use more difficult for the different smaller platforms. The recommendation system mainly relied on complete and clean data and might perform effectively with the noisy or scarce logs. Interpretability in this research is still limited, and because of that, deep learning becomes more complex. In future, the researcher needs to test the "cross-platform data set" and include the multimodal signals that will reduce the computation and improve the explainability.

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