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Research Article

CoSPARP: Collaborative and Social-Personality Aware Recommendation of Programmes

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Globally, the selection of tertiary programmes for higher education in a university by prospective applicants is a daunting task. Different universities offer a wide range of programmes using different education delivery modes for teaching and learning. This creates information overload in the context of tertiary programmes. To tackle the information overload problem of tertiary programmes in the context of higher education institutions (HEIs), this paper, therefore, proposes a novel recommendation model called *Collaborative and Social-Personality Aware Recommendation of Programmes* (*CoSPARP*) for tertiary programme selection. *CoSPARP* utilizes a hybrid filtering system that incorporates the computation of similarities relating to the CF, personality traits, and the tie strength of users (prospective applicants) to generate effective programme recommendations for a tertiary programme applicant (*TPA*). The proposed *CoSPARP* recommendation method employs the above recommendation entities to create profiles of the *TPAs* as a basis of profile similarity for tertiary programme recommendations. Results of benchmarking experiments showed that *CoSPARP* overcomes cold-start due to the proposed (innovative) hybridization process. Additionally, using a relevant real-world dataset and suitable evaluation metrics such as precision, recall, and F-measure, *CoSPARP* produces more favourable outcomes in comparison to other state-of-the-art methods.

1. Introduction

Globally, the process of finding information about higher education using numerous websites is a very difficult, time-consuming, and challenging one. Consequently, prospective applicants of various higher educational institutions (HEIs) face numerous challenges and difficulties concerning selecting the right tertiary programme and HEI that are suitable for their individual needs and careers [1–4]. In this paper, the term "*programme*" refers to a combination of courses relating to graduate and undergraduate education.

As a result of information overload regarding different programmes of study being offered by various HEIs, students/applicants are required to search, use resources, and organize themselves so that they can match their current level of knowledge, career goals, and programme [1–4]. Because such a process involves accessing different platforms, searching for available programmes, carefully reading programme curricula, and then finally choosing the most suitable programme, it is a very challenging, difficult, and time-consuming process [1–4]. Additionally, although some programme titles are similar, they might have different programme objectives, which may lead to different career goals and paths.

Relevant literature has shown that usually career goals, personal interests, and background are factors that influence students/applicants choice of programmes [1–5]. It has also been revealed by Ibrahim et al. [1] that three out of every four students/applicants were tentative or uncertain about career goals, progression, and selection at the HEI entry. It is worth noting that although programme information is provided on the websites of many HEIs, there is no guarantee that students/applicants have the cognitive abilities to evaluate all programmes they come across [1–5].

With reference to the enumerated challenges of tertiary programme selection, recommender systems provide a favourable approach for information filtering [6] since they help users to find the most suitable items. Traditionally, recommender systems are classified into three main techniques, namely: collaborative filtering (CF), content-based filtering (CBF), and hybrid filtering (HF) [6]. Furthermore, quite recently, context-aware recommender systems (CAR) [6] and socially-aware recommender systems [7–10] have also been developed to further improve issues regarding cold-start and data sparsity [11].

Currently, many web-based systems use tools such as data mining and association-based rules [12, 13], CF [14], and prior knowledge of the programme(s) to search for HEI programmes [15]. Although tertiary programme recommender systems have been successful during the past decades, they have encountered some limitations. These limitations include keywords failing to address a user's required programme recommendation; the unavailability of historical information relating to methods such as CF and data mining; and lastly, the absence of career progression in relation to recommended tertiary programmes [1–5]. By categorizing the requirements of students/applicants and their programmes of interest, there is an innovative possibility of recommending suitable programmes. Additionally, it should be possible to select a tertiary programme by developing methods that will incorporate data from multiple and heterogeneous sources. This will pave the way for the establishment of valuable programme-related information across [1–5, 16].

User modeling research has shown that human factors, such as personality and cognitive/learning styles, have been demonstrated to play an important role in the personalization process [9, 10, 17]. Furthermore, previous studies have also illustrated that personality influences the human decision-making process and reveals a person's long-term tastes [9, 10, 17]. Using a reflection of the intrinsic and interrelated patterns between personalities and users' interests/behaviors, many researchers have recently investigated the incorporation of human personality into recommender systems and have achieved promising results [9, 10, 17]. This paper proposes a recommender algorithm called Collaborative and Social-Personality Aware Recommendation of Programmes (*CoSPARP*). The main research questions involved in this paper include the following: (i) *whether* an innovative linear hybridization of CF with personality traits and tie strength of tertiary education applicants can deal with the cold-start problem (due to lack of sufficient ratings) and effectively provide a reliable recommendation of tertiary programmes? (ii) *How* to establish an effective procedure for combining CF, tie strength, and personality traits for tertiary programme recommendation? (iii) *When* these recommendation entities can work more successfully in tertiary programme recommendations?

Furthermore, the main contributions of this paper are as follows:

(i) A comprehensive recommendation model called *CoSPARP*, which is a recommender algorithm that linearly (hybrid) combines CF, personality, and tie strength data to overcome the information overload and new user cold-start problems in tertiary programme recommendation, is proposed in this paper. The new user cold-start problem in CF occurs when the user has not provided any ratings for items yet. However, the hybridization procedure in *CoSPARP* provides other recommendation entities, namely tie strength and personality, which can be used to efffectively substantiate the recommendation process.

(ii) The proposed recommendation methodology, *CoSPARP*, algorithmically tackles the new user cold-start problem by calculating the Pearson (personality and CF) similarity and tie strength existing between the tertiary education applicant profiles. The proposed solution provides a pathway for successful admission and enrolment of an applicant in a tertiary education programme that matches his/her interests and requirements.

(iii) Scientific benchmarking experiments are conducted to compare the performance of the *CoSPARP* in terms of two categories of evaluation metrics, namely recommendation prediction—MAE, RMSE, and recommendation quality—precision, recall, and F-measure. Experimental results are presented in the last but one section of the paper.

This paper is structured as follows: in Section 2, related studies that are relevant to this paper are discussed. Section 3 presents the proposed methodological solution and elaborates on the proposed recommendation process. Section 4 presents the experimental procedure and the corresponding experimental results, and finally, Sections 5 and 6 respectively present discusion and the concluding remarks.

2. Review of Literature and Related Studies

This section presents related studies and literature about the study. This section focuses on related studies regarding (i) recommender systems in the domain of education, (ii) social recommender systems through tie strength, and (iii) personality-aware recommender systems.

2.1. Recommender Systems in the Domain of Education. A substantial number of recommender systems have been proposed by various researchers in the domain of education. In the domain of education, students and teachers/academic advisors are the target users, and the recommendable items are educational materials, universities, or information, such as programmes, courses, topics, student performance, and the field of study [1–4].

Ibrahim et al. [1] proposed a novel approach that personalizes course recommendations that will match the individual needs of users. Their proposed approach developed a framework for an ontology-based hybrid-filtering system called the ontology-based personalized course recommendation (OPCR). The recommendation approach in [1] aimed to integrate information from multiple sources based on the similarity of the hierarchical ontology to improve efficiency and user satisfaction and to provide students with appropriate recommendations. The proposed OPCR in [20] combines CF with CBF. Similar to [1], Asabere and Amoako [2] aimed to enhance the efficiency and effectiveness of providing students with suitable recommendations. They, therefore, proposed a course recommender that takes into consideration knowledge about the user (the student's profile) and course content, as well as knowledge about the domain that is being learned. Ontology was used for both models and represents such forms of knowledge. Similar to [1, 2], Bozyiğit et al. [21] proposed a novel collaborative filtering (CF) based course recommender system that considered the case of repeating a course and students' grades in the course for each repetition. They experimented with different ordered weighted averaging (OWA) operators to justify their proposed system.

