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Personalized Services for Students in a Smart Campus through Hybrid Recommendations

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Abstract. The advancement of AI and pervasive technologies is reshaping intelligent environments, enabling digital systems to adapt to users' specific needs. In the academic domain, students navigate complex digital and physical spaces where the lack of personalized support can lead to inefficiencies in decision-making and underutilization of resources. This paper presents novel context-aware hybrid recommendation framework for Smart Campus environments that seamlessly integrates data from IoT sensors, personal smart devices, and user profiles through advanced AI techniques. By integrating hybrid collaborative and content-based filtering with Transformer-based language models, the proposed system provides dynamic, personalized recommendations for study groups, subjects, and thesis topics, thereby enhancing student engagement and optimizing campus resource utilization. Preliminary evaluations conducted on two real-world datasets demonstrate that the proposed approach achieves superior recommendation accuracy compared to state-of-the-art models. These results highlight its potential to transform campuses into more engaging and supportive environments, paving the way for a new generation of user-centered services.

Keywords: Smart Campus · Hybrid Recommender · NLP · Graph-based Model.

1 Introduction and Related Work

The rapid advancement of pervasive technologies and artificial intelligence (AI) has paved the way for the development of smart environments that can significantly enhance user experiences through personalized interactions. In the context of higher education, the concept of a Smart Campus [1] has emerged as a promising approach to improve the academic experience of students and optimize the use of campus resources [2]. A Smart Campus leverages Internet of Things (IoT) devices, AI-driven analytics, and advanced recommendation systems to provide context-aware and personalized services to students [3]. Despite the potential benefits, students in modern universities often face challenges in navigating an environment inundated with vast amounts of information. The lack of personalized guidance can lead to suboptimal decision-making and underutilization of available resources. Existing solutions, such as virtual assistants [4], do not fully exploit the rich contextual data generated by IoT devices and personal smart devices [5].

This paper presents a novel framework for Smart Campus environments that combines hybrid recommendation techniques with NLP to provide personalized, context-aware recommendations. By integrating data from students' devices [6] and IoT sensors [7], the system delivers tailored suggestions for both individuals and groups, enhancing academic experiences and fostering student interactions.

The development of personalized recommender systems has been extensively studied in the literature, including in educational contexts. These systems aim to enhance the user experience by tailoring suggestions to individual needs and preferences [8, 9]. However, no existing solution integrates user data, contextual information, and environmental factors as proposed in this work. Several recommendation approaches have been widely used to match user preferences in the context of book sales [10]. Book features are analyzed to recommend similar books to those already preferred by the user through content and collaborative based filtering techniques. In [11], both techniques are combined to improve accuracy, while also integrating algorithms such as ECLAT to identify further associations between items in the dataset. The authors of [12] conducted a systematic review on the use of ontologies in e-learning recommender systems. Their employment enables a structured representation of knowledge, improving the ability of systems to understand the relationships between different content elements and user preferences [13]. However, the dependence on high-quality data can pose significant challenges to the effectiveness of such systems [14]. In [15] a university recommendation system based on student profiles is developed, using weighted features and K-Nearest Neighbors algorithms to facilitate students' admission to appropriate programs of study. However, it suffers from limitations related to dependence on specific historical data and lack of robust inclusion of contextual variables. The core contribution of the proposed work is a hybrid recommendation system that integrates **Bert4Study**, a Transformer-based model capturing sequential learning patterns, and **ASGRE**, a graph-based model leveraging structured user-item relationships for study group recommendations. This approach unifies sequential learning and graph-based modeling, incorporates contextual and structural campus data, and outperforms traditional models like Matrix Factorization (MF) and Neural Collaborative Filtering (NCF) on real-world datasets. The rest of the paper is structured as follows: Section 2 details the proposed framework. Section 3 presents the experimental evaluation and results. Section 4 concludes the paper and outlines future research directions.

