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# Women's Outfit Recommendation System for Fashion Product Personalization Using the BERT4Rec Method

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## **Keywords**

BERT4Rec; fashion recommendation; personalization; sequential recommendation; Transformer; e-commerce

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## **Abstract**

The fashion industry today focuses on understanding individual customer preferences rather than merely following global trends. The massive growth of e-commerce platforms and the emergence of fast fashion have exposed consumers to a vast range of outfit choices, making it challenging to identify products that match their personal style. This study aims to design and implement a women's outfit recommendation system using the BERT4Rec (Bidirectional Encoder Representations from Transformers for Sequential Recommendation) method to provide relevant and personalized product recommendations based on user interaction sequences. The research uses the ModCloth public dataset containing user-item interactions and women's outfit attributes. The process includes data preprocessing, user sequence generation, model training using the Transformer encoder architecture, and performance evaluation using Hit Ratio (HR@K) and Normalized Discounted Cumulative Gain (nDCG@K). Experimental results on the ModCloth dataset show that the BERT4Rec model effectively captures user sequential behavior and achieves strong recommendation accuracy, with HR@10 = 0.2532 and nDCG@10 = 0.1293. These results indicate the model's capability to predict user preferences with significant accuracy and to generate contextually relevant outfit suggestions. The findings highlight the potential of BERT4Rec in supporting personalization across e-commerce platforms, virtual fashion assistants, and intelligent retail systems, paving the way for adaptive fashion recommendation technologies.

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## **1. Introduction**

The modern fashion industry is shifting its focus from mass production and global trends toward understanding individual customer preferences (Jones & Wang, 2022). The rapid growth of e-commerce platforms and social media has exposed users to thousands of products every day, creating challenges in

helping consumers identify items that match their personal style and interests (Xu & Sang, 2022). Recommender systems have become a crucial solution, as they can predict which products users are most likely to prefer based on behavioral patterns and product characteristics (Shirkhani et al., 2023).

The emergence of *fast fashion* further intensifies this challenge, as fashion trends and collections change rapidly, sometimes within weeks (Jung et al., 2025). Traditional recommendation methods, such as Collaborative Filtering (CF) and Content-Based Filtering (CBF), are limited in their ability to capture the dynamic and sequential nature of user preferences (Roy & Dutta, 2022). CF often suffers from the *cold-start* problem when dealing with new users or items, while CBF cannot effectively model the temporal order of user interactions. In the fashion domain, where preferences evolve according to time, trends, and combinations of style or color, a sequential recommendation model is required to interpret user behavior more contextually (S. Zhang et al., 2020).

The *Bidirectional Encoder Representations from Transformers for Sequential Recommendation* (BERT4Rec) method was developed to overcome these limitations. Built upon the Transformer architecture used in natural language processing, BERT4Rec enables bidirectional context modeling of user-item interaction sequences (B et al., 2020). This approach allows the system to learn relationships among items across the entire user history, resulting in more contextual and accurate predictions.

This study aims to design and implement a women's outfit recommendation system using the BERT4Rec method to support fashion product personalization. The research employs the ModCloth public dataset containing user-item interaction data for women's apparel. The process includes data preprocessing, user sequence generation, model training using the Transformer encoder architecture, and performance evaluation using *Hit Ratio* (HR@K) and *Normalized Discounted Cumulative Gain* (nDCG@K). Experimental results demonstrate that the BERT4Rec model effectively captures users' sequential behavior and produces relevant and contextual recommendations. These findings highlight the potential of BERT4Rec in enhancing personalization across e-commerce platforms and adaptive fashion recommendation technologies.

## 1.1 Literature Review

Recommendation systems are designed to help users discover relevant items from extensive datasets by analyzing user preferences and interaction histories (Hariri & Rochim, 2022; Li et al., 2024). In the fashion domain, these systems mitigate information overload and enhance satisfaction by presenting products aligned with user preferences for style, color, and category (Rachmaniar et al., 2025; G. Zhang et al., 2023). Generally, the recommendation ecosystem consists of three entities: users, items, and user-item interactions such as clicks, purchases, or ratings. Data can be explicit (ratings, reviews) or implicit (click frequency, visit duration), and combining both types improves recommendation accuracy (Rizki & Rianto, 2024).