Qomariyah and Fajar [22] proposed the design and implementation of an e-learning recommender system based on a logic approach called active pairwise relation learner (*APARELL*). Their proposed e-learning recommender system helped students to select the best materials according to their preferences. The authors in [22] justified the big potential to implement a personalized recommender system in e-learning based on the student's learning styles using an ontology of material content based on different learning styles. Similar to [22], Li et al. [20] proposed a personalized semantic recommendation system (*PSRS*) for E-Learning. The proposed *PSRS* system in [20] employs a video structurized description (VSD) technique to extract the initial keyword description of the learning contents. Similar to [20, 22], Hsu et al. [23] proposed a personalized recommendation-based mobile language learning approach. They developed a mobile learning system based on the approach by providing a reading material recommendation mechanism for guiding English as a foreign language (EFL) students to read articles that match their preferences and knowledge levels.

Rodriguez-Cerezo et al. [24] analyzed how the combination of repositories of learning objects and recommender systems can support self-regulated learning in technical domains. They supported their position with a case study concerning the domain of compiler construction in Computer Science Advanced Education. Similar to [24], Samin and Azim [25] presented a case study showcasing the use of probabilistic topic models for generating recommendations to users in academia through appropriate course allocation and supervisor assignment. The proposed system in [25] called *ScholarLite* connects the power of machine learning to extract research themes from faculty members' past publications, mines research interests from their resumes, and combines it with their educational background to generate recommendations for course teaching, research supervision, and industry-academia collaboration.

Garrido et al. [26] proposed *myPTutor*, an effective and general approach that uses AI planning techniques to develop fully tailored learning routes as sequences of learning objects (LOs) that fit the requirements of pedagogy and students. Similar to [26], Gulzar et al. [27] presented a recommender system that will suggest and guide a learner in selecting courses as per his/her requirement. The hybrid methodology in [27] has been used along with ontology to retrieve useful information and make accurate recommendations.

2.2. Social Recommender Systems through Tie Strength. Tie strength, which measures the characteristics between two nodes in a social network, has been under investigation by social network theories for some time. It was first introduced by Granovetter [28], who analyzed the interpersonal structure between two persons and divided relationship strength into three possible conditions: strong tie, weak tie, or absent tie. The latter refers to a lack of a relationship or ties, with a mere "nodding relationship" [28, 29].

Social recommender systems use data regarding the social relationships of users to filter relevant information. To date, research results from various researchers [7–10] show that incorporating social data beyond only profile similarity is very beneficial [7–10, 30].

Arazy et al. [31] designed, developed, and tested a recommender system based on the principle that some types of social relationships, such as tie strength, yield recommendation accuracy. The striking correspondence, as evidenced in [31], highlighted the importance of behavioural theory in guiding system design. Similar to [31], Arazy et al. [32] developed a social filtering model that integrates various social measures such as trust, reputation, interaction frequency, and relationship duration. They conducted an empirical study to test the model. The results from the study show small but significant, recommendation accuracy improvements for various social relationships.

Oechslein and Hess [33] developed a research model and evaluated it in an online experiment using Facebook data for the use case of online news with 193 participants. Experimental results of the structural equation model in [33] validated that a strong tie relationship has a positive influence on the value of a recommendation. Similar to [33], Carmagnola et al. [34] proposed *SoNARS*, a new algorithm for recommending content in social recommender systems. *SoNARS* targets users as members of social networks, suggesting items that reflect the trend of the network itself, based on its structure and the influence relationships among users. Similar to [33, 34], Felicio et al. [35] proposed *Social PrefRec*, a social pairwise preference recommender system based on preference mining techniques. They focused on leveraging social information on a pairwise preference recommender system, substantiating the idea that matching new people with existing similar people helps in the provision of accurate recommendations.

Liberatore and Quijano-Sanchez [36] empirically show the relative importance of different social variables for the computation of *tie strength* and propose a computational social recommendation model. Their experiments were based on a dataset obtained from a survey that involved more than 100 participants and comprised more than 500 social ties. Similar to [36], Zhong et al. [37] presented a novel method of generating recommendations by leveraging tie strength, and an integrated social relationship measurement calculated from various user information gathered from social media. Wang et al. [38] presented an EM-based algorithm that simultaneously classifies strong and weak ties in a social network concerning optimal recommendation accuracy and learns latent feature vectors for all users and all items. Similar to [38], Chen et al. [39] proposed a recommendation approach based on quantified social tie strength. They proposed an unsupervised method to estimate tie strength from user similarity and online social interactions to improve social recommendation accuracy with quantified social tie strength.

2.3. Personality-Aware Recommender Systems. In addition to recommender systems in domains such as personalized travel [40], wireless networks [41], data-driven clustering [42], and anchors on live streaming platforms [43], personality-aware recommender systems have shown great success in identifying similar users based on their personality types. In relation to personality-aware recommendations in the domains of education and academia, many researchers have worked in this area. Specifically, some researchers have used personality traits for course/programme recommendations, conference attendee recommendations, and research paper recommendations.

Xia et al. [10] proposed a recommender algorithm called social and personality aware recommendation of participants (*SPARP*). In the context of a smart conference, *SPARP* linearly hybridizes interpersonal relationships and personality traits among academic conference participants. Initially, *SPARP* computes the social ties of participants based on past and present social ties from the dataset. Then, the personality similarity between the conference participants based on explicitly tagged data from the personality ratings is also computed, and the hybridization of these entities is used to generate participant recommendations. Similar to [10], Asabere et al. [9] proposed a recommender algorithm for conference attendees called personality and socially aware recommender (*PerSAR*). *PerSAR* is based on a hybrid approach of social relations and personality characters of the conference participants.

To improve academic choice for newly enrolled students, Uddin et al. [44] proposed a personality-aware recommendation model. Their proposed recommendation model makes use of predicting educational relevance for an efficient classification of talent, which uses stochastic probability distribution modeling to help the student to choose the relevant academic field. Similar to [44], Elahi et al. [45] proposed a novel active learning (AL) approach that exploits the user's personality—using the five-factor model (FFM). They evaluated their approach in a user study by integrating it into a mobile, context-aware recommender system that provides users with recommendations for places of interest (POIs). Similar to [44, 45], Hariadi and Nurjanah [46] proposed a personality-aware book recommendation system that combines the attributes and personality traits of users. The proposed system in [46] leverages the MSV-MSL (most similar visited material to the most similar learner) method to compute the similarity between users and form the personality neighborhood.

The related studies described above illustrate that some notable research work has been conducted by various researchers on personality-aware recommendations in education. However, in this rapidly advancing area, the exploitation of entities involving a combination of CF, tie strength, and personality remains a vacuum. This paper, therefore, employs these entities to generate tertiary programme recommendations. To the best of relevant knowledge in the education and academia domains, this is the first time such entities are being utilized.