2 Proposed System

The proposed system leverages pervasive technologies and AI to create a Smart Campus that delivers personalized context-aware recommendations. Using hybrid recommendation techniques and NLP, it integrates data from IoT devices,

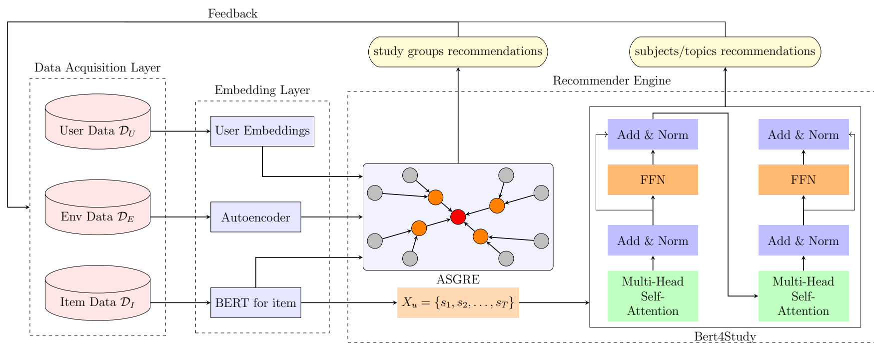

Fig. 1: Architecture of the proposed recommendation framework.

personal smart devices, and student-provided information. By combining environmental, contextual, and preference-based data, the system suggests study groups based on location availability, student goals, and cyber-physical infrastructure (e.g., access control). It also analyzes academic experiences and available proposals to recommend relevant subjects or thesis topics. The goal is to enhance the student experience and optimize campus resource utilization through dynamic, tailored recommendations.

The proposed recommendation framework, presented in Figure 1, has three main layers, each designed to address specific stages of the recommendation process. The **Data Acquisition Layer** deals with collecting heterogeneous data from different sources, such as users [16], academic data [17], and environmental sensors [18, 19], ensuring complete and accurate acquisition. The **Embedding Layer** subsequently processes these data, employing normalization and transformation techniques to map them back to a homogeneous semantic space. Finally, the **Recommendation Engine** employs embedding-based representations to generate precise and personalized recommendations. It integrates the information processed in the preceding layers to deliver high-value suggestions, enhancing the overall effectiveness and user satisfaction of the recommendation system. The *Data Acquisition Layer* collects, aggregates and pre-processes heterogeneous data essential for generating personalized recommendations in the smart campus into a single dataset $\mathcal{D}$. The dataset $\mathcal{D}$ is divided into three main categories: user data $\mathcal{D}_U$, recommended object data $\mathcal{D}_I$, and environmental data $\mathcal{D}_E$. User data ($\mathcal{D}_U$) includes students' interactions with the system, through a mobile app, such as questionnaire responses [20] on academic preferences, academic performance, course evaluations, and participation in study groups. This information is divided into three basic parts, a preference vector $\mathbf{q}_{u_i}$, which represents students' individual preferences; an academic interaction matrix $\mathbf{I}'$, which associates students, grades, and course evaluations; and a study group participation matrix $\mathbf{I}''$, which measures involvement in collaborative learning. Data on recommended items ($\mathcal{D}_I$) describe entities such as thesis topics, courses and study groups. Specifically, $\mathcal{D}_I$ consists of: a set $\mathcal{S}$ containing descriptions and abstracts of thesis topics; a set $\mathcal{G}$ representing study groups, including information about members, schedules, and modes of interaction (physical spaces or digital platforms). Environmental data ($\mathcal{D}_E$) come from IoT sensors installed in the study areas and include information on space availability, air quality and lighting conditions. These data are modeled as a time series $\mathcal{A}(t)$. In addition, the student-environment interaction matrix $\mathbf{A}$ maintains a space utilization history, which is essential for optimizing campus resources. The integration of these data requires a preprocessing step, which ensures the consistency and quality of the information before it is used in the recommendation system.

