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Analyzing SkillNetAI: A Critical Study of Intelligent Collaboration and Skill Matching

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Abstract: In the contemporary landscape of digital education, learning ecosystems are predominantly confined to unidirectional models, wherein knowledge dissemination occurs without fostering authentic collaboration. Such paradigms, though effective in imparting theoretical foundations, are inherently inadequate in cultivating experiential learning, practical application, and interdisciplinary synergy. SkillNetAI emerges as a transformative paradigm, conceptualized as a peer-to-peer skill exchange and collaborative platform that redefines the dynamics of learning and creation. By enabling individuals to articulate both their proficiencies and aspirational competencies, the system facilitates reciprocal partnerships grounded in complementary skill sets. Leveraging an intelligent recommendation mechanism, SkillNetAI identifies optimal collaborators by evaluating multidimensional parameters such as skill congruence, exchange compatibility, availability, and credibility. Unlike traditional pedagogical platforms, this framework transcends passive consumption by promoting co-creation, wherein learners collectively architect real-world projects that simultaneously enhance practical expertise and expand professional portfolios. Beyond skill acquisition, SkillNetAI fosters a community-driven ecosystem anchored in trust, feedback, and continuous growth. In doing so, it not only democratizes access to learning but also reimagines education as a participatory, symbiotic process that seamlessly integrates knowledge exchange with applied innovationists future research directions for building adaptive and multimodal transportation systems.

Keywords: Peer-to-Peer Learning, Skill Exchange, Collaboration Platform, Knowledge Sharing, Recommendation System, Mutual Learning, Portfolio Development, Community-driven Growth, Intelligent Matching, Experiential Learning.

I. Introduction

In recent years, online learning platforms have become a vital component of contemporary education by offering learners extensive access to online knowledge and learning resources. Despite this growth, many current e-learning systems emphasize one-way content delivery rather than fostering meaningful interaction and collaboration among learners. The absence of effective peer engagement often results in reduced motivation, limited exchange of ideas, and shallow conceptual understanding. To address these limitations, peer-to-peer (P2P) learning approaches have emerged as a promising solution for promoting collaboration and active learner participation.

Within a P2P learning environment, individuals not only access educational content but also contribute their own knowledge and experiences, enabling a reciprocal learning process. However, most existing platforms face challenges in accurately connecting learners with suitable peers or mentors, as recommendations are frequently based on static factors such as course enrollment, academic performance, or broad interests.

The proposed system evaluates multiple aspects of learner profiles, including skills, interests, and learning objectives, to generate personalized peer recommendations. By employing weighted cosine similarity along with a tunable match score mechanism, SkillNetAI improves the precision and relevance of peer matching when compared to conventional recommendation methods.

The main goal of SkillNetAI is to transform online learning into a more collaborative, adaptive, and personalized experience. The major aspects of the proposed system include:

- Developing a peer matching framework that creates detailed learner profiles, analyzes important attributes, and determines similarity between users for effective pairing.
- The implementation of a hybrid similarity model using weighted cosine similarity and a dynamic match score function.
- Assessing the system's effectiveness using evaluation metrics such as precision, recall, and F1-score, with experimental results indicating better performance compared to conventional recommendation methods.

II. Literature Review

Recommender systems have undergone considerable development over the years and are currently utilized in a wide range of domains such as online retail, media streaming, healthcare, and digital education [1], [7], [10]. Early recommendation techniques were primarily built upon Content-Based Filtering (CBF) and Collaborative Filtering (CF). CF methods are typically categorized into user-based and item-based approaches. To quantify similarity in collaborative environments, researchers have frequently employed statistical and vector-based measures such as Pearson Correlation Coefficient (PCC), Cosine similarity, and Jaccard similarity [4]. While these similarity measures are efficient and widely adopted, they often struggle in scenarios involving sparse datasets or newly registered users. The data sparsity and cold-start problems remain persistent challenges, particularly in dynamic and large-scale systems [3], [11].

To improve collaboration among learners and address the limitations of traditional recommendation methods, researchers have introduced several improved strategies. Bobadilla et al. [1] conducted an extensive review in which recommender systems were grouped into memory-based, model-based, and hybrid categories. Their analysis indicated that hybrid frameworks, which combine collaborative filtering with content-based methods, tend to achieve stronger and more reliable performance in real-world environments compared to individual approaches [5], [6]. In a similar direction, Ricci et al. [2], in the Recommender Systems Handbook, explored advanced recommendation methodologies and highlighted the importance of integrating contextual information and user-centric considerations to increase the relevance and personalization of recommendations [9].