3. Proposed *CoSPARP* Solution

In this section, the framework and proposed solution involving the *CoSPARP* method are presented. Figure 1 depicts the basic recommendation procedure of *CoSPARP* and Figure 2 illustrates the recommendation framework of *CoSPARP*. *CoSPARP's* framework and recommendation process can be broken into three major steps: (i) computation of rating-based similarity of users, i.e., tertiary programme applicants (*TPAs*), through the CF Pearson correlation; (ii) computation of the tie strength of *TPAs;* and (iii) computation of personality similarity of *TPAs*.

In the first step, the CF Pearson correlation process CF identifies the most similar users to form "neighbors" for a target *TPA*. The main issue is how similarities between *TPAs* can be accurately measured? In the literature, various similarity measures have been proposed by researchers [6, 17]. Among different similarity-measuring processes, the Pearson correlation coefficient is one of the most commonly adopted similarity measures. Accordingly, the proximity between TPA_1 and TPA_2 is computed as [6, 17]:

$$SimCF(c,d) = \frac{\sum_{i\in I}\left(r_{c,i} - \overline{r}_c s\right)\left(r_{d,i} - \overline{r}_d\right)}{\sqrt{\sum_{i\in I}\left(r_{c,i} - \overline{r}_c\right)^2}\sqrt{\sum_{i\in I}\left(r_{d,i} - \overline{r}_d\right)^2}}. \quad (1)$$

In equation (1), TPA_1 and TPA_2 are represented as c and d, respectively. Therefore, the similarity between TPA_1 and TPA_2 is denoted by $SimCF(c, d)$. The ratings of c and d for item i (where $i \in I$ and I is the set of items) are denoted by $r_{c,i}$, and $r_{d,i}$, respectively. The average ratings of c and d are denoted by $\overline{r}_c$ and $\overline{r}_d$, respectively [6, 17].

In the second step, using equation (2), we measure and estimate the tie strength (*TS*) between TPA_1 and TPA_2, denoted as c and d, respectively. In equation (2), $d_{c,d}(t)$ is the contact duration between TPA_1 and TPA_2 in the time frame T, and $\lambda_{c,d}$ is their contact frequency (i.e., the number of times TPA_1 and TPA_2 have been in contact within the time frame T) [8–10].

$$TS_{c,d}(t) = \frac{\left(\lambda_{c,d} \times d_{c,d(t)}\right)}{T}. \quad (2)$$

In the third step, the the field of personality is explored and the personality similarities of TPAs are computed using equation (3). The exploration revealed that the Big Five Personality Traits (BFPT) [7, 9, 10], as shown in Figure 3 are very reliable and dependable in this regard. BFPT involves the following:

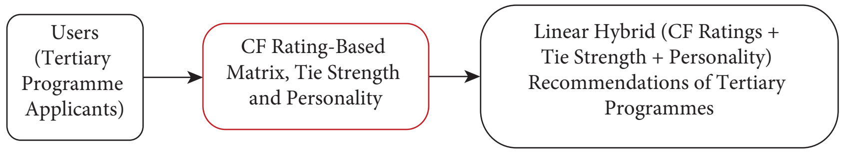

Figure 1: Basic recommendation procedure of CoSPARP.

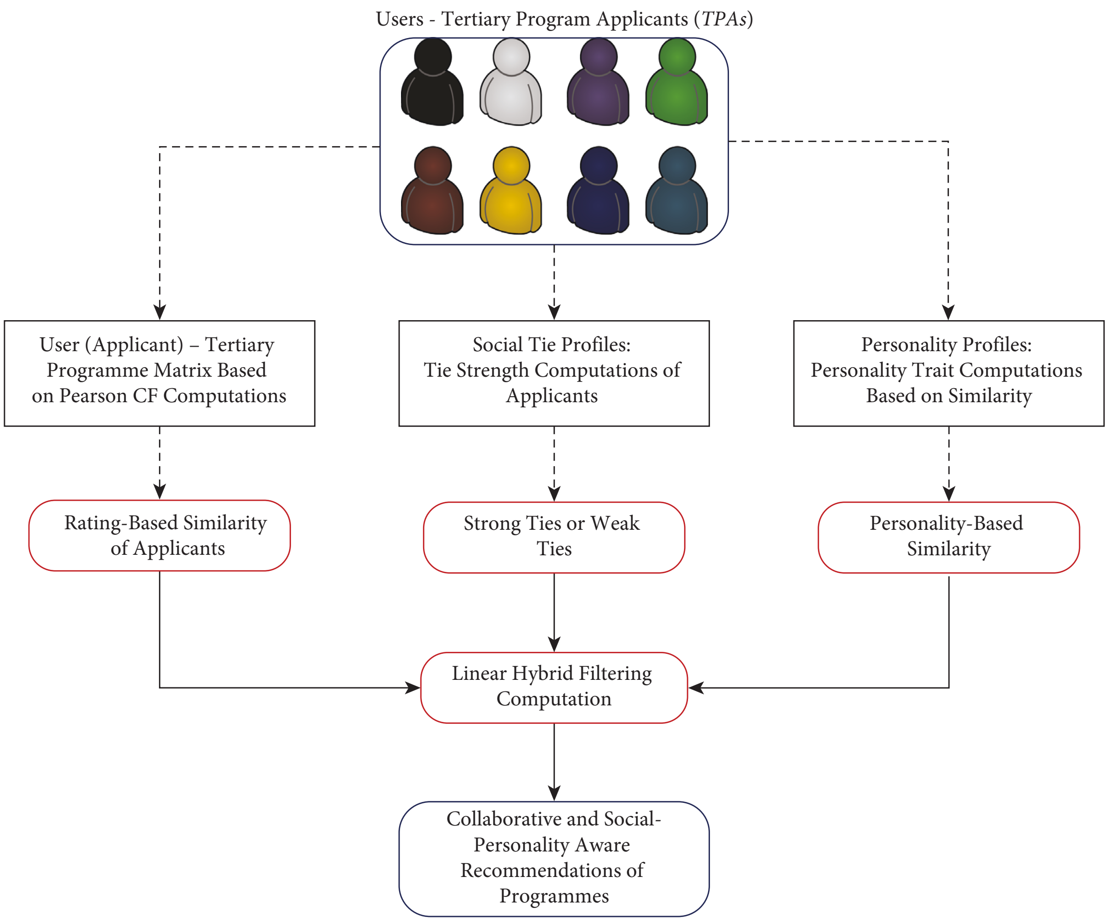

Figure 2: Recommendation framework of *CoSPARP*.

(i) Agreeableness: this domain represents a person's cooperativeness, trust level, generousity, willingness to help, and nurturing. (ii) Conscientiousness: this domain denotes a person's preservation ability, organization, and responsibility level. (iii) Extroversion: this domain means that a person is unreserved, active, sociable, outgoing, assertive, and amicable. (iv) Neuroticism (emotional stability): the domain signifies how a person is not moody, easily stressed, easily upset, self-confident, and relaxed (v) Openness to Experience: this domain means that a person is unconventional, open-minded, creative, reflective, and curious [7, 9, 10].

Equation (3) below computes the personality similarity between TPA_1 and TPA_2 represented as c and d using their personality trait ratings) [7, 9, 10, 17].