The *Embedding Layer* deals with the transformation of raw data acquired from the previous layer into structured representations optimized for the recommendation process. This phase is critical to guarantee that information acquired from heterogeneous sources is compatible with the architecture of the recommendation model, while ensuring proper normalization and enrichment of information. In general, embeddings are generated at this stage to obtain a representation of the entities involved in the recommendation system, such as students, subjects, study groups, and environmental data. These embeddings are then aligned in a common space to capture the latent relationships between the different entities.

The User Embedding Module (UEM) is responsible for representing user data in a dense vector space, providing data in a form compatible with the recommendation system. User data is processed differently depending on its nature. The responses of the questionnaire and the historical information are first normalized and cleaned to handle missing values or anomalies. This layer maps sparse and structured information into a continuous latent space of fixed dimension. Let $\mathbf{q}_u$ represent the questionnaire responses and $I'_{u_i,s}$ the historical data, the output embeddings are $\mathbf{e}_{\text{ques}} = f_{\text{embed}}(\mathbf{q}_u)$ and $\mathbf{e}_{\text{hist}} = f_{\text{embed}}(I'_{u_i,s})$, where f_{embed} is the function of the embedding layer. These embeddings are then concatenated to obtain a unified user representation $\mathbf{e}_{\text{u}} = [\mathbf{e}_{\text{ques}}; \mathbf{e}_{\text{hist}}]$, ensuring that the different sources of information are integrated into a single latent vector.

The Item Embedding Module (IEM) is responsible for representing items, which can be study subjects, study groups, or thesis proposals. The item data are first processed and normalized to ensure compatibility with the recommendation model. The textual descriptions of items are processed using a pre-trained BERT model [21] to generate semantic embeddings. For each item description d ($s_i \in \mathcal{S}$, $g_j \in \mathcal{G}$), the embedding is given by $\mathbf{e}_{\text{item}} = \text{BERT}(d)$, where $\mathbf{e}_{\text{item}} \in \mathbb{R}^d$.

The Environmental Embedding Module (EEM) is responsible for representing environmental data [22], providing information on the status and utilization of study spaces. Environmental data is first aggregated over significant time intervals (e.g., hourly or daily) and normalized to reduce noise. To compress this information into a low-dimensional embedding, an autoencoder-based technique is adopted. The autoencoder learns a compact representation $\mathbf{e}_{\text{amb}}$ that preserves the relevant statistical information (such as mean, variance, and frequency of specific events) of the environmental data. In this way, the vector $\mathbf{e}_{\text{amb}}$ provides a synthetic description of the environmental conditions and their impact on user experience.

The *Recommendation Engine* is the core component of the proposed framework, responsible for generating personalized recommendations for students. The engine leverages embeddings from the previous layer to deliver accurate, context-aware suggestions and consists of two key modules: the Adaptive Study Group Recommendation Engine (ASGRE) and the BERT4Study recommendation model. ASGRE provides study group recommendations using a hybrid approach inspired by group-buying recommendation systems. This module integrates diverse data sources (e.g. social interactions, academic history, questionnaires, group metadata, contextual factors, and environmental tracking) to generate dynamic, personalized suggestions to participate in study groups. ASGRE models Student-Group relationships as a bipartite graph, where students ($\mathcal{U}$) and study groups ($\mathcal{G}$) are connected via associations (E'), derived from profile similarities and interaction data. Additionally, a *Student Graph* $(\mathcal{U}, E)$ captures student interactions (e.g., collaborations, shared spaces), potentially weighted by intensity or frequency. To enhance recommendation quality, ASGRE employs Graph Neural Networks (GNNs) to encode the relational structure and generate meaningful embeddings for students and groups.

