

Hybrid Recommender Systems for Course Selection Using Collaborative Filtering and Multi-Criteria Decision-Making

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Abstract

The rapid growth of Massive Open Online Course (MOOC) catalogs has made it increasingly difficult for learners to identify courses that are simultaneously aligned with their personal interests and objectively of high quality. Single-technique recommender systems tend to address only one of these two dimensions: collaborative filtering (CF) captures personalized preference but ignores objective course attributes, whereas multi-criteria decision-making (MCDM) evaluates objective quality but disregards individual taste. This study proposes and demonstrates a hybrid recommender system that integrates User-Based Collaborative Filtering with Cosine Similarity and the Simple Additive Weighting (SAW) method to generate course recommendations that balance personalization with objective merit. A dummy dataset consisting of 10 MOOC items, 8 users, and 5 evaluation criteria (average rating, relevance to interest, difficulty level, duration, and price) was constructed to test the proposed method end-to-end. The Collaborative Filtering component predicted preference scores for a target user through similarity-weighted aggregation of the top-3 nearest neighbors, while the SAW component produced an objective preference value for each course through max-normalization and weighted summation across the five criteria. The two outputs were linearly combined using an equal-weighted hybridization coefficient ($\alpha = 0.5$) to produce a final ranked list. Results show that the hybrid model reorders the recommendation list relative to either technique used alone, promoting courses that are both well-matched to the target user's demonstrated preferences and objectively strong on relevance, quality, and cost-efficiency. The proposed pipeline is technique-agnostic and can be re-parameterized for other selection domains that require a combination of personalized filtering and objective multi-criteria evaluation.

Keywords: Hybrid Recommender System, Collaborative Filtering, Multi-Criteria Decision-Making, Simple Additive Weighting, MOOC.

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1. Introduction

The proliferation of Massive Open Online Course (MOOC) platforms has expanded access to education (Buhu & Buhu, 2015; Li et al., 2016; Setiadi et al., 2021), but it has also produced an information overload problem: learners routinely face catalogs containing thousands of courses spanning overlapping subjects, skill levels, and price points. Systematic reviews of course recommender systems confirm that collaborative filtering, content-based filtering, and hybrid approaches remain the dominant paradigms used to address this problem, with hybrid designs increasingly favored because they mitigate the cold-start and sparsity weaknesses inherent to collaborative filtering used in isolation.

Collaborative filtering (CF) recommends items by identifying users with similar historical preferences and propagating their ratings to the target user (SIVARAMAN, 2014; Wan & Niu, 2020; Weng & Liu, 2004). This approach is effective at capturing implicit, personalized taste, but it says nothing about whether a recommended course is, in absolute terms, well-designed, appropriately priced, or suitably difficult. Multiple recent course-recommendation studies have therefore combined CF with complementary techniques - content-based filtering, knowledge graphs, or multi-criteria evaluation - to compensate for this blind spot.

Multi-criteria decision-making (MCDM) methods (Patria et al., 2024), by contrast, evaluate alternatives against several explicit, often conflicting, criteria to produce an objective preference ranking (Afshari et al., 2010; Vinodh & Girubha, 2012; Yanie et al., 2018). Simple Additive Weighting (SAW), one of the oldest and most widely used MCDM

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techniques, ranks alternatives by normalizing a decision matrix and computing a weighted sum of criteria values; its simplicity, transparency, and compensatory nature make it attractive for decision-support contexts such as course, laptop, or placement-readiness evaluation (Angelina et al., 2019; Basri & Assidiq, 2017; Haswan, 2017; Rusdiyanto et al., 2020; Terttiaavini, 2024). However, SAW alone treats every user identically and cannot express personalized preference.

The premise of this study is that CF and SAW are complementary rather than competing techniques: CF answers the question “what would this specific learner like, based on people like them?” while SAW answers the question “which course is objectively the strongest option given multiple measurable criteria?” A hybrid model that combines both outputs into a single score can therefore recommend courses that are simultaneously personalized and objectively defensible a property that is particularly valuable in MOOC contexts, where learners often cannot rely on an academic advisor and must weigh cost, difficulty, and relevance for themselves.