Traditional recommendation approaches include *Content-Based Filtering* (CBF) and *Collaborative Filtering* (CF). CBF recommends new items based on the similarity of attributes from previously liked items, allowing for personalization but suffering from overspecialization and limited sequential understanding (Rachmaniar et al., 2025). CF, meanwhile, identifies patterns of similarity across users or items but faces *cold-start* and *sparsity* challenges (Murillo et al., 2022). In fashion, user preferences change rapidly according to trends, time, and style combinations, making sequential models essential for capturing behavioral dynamics that static CBF and CF cannot represent (S. Zhang et al., 2020).

Deep learning-based models offer advanced capabilities in capturing sequential patterns. BERT4Rec, proposed by Sun et al 2019, adapts the Transformer architecture for bidirectional context modeling in user interaction sequences. It employs a *masked item prediction* strategy that enables the model to learn relationships between preceding and succeeding items within the same sequence (Xiao et al., 2023). This bidirectional approach enhances contextual understanding and accuracy, particularly valuable in domains such as fashion, where preferences are volatile and context-dependent. The *self-attention* mechanism of the Transformer allows the model to compute relations among all positions in a sequence in parallel, while the encoder structure supports

effective contextual modeling of non-adjacent dependencies (Hosseinzadeh & Sadeghzadeh, 2025; Chen et al., 2024).

Several hybrid and multi-criteria models have also been explored to overcome the limitations of single-method approaches. Hybrid systems combine CBF and CF through techniques such as *weighted* or *cascade hybridization*, reducing *cold-start* and *sparsity* issues while maintaining feature-based relevance (Rizki & Rianto, 2024)(Rachmaniar et al., 2025). Multi-criteria recommendation extends personalization by incorporating multiple evaluation factors—such as quality, comfort, and design—but introduces higher computational complexity due to normalization and aggregation requirements (AL-Ghuribi et al., 2025). Evaluation of these models typically uses top-K metrics, namely *Hit Ratio* (HR@K) to assess coverage and *nDCG@K* to evaluate ranking quality (Mai et al., 2020).

Most previous studies on fashion recommendation still rely on static CBF and CF methods that do not model bidirectional or sequential contexts explicitly (Wu et al., 2023). Although sequential models have shown potential, empirical applications specifically targeting women’s outfit personalization using the ModCloth dataset remain limited. Furthermore, few studies provide transparent reporting of HR@10 and nDCG@10 values or reproducible preprocessing and sequence-windowing procedures. This study addresses those gaps by implementing BERT4Rec for personalized women’s outfit recommendation, establishing a reproducible data preprocessing pipeline, and evaluating model performance through HR@10 and nDCG@10 metrics to offer empirical evidence applicable to the e-commerce fashion context.

## 2. Research Methods

This study employed an experimental research design to develop and evaluate a sequential recommendation system for women’s fashion products using the BERT4Rec method. The research process consisted of several main stages: data collection, data preprocessing, model training, and model evaluation. Each step was designed to ensure the validity and reproducibility of the proposed method.

### 2.1. Sampling and Data Collection

This study used the ModCloth public dataset obtained from Kaggle, which contains user–item interaction data from an online women’s fashion retail platform. The dataset reflects actual user-performed purchase and review activities, such as product browsing, rating, and purchase. It was selected because it offers extensive data for modeling sequential user behavior in the fashion industry, is publically available, and is frequently utilized in recommendation system research.

The ModCloth dataset used in this study contains several key attributes relevant to constructing the recommendation model. Each record consists of a *user\_id*, representing a unique identifier for each user, and an *item\_id*, which uniquely identifies every fashion product in the platform. The *rating* attribute indicates the numerical score given by users to express their satisfaction with a product, while *review\_text* provides qualitative feedback or user opinions in textual form. In addition, the *category* attribute specifies the fashion classification of each item, such as dresses, tops, or skirts. These attributes collectively describe the behavioral and contextual aspects of user interactions, enabling the model to learn both quantitative and qualitative preferences for fashion items.

