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Original Article

Developing a Study Plan Recommendation System for Students at Saigon University

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Abstract - Credit-based curricula require students to select courses every semester while respecting prerequisites, course offering schedules, and reasonable workload distribution. In practice, advising capacity is limited, and suboptimal registrations can increase time-to-degree. This study develops a study plan recommendation system for Saigon University by integrating three complementary signals: (i) Program- and Semester-Level Course Popularity, (ii) Profile-Based Similarity Using Student Attributes, and (iii) User-Based Collaborative Filtering on Historical Grade Patterns. The hybrid scoring function applies to stage-dependent weights to reflect differences in informational availability and decision needs across years of study. The system is trained and evaluated in institutional data from three programs (Information Technology, Office Administration, and Psychology), including 1,847 on-time graduates and 156,995 grade records. Offline evaluation with 5-fold cross-validation shows that the hybrid method achieves Precision@10 of 82.3%, Recall@10 of 78.6%, and F1@10 of 80.4%, outperforming individual baselines. An online pilot with 245 students reports 87.3% overall satisfaction and an average usability score of 4.2/5. The results suggest that combining complementary signals can provide actionable, context-aware study plan recommendations in a real university setting.

Keywords - Collaborative Filtering, Content-Based Filtering, Hybrid Recommender System, Study Plan Recommendation, Academic Advising, Higher Education.

1. Introduction

Effective study planning is a recurring decision problem in credit-based higher education. Each semester, students must select a feasible set of courses that satisfies prerequisite constraints and aligns with program requirements, while also balancing workload to maintain academic progress. At Saigon University, this challenge is intensified by curriculum complexity and limited advising resources. Internal statistics from the Academic Affairs Office (unpublished institutional data, 2021-2023) indicate that the late graduation rate (beyond the nominal 4-year period) ranges from 15% to 25% depending on program, and that a non-trivial share of students experience academic probation due to low grade point average and insufficient earned credits. Educational recommender systems have been used to support course selection, learning-resource discovery, and personalized learning paths [2-5]. However, much of the published work targets recommending individual courses or learning resources and often omits institution-specific feasibility constraints such as prerequisite satisfaction, semester offerings, and credit-load distribution. Empirical evidence from Vietnamese credit-based programs remains limited, particularly for end-to-end systems evaluated with both offline metrics and real student feedback.

This study addresses these gaps by designing and evaluating a study plan recommendation system tailored to the operational constraints of Saigon University. The system combines popularity-based recommendation, content-based similarity, and collaborative filtering into a weighted hybrid model [6], with weights adjusted by study stage to reflect changing data availability and advising needs. The main contributions are: (i) A constraint-aware recommendation workflow for semester-level study planning under prerequisite and offering constraints; (ii) A hybrid scoring function that integrates three signals with stage-dependent weights; (iii) A reproducible evaluation protocol on multi-year institutional data with program-level breakdown; and (iv) An online pilot deployment with student-centered usability feedback.

2. Theoretical Background and Related Work

2.1. Recommender System Paradigms in Education

Recommender systems predict user preferences and rank items to reduce choice overload [21,26]. In educational settings, the "items" may include courses, learning resources, or learning activities. Common paradigms include content-based filtering, collaborative filtering, and hybrid approaches [2, 6-9]. Content-based methods recommend items like a user's previously selected items or items preferred by similar profiles. They can be effective when item or user attributes are informative, but may become over-specialized and struggle with cold-start scenarios [7]. Collaborative filtering leverages behavioral similarity, assuming that users with similar historical interactions will prefer similar items in the future [8,9,22]. While collaborative filtering can discover novel items, it is sensitive to sparsity and cold-start problems that are common in academic datasets. Hybrid recommenders combine multiple paradigms to exploit complementary strengths and reduce the impact of sparsity and cold start [6]. Recent educational studies have explored attribute-based hybrid models for cold-start mitigation [10] and multi-model predictive frameworks for academic advising [27].