This paper makes three contributions. First, it proposes a hybrid course-recommendation framework that fuses User-Based Collaborative Filtering with Cosine Similarity and the SAW method through a linear hybridization scheme. Second, it operationalizes the framework end-to-end on a controlled dummy dataset of 10 MOOC items, 8 users, and 5 evaluation criteria, so that every intermediate computation, similarity, normalization, and weighted summation - can be verified and reproduced. Third, it discusses how the framework generalizes to other selection domains that require balancing personalized history with objective multi-attribute evaluation.

2. Methods

2.1 Research Framework

This study follows a design-and-simulation methodology: a hybrid recommendation pipeline is specified analytically, implemented computationally, and then exercised on a controlled dummy dataset to verify that every stage produces numerically consistent output (Ganiem & Agustina, 2023; Harahap et al., 2023). The pipeline consists of four stages, illustrated in Figure 1: (1) construction of a sparse user-item rating matrix and a course-attribute matrix; (2) computation of personalized preference scores through User-Based Collaborative Filtering; (3) computation of objective preference values through the SAW method; and (4) linear fusion of the two scores into a final hybrid ranking.

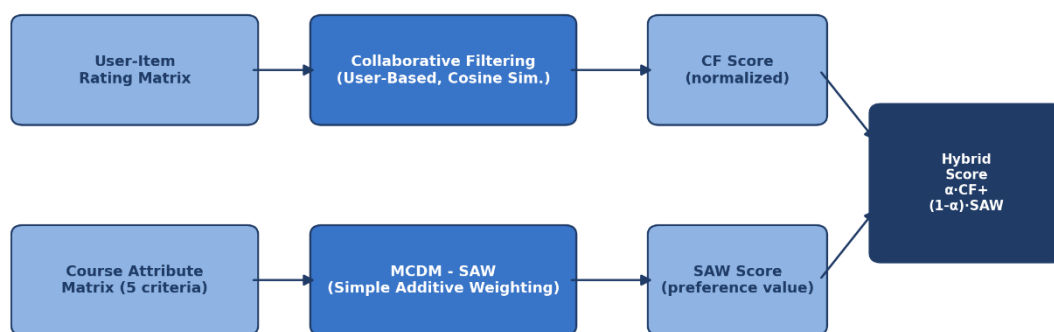


Fig 1. Hybrid recommender system architecture combining Collaborative Filtering and SAW.

2.2 Dataset

Because the objective of this study is to validate the mechanics of the hybrid method rather than to benchmark predictive accuracy on a live platform, a controlled dummy dataset was constructed with 10 MOOC courses (items, coded C01-C10) covering common online-learning subject areas (data science, machine learning, web development, digital marketing, design, cloud computing, business analytics, cybersecurity, mobile development, and financial modeling) and 8 synthetic users (U1-U8) with partially overlapping rating histories on a 1-5 Likert scale. U1 is treated as the target user for whom recommendations are generated; the remaining seven users act as the candidate neighborhood for collaborative filtering. Table 1 presents the resulting sparse rating matrix; unrated user-item pairs are denoted with a dash and are the entries the recommender must predict or evaluate.

For the MCDM component, each course was additionally described by five evaluation criteria commonly relevant to MOOC selection: average learner rating (benefit), relevance to the target user's stated interest area expressed as a percentage match (benefit), difficulty level on a 1-5 scale (cost), course duration in hours (cost), and price in USD

(cost). Table 2 lists the criteria, their type, and the weight assigned to each; weights were elicited to reflect a decision-maker who prioritizes course quality and topical fit above cost and time investment, and they sum to 1.00. Table 3 reports the full decision matrix used as input to SAW.

Table 1. Dummy user-item rating matrix (8 users $\times$ 10 courses, 1-5 scale, “-” = not rated).

User	C01	C02	C03	C04	C05	C06	C07	C08	C09	C10
U1	5	4	-	-	2	-	3	-	-	-
U2	4	5	-	-	1	4	-	2	-	-
U3	-	4	3	2	-	-	4	-	-	3
U4	5	5	-	-	2	3	-	-	-	-
U5	2	-	4	5	4	-	-	-	3	-
U6	-	-	5	4	5	-	-	-	4	-
U7	3	4	-	-	-	4	4	3	-	4
U8	-	3	4	5	3	-	-	-	-	-

Table 2. SAW evaluation criteria, type, and assigned weights.