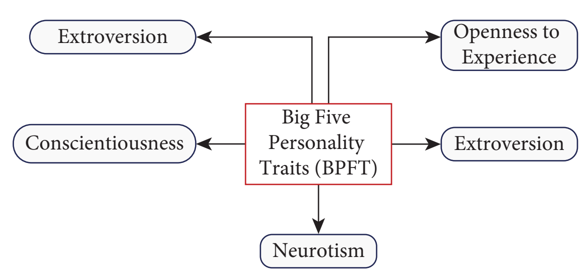

Figure 3: BFPT.

$$PSim(c,d) = \frac{\sum_{l\in L}\left(P_c^l - \overline{p}_c\right)\left(p_d^l - \overline{p}_d\right)}{\sqrt{\sum_{l\in L}\left(P_c^l - \overline{p}_c\right)^2}\sqrt{\sum_{l\in L}\left(p_d^l - \overline{p}_d\right)^2}}. \quad (3)$$

In equation (3), the average of all personality trait ratings for c and d are represented by $\overline{p}_c$ and $\overline{p}_d$, respectively. Furthermore, the personality trait ratings of c and d with one of the personality traits l are denoted by P_c^l and P_d^l respectively [7, 9, 10, 17].

3.1. Linear (Weighted) Hybrid Recommendation. One intuitive way to combine personality with ratings in the framework of CF and tie strength is to linearly integrate them into one similarity measure. More specifically, the similarity between $TPA_1(c)$ and $TPA_2(d)$ is computed using

$$Sim(c,d) = \lambda * SimCF(c,d) + (1-\lambda) * PSim(c,d)$$
&9; $$+TS_{c,d}(t) \tag{4}$$

In equation (4), $SimCF(c, d)$, $PSim(c, d)$, and $TS_{c,d}(t)$, respectively represent the item-based similarity, personality-based similarity, and the tie strength between $TPA_1(c)$ and $TPA_2(d)$. Additionally, λ is a weight parameter that controls the percentage of the contribution the rating-based similarity makes to the final similarity measure. During the experimentation procedure, equation (5) is set to automatically adapt to the sparsity level of a dataset. (Algorithm 1)

Specifically, when rating data is reliable enough to make a prediction, λ is highly weighted, and vice versa. The experimental procedure slightly inclines towards the personality-based similarity measure by introducing a constant multiplier of 0.6 to reduce the relative weight of the rating-based similarity. The value is chosen based on experimental pretrials.

$$\lambda = \frac{0.6 * |I_c \cap I_d|}{|I_c \cap I_d| + 5}. \tag{5}$$

Furthermore, to set a viable threshold for equation (4), the experimentation procedure employs a variable α in equation (6), which enables the attainment of reliable linear hybrid recommendations for *TPAs*. The algorithm (pseudocode) for the *CoSPARP* recommendation framework is depicted above in Algorithm 1.

$$Sim(c,d) \geq \alpha. \tag{6}$$

In the *CoSPARP* algorithm (Algorithm 1), relevant variables are declared in steps 1–4, and the computations and hybridization of item-based similarity, personality-based similarity, and the tie strength concerning *TPAs* are shown in steps 5–14. The generation of linear hybrid recommendations related to attendees at a smart conference is depicted in steps 15–21, which are the final steps of the *CoSPARP* algorithm (Algorithm 1).

4. Performance Evaluation of CoSPARP

To verify the performance of the proposed *CoSPARP* method, a series of scientific experiments were conducted through benchmark comparison with other (relevant and contemporary) state-of-the-art methods. In addition to authenticating the overall performance of *CoSPARP*, during the experimentation procedure, questions relating to when and how personality and tie strength profiles can work effectively on making predictions in a cold-start (unavailability of rated items and users who have not rated) situation were the main issues to verify and authenticate.

4.1. Experimental Data. The dataset utilized in this paper involves relevant data collected from selected final-year high school students in Accra, Ghana. The *CoSPARP* dataset utilized contains a total of 4396 *TPAs* (2421 males representing 55.07% and 1975 females representing 44.93%). The *CoSPARP* dataset also contains the tie strength data, which comprises computations of contact frequencies (Figure 4) and contact duration (Figure 5) of ATU students (users). The ATU dataset also comprises personality trait ratings (scale of 1 to 5) of all users per the Big Five Personality Traits (BFPT). The total number of personality ratings for all the traits combined in the ATU dataset is 22,541.

Figure 6 illustrates the personality traits data utilized in the *CoSPARP* dataset for experimentation. Additionally, to ensure and substantiate recommendation accuracy in the experimental procedure, the tertiary programme interests of *TPAs* per the following were gathered: Science and Engineering related tertiary programmes (*Computer Science, Applied Mathematics and Statistics, Medical Laboratory Science, Electrical Engineering, and Mechanical Engineering*); Humanities and Arts related tertiary programmes (*Accounting and Finance, Marketing, Procurement, Economics, and Public Administration*); Tables 1 and 2 illustrate data regarding the tertiary programme interests of *TPAs* in the *CoSPARP* dataset in accordance to their ratings.

4.2. Evaluation Metrics. In accordance with equations (7)–(9), *precision* (*P*), *recall* (*R*), and *F-measure* (*F*1) were utilized to initially evaluate the recommendation quality of the proposed *CoSPARP* method. *A*, *R*, and *F*1 are defined as follows [6, 47]:

$$P = \frac{Good\,Tertiary\,\text{Programmes}\,\text{Recommended}}{All\,Good\,\text{Recommendations}}, \tag{7}$$

$$R = \frac{Good\,Tertiary\,\text{Programmers}\,\text{Recommended}}{All\,Good\,Tertiary\quad\text{Programmes}}, \tag{8}$$

$$F1 = \frac{2 \times P \times R}{P + R}. \tag{9}$$

Furthermore, in accordance with equations (10) and (11), mean absolute error (*MAE*) and normalized MAE (*NMAE*) were employed to evaluate the prediction accuracy of the proposed *CoSPARP* method. MAE and NMAE are defined as follows [6, 47]:

$$MAE = 1 - Accuracy, \tag{10}$$

$$\text{NMAE} = \frac{\text{MAE}}{\text{r}_{\text{max}} - \text{r}_{\text{min}}}. \tag{11}$$

Higher resulting values of and equations (7)–(9) corroborate the favourable performance of a particular

```
//Declare and initialize variables
c, d, e, n and m; //integer variables
TS[n], PSim[n], SimCF[n] hybrid_sim[m], and threshold_val; //floating variables
TPAs[n]; //array of tertiary programme applicants of size n
For c = 0 to n
Increase c//c++
For d = 0 to n
Increase d//d++
Use equation (1) to compute SimCF and store in SimCF[n]
Use equation (2) to compute TS and store in TS[n]
Use equation (3) to compute PSim and store in PSim[n]
Use equation (4) to hybridize SimCF[c, d], TS[c, d] and PSim[c, d] and store in hybrid_sim[m]
End for
End for
//Linear hybrid recommendation
For e = 0 to m
Increase e
If (hybrid_sim[m] ≥ threshold_val) then
Generate hybrid recommendation
End if
End for
```

ALGORITHM 1: *CoSPARP* algorithm—pseudocode for linear hybrid recommendation of tertiary programmes.