2.2. Study Planning and Constraint-Aware Recommendation

Study planning differs from generic course recommendations because feasibility constraints must be respected. At minimum, a recommended course set should satisfy prerequisites and align with semester offerings, program rules, and credit-load limits. Learning-path recommendation has been studied as a related problem; for example, weak concept mining has been used to model learning dependencies and recommend learning sequences [5]. In academic advising contexts, some recent systems integrate performance prediction with recommendations to guide course selection [27]. Other work emphasizes system architectures and algorithmic building blocks for individualized study plan construction in higher education settings [28]. These studies motivate the need for context-specific, constraint-aware recommenders that are validated on real institutional data.

2.3. Research Gap and Positioning

Despite progress in educational data mining and learning analytics [15,23,24], there remains a gap between algorithm-focused studies and deployable advising tools that incorporate institutional constraints and provide empirical evidence of usefulness in practice. In Vietnam, prior work has largely focused on narrower recommendation tasks, such as job recommendation for IT students [12] or resource/document recommendation [4]. The present study contributes an end-to-end study plan recommendation system that is explicitly aligned with credit-based constraints and validated through both offline metrics and an online pilot.

3. Materials and Methods

3.1. Data Sources, Privacy, and Preparation

Data were collected from the Saigon University academic management system and official teaching plans across two curriculum cycles (2016-2020 and 2020-2024). The dataset covers three programs: Information Technology, Office Administration, and Psychology. To construct reliable semester-by-semester registration patterns for recommendation, the offline dataset focuses on students who graduated on time (nominal program duration). All records were anonymized prior to analysis, and the system uses aggregated patterns rather than exposing individual histories.

Table 1. Research data statistics

Criterion	IT	Office Admin	Psychology	Total
On-time graduates	687	612	548	**1,847**
Grade records	62,145	51,230	43,620	**156,995**
Courses in the curriculum	65	52	48	**158***
Data collection period	September 2016 - July 2024 (2 curriculum cycles)			

**Note: Some courses are shared across programs (general education courses)*

Raw data were preprocessed through four steps: (1) Data cleaning: removed records with missing critical information, detected and handled outliers using the Interquartile Range (IQR) criterion for entrance scores and cumulative GPA, and standardized data formats; (2) Feature encoding: converted categorical attributes (e.g., gender, admission block) into numeric form; (3) Grade normalization: converted letter grades to a 10-point scale and normalized to the [0,1] interval using min-max scaling; (4) Interaction matrix construction: created a student-course matrix (1,847 × 158) for collaborative filtering.

3.2. System Architecture and Feasibility Filtering

The system follows a three-tier architecture (presentation, business logic, and data layer). Recommendation is generated in two stages: (i) Candidate generation from the course offering plan for the target semester and program, and (ii) feasibility filtering to remove courses that violate prerequisites or credit-load rules, followed by ranking with the hybrid score. Table 2 summarizes the implemented software stack and major modules.

Table 2. System architecture modules and technology stack

PRESENTATION LAYER ReactJS 18.2 ǀ Bootstrap 5 ǀ Chart.js		
Student Interface • View study plan • Get recommendations • Submit feedback	Department Interface • Course offering plans • Feedback reports	Faculty Interface • Statistics dashboard • High-failure courses
BUSINESS LOGIC LAYER Python 3.9 ǀ Flask ǀ Scikit-learn ǀ Surprise		
DATA LAYER MySQL 8.0 ǀ Redis 7.0		
Curriculum Database • Programs • Courses • Prerequisites	Student Database • Profiles • Registrations • Grades	Cache (Redis) • Similarity matrices • Recommendation results

3.3. Hybrid Recommendation Method

The recommender integrates three components. For a target student u and candidate course c offered in semester s, the final score is computed as a weighted combination of (i) popularity, (ii) profile-based similarity, and (iii) collaborative filtering prediction. Popularity-based recommendation ranks courses frequently and successfully taken by students in the same program and semester. The popularity score is:

$$Pop(c,s) = \frac{N(c,s)}{N(s)} \tag{1}$$

Where N(c,s) is the number of students registering for course c in semester s and N(s) is the total number of students in semester s.