Criterion	Type	Weight
Avg Rating (1-5)	Benefit	0.30
Relevance to Interest (%)	Benefit	0.25
Difficulty Level (1-5)	Cost	0.15
Duration (hours)	Cost	0.15
Price (USD)	Cost	0.15

Table 3. Dummy course-attribute decision matrix used as SAW input.

Course	Avg Rating	Relevance (%)	Difficulty	Duration (h)	Price (USD)
C01	4.6	88	3.0	20	49
C02	4.8	95	4.0	30	79
C03	4.2	70	2.0	25	39
C04	4.0	60	1.0	10	19
C05	4.5	65	2.0	15	29
C06	4.7	80	4.0	35	89
C07	4.3	75	3.0	18	45
C08	4.4	72	3.0	22	55
C09	4.1	68	4.0	28	59
C10	3.9	55	2.0	12	25

2.3 Collaborative Filtering Method

The collaborative filtering component uses User-Based Collaborative Filtering with Cosine Similarity, a memory-based technique selected for its transparency and suitability for small, illustrative datasets (Fopa et al., 2022; Harahap et al., 2026). Given the rating matrix R , the similarity between the target user a and another user b is computed only over the items rated by both users, referred to as co-rated items. The cosine similarity is calculated using Equation (1):

$$\text{sim}(a, b) = \frac{\sum_{i \in I_{ab}} r_{a,i} r_{b,i}}{\sqrt{\sum_{i \in I_{ab}} r_{a,i}^2} \sqrt{\sum_{i \in I_{ab}} r_{b,i}^2}} \quad (1)$$

where I_{ab} represents the set of items co-rated by users a and b , while $r_{a,i}$ and $r_{b,i}$ denote the ratings assigned to item i by users a and b , respectively. Neighbors with fewer than two co-rated items are assigned a similarity value of zero to avoid unstable estimates resulting from single-item overlap.

The $k = 3$ users with the highest similarity values to the target user, excluding the target user, form the active neighborhood. For each course that the target user has not yet rated, the predicted rating is calculated using the mean-centered weighted-sum formula presented in Equation (2). This formulation accounts for differences in rating-scale severity among neighboring users:

$$\hat{r}_{a,i} = \bar{r}_a + \frac{\sum_{b \in N_k(a)} \text{sim}(a,b)(r_{b,i} - \bar{r}_b)}{\sum_{b \in N_k(a)} |\text{sim}(a,b)|} \quad (2)$$

where $N_k(a)$ denotes the set of the top- k nearest neighbors of target user a , $\bar{r}_a$ represents the mean rating of the target user, and $\bar{r}_b$ represents the mean rating of neighbor b . The mean ratings are calculated only from the items rated by each respective user.

For courses that the target user has already rated, the observed rating is directly retained as the collaborative filtering score because no prediction is required. All collaborative filtering scores, including predicted and observed ratings, are subsequently normalized to a range of 0 to 1 by dividing each score by the maximum rating value of 5. The normalized collaborative filtering score is calculated using Equation (3):

$$CF_{\text{norm}}(a, i) = \frac{CF(a, i)}{5} \quad (3)$$

where $CF(a, i)$ represents either the predicted rating $\hat{r}_{a,i}$ for an unrated course or the observed rating $r_{a,i}$ for a previously rated course. The resulting normalized score, $CF_{\text{norm}}(a, i)$, is then used in the hybrid fusion stage.

2.4 Multi-Criteria Decision-Making Method (SAW)

The Simple Additive Weighting method evaluates each course as an alternative against the five criteria presented in Table 2 through three main steps. First, the decision matrix $X = [x_{ij}]$, where i represents the course and j represents the criterion, is normalized according to the type of criterion. Benefit criteria are normalized by dividing each value by the maximum value in the corresponding column, whereas cost criteria are normalized by dividing the minimum value in the column by each observed value. Consequently, higher normalized values consistently indicate more favorable outcomes. The normalization procedure is expressed in Equation (4):

$$r_{ij} = \begin{cases} \frac{x_{ij}}{\max_i(x_{ij})}, & \text{if criterion } j \text{ is a benefit criterion,} \\ \frac{\min_i(x_{ij})}{x_{ij}}, & \text{if criterion } j \text{ is a cost criterion.} \end{cases} \quad (4)$$

where r_{ij} denotes the normalized value of course i for criterion j , and x_{ij} denotes the original value in the decision matrix.