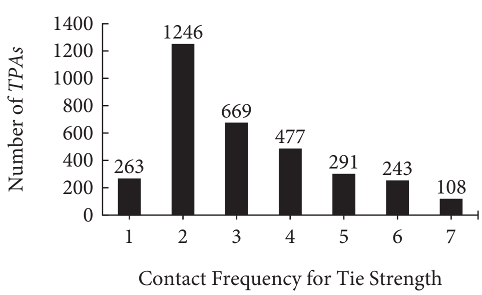

FIGURE 4: CoSPARP dataset–contact frequency trends.

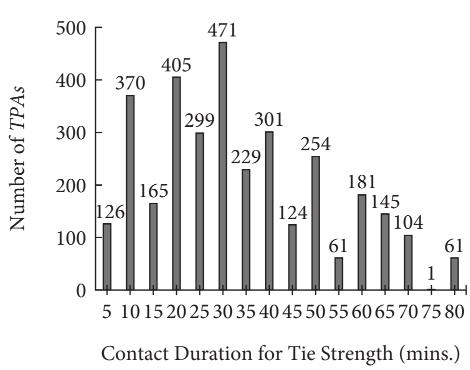

FIGURE 5: CoSPARP dataset–contact duration trends.

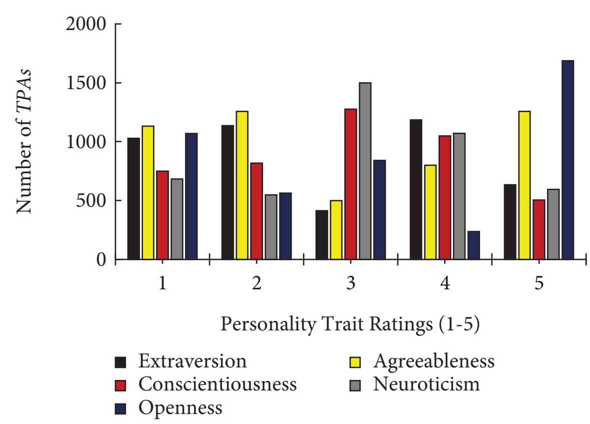

FIGURE 6: CoSPARP dataset–personality data.

TABLE 1: CoSPARP dataset–science and engineering related programmes ratings.

Tertiary programme	Ratings (1–5)				
	1	2	3	4	5
Computer science	1890	2139	85	170	112
Applied mathematics and statistics	167	1941	2039	146	1941
Medical laboratory science	114	108	1951	148	2075
Electrical engineering	120	1477	525	1702	572
Mechanical engineering	164	1805	129	2007	291
Total ratings	2456	7472	4732	4177	4996
Grand total of all ratings			**23,833**		

recommender algorithm. Furthermore, lower resulting values of equations (10) and (11) substantiate the favourable performance of a particular recommender algorithm.

4.3. Baseline Methods and Experimental Parameters. The experimental procedure in this paper involved the comparison of *CoSPARP* to the work in Bozyiğit et al. [21], and Gulzar et al. [27] where TP_1 and TP_2 represent these methods, respectively. As stated in Section 2, both TP_1 and

Table 2: CoSPARP dataset–arts and humanities related programmes ratings.

Tertiary programme	Ratings (1–5)				
	1	2	3	4	5
Accounting and Finance	1975	0	0	0	2421
Marketing	1381	594	2421	0	594
Procurement	2978	108	570	148	592
Economics	1381	0	594	1483	938
Public administration	1381	2077	0	938	0
Total ratings	9097	2781	3588	2573	4550
Grand total of all ratings			**22,589**		

TP_2 methods provide programme recommendations through CF and hybrid-filtering processes, respectively, which are fairly related to *CoSPARP*. This enabled an experimental comparison to be conducted between *CoSPARP*, TP_1, and TP_2.

During the experimental procedure, the computations of hybrid similarity ranged from 1.0 to 2.0. Therefore, linear hybrid computations ranging between 1.5 and 2.0 were used for testing and the rest of the computed data for training. During the experimental procedure, it was noticed that linear hybrid computation results of *TPA*s between 1.8 and 2.0 were more reliable and favourable for effective attendee recommendations. The above range was therefore used as a threshold to corroborate recommendation accuracy and quality.

4.4. Experimental Results and Analysis. In the experimentation procedure, "*Good Tertiary Programmes Recommended*" in equations (7) and (8), are categorized as *TPA*s that substantiate similar personality traits, user-based tertiary programme similarity, and high tie strength and, as such, fall within the linear hybrid similarity computation thresholds. Consequently, "*All Good Recommendations*" and "*All Good Tertiary Programmes*" are relative as a result of different entity ranges regarding linear hybrid recommendations in the dataset.

In relation to precision (P), illustrated in Figure 7, the experimental results of the linear hybrid computations of *CoSPARP* are more accurate, particularly at higher linear hybrid computations. With reference to Figure 7, at the highest linear hybrid computation (2.0), *CoSPARP* achieved the greatest precision (5%) in comparison to that of TP_1 (4%) and TP_2 (2%). Consequently, *CoSPARP* reduced more false positive (*fp*) errors in comparison to TP_1 and TP_2. These results in the experimental procedure substantiate the fact that *CoSPARP* demonstrates the ability to deliver more suitable and relevant tertiary programmes for *TPAs* in comparison to TP_1 and TP_2.

In terms of recall (R) depicted in Figure 8, the experimental results of the linear hybrid computations of *CoSPARP* are higher than those of TP_1 and TP_2. Furthermore, *CoSPARP* covered more appropriate tertiary programmes for effective recommendations and reduced more false negative (*fn*) errors. Referring to Figure 8, the highest linear hybrid computation (2.0) corresponds to *CoSPARP*

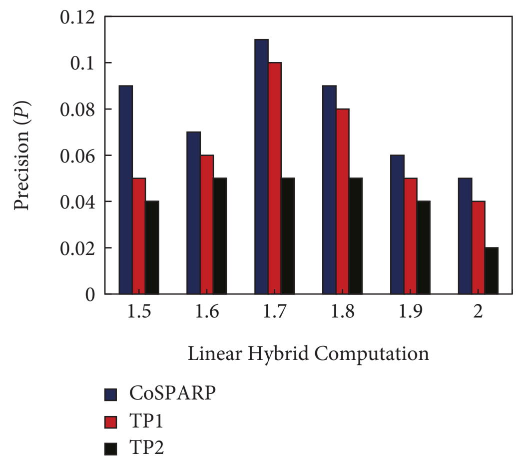

Figure 7: Precision performance on the dataset.