The dataset was processed to remove duplicates and null values before analysis. Only users with at least *five recorded interactions* were retained to ensure that each user had sufficient behavioral history for sequential modeling. After data cleaning, the dataset contained 82,534 total user–item interactions, consisting of 17,000 unique users and 8,000 unique items. The overall statistics of the dataset are presented in Table 1.

Table 1. General Statistics of the ModCloth Dataset

No	Description	Count
1	Total unigue users	17,000

2	Total unique items	8,000
3	Total user-item interactions	82,534
4	Average interactions per user	4.85
5	Average rating value	4.12

The use of the ModCloth dataset aligns with prior works that focus on sequential recommendation (Petrov & MacDonald, 2022) (S. Zhang et al., 2020). Its structure and scale provide sufficient diversity and behavioral depth to evaluate the model’s ability to generate personalized and context-aware outfit recommendations.

## 2.2. Data Preprocessing

Before model training, several preprocessing steps were conducted to clean, transform, and structure the ModCloth dataset to ensure that it met the requirements for sequential recommendation modeling. The preprocessing phase began with data cleaning, where duplicate records were removed, missing values in essential attributes such as *user\_id* and *item\_id* were handled, and inconsistent data formats were standardized. This process ensured the reliability and consistency of the dataset prior to encoding.

Subsequently, both *user\_id* and *item\_id* were *numerically encoded* to generate sequential identifiers (*user\_id\_enc*, *item\_id\_enc*) that facilitated efficient computation and optimized the model’s ability to process large-scale data. In addition, an *item mapping file* was created to connect the original *item\_id* values with their corresponding encoded indices and product names. This mapping was later used to interpret the model’s output and visualize recommendation results in a readable format.

After encoding, user–item interaction histories were chronologically sorted to construct ordered behavioral sequences representing individual user preferences over time. A *windowing strategy* was applied to divide long interaction histories into shorter sub-sequences, simulating real-world scenarios where recommendations are generated incrementally as users engage with the system. This step was critical in preparing data for the BERT4Rec model, which relies on contextual dependencies between items to predict the next potential interaction.

Finally, the preprocessed data were partitioned into three subsets, consisting of 80% for training, 10% for validation, and 10% for testing, following standard practice in recommendation system research. This data split ensured that model evaluation could be performed objectively and that the generalization capability of the trained model could be effectively assessed.

Table 2. Preprocessing Summary

No	Step	Description	Output/Purpose
1	Data Cleaning	Remove duplicates, handle missing values, and standardize formats.	Cleaned dataset ready for encoding.
2	Encoding	Convert <i>user_id</i> and <i>item_id</i> to sequential numerical indices.	Encoded columns ( <i>user_id_enc</i> , <i>item_id_enc</i> ).
3	Item Mapping	Create mapping file linking original IDs to product names.	Used for recommendation interpretation.
4	Sequence Generation	Sort interactions chronologically and segment into windows.	Sequential dataset for modeling.
5	Dataset Splitting	Divide data into train (80%), validation (10%), test (10%).	Ensures generalization during evaluation.

Each stage was performed sequentially to ensure that the dataset was clean, structured, and suitable for training the BERT4Rec sequential recommendation model.

## 2.3. Measures

The model adopted BERT4Rec, a Transformer encoder-based architecture that learns bidirectional contextual relationships between items in user interaction sequences. Training was conducted using the Adam optimizer, a learning rate of 0.0001, batch size of 128, and 20 epochs. The Masked Item Prediction (MIP) strategy was applied, where random items in a user’s sequence were masked, and the model was trained to predict them using bidirectional context. The training objective minimized Cross-Entropy Loss, ensuring the model effectively captured sequential dependencies.