Study Group Participation Recommendation provides, for each student $u \in \mathcal{U}$ and each existing study group $g \in \mathcal{G}$, a compatibility score $S(u, g)$ defined as a combination of multiple signals as follows: *Content-Based Signal*, *Collaborative Signal*, and *Contextual Signal*. The *Content-Based Signal* compares the student's profile, represented by the vector $\mathbf{e}_{\mathrm{u}}$, with the semantic embedding of the group $\mathbf{e}_{\mathrm{item}}$, using cosine similarity $S_{CB}(u, g) = \cos(\mathbf{e}_{\mathrm{u}}, \mathbf{e}_{\mathrm{item}})$.

The *Collaborative Signal* leverages the student graph and historical participation to define a collaborative score:

$$S_{CF}(u, g) = \sum_{v \in \mathcal{N}(u)} w_{uv} \cdot \mathbb{I}(v \in g), \tag{1}$$

where $\mathcal{N}(u)$ represents the neighborhood (similar students or strong relationships) of u, w_{uv} is a similarity weight, and $\mathbb{I}(v \in g)$ is an indicator function that is 1 if v is a member of group g, 0 otherwise.

The *Contextual Signal* integrates contextual information such as temporal availability, location, and environmental conditions through a modulating function $f_{context}(\cdot)$:

$$S_{context}(u, g) = f_{context}(c_{u,g}), \tag{2}$$

where $c_{u,g}$ is a vector containing contextual information related to the user u and the group g. The final recommendation score for participation in a study group is defined as $S_{join}(u, g) = \gamma_1 \cdot S_{CB}(u, g) + \gamma_2 \cdot S_{CF}(u, g) + \gamma_3 \cdot S_{context}(u, g)$, where $\gamma_1, \gamma_2, \gamma_3 \geq 0$ and $\gamma_1 + \gamma_2 + \gamma_3 = 1$.

BERT4Study Recommendation Model extends the BERT4Rec [23] to academic settings and models a student's academic journey as a temporal sequence of subjects and interactions, leveraging a bidirectional Transformer architecture. The model serves two key functions: predicting the next subject to optimize learning progression and suggesting a thesis topic aligned with the student's academic trajectory. Given a sequence of previously studied subjects, the model selects the next subject that best fits the student's learning path. Using the final sequence representation, it also identifies a thesis topic that aligns with the student's academic history and interests. Formally, for each student u, the studied subjects are represented as a sequence $X_u = \{s_1, s_2, \ldots, s_T\}$, where s_t is the subject at time t, and its embedding is $\mathbf{x}_t = E(s_t) \in \mathbb{R}^d$. To preserve temporal order, position embeddings $\mathbf{p}_t$ are added, while segment embeddings α_t distinguish subject types (e.g., mandatory courses, electives, projects). The final input representation is defined as $\mathbf{z}_t = \mathbf{x}_t + \mathbf{p}_t + \alpha_t$, incorporating both sequence position and contextual data. The sequence $\{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_T\}$ is processed by a Transformer-based encoder:

$$H = \text{Transformer}(\{\mathbf{z}_t\}_{t=1}^{T}) \in \mathbb{R}^{T \times d} \tag{3}$$

where $H = [\mathbf{h}_1, \mathbf{h}_2, \ldots, \mathbf{h}_T]$ represents the contextualized subject representations. Inspired by the Masked Language Modeling (MLM) mechanism of BERT, during training, some positions in the sequence are randomly masked. The model's task is to predict the masked subject:

$$P(s_t \mid X_s \setminus \{s_t\}) = \text{softmax}(W\mathbf{h}_t + b), \tag{4}$$

where W and b are learned parameters. The training loss is a cross-entropy calculated on the masked positions:

$$\mathcal{L}_{MLM} = -\sum_{t \in \mathcal{M}} \log P(s_t \mid X_s \setminus \{s_t\}), \tag{5}$$

where $\mathcal{M}$ is the set of masked positions. For the inference phase, the final representation $\mathbf{h}_T$ to predict the next subject is used:

$$P(\hat{m} \mid X_s) = \text{softmax}(W_{\text{next}}\mathbf{h}_{\text{agg}} + b_{\text{next}}), \tag{6}$$

where $\mathbf{h}_{\text{agg}}$ can be, for example, a weighted average or the output of the last token, and $W_{\text{next}}, b_{\text{next}}$ are parameters for the prediction.