Second, the normalized decision matrix $R = [r_{ij}]$ is combined with the criterion weights w_j , as presented in Table 2. The weights satisfy the following condition:

$$\sum_{j=1}^5 w_j = 1. \quad (5)$$

The preference value V_i for each course is then calculated using the weighted-sum formula shown in Equation (6):

$$V_i = \sum_{j=1}^5 w_j r_{ij}. \quad (6)$$

where V_i represents the overall preference score of course i , w_j represents the weight assigned to criterion j , and r_{ij} represents the normalized performance value of course i under criterion j .

Third, the courses are ranked in descending order according to their V_i values. A higher V_i indicates that a course performs better across the weighted combination of quality, relevance, and cost-efficiency criteria. This ranking is generated independently of the individual user's previous rating history.

2.5 Hybridization Scheme

The normalized collaborative filtering score and the SAW preference value are combined using linear weighted fusion, as presented in Equation (7):

$$\text{Hybrid}_i = \alpha CF_{\text{norm},i} + (1 - \alpha)V_i \quad (7)$$

where $\alpha \in [0,1]$ controls the relative influence of personalized preferences and objective multi-criteria quality. A larger value of α increases the contribution of the collaborative filtering component, whereas a smaller value gives greater importance to the SAW preference value.

This study uses $\alpha = 0.5$ to assign equal importance to both dimensions in the demonstration. Therefore, Equation (8) can be expressed as:

$$\text{Hybrid}_i = 0.5 CF_{\text{norm},i} + 0.5 V_i \quad (8)$$

In a deployed system, the value of α could be optimized through offline validation, such as cross-validated ranking accuracy, or provided as a user-adjustable parameter representing the preferred balance between personalized and objective recommendations. The final course recommendations for the target user are generated by ranking all 10 courses in descending order according to their Hybrid_i values.

3. Result and Discussion

3.1. User Similarity and Neighborhood Selection

Cosine similarity was computed between the target user U1 and each of the other seven users based on co-rated courses. Table 4 reports the resulting similarity values. Three users - U4 (sim = 0.994), U3 (sim = 0.990), and U2 (sim = 0.966) - were selected as the top-k = 3 neighborhood, all exceeding a similarity of 0.94, indicating strongly aligned rating patterns with the target user. U6 could not be compared to U1 because the two users share no co-rated courses, and was consequently assigned a similarity of zero and excluded from the neighborhood.

Table 4. Cosine similarity between the target user (U1) and candidate neighbors.

User	Cosine Similarity to U1	In Top-3 Neighborhood
U2	0.966	Yes
U3	0.990	Yes
U4	0.994	Yes
U5	0.747	No
U6	0.000	No
U7	0.950	No
U8	0.949	No

3.2. Collaborative Filtering Scores

Table 5 presents the CF score for every course. For the three courses U1 had already rated (C01, C02, C05, C07 - four courses were previously rated), the observed rating was retained directly. For the remaining courses, the mean-centered weighted-sum formula (Equation 2) produced predicted ratings using only the top-3 neighborhood. The highest CF score belongs to C01 - Python for Data Science (5.00, observed), reflecting U1's own top rating, while the strongest predicted (previously unrated) course is C06 - Cloud Computing with AWS (3.51), driven largely by the consistently high ratings U4 and U2 gave that course.

Table 5. Collaborative Filtering scores per course for target user U1.

Course	CF Score (raw, 1-5 scale)	CF Score (normalized, 0-1)
C01	5.0 (observed)	1.000
C02	4.0 (observed)	0.800
C03	3.30 (predicted)	0.660
C04	2.30 (predicted)	0.460
C05	2.0 (observed)	0.400
C06	3.51 (predicted)	0.703
C07	3.0 (observed)	0.600
C08	2.30 (predicted)	0.460
C09	3.50 (predicted)	0.700
C10	3.30 (predicted)	0.660

3.3. SAW Preference Values

The course-attribute decision matrix (Table 3) was normalized per Equation (3) and combined with the criteria weights (Table 2) per Equation (4) to produce a SAW preference value for each course. Table 6 reports the resulting values. C04 - Digital Marketing Fundamentals achieved the highest SAW value (0.858), driven by its comparatively low difficulty, short duration, and low price, despite having the lowest average rating in the dataset. C09 - Mobile App Development received the lowest SAW value (0.575), reflecting its longer duration and higher difficulty relative to other courses.