To evaluate the model’s performance, two standard top-K recommendation metrics were used, namely Hit Ratio (HR@K) and Normalized Discounted Cumulative Gain (nDCG@K). The HR@K metric measures how often relevant items appear among the top-K recommended items, while nDCG@K accounts for the ranking positions of relevant items within the recommendation list. Both metrics were computed with K = 10 to assess the model’s ability to generate accurate and well-ranked recommendations.

The experiment was conducted using multiple configurations to determine the optimal training epoch for the BERT4Rec model on the ModCloth dataset. The evaluation results for each configuration are presented in Table 3, which summarizes the model’s performance based on HR@10 and nDCG@10 values.

Table 3. Model Performance Result of BERT4Rec on the ModCloth Dataset

No	Configuration	Epoch	Learning Rate	Batch Size	HR@10	nDCG@10
1	Model-1	10	0.0001	128	0.2244	0.1130
2	Model-2	15	0.0001	128	0.2340	0.1185
3	<b>Model-3 (Best)</b>	<b>20</b>	<b>0.0001</b>	<b>128</b>	<b>0.2532</b>	<b>0.1293</b>
4	Model-4	25	0.0001	128	0.2499	0.1281
5	Model-5	50	0.0001	128	0.2457	0.1310

The experimental results of BERT4Rec with different training epochs. The model achieved the highest performance at 20 epochs, yielding an HR@10 value of 0.2532 and an nDCG@10 value of 0.1293. Beyond 20 epochs, performance slightly decreased due to potential overfitting, indicating that this configuration provides the best trade-off between learning depth and generalization.

#### 2.4. System Implementation

The implementations of the proposed recommendation system was carried out using the Python 3.10 programming language within the Google Colab environment. This cloud based development platform was selected due to its integration with GPU acceleration, which significantly enhances training efficiency for deep-learning models. The system utilized several open source libraries, including PyTorch for model construction and training, NumPy and Pandas for data manipulation, and Transformers for leveraging pre-trained Transformers based architectures. The overall workflow was managed through Google Drive integration, allowing seamless access to datasets, model checkpoints, and output files during experimentation.

To guarantee consistency and reproducibility, the model training and evaluation procedures were carried out in a controlled setting. Data loading, preprocessing, model setup, training, and evaluation were all carried out automatically by Python scripts in the same order for every experiment. As shown in Section 2.3, hyperparameters including the number of epochs, learning rate, and batch size were set according on the outcomes of the experimental phase. In order to provide transparent performance tracking throughout the experiment, the system additionally included a logging mechanism to document training losses, assessment metrics, and execution times.

The algorithm generated Top-N recommendation outputs when the training phase was over, giving each user a list of fashion items that were most pertinent to their past interactions. The trained BERT4Rec model, which recorded sequential user activity and contextual dependencies among fashion products, was used to generate these suggestions. User identities, item indices, and predicted relevance scores were included in the tabular format of the findings, which could subsequently be mapped to actual product names using the previously

created item mapping file. Future integration into web-based or mobile fashion recommendation services is made possible by this implementation architecture.

Table 4. Example of Top-10 recommendation result for a ModCloth user

No	Recommendation for User ID: 234521
1.	Red Rose White & Purple Nightdress (item_id_enc: 571)
2.	Pitaraa Women Bronze Beaded Bracelet (item_id_enc: 6)
3.	Aneri Women Gauri White Kurta (item_id_enc: 1053)
4.	Revlon Gold Dust Poussiere Doree Colorburst Lip Gloss 024 (item_id_enc: 83)
5.	Mother Earth Women Magenta Kurta (item_id_enc: 76)
6.	109F Women Cream Printed Top (item_id_enc: 560)
7.	Peperone Women Beige Handbag (item_id_enc: 586)
8.	FNF Green Wedding Collection Sari (item_id_enc: 56)
9.	Fossil Women Copper Chronograph Watch CH2589 (item_id_enc: 13)
10.	Urban Yoga Women Printed Rust T-shirt (item_id_enc: 290)

Demonstrate the trained BERT4Rec model's contextual correctness and ranking ability. For example, women's clothing and accessories (such as kurta, top, purse, and sari) make up the majority of the recommendations, which is consistent with the user's past browsing and buying habits. This shows that the system models semantic relationships across product categories in addition to capturing direct item preferences, allowing for contextually consistent and customized outfit recommendations. The model's sequential learning performance is qualitatively validated by this output visualization, which verifies that BERT4Rec successfully modifies bidirectional Transformer structures for fashion recommendation scenarios.