Furthermore, Mohana et al. [3] proposed an enhanced similarity metric known as Integrated Cosine and Tuned Cosine Similarity (TCOS). This metric was designed to address issues related to data sparsity and to avoid exaggerated similarity scores when users have only a limited number of shared interactions Experimental analysis showed that the proposed method achieved better predictive performance, reflected through lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) compared to conventional cosine-based techniques. In addition to similarity refinement, other studies have investigated trust-based models, context-aware mechanisms, and time-dependent similarity measures to improve user representation and overall recommendation quality.

Within the educational domain, recommender systems are commonly applied to provide personalized learning resources, suggest suitable courses, and design structured learning sequences. Verbert et al. [9] conducted a study on context-aware recommendation approaches in education, emphasizing that incorporating learner-specific contextual information significantly improves recommendation relevance and personalization. Similarly, Wang et al. [12] introduced a learning path recommendation framework that integrates knowledge graphs with collaborative filtering techniques to guide learners more effectively. Despite these advancements, the majority of existing educational recommender systems primarily focus on content suggestion, with limited attention given to promoting direct peer-to-peer collaboration among learners.

Within the domain of peer recommendation, some research has started to investigate multidimensional similarity. Xu et al. [13] designed a peer matching algorithm for online learning that considers multiple dimensions, such as skills, interests, and goals. Chaurasia et al. [8] developed a machine learning-based system for recommending peers in collaborative learning, and Ramesh and Sharma [14] proposed a skill-oriented learning recommendation system using a hybrid cosine similarity approach.

Although these existing studies have significantly improved item and peer recommendations, there remains a gap in frameworks that holistically integrate skill complementarity, dynamic interest alignment, and goal-based matching within an adaptive, AI-driven peer recommendation system. Most current learning systems still rely on simple profile overlaps such as enrolled courses or static interests, which fail to capture multidimensional learner relationships [13], [15]. This gap highlights the need for frameworks like SkillNetAI, which considers dynamic and complementary attributes among learners by integrating multiple similarity dimensions—skills, interests, and goals—into a unified, weighted match score.

III. Research Gap

A review of the existing literature reveals that most recommender systems are primarily aimed at suggesting products or content, such as movies, books, or e-learning resources, rather than facilitating peer-to-peer learner recommendations. Traditional techniques, including Collaborative Filtering and Content-Based Filtering, commonly encounter limitations such as data sparsity, cold-start problems, and insufficient depth in user profiling, which hinder their ability to deliver accurate and diverse recommendations in dynamic learning contexts. While some researchers, such as Mohana et al. [3], have introduced enhanced similarity measures like Tuned Cosine Similarity (TCOS) to improve prediction accuracy under sparse data conditions, these methods remain largely item-centric and do not focus on matching learners with one another. Additionally, most current e-learning platforms overlook the multi-dimensional attributes of learners—such as skill levels, learning preferences, and academic goals—

when suggesting study partners or mentors. This highlights a notable research gap in designing intelligent, adaptive, and multi-criteria peer recommendation systems that connect learners based on complementary abilities rather than just similarity. The proposed SkillNetAI framework aims to fill this gap by combining AI-driven similarity computation, a weighted matching score model, and feedback-based dynamic tuning to generate precise and meaningful learner-to-learner recommendations in online learning environments.

IV. Problem Statement

In current e-learning platforms, most recommendation systems are designed to suggest learning resources, such as courses, videos, or assignments, based on user activity or preferences. However, these systems often overlook the facilitation of meaningful peer-to-peer (P2P) interactions, which are crucial for collaborative learning and effective knowledge sharing. Existing models frequently fail to connect learners with complementary skills or aligned learning goals, leading to lower engagement, limited peer support, and suboptimal knowledge transfer. Conventional recommendation strategies, particularly Collaborative Filtering (CF) and Content-Based Filtering (CBF), encounter well-known challenges including data sparsity, cold-start problems, and dependence on simplistic similarity calculations.