Assume the existence of a set T of possible items, each described by an embedding $E_t \in \mathbb{R}^d$. The aggregated representation $\mathbf{h}_{\text{agg}}$ is used to predict the item that best aligns with the student's academic path and interests. The prediction is based on the similarity between the student's profile and the item embeddings. The final recommendation is the item with the highest similarity score:

$$\hat{t} = \arg\max_{t \in T} \text{sim}(\mathbf{h}_{\text{agg}}, E_t) = \arg\max_{t \in T} \frac{\mathbf{h}_{\text{agg}} \cdot E_t}{\|\mathbf{h}_{\text{agg}}\| \|E_t\|}. \tag{7}$$

3 Model Evaluation

In the proposed evaluation two real-world datasets, selected for their complementary characteristics in modeling academic interactions and campus behaviors, were employed. For BERT4Study, the Book-Crossing dataset [24] was used.

This dataset includes user, book, and rating data, enabling comparisons with existing methods. Although originally designed for a general book recommendation scenario, its structured user-item interaction patterns align with how students engage with academic resources (e.g., books, papers, or course materials). Review text data was tokenized and embedded using pre-trained BERT representations, enriching user and item profiles with semantic information. User interactions were chronologically ordered to reflect realistic behavioral patterns, and users with fewer than 25 interactions were retained to mirror the typical workload of students within an academic term, where engagement is generally focused and domain-specific. The ASGRE recommender was evaluated using the StudentLife dataset [17], an anonymized dataset from 48 Dartmouth College students, incorporating sensor data, survey responses, and academic records. Its rich contextual signals and behavioral traces make it highly representative of a smart campus environment enhanced by IoT infrastructures. This dataset enabled the evaluation of our system's capacity to incorporate environmental and social context into recommendation generation. To evaluate the proposed model for the prediction of the next course and the recommendation of the next study group, the leave-one-out evaluation protocol, widely used in recommendation research [25], has been adopted. For each user u, the sequence of enrolled courses or study groups is represented as $X_u = \{s_1, s_2, \ldots, s_T\}$. The model is trained on $\{s_1, s_2, \ldots, s_{T-2}\}$, validated using s_{T-1} to fine-tune hyperparameters, and tested on s_T, which serves as the ground truth. To ensure fair evaluation, s_T is paired with 10 randomly selected negative samples, items the user has not interacted with, following the BERT4Rec sampling strategy, which considers item popularity. Performance is measured using **Hit Ratio (HR@K)**, **Normalized Discounted Cumulative Gain (NDCG@K)**, and **Mean Reciprocal Rank (MRR)**. HR@K assesses the proportion of users for whom the ground-truth item appears in the top K recommendations, while NDCG@K assigns higher scores to correctly recommended items appearing earlier in the ranking. MRR evaluates ranking quality by considering the position of the first relevant item. HR is computed for $K = 1, 5, 10$, while NDCG is assessed for $K = 5, 10$, with higher values indicating better performance. The proposed model was compared against two state-of-the-art (SOTA) recommendation models. Matrix Factorization (MF) is a collaborative filtering technique that leverages implicit user feedback to learn user and item representations. Neural Collaborative Filtering (NCF) [26] integrates Generalized Matrix Factorization (GMF) with a Multi-Layer Perceptron (MLP) to capture nonlinear user-item interactions. The experimental results, presented in Figure 2, report the comparative analysis of the proposed system against the baseline methods on the Book-Crossing and StudentLife datasets. The first row shows the performance of Bert4Study on the Book-Crossing dataset, while the second row presents the results of ASGRE on the StudentLife dataset. The evaluation metrics include HR@1, HR@5, HR@10, NDCG@5, NDCG@10, and MRR. The highest values of HR@1 and MRR for Bert4Study (0.1006 and 0.2005) on the Book-Crossing dataset indicate that the model is highly effective in ranking relevant items at the top of the recommen-