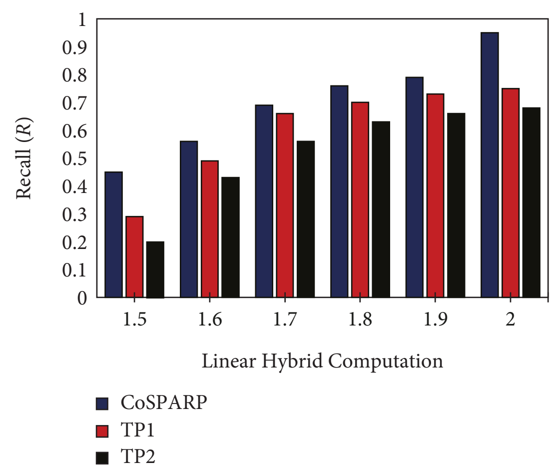

Figure 8: Recall performance on the dataset.

achieving the highest higher recall value of 95%, in comparison to TP_1 (75%), and TP_2 (68%). The experimental results, therefore, authenticate the fact that in comparison to TP_1 and TP_2, *CoSPARP* covers more dependable and appropriate tertiary programmes. Therefore, as illustrated in Figure 8, an increase in linear hybrid computation is connected to the rise of recall, and this validates *CoSPARP*'s strong ability to cover more relevant and appropriate tertiary programmes to generate effective recommendations for *TPAs*.

As stated above, the experimental procedure further involved the utilization of the F-measure ($F1$) evaluation metric. The results of $F1$ using equation (9) relate to the computation of recall and precision results in Figures 7 and 8, and were therefore computed. In terms of $F1$, experimental results in Figure 9 illustrate that *CoSPARP* is more robust and outperforms TP_1 and TP_2. Figure 10 demonstrates the NMAE evaluation results of *CoSPARP*, TP_1, and TP_2. Lower NMAE values of *CoSPARP*, as verifiable in Figure 10 corroborate its outperformance in comparison to TP_1 and TP_2. Figure 10, illustrates that *CoSPARP's* NMAE is

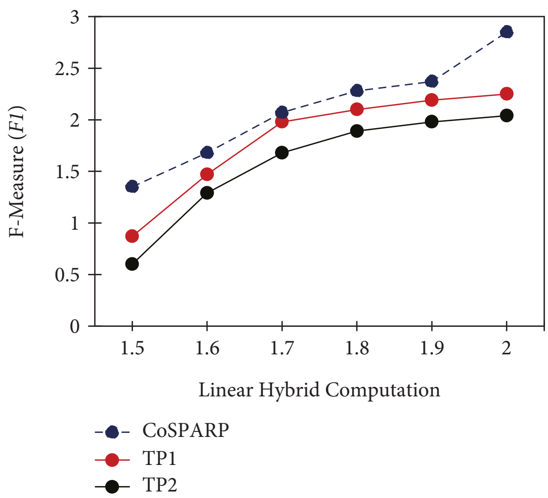

Figure 9: *F*-measure (*F*1) performance on the dataset.

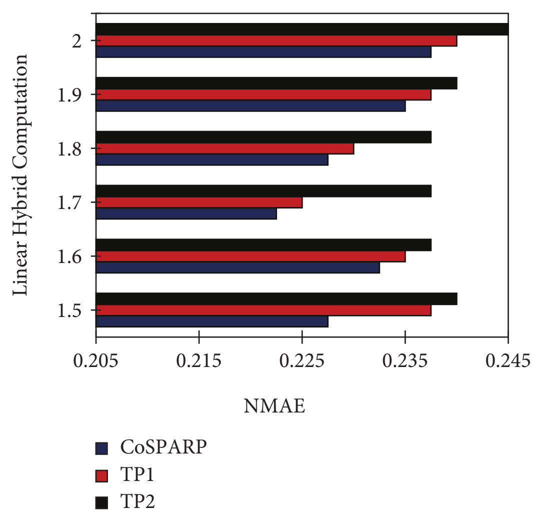

Figure 10: NMAE performance on the dataset.

23.75% at the highest linear hybrid computation (2.0), which is lower when compared to TP_1 (24%) and TP_2 (24.5%). Figure 11 also depicts that *CoSPARP's* MAE attained the lowest MAE (98%) in comparison to that of TP_1 (96%) and TP_2 (98%), at the linear hybrid computation of 2.0. Consecutive experimental results of MAE in Figure 11 further corroborate the effectiveness of *CoSPARP* in comparison to TP_1 and TP_2.

A summary of evaluation results relating to precision, recall, *F*1, MAE, and NMAE in terms of the utilized experimental thresholds for linear hybrid computations is presented in Tables 3 and 4. In Table 3, higher precision and recall substantiate outperformance. Concerning precision and recall, Table 3 depicts the apparent outperformance of *CoSPARP* in comparison to TP_1 and TP_2.

Furthermore, Table 3 illustrates that in all instances per row, TP_1 outperforms TP_2 and *CoSPARP* outperforms TP_1 in terms of precision and recall. Table 4 shows that the MAE and NMAE of *CoSPARP* are the lowest, which corroborates and signifies better performance. Additionally, with reference to Table 4, it can be comprehended that in all instances per row, TP_1 performs better than TP_2 and *CoSPARP* performs better than TP_1 in terms of MAE and NMAE. Therefore, the evaluation results corroborate that *CoSPARP* outperforms TP_1 and TP_2 in terms of MAE and NMAE. It can consequently be implied that the innovative hybridization of CF similarity, tie strength, and personality traits corroborate the outperformance of *CoSPARP*. In a social network, such an innovative hybridization can be used to achieve substantial knowledge from user and users clusters to achieve effective recommendation quality and accuracy in terms of tertiary programmes.

Additionally, from the results displayed in Figures 7–11, as well as Tables 3 and 4, it is evident that *CoSPARP* outperforms TP_1 and TP_2. The experimentation procedure also solved the cold-start problem by permitting effective linear hybrid recommendations (i.e., linear hybrid computations between 1.7 and 2.0) to be generated for *TPAs* who may not have rated tertiary programmes in the dataset but have similar personalities and high tie strengths.

5. Discussion

Globally, the process of selecting a higher education tertiary programme at a university is an immense decision for tertiary programme applicants (*TPAs*). Recommender systems in education play a significant role in overcoming the problem of information overload and big data and helping students to find relevant and useful tertiary programmes from the many resources that are available on the internet.

Despite the extensive prior research on hybrid recommendations in social networks, the combination of weights relating to user personalization and social property perspectives has been generally underutilized in the context of tertiary programme recommendation.

To address this gap, this paper proposed a new recommendation strategy for *TPAs* based on an implicit community of interest, prospectively producing more effective tertiary programme recommendations and positively diversifying the *TPAs*' social networks in terms of tertiary programmes through the tie strength, personality traits, and ratings of tertiary programmes by *TPAs*.

A summary of the experimental results provides empirical pieces of evidence that correspond to the fact that the leverage of personality and tie strength can indeed alleviate the cold-start problem existing in rating-based CF recommender systems relating to tertiary programmes.

Concerning the research questions, experimental results show that it is possible that an innovative linear hybridization of CF with personality traits and tie strength of tertiary education applicants can deal with the cold-start problem (due to a lack of sufficient ratings) and effectively provide a reliable recommendation of tertiary programmes through *CoSPARP*. Furthermore, these recommendation entities can work more successfully in tertiary programme recommendations when applicants effectively utilize their

Table 3: Experimental comparisons of precision and recall over the dataset.

Linear hybrid computation	Precision evaluation			Recall evaluation		
	TP_1 (%)	CoSPARP (%)	TP_2 (%)	TP_1 (%)	CoSPARP (%)	TP_2 (%)
1.8	8	**9**	5	70	**76**	63
1.9	5	**6**	4	73	**79**	66
2.0	4	**5**	2	75	**95**	68

Table 4: Experimental comparisons of MAE and NMAE over the dataset.