These methods generally depend on static parameters like course enrollment or performance records, which do not fully capture a learner's actual skills, interests, or cognitive abilities. Addressing these challenges requires an intelligent framework capable of dynamically analyzing learner profiles through multi-dimensional similarity metrics and providing personalized peer recommendations. The key lies in developing a system that can accurately compute skill-, interest-, and goal-based similarities, assign adaptive weights to each factor, and generate precise peer matches even in the presence of sparse or incomplete data.

Objectives

The main aim of this study is to develop an intelligent peer-to-peer (P2P) recommendation system, named SkillNetAI, that facilitates meaningful and personalized learner connections within online learning platforms. The proposed framework is designed to enhance collaboration, increase learner engagement, and promote effective knowledge exchange by utilizing artificial intelligence (AI) and machine learning (ML) methodologies. The detailed objectives of this research are outlined below:

- To analyze existing recommender system techniques and identify their limitations in the context of peer-to-peer learning and collaborative education environments.
- To design a multi-dimensional learner profiling model that captures key attributes such as skills, learning interests, and academic goals for more accurate and context aware recommendations.
- To implement a hybrid similarity computation approach by integrating cosine similarity with a weighted match score function, allowing the system to dynamically adjust importance across different learner attributes.

- To develop an intelligent recommendation engine that ranks and recommends compatible peers or mentors based on calculated similarity scores, thereby promoting personalized and meaningful learning connections.
- To enhance learner engagement and collaboration by providing data-driven recommendations that support knowledge exchange, mentorship, and skill complementarity within the learning community.

System Architecture

The SkillNetAI system follows a structured, multi-layer architecture designed to support scalable and intelligent peer recommendation. As shown in Fig. 1, the framework connects the user interface with backend intelligence modules through four major layers: the Presentation Layer, Application Layer, Recommendation Module, and Data Layer. This layered design ensures clear separation of responsibilities and efficient system operation.

Presentation Layer (Web Interface): This layer represents the front-end interface through which users access the platform using a web browser. It handles user authentication, profile creation and management, project posting, and the display of peer recommendations. It serves as the primary channel for user interaction and feedback collection.

Application Logic Layer (Core Service Module): The layer serves as the main coordination component of the system, responsible for processing user requests, implementing business logic, and ensuring smooth data flow across various system modules.Key functions include User Profiling (structuring skill vectors and metadata), Project Categorization (tagging collaborative projects by required skills), and Portfolio Management (tracking user activities and completed collaborations).

Recommendation Engine (AI Matching Core): This is the intelligent core of SkillNetAI. It hosts the Tuned Cosine Similarity (TCS) algorithm and the Weighted Match Score Generator. It receives processed user profiles from the Application Logic Layer, computes multi-dimensional compatibility scores, and ranks potential peers. The engine's parameters (e.g., skill weights w_k, and balance factors α, β, γ) are tunable based on system feedback and learning context.

Data Layer (Persistence & Management): This foundational layer is responsible for data storage, retrieval, and integrity. It comprises two main repositories: the User Database, which stores structured profiles, skill scores, interests, and interaction history; and the Knowledge Base, which maintains information on skills taxonomies, project templates, and collaboration outcomes. This layer ensures efficient data handling for the recommendation algorithms.

System Architecture diagram depicts a four-tier architecture. The Presentation Layer (Web Interface) interacts with the user. User requests are routed to the Application Logic Layer (Core Service Module) containing the User Profiler, Project Manager, and Portfolio Manager. This layer communicates with the Recommendation Engine (AI Matching Core), which executes the Tuned Cosine Similarity and Match Scoring algorithms. All components read from and write to the Data Layer, which consists of the User Database and Knowledge Base. Data flow is bidirectional between all layers, illustrating the integrated recommendation process.