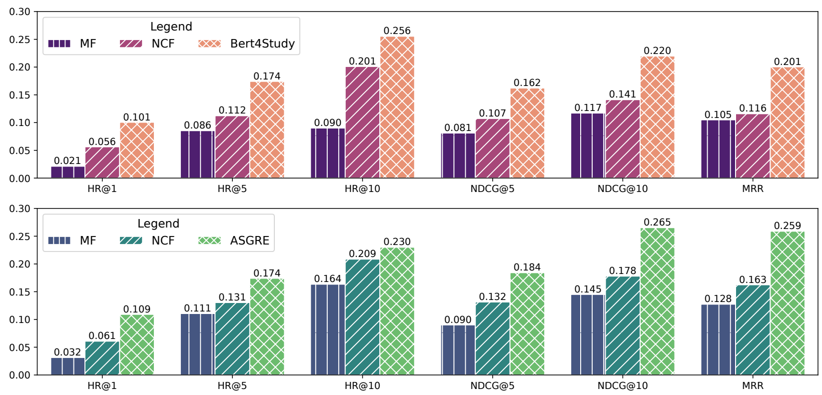

Fig. 2: Comparison of the performance of recommendation models on the *Book-Crossing* dataset (top) and *StudentLife* dataset (bottom).

dation list. This is crucial for recommendation systems, as users tend to consider only the top-ranked results. Bert4Study integrates bidirectional attention mechanisms, leveraging both content-based filtering (CBF) and collaborative filtering (CF) information. While MF and NCF rely exclusively on user-item interactions, Transformer-based models utilize the entire historical sequence of interactions and, in some cases, sequences of *neighboring* or correlated users. This hybrid integration enhances the model's ability to capture user preferences, leading to improved evaluation metrics. The obtained values of NDCG@5 = 0.1843 and NDCG@10 = 0.2654 demonstrate ASGRE's superior ability to maintain a more coherent and meaningful ranking compared to alternative methods. Additionally, the HR@5 = 0.1742 and HR@10 = 0.2301 results indicate that ASGRE generates relevant recommendations across a broader range of ranking positions. The advantage over NCF (NDCG@5 = 0.1315) highlights how the graph-based architecture effectively captures structural information to refine recommendation rankings. Graph structures allow the model to better understand connectivity between users and items, improving the likelihood of suggesting relevant content. Unlike MF and NCF, ASGRE leverages a structured graph-based data representation, effectively modeling the relationships between users, items, and context data. This enables the model to capture implicit relationships that methods like MF and NCF fail to learn. Leveraging both structured graph-based modeling (ASGRE) and attention-based sequence modeling (Bert4Study) allows to obtain more accurate and personalized recommendations.

4 Conclusions

This paper presents a novel hybrid recommendation framework designed to enhance the academic experience of students in Smart Campus environments. By integrating Transformer-based architectures (Bert4Study) and graph-based approaches (ASGRE), the system proposed here effectively combines information from heterogeneous sources to generate highly personalized and relevant recommendations. The experimental evaluation, conducted on the StudentLife and Book-Crossing datasets, demonstrates that the proposed models significantly outperform traditional recommendation methods. Bert4Study leverages bidirectional attention mechanisms to improve sequential recommendation accuracy, while ASGRE exploits graph-based representations to capture complex user-item relationships. The results indicate that these models are particularly effective at ranking relevant study resources and forming meaningful study groups, ultimately fostering a more engaging and productive academic environment. This study emphasizes that integrating contextual and structural information, through multi-head attention and graph representations, enhances recommendation accuracy and delivers more precise, context-aware suggestions.

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