Linear hybrid computation	MAE evaluation			NMAE evaluation		
	TP_1 (%)	CoSPARP (%)	TP_2 (%)	TP_1 (%)	CoSPARP (%)	TP_2 (%)
1.8	92	**91**	95	23	**22.75**	23.75
1.9	95	**94**	96	23.75	**23.5**	24
2.0	96	**95**	98	24	**23.75**	24.5

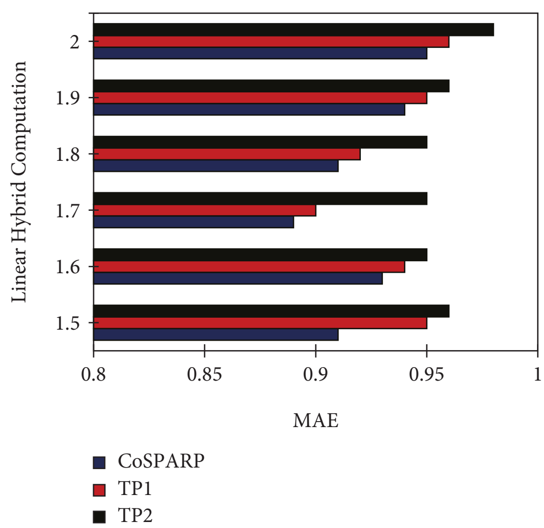

Figure 11: MAE performance on the dataset.

relationships in terms of the tie strength, personality traits, and tertiary programme ratings.

6. Concluding Remarks

In this paper, the novelty of the proposed recommendation strategy lies in linearly combining a computation of tertiary programmes ratings by *TPAs* with their corresponding personality traits and tie strengths. The findings illustrate that the proposed method *CoSPARP* outperforms baseline methods TP_1 and TP_2 in terms of precision, recall, $F1$, MAE, and NMAE, and that these methods are indeed distinct from each other concerning the above evaluation metrics. Throughout the experimental procedure, it was noticed that developing a new hybrid recommendation system that combines CF, personality traits, and the tie strength improves the information overload problem and solves cold-start-related issues relating to tertiary programmes.

In the future, the dataset repository in this paper has to be enriched by absorbing more tertiary programmes, user information, and heterogeneous data sources. Furthermore, there is a plan to integrate additional user contexts, for example, available student behavior, learning styles, and learning interests, into the *CoSPARP* recommendation process to make *CoSPARP* more intelligent and comprehensive.

Additionally, to consider more aspects and techniques related to *CoSPARP*, relevant feedback information from *TPAs* is vital for effective tertiary programme recommendations. Furthermore, in addition to considering online learning recommender systems using CF, personality traits, and the tie strength, there is a plan to conduct more experiments in *CoSPARP* with a variety of actual *TPAs* from different high schools from various academic backgrounds to prove its flexibility.

Data Availability

This manuscript's supplementary material consists of the utilized dataset and a video link as follows: which illustrates ideas, processes and content relating to the paper. (https://drive.google.com/file/d/1Fey-Dq5XCFXT1lU3dARUkKxlTbUCJEd3/view?usp=sharing).

Conflicts of Interest

The author declares that there are no conflicts of interest.

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Supplementary Materials

Supplementary materials and experimental datasets are given in the following link: (https://drive.google.com/file/d/1Fey-Dq5XCFXT1lU3dARUkKxlTbUCJEd3/view?usp=sharing). (https://docs.google.com/spreadsheets/d/1NBVeCjfpZ_JvThlGIhHgjGM4To0uHbQM/edit?usp=sharing&ouid=108807310463757292140&rtpof=true&sd=true). (*Supplementary Materials*)

References

[1] M. E. Ibrahim, Y. Yang, D. L. Ndzi, G. Yang, and M. Al-Maliki, "Ontology-based personalized course recommendation framework," *IEEE Access*, vol. 7, pp. 5180–5199, 2019.

[2] N. Y. Asabere and E. Amoako, "Improving career decision-making for high school students through a web-based expert system: field testing in Ghana," *International Journal of ICT Research in Africa and the Middle East (IJICTRAME)*, vol. 9, no. 1, pp. 1–23, 2020.

[3] M. E. Ibrahim, Y. Yang, and D. Ndzi, "Using ontology for personalized course recommendation applications," in *Proceedings of the International Conference on Computational Science and its Applications*, pp. 426–438, Springer, Cham, 2017.

[4] N. Y. Asabere, A. Acakpovi, E. O. Yeboah-Boateng, W. K. Torgby, and E. Amoako, "Towards career development for high school students: a case study of a web-based expert system in Ghana," in *Developing Countries And Technology Inclusion In the 21st Century Information Society, IGI Global*, pp. 56–86, 2021.

[5] F. Le Roux, E. Ranjeet, V. Ghai, Y. Gao, and J. Lu, "A course recommender system using multiple criteria decision-making method," in *Proceedings of the International Conference on Intelligent Systems and Knowledge Engineering*, pp. 1–5, Atlantis Press, 2007.

[6] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender systems survey. Knowledge-based systems," *Recommender systems survey*, vol. 46, pp. 109–132, 2013.

[7] N. Y. Asabere and A. Acakpovi, "ROPPSA: TV pgram recommendation based on personality and social awareness," *Mathematical Problems in Engineering*, vol. 2020, Article ID 1971286, 15 pages, 2020.

[8] N. Y. Asabere, B. Xu, A. Acakpovi, and N. Deonauth, "SARVE-2: exploiting social venue recommendation in the context of smart conferences," *IEEE Transactions on Emerging Topics in Computing*, vol. 9, no. 1, pp. 342–353, 2021.

[9] N. Y. Asabere, A. Acakpovi, and M. B. Michael, "Improving socially-aware recommendation accuracy through personality," *IEEE Transactions on Affective Computing*, vol. 9, no. 3, pp. 351–361, 2018.

[10] F. Xia, N. Y. Asabere, H. Liu, Z. Chen, and W. Wang, "Socially aware conference participant recommendation with personality traits," *IEEE Systems Journal*, vol. 11, no. 4, pp. 2255–2266, 2017.

[11] J. Wei, J. He, K. Chen, Y. Zhou, and Z. Tang, "Collaborative filtering and deep learning-based recommendation system for cold start items," *Expert Systems with Applications*, vol. 69, pp. 29–39, 2017.

[12] H. Zhang, H. Yang, T. Huang, and G. Zhan, "DBNCF: personalized courses recommendation system based on DBN in MOOC-environment," in *Proceedings of the IEEE International Symposium on Educational Technology*, pp. 106–108, ISET), 2017.

[13] N. Bendakir and E. Aïmeur, "Using association rules for course recommendation," in *Proceedings of the AAAI Workshop on Educational Data Mining*, pp. 1–10, 2006.

[14] H. Zhang, T. Huang, Z. Lv, S. Liu, and Z. Zhou, "MCRS: a course recommendation system for MOOCs," *Multimedia Tools and Applications*, vol. 77, no. 6, pp. 7051–7069, 2018.

[15] S. C. Wang and Y. Tanaka, "Topic-oriented query expansion for web search," in *Proceedings Of the 15th International Conference On World Wide Web*, pp. 1029-1030, 2006.