Table 6. SAW preference values for all 10 courses (objective, independent of user history).

Course	SAW Preference Value (V_i)
C01	0.702
C02	0.674
C03	0.655
C04	0.858
C05	0.726
C06	0.617
C07	0.663
C08	0.634
C09	0.575
C10	0.702

3.4. Score Comparison and Hybrid Ranking

Figure 2 visualizes the sparse input rating matrix, and Figure 3 compares the normalized CF score, SAW value, and final hybrid score for every course side by side. The comparison illustrates the complementary behavior of the two techniques: C01 scores highest on CF (1.000) but only moderately on SAW (0.702), while C04 scores highest on SAW (0.858) but comparatively low on CF (0.460), confirming that neither technique alone would surface the same course as top-ranked.

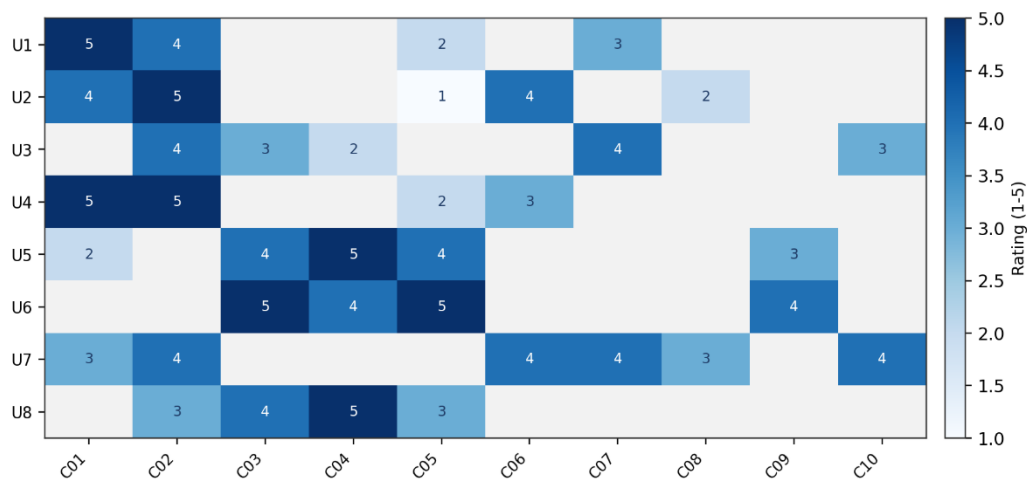


Fig 2. Dummy user-item rating matrix visualized as a heatmap.

Applying Equation (5) with $\alpha = 0.5$ produced the final hybrid ranking shown in Table 7 and Figure 4. C01 - Python for Data Science ranked first (hybrid = 0.851), followed by C02 - Introduction to Machine Learning (0.737) and C10 - Financial Modeling with Excel (0.681). Notably, C10 was not previously rated by U1 and ranked only sixth on CF-normalized score, but its strong SAW value (0.702, reflecting good relevance and moderate cost) lifted it into third place overall - directly illustrating how the hybrid model can surface unrated courses that a CF-only system would rank lower. Conversely, C04, which led on the SAW criterion alone, dropped to fifth place once personalized preference was taken into account, since U1's own rating history showed comparatively weak affinity for that course category.