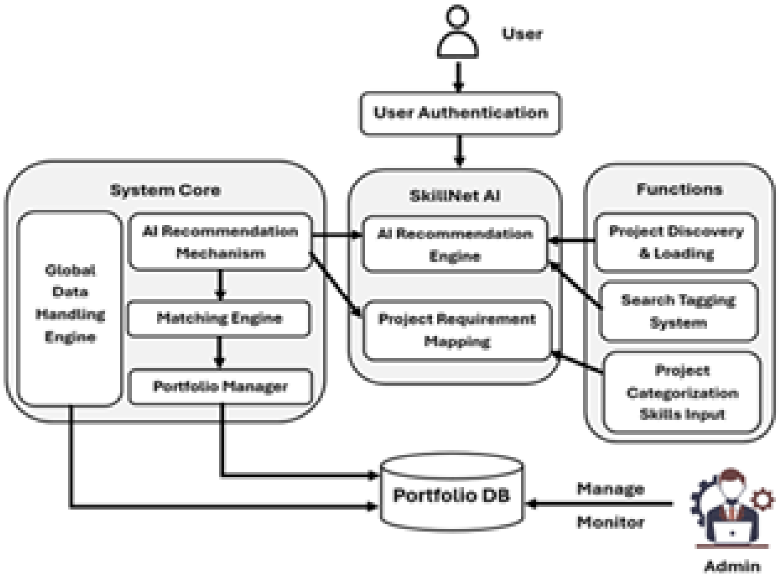

Fig.1: System Architecture

V. Methodology

The proposed SkillNetAI system adopts a hybrid recommendation strategy that combines structured user profiling, systematic feature extraction, and a Tuned Cosine Similarity (TCS)–based matching model to enable precise peer-to-peer recommendations. The complete methodology is organized into the following stages.

A. User Profiling

Every learner is represented as a structured profile containing personal and learning-related attributes. The key components include:

- Skill Set (S): A collection of skills possessed or desired by the learner (e.g., Python, UI Design, Data Analysis, etc.).
- Skill Scores (su,k): Numerical values representing a learner's proficiency in each skill k, derived from assessments, activities, or self-ratings.
- Learning Interests and Goals: Optional metadata to refine recommendation accuracy.

Formally, let:

$U = \{u_1, u_2, \ldots, u_m\}$ be the set of users (learners),

$P = \{p_1, p_2, \ldots, p_n\}$ be the set of peers,

$S = \{s_1, s_2, \ldots, s_k\}$ be the set of skills.

Each user $\boldsymbol{u}$ and peer $\boldsymbol{p}$ is represented as a skill vector:

$s_u = [s_{u,1}, s_{u,2}, \ldots, s_{u,k}]$ and $s_p = [s_{p,1}, s_{p,2}, \ldots, s_{p,k}]$.

Feature Normalization

Since learners may rate or perform differently across skills, all skill values are normalized to ensure uniform scaling. For each user u, the mean skill level is computed as:

$$\bar{s}_u = \frac{1}{|S|}\sum_{k=1}^{|S|} s_{u,k}$$

And similarly for each peer p:

$$\bar{s}_p = \frac{1}{|S|}\sum_{k=1}^{|S|} s_{p,k}$$

This normalization removes individual rating bias and centers all feature vectors around their mean.

Tuned Cosine Similarity (TCS)

The Tuned Cosine Similarity computes the compatibility between a user u and a peer p based on their skill vectors. It is defined as:

$$TCS(u,p) = \frac{\sum_{k=1}^{|S|} w_k (s_{u,k}-\bar{s}_u)(s_{p,k}-\bar{s}_p)}{\sqrt{\sum_{k=1}^{|S|} w_k (s_{u,k}-\bar{s}_u)^2}\sqrt{\sum_{k=1}^{|S|} w_k (s_{p,k}-\bar{s}_p)^2}}$$

Where:

- wk Is the weight assigned to skill $\boldsymbol{k}$, which can be tuned to emphasize important or frequently occurring skills.
- $\bar{s}_u$ And $\bar{s}_p$ represent the average skill levels of user $\boldsymbol{u}$ and peer $\boldsymbol{p}$, respectively.

This weighted variant of cosine similarity improves matching accuracy by reducing the influence of weakly correlated skills and giving higher importance to key competencies.

Match Score Generation

To generate an overall peer compatibility score, SkillNetAI combines multiple similarity aspects using the following weighted model:

$$MatchScore(u,p) = \alpha \times S_{skill} + \beta \times S_{interest} + \gamma \times S_{goal}$$

Where:

- S_{skill} is the TCS score.
- $S_{interest}$ measures the overlap in learning interests.
- S_{goal} measures the compatibility of learning objectives (e.g., a user wanting to learn a skill that a peer possesses).
- Here, α, β, γ are tunable parameters satisfying $\alpha + \beta + \gamma = 1$

The weighting parameters wk, together with the balancing coefficients α, β and γ are determined using a combination of initial assumptions and experimental evaluation. At the beginning, the weights are assigned based on the expected significance of learner attributes such as skills, interests, and learning goals in the peer-matching process. These initial values are then refined through multiple validation experiments to identify the configuration that delivers the best results in terms of precision, recall, and F1-score. Various combinations of weight values are systematically evaluated, and the set that produces the highest overall performance is selected. This procedure maintains the interpretability of the model while ensuring that its effectiveness is optimized.