[16] C. Y. Huang, R. C. Chen, and L. S. Chen, "Course-recommendation system based on ontology," in *Proceedings of the IEEE International Conference on Machine Learning and Cybernetics*, pp. 1168–1173, 2013.

[17] R. Hu and P. Pu, "Enhancing collaborative filtering systems with personality information," in *Proceedings Of the 5th ACM International Conference On Recommender Systems*, pp. 197–204, 2011.

[18] M. Tkalčič, "Emotions and personality in recommender systems: a tutorial," in *Proceedings Of the 12th ACM International Conference On Recommender Systems*, pp. 535-536, 2018.

[19] A. Felfernig, L. Boratto, M. Stettinger, and M. Tkalčič, "Personality, emotions, and group dynamics," in *Group Recommender Systems*, pp. 157–167, Springer, Cham, 2018.

[20] Y. Li, L. Mei, and J. Wang, "A personalized recommendation system in E-Learning environment based on semantic analysis," in *Proceedings Of 6th IEEE International Conference On New Trends In Information Science*, pp. 802–807, Service Science and Data Mining, 2012.

[21] A. Bozyiğit, F. Bozyiğit, D. Kilinç, and E. Nasiboğlu, "Collaborative filtering based course recommender using OWA operators," *(SIIE)*, in *Proceedings of the IEEE International Symposium on Computers in Education*, pp. 1–5, 2018.

[22] N. N. Qomariyah and A. N. Fajar, "Recommender system for e-learning based on personal learning style," in *Proceedings of the IEEE International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, pp. 563–567, 2019.

[23] C. K. Hsu, G. J. Hwang, and C. K. Chang, "A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students," *Computers & Education*, vol. 63, pp. 327–336, 2013.

[24] D. Rodriguez-Cerezo, M. Gomez-Albarr, and J. L. Sierra, "Supporting self-regulated learning in technical domains with repositories of learning objects and recommender systems," in *Proceedings Of the 11th IEEE International Conference On Advanced Learning Technologies*, pp. 613-614, 2011.

[25] H. Samin and T. Azim, "Knowledge based recommender system for academia using machine learning: a case study on higher education landscape of Pakistan," *IEEE Access*, vol. 7, pp. 67081–67093, 2019.

[26] A. Garrido, L. Morales, and I. Serina, "On the use of case-based planning for e-learning personalization," *Expert Systems with Applications*, vol. 60, pp. 1–15, 2016.

[27] Z. Gulzar, A. A. Leema, and G. Deepak, "Pcrs: personalized course recommender system based on hybrid approach," *Procedia Computer Science*, vol. 125, pp. 518–524, 2018.

[28] M. S. Granovetter, "The strength of weak ties," *American Journal of Sociology*, vol. 78, no. 6, pp. 1360–1380, 1973.

[29] E. Huszti, B. Dávid, and K. Vajda, "Strong tie, weak tie and in-betweens: a continuous measure of tie strength based on contact diary datasets," *Procedia-Social and Behavioral Sciences*, vol. 79, pp. 38–61, 2013.

[30] N. Y. Asabere and A. Acakpovi, "ROVETS: search based socially-aware recommendation of smart conference sessions," *International Journal of Decision Support System Technology*, vol. 11, no. 3, pp. 30–46, 2019.

[31] O. Arazy, N. Kumar, and B. Shapira, "A theory-driven design framework for social recommender systems," *Journal of the Association for Information Systems*, vol. 11, no. 9, pp. 455–490, 2010.

[32] O. Arazy, I. Elsane, B. Shapira, and N. Kumar, "Social relationships in recommender systems," in *Proceedings Of the*

17th Workshop On Information Technologies & Systems, pp. 1–6, 2007.

[33] O. Oechslein and T. Hess, "The value of a recommendation: the role of social ties in social recommender systems," in *Proceedings Of the 47th IEEE International Hawaii Conference On System Sciences*, pp. 1864–1873, 2014.

[34] F. Carmagnola, F. Vernero, and P. Grillo, "Sonars: a social networks-based algorithm for social recommender systems," in *Proceedings of the International Conference on User Modeling, Adaptation, and Personalization*, pp. 223–234, 2009.

[35] C. Z. Felıcio, K. V. Paixão, G. Alves, and S. de Amo, "Social prefrec framework: leveraging recommender systems based on social information," in *Proceedings Of the 3rd Symposium On Knowledge Discovery*, pp. 66–73, Mining and Learning, 2015.

[36] F. Liberatore and L. Quijano-Sanchez, "What do we really need to compute the Tie Strength? An empirical study applied to Social Networks," *Computer Communications*, vol. 110, pp. 59–74, 2017.

[37] Y. Zhong, J. Yang, and R. Nugroho, "Incorporating tie strength in robust social recommendation," in *Proceedings of the IEEE International Congress on Big Data*, pp. 63–70, 2015.

[38] X. Wang, W. Lu, M. Ester, C. Wang, and C. Chen, "Social recommendation with strong and weak ties," in *Proceedings Of the 25th ACM International On Conference On Information And Knowledge Management*, pp. 5–14, 2016.

[39] L. Chen, C. Shao, and P. Zhu, "Social recommendation using quantified social tie strength," in *Proceedings Of the 7th International Conference On Advanced Computational Intelligence (ICACI)*, pp. 84–88, 2015.

[40] P. Nitu, J. Coelho, and P. Madiraju, "Improvising personalized travel recommendation system with recency effects," *Big Data Mining and Analytics*, vol. 4, no. 3, pp. 139–154, 2021.

[41] T. Li, C. Li, J. Luo, and L. Song, "Wireless recommendations for Internet of vehicles: recent advances, challenges, and opportunities," *Intelligent and Converged Networks*, vol. 1, no. 1, pp. 1–17, 2020.

[42] Y. Tian, R. Zheng, Z. Liang, S. Li, F.-X. Wu, and M. Li, "A data-driven clustering recommendation method for single-cell RNA-sequencing data," *Tsinghua Science and Technology*, vol. 26, no. 5, pp. 772–789, 2021.

[43] S. Zhang, H. Liu, J. He, S. Han, and X. Du, "Deep sequential model for anchor recommendation on livestreaming platforms," *Big Data Mining and Analytics*, vol. 4, no. 3, pp. 173–182, 2021.

[44] M. F. Uddin, S. Banerjee, and J. Lee, "Recommender system framework for academic choices: personality based recommendation engine (PBRE)," in *Proceedings Of the 17th IEEE International Conference On Information Reuse And Integration (IRI)*, pp. 476–483, 2016.

[45] M. Elahi, M. Braunhofer, F. Ricci, and M. Tkalcic, "Personality-based active learning for collaborative filtering recommender systems," in *Proceedings of the Congress of the Italian Association for Artificial Intelligence*, pp. 360–371, 2013.

[46] A. I. Hariadi and D. Nurjanah, "Hybrid attribute and personality based recommender system for book recommendation," in *Proceedings of the IEEE International Conference on Data and Software Engineering (ICoDSE)*, pp. 1–5, 2017.

[47] F. Hernández del Olmo and E. Gaudioso, "Evaluation of recommender systems: a new approach," *Expert Systems with Applications*, vol. 35, no. 3, pp. 790–804, 2008.