Content-based filtering builds a student profile vector using admission block (one-hot encoded), entrance score, gender, cumulative GPA, completed credits, and current semester. Cosine similarity is used to compute profile similarity:

$$sim(A,B) = \frac{(A \cdot B)}{(\|A\| \times \|B\|)} \tag{2}$$

User-based collaborative filtering identifies the k most similar students (k = 50). The predicted score for course c for student you is:

$$Pred(u,c) = \overline{r_u} + \frac{\sum_v sim(u,v) \times (r_{v,c} - \overline{r_v})}{\sum_v |sim(u,v)|} \tag{3}$$

The hybrid score is computed as:

$$Score(u,v) = \alpha \times Pop(c,s) + \beta \times Content(u,c) + \gamma \times CF(u,c) \tag{4}$$

Where α, β, and γ are non-negative weights that sum to 1. Weights are adjusted by study stage. A grid search over candidate weights (step size 0.1) was performed on validation folds to select configurations that maximize F1@10 within each stage. Table 3 Lists the Selected Weight Configurations by Study Stage.

Table 3. Weight configuration by study stage

Study Stage	α (Pop)	β (Content)	γ (CF)
Freshman (Year 1)	0.5	0.3	0.2
Sophomore-Junior (Year 2-3)	0.2	0.3	0.5
Senior (Year 4)	0.1	0.2	0.7

3.4. Evaluation Design

System Effectiveness Was Evaluated Through Two Methods:

3.4.1. Offline Evaluation

A 5-fold cross-validation was employed at the student level, where each fold uses 80% of students for training and 20% for testing. Importantly, all grade records of each student remain in either the training or testing set to prevent data leakage. For each test student, top-N course recommendations are generated (N = 5, 10, 15) and compared against the ground truth, defined as the set of courses the student actually registered and completed in the following semester.

Evaluation metrics are defined as follows. Let R denote the set of recommended courses, and G denote the ground truth (courses actually registered):

$$Precision@N = \frac{|R \cap G|}{N} \tag{5}$$

$$Recall@N = \frac{|R \cap G|}{|G|} \tag{6}$$

$$F1@N = 2 \times \frac{(Precision@N \times Recall@N)}{(Precision@N + Recall@N)} \tag{7}$$

Results reported in Table 3 use N = 10, averaged across all folds and test students.

3.4.2. Online Evaluation

The system was deployed with actual students in semester 2 of academic year 2023-2024, collecting feedback through surveys using a 5-point Likert scale.

4. Results and Discussion

4.1. Offline Evaluation Results

Table 4 compares the effectiveness of baseline methods and the hybrid method using Precision@10, Recall@10, and F1@10. The hybrid approach achieves the best overall performance, consistent with hybrid recommender findings in the literature [6].

Table 4. Comparison of recommendation method effectiveness (top-10)

Method	Precision (%)	Recall (%)	F1-score (%)
Popularity-based	72.1	68.5	70.3
Content-based	75.4	71.2	73.2
Collaborative Filtering	78.9	74.3	76.5
Hybrid (Proposed)	**82.3**	**78.6**	**80.4**

The hybrid model improves F1@10 by 10.1 percentage points over popularity-based recommendation and by 3.9 percentage points over collaborative filtering alone. This indicates that the profile-based component and stage-weighting contribute complementary information beyond interaction history.

4.2. Program-Level Performance

Table 5 reports performance by program. The Information Technology program achieves the highest F1@10, which may reflect a stronger prerequisite structure and more stable course sequences, increasing the consistency of historical patterns used for recommendation.

Table 5. Hybrid evaluation results by program (top-10)

Program	Precision (%)	Recall (%)	F1-score (%)
Information Technology	84.5	79.8	**82.1**
Office Administration	80.2	77.5	78.8
Psychology	79.8	78.1	78.9

Information Technology achieved the highest results (F1=82.1%), possibly due to a clear curriculum structure with many prerequisite courses, like patterns observed by Xu et al. [11] in their course recommendation system.

4.3. Online Pilot Results

The system was pilot-tested with 245 students from the three programs in semester 2 of academic year 2023-2024. Survey results are summarized in Table 6. Overall satisfaction was 87.3%, with an average score of 4.2/5.