### 3. Result and Discussion

An analytical interpretation of the experimental results presented in Section 2.3 is provided in the results and discussion section. The results of the BERT4Rec-based recommendation model show how well it can capture bidirectional contextual linkages and sequential dependencies between user-item interactions.

#### 3.1. Quantitative Analysis

The BERT4Rec model performed optimally on the ModCloth dataset with an HR@10 of 0.2532 and a nDCG@10 of 0.1293, as was covered in Section 2.3. According to these findings, almost 25% of the pertinent things were found in the top-10 recommendations and were ranked near the highest positions. The model successfully learns user behavioral patterns by bidirectional Transformer encoding, as demonstrated by the improvement seen over various epochs (see Fig.1).

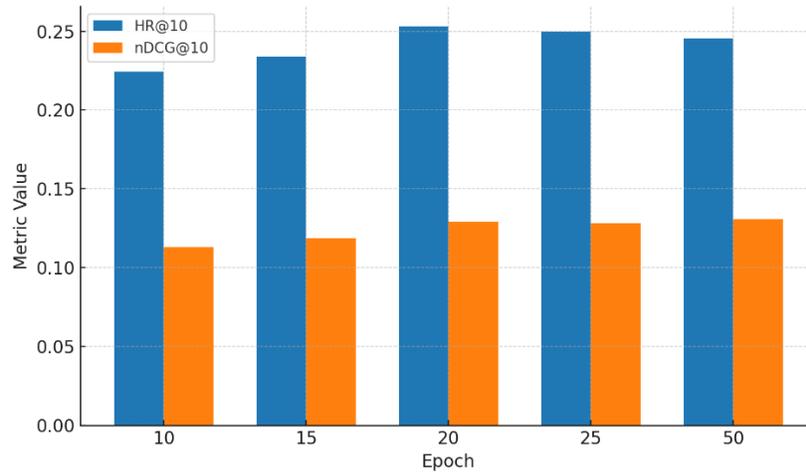


Fig 1. Model performance Across Epoch showing the variations of HR@10 and nDCG@10 metrics for different training epochs of the BERT4Rec model

The model's effectiveness in identifying contextual trends across sequences is seen by the modest but steady improvement in both metrics. Slight performance variations beyond the 20th epoch, however, point to possible overfitting and suggest that further optimization strategies, like dropout regularization or early halting, might improve generalization. These patterns align with earlier research by Sun et al., (B et al., 2020) dan (Petrov & MacDonald, 2022), who found comparable stability patterns in Transformer-based sequential recommendation frameworks. The study's convergence pattern supports the BERT4Rec architecture's resilience in simulating user-item sequences in fashion recommendation systems.

### 3.2. Qualitative Interpretation

The trained BERT4Rec model demonstrates the ability to generate contextually coherent recommendations based on user's historical interactions. For instance, Fig.2 illustrates top-10 recommendations result for a ModCloth user (User ID : 234521). Most of the recommended items consist of women's apparel and accessories- such as kurtas, tops, handbags, and jewelry, which align with the user's past browsing and purchasing patterns.