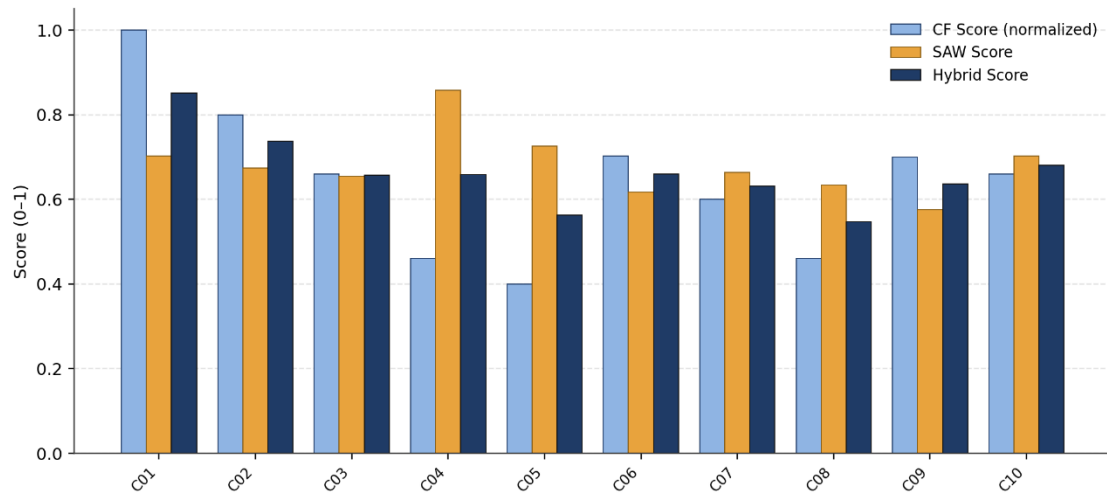


Fig 3. Comparison of normalized CF score, SAW value, and hybrid score per course.

Table 7. Final hybrid recommendation ranking for target user U1 ($\alpha = 0.5$).

Rank	Course	CF (norm)	SAW (V_i)	Hybrid Score	Status for U1
1	C01 - Python for Data Science	1.000	0.702	0.851	Rated
2	C02 - Introduction to Machine Learning	0.800	0.674	0.737	Rated
3	C10 - Financial Modeling with Excel	0.660	0.702	0.681	New
4	C06 - Cloud Computing with AWS	0.703	0.617	0.660	New
5	C04 - Digital Marketing Fundamentals	0.460	0.858	0.659	New
6	C03 - Web Development Bootcamp	0.660	0.655	0.657	New
7	C09 - Mobile App Development	0.700	0.575	0.637	New
8	C07 - Business Analytics	0.600	0.663	0.631	Rated
9	C05 - UI/UX Design Principles	0.400	0.726	0.563	Rated
10	C08 - Cybersecurity Essentials	0.460	0.634	0.547	New

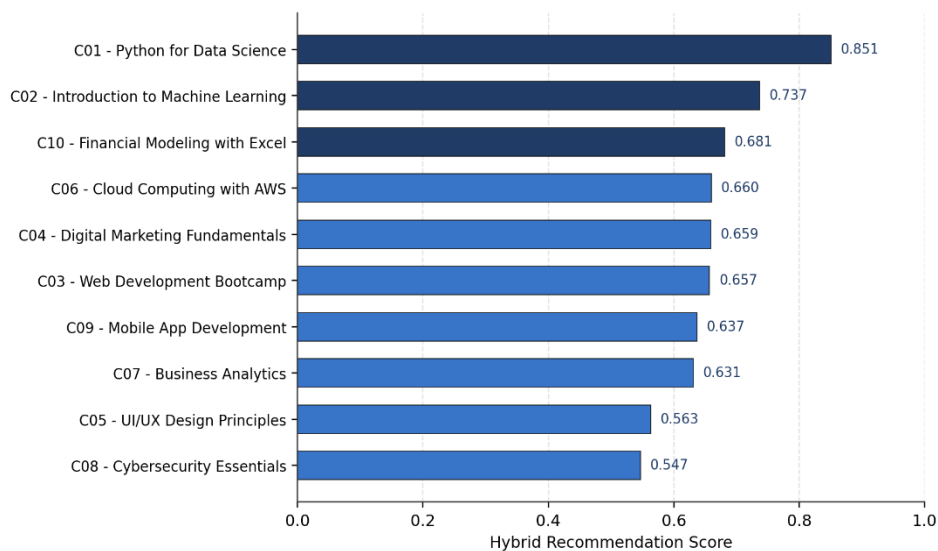


Fig 4. Final top-10 course ranking for target user U1 under the hybrid model.