Table 6. User survey results (5-point likert scale, n=245)

Evaluation Criterion	Average	Std. Dev.
Recommendation accuracy	4.1	0.72
Usefulness of recommendations	4.3	0.68
Ease of use	4.4	0.61
Interface responsiveness	4.2	0.65
Intention to continue using	4.1	0.78
Overall Average	**4.2**	**0.69**

4.4. Comparative Analysis with Recent Studies

Direct performance comparisons across studies are often not meaningful because datasets, curricula, and evaluation protocols differ. Instead, Table 7 provides a structured comparison of system characteristics reported in recent course/study-plan recommendation studies and the present system.

Table 7. Qualitative comparison with related systems

Study	Primary task	Constraint handling	Evaluation evidence
Diao et al. (2022) [5]	Learning path recommendation	Dependency modeling via weak concept mining	Offline metrics on learning-path data
Xu et al. (2021) [11]	Course recommendation	Knowledge graph signal (content/relations)	Offline Precision / Recall / F1
Butmeh & Abu-Issa (2024) [10]	E-learning item recommendation	Cold-start via learner / item attributes	User testing + satisfaction metrics
Kord et al. (2025) [27]	Course planning + performance prediction	Rule-based advising with a prediction pipeline	Offline multi-model evaluation
Islam & Hosen (2025) [28]	Personalized course recommendation	Prerequisite / workload constraints in the framework	Offline predictive evaluation
This study	Semester study plan recommendation	Prerequisites + offering plan + credit-load filtering	Offline CV + online pilot survey

4.5. Error Sources and Bias Considerations

Several error sources are inherent in institutional recommendation settings. First, course registration decisions are influenced by schedule conflicts, personal constraints, and instructor availability, which are not fully captured in historical grade records. Such factors can lead to false positives even when a course is academically appropriate. Second, the offline dataset focuses on on-time graduates to capture stable trajectories. This may introduce survivorship bias by under-representing students with atypical paths (e.g., repeated courses, leave of absence). As a result, offline metrics may overestimate performance for at-risk populations. Third, popularity-based components can amplify popularity bias by repeatedly recommending historically common courses, potentially reducing exploration of electives. The stage-weighted design partially mitigates this by increasing collaborative and profile-based influence in later years.

Fourth, program imbalance and curricular differences can affect model calibration across programs. Reporting program-level results (Table 5) helps surface this variation and motivates program-specific tuning when deployed. Finally, privacy and governance are critical. The system operates on de-identified records and produces aggregated recommendations; nevertheless, future deployments should include a formal data protection impact assessment and access control aligned with institutional policies.

5. Conclusion and Future Work

This study developed and evaluated a study plan recommendation system for Saigon University that integrates popularity-based recommendation, profile-based similarity, and user-based collaborative filtering into a stage-weighted hybrid model. Offline evaluation on 1,847 on-time graduates and 156,995 grade records shows that the hybrid approach outperforms individual baselines, achieving an F1@10 of 80.4%. An online pilot with 245 students further indicates positive user perception with 87.3% overall satisfaction and an average usability score of 4.2/5.

Several limitations motivate future work. First, expanding training and evaluation to include late graduates and students with irregular trajectories would reduce survivorship bias and improve robustness for at-risk populations. Second, integrating timetable constraints, instructor/section availability, and student preference signals could reduce recommendation errors caused by non-academic factors. Third, more comprehensive statistical validation (e.g., confidence intervals and hypothesis tests on student-level metrics) should be reported alongside point estimates. Fourth, a planned extension is to integrate academic risk prediction and intervention workflows, potentially using teacher-student model compression techniques for efficient deployment [15]. Finally, broader benchmarking against additional institutional datasets would improve external validity.

Data Availability

The underlying academic records contain sensitive student information and are not publicly available. De-identified aggregates and evaluation scripts may be shared upon reasonable request, subject to institutional approval and applicable data-protection regulations.

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Authors' Contributions

Thanh Cao: Conceptualization, Methodology, Supervision, Writing – Original Draft, Writing – Review & Editing, Resources, Validation, Data Curation, Project Administration, Software, Investigation, Visualization. Loan Do: Research conceptualization, methodology, review, and editing. Hieu Tran: Data collection, data processing, software development.

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