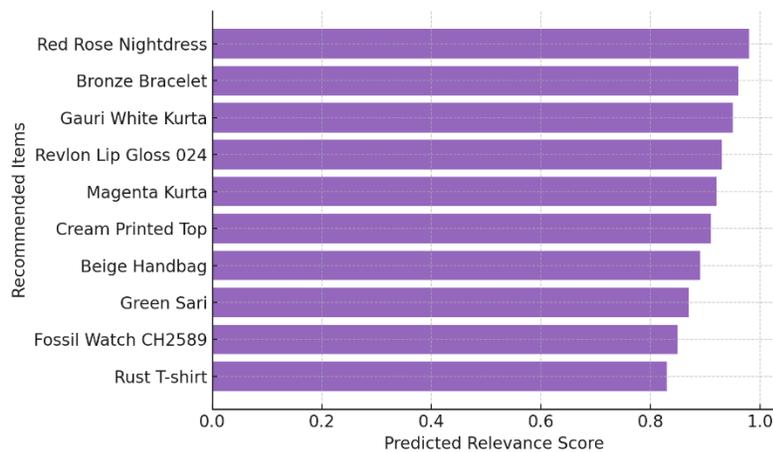


Fig 2. Top-10 Recommendation Result for User ID 234521 showing the predicted relevance scores of each recommended fashion item generated by the BERT4Rec model

This visualization confirms that the model effectively captures semantic relationships among product categories and maintains consistency with user's fashion preferences. Such result highlight the model's ability to provide contextually relevant and personalized outfit recommendations.

Additionally, this visualization offers qualitative proof that the Transformer encoder architecture has been successfully modified by the model for the sequential recommendation task. The system generates customized and aesthetically coherent recommendations by comprehending both the previous and subsequent items in a user's interaction history. By providing context-aware recommendations that take into account users' unique aesthetic tastes, this behavior validates the model's ability to generalize beyond explicit input.

### **3.3. Discussion**

The results underscore the significance of Transformer-based sequential modeling in enhancing personalization within fashion recommendation systems. Unlike conventional RNN-based or unidirectional models such as GRU4Rec and SASRec, the bidirectional architecture of BERT4Rec enables the model to simultaneously consider both preceding and succeeding user interactions, resulting in richer contextual understanding and more accurate sequential predictions.

The incorporation of bidirectional contextual dependencies contributes to generating more diverse and user-specific recommendation lists that align with implicit style preferences. The observed improvement in HR@10 and nDCG@10 validates the model's ability to capture behavioral patterns effectively. Nonetheless, the moderate scale of accuracy metrics suggests potential areas for enhancement. Future studies could explore the integration of auxiliary item metadata—such as textual descriptions, product keywords, or visual embeddings—to further improve contextual representation and recommendation relevance, as suggested by (B et al., 2020).

Overall, the findings confirm that BERT4Rec effectively adapts the Transformer architecture from natural language processing to model complex sequential dependencies in fashion e-commerce datasets. This approach provides a robust foundation for developing personalized outfit recommendation systems that dynamically adapt to evolving user preferences and behavioral trends, offering both theoretical and practical contributions to sequential recommendation research.

## **4. Conclusions**

This study developed and evaluated a fashion recommendation system based on the BERT4Rec (Bidirectional Encoder Representations from Transformers for Sequential Recommendation) method using the ModCloth dataset. The model successfully captured bidirectional contextual dependencies within user-item interaction sequences, enabling more accurate and personalized recommendations. Quantitative evaluation results showed that the model achieved an HR@10 of 0.2532 and an nDCG@10 of 0.1293, confirming its ability to learn sequential user behavior and generate contextually relevant recommendations.

Qualitative analysis further demonstrated that the model effectively produced coherent outfit suggestions aligned with users' implicit fashion preferences. The recommendations captured semantic relationships among apparel and accessory categories, validating the adaptability of Transformer-based architectures for sequential recommendation tasks in the fashion domain. The research confirms that integrating bidirectional Transformer encoders provides a strong foundation for modeling complex sequential dependencies in e-commerce environments. Although the achieved performance metrics are promising, further improvements can be made by incorporating textual, visual, or multimodal product features to enrich contextual understanding.

For future work, researchers may explore hybrid BERT4Rec architectures that combine collaborative signals, user metadata, and attention-based keyword extraction (as proposed in KBERT4Rec), aiming to further improve recommendation diversity and personalization. The findings of this study contribute both empirically and methodologically to advancing sequential recommendation research, particularly within the rapidly evolving field of fashion e-commerce.

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