The results demonstrate that the hybrid CF-SAW model produces a course ranking that differs meaningfully from either constituent technique used in isolation. This is consistent with prior hybrid course-recommendation research, which has repeatedly shown that combining collaborative signals with independent, objective evaluation criteria improves the

practical relevance of recommendations, particularly for items with limited or no rating history from the target user - the classic cold-start scenario. In the present demonstration, C10 - Financial Modeling with Excel exemplifies this benefit: despite having no prior rating from U1, its strong performance across relevance, duration, and price criteria allowed the SAW component to elevate it into the top three, a result a CF-only recommender could not have produced with the same confidence given only moderate predicted-rating support.

The complementary strength observed between CF and SAW aligns with the broader multi-criteria decision-making literature, where SAW's compensatory, transparent scoring is valued precisely because a weak criterion can be offset by strong performance elsewhere in the profile - the same property that let C04 achieve the highest SAW score in this dataset despite a relatively low average rating. However, this compensatory behavior is also a limitation: because a single very strong criterion can offset several weak ones, SAW may occasionally rank an alternative highly even when it performs only adequately overall (Saragih et al., 2025; Siahaan et al., 2017; Taherdoost, 2023), a general critique also raised in the MCDM literature regarding weighted-sum methods. In a hybrid system, this risk is partially mitigated because the CF component independently constrains the ranking based on demonstrated user preference, but a course that is both objectively unbalanced and unrated by the target user could still be over-ranked; sensitivity analysis on the criteria weights and the hybridization coefficient α would be a prudent addition before operational deployment.

The choice of $\alpha = 0.5$ in this demonstration is a simplification. Because CF and SAW answer different questions - personalized affinity versus objective merit - the appropriate balance between them is arguably use-case dependent. A learner exploring an entirely new subject area, with little or no rating history, would benefit from an α weighted more heavily toward SAW, since CF predictions in a cold-start setting are unreliable; conversely, a learner with a rich rating history in a stable subject area could be served well by an α weighted toward CF. This suggests that a practical deployment of the proposed framework should treat α as an adaptive parameter - for example, decreasing automatically as a function of the number of items a user has rated - rather than a fixed constant, an extension consistent with hybridization strategies discussed in prior hybrid recommender-system studies for education.

The generalizability of the proposed framework is also worth noting. Neither the collaborative filtering component nor the SAW component is intrinsically tied to the course-recommendation domain: the user-item rating matrix and the multi-criteria decision matrix are generic data structures that appear in many other selection problems - product recommendation, vendor selection, job-candidate shortlisting, or housing search, among others. The primary domain-specific work required to adapt the framework to a new context is (1) defining an appropriate set of MCDM criteria and their benefit/cost orientation, and (2) sourcing a sufficiently dense rating matrix to support reliable similarity estimation.

4. Conclusion

This study proposed and demonstrated a hybrid course-recommendation framework that combines User-Based Collaborative Filtering with Cosine Similarity and the Simple Additive Weighting MCDM method through linear score fusion. Using a controlled dummy dataset of 10 MOOC courses, 8 users, and 5 evaluation criteria, the complete pipeline - similarity computation, rating prediction, criteria normalization, weighted summation, and hybrid ranking - was implemented and traced end-to-end. The results confirmed that the hybrid ranking differs from both the CF-only and SAW-only rankings, most notably by elevating an objectively strong but previously unrated course (C10) above several courses with only moderate personalized or objective support, and by tempering the influence of a course that scored highest on objective criteria alone (C04) once the target user's demonstrated preferences were incorporated.

The framework's principal practical value lies in its transparency and modularity: each component (CF and SAW) produces an independently interpretable score, and the hybridization weight α offers an explicit, tunable control over the balance between personalization and objective merit - a property valuable for MOOC platforms, where explaining a recommendation is often as important as the recommendation itself. Future research should (1) validate the framework on real learner interaction data with held-out ratings to compute standard accuracy metrics; (2) explore adaptive or user-controlled α as discussed in Section 4; (3) compare SAW against alternative MCDM methods such as TOPSIS or AHP-weighted SAW to assess ranking stability; and (4) extend the collaborative filtering component to item-based or matrix-factorization variants to evaluate scalability on larger course catalogs.

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