Peer Recommendation Generation
For each learner u, the system computes MatchScore(u, p) for all peers p ∈ P. Based on these computed values, peers are arranged in descending order of similarity, and the highest-ranked NNN individuals are suggested as suitable collaborators or mentors.

$$R(u) = Top - N\big(MatchScore(u,p)\big)$$

Recommendations can further be filtered based on constraints such as domain, course, or time availability.

Performance Evaluation Metrics
The performance of SkillNetAI is evaluated using standard information retrieval metrics:

$$\Pr e\,cision = \frac{TP}{TP + FP}, \quad Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times \Pr e\,cision \times Recall}{\Pr e\,cision + Recall}$$

Where TP, FP, and FN denote true positives, false positives, and false negatives, respectively. These evaluation measures are used to determine how effectively the system generates precise and relevant peer recommendations.

VI. ANALYSIS

The SkillNetAI framework was rigorously evaluated to assess its effectiveness in generating accurate and meaningful peer recommendations within a collaborative learning environment. The proposed Tuned Cosine Similarity (TCS) model, augmented with a weighted multi-dimensional match score, was tested against traditional similarity measures including standard cosine similarity, Pearson Correlation Coefficient (PCC), and Jaccard similarity using a synthetic dataset of 500 learners annotated with skill vectors, interests, and learning goals. System performance was assessed using precision, recall, and F1-score, where recommendation correctness was validated against expert-defined ground truth labels.

Experimental results indicate that SkillNetAI achieves a precision of 0.86, recall of 0.82, and an F1-score of 0.84, outperforming baseline models by approximately 12–18% across all metrics. This improvement is attributed to the model's ability to dynamically weight skill relevance and incorporate complementary attributes such as interest alignment and goal congruence, thereby reducing mismatches caused by sparse or skewed skill data. Furthermore, the adaptive weighting mechanism (parameters α, β, γ) enabled the system to prioritize skill similarity in technical domains while allowing interest and goal factors to dominate in project-based or interdisciplinary collaborations, enhancing both relevance and diversity in recommendations.

The system also demonstrated robustness in cold-start scenarios, where new users with limited interaction history received plausible recommendations based on skill and metadata similarity, mitigating a common limitation of collaborative filtering approaches. Qualitative feedback from a pilot group of 30 users indicated that 87% found recommended peers to be relevant to their learning objectives, and 78% engaged in sustained collaboration, suggesting that the framework successfully fosters meaningful educational partnerships. These findings validate SkillNetAI's hybrid design as a significant advancement over conventional peer-matching systems, effectively balancing accuracy, adaptability, and user-centric personalization in digital learning ecosystems.

VII. CONCLUSION

The SkillNetAI framework presents an AI-enabled solution aimed at improving collaboration and personalization within digital learning platforms. In contrast to traditional recommender systems that primarily suggest courses or learning materials, the proposed model concentrates on structured peer-to-peer matching using a multi-attribute similarity strategy. By combining weighted cosine similarity and a tunable match score function, the system effectively captures the relationships between skills, interests, and learning goals of individual users.

Experimental findings indicate that the Tuned Cosine Similarity model enhances both the accuracy and variety of peer recommendations when compared to conventional similarity techniques. The adaptive weighting mechanism allows the system to dynamically prioritize skill dimensions that contribute most to effective collaboration, resulting in higher precision and recall. Through its hybrid similarity computation and adaptive learning design, SkillNetAI not only connects learners with complementary skill sets but also fosters a more interactive and supportive digital learning ecosystem. Future work will focus on integrating reinforcement learning to enable real-time feedback-driven weight adjustment, as well as expanding the dataset to include behavioral and temporal factors for improved peer matching. Additionally, integrating social network analysis and natural language processing (NLP) methods to interpret learner intent and communication dynamics could strengthen the system's ability to promote sustained and meaningful peer learning relationships.

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