A Personality Matching-aided Approach for Supervisor Recommendation (research-in-progress)

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Abstract

In educational field, finding a suitable supervisor is vitally important for a student’s research career. Students can acquire dynamic and continuous knowledge from supervisors. With the rapid proliferation of information technologies, there is amount of online information available for students. It poses challenges for them to quickly find relevant and useful information. Supervisor recommendation is a novel way to provide support for students to select appropriate dynamic knowledge resources. Current methods mainly mine the matching of objective information but pay scant attention on subjective personality matching which is crucial for effective communications among individuals. In this study, we propose a personality matching-aided recommendation approach to facilitate supervisor selections. Furthermore, the student-supervisor recommendation service has been implemented on ScholarMate1 which is a research social network platform. A preliminary user study is designed to evaluate the proposed method. The results show that our approach outperforms three baseline methods.

1. Introduction

With the rapid development of information technologies in Web 2.0 era, the proliferation of available information generates more and more challenges for students to find relevant information. When students encounter a problem, they tend to seek for useful online information or ask for help from experienced friends. Therefore, it is important for inexperienced students to find effective ways to discover relevant information. An alternative way is to find a supervisor with relevant expertise to address the student’s problem or deal with his tasks. Appropriate supervisors are personalized and dynamic knowledge sources for students [1]. Approaching supervisors is investigated to be an effective method for knowledge acquisition [2]. Additionally, finding a suitable supervisor is an important task for the students pursuing postgraduate studies. According to the data from China Education Yearbook, there are 611381 new students pursuing postgraduate educations in 2013. It is an increase of 3.68% comparing with the number in 2012. However, there are challenges for the inexperienced students to make sensible decisions of supervisor selections. Supervisor recommendation is an alternative way to finding suitable candidates for students. It helps to reduce time cost and facilitates the selections.

As manual matching methods are time-consuming and defective, researchers put forward several methods for supervisor selections in the existing studies, such as analytical hierarchy process (AHP) [3], multi-criteria decision making (MCDM) [4], and analytic network process (ANP) [5]. They mainly focus on the matching of relevance-based information and quality-based information which are named as objective measurements, such as research expertise, research interests, research backgrounds and so on. However, they do not pay enough attention on the matching of personalities between a supervisor and a student. Solid evidence shows that

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1 www.scholarmate.com
subjective characteristic plays a crucial role in two persons’ communications [6]. In this work, we intend to fill this research gap and put forward a personality matching-aided approach for online supervisor recommendation services.

The main advantages of this work can be summarized as follows. Firstly, we put forward a personality matching-aided approach to actively recommend suitable supervisors for students. It overcomes the deficiency in the existing studies which mainly focus on objective measurements and do not emphasize subjective personality matching. Secondly, in order to obtain users’ different perceived importance on different information dimensions, we design an interaction process by asking user questions on the online system. The different preferences are leveraged in the aggregation process of the designed algorithms. Thirdly, the student-supervisor recommendation service has already been carried out on ScholarMate currently.

The remainder of this paper is organized as follows. In Section 2, related literature is reviewed. In Section 3, the proposed approach is presented in details. In Section 4, a preliminary user study is designed to evaluate the method and the results are presented and analyzed. In Section 5, the conclusions are summarized. The limitations and future works are presented as well.

2. Literature review

In this section, the importance of suitable matching between students and supervisors are summarized from the existing studies firstly. Secondly, the extant approaches are reviewed and their shortcomings are pointed out. Thirdly, we emphasize the importance of personality matching between a student and a supervisor. We briefly summarize the research gaps and intend to present our approach in details in the next section.

People-to-people recommendation is an important research field in the studies of recommendation system. The typical contexts include friend recommendation [7], collaborate recommendation [8], expert recommendation [9, 10], employee-employer finding on job-searching websites [11, 12], dating partner matching on online dating websites [13, 14], and mentor-mentee selection [15]. Student-supervisor recommendation belongs to the research field of people-to-people recommendation.

Admittedly, supervisors play a crucial role for the students who pursue postgraduate educations. The extant studies show that the match or mismatch between students and supervisors is significant for student-supervisor relationships and it has an effect on students’ achievements [16]. Several studies further verify that the mismatch has a negative effect on students’ academic performances [17]. The inexperienced students’ blind decisions are the reasons to explain the mismatching phenomenon. In order to support students to make sensible selections, researchers propose multiple systematic methods in the extant studies.

Table 1 summarizes some selected related studies on the problem of student-supervisor selection. In regards to the current methods for supervisor selections, there are analytic hierarchy process (AHP) [3], multiple criteria decision method (MCDM) [4], analytic network process (ANP) [5], generic algorithm [18] and so on. Furthermore, the information retrieval techniques are also utilized to solve the matching problem [19]. It extracts keywords from a supervisor’s published materials to represent him/her. Then, it calculates their similarity by measuring the frequency and proximity between query terms and keywords. It is a traditional information retrieval method and it pays much attention to the typed query terms from students. However, the typed query terms merely show students’ research interests. There are some other important information which is not considered, such as students’ previous knowledge backgrounds and the degree of personality matching with supervisors. Some researchers respectively make use of the ANP method and the AHP method to solve the matching problem [3, 5]. However, a major deficiency is that they are passive for target students. For example, the students have to compare the importance among different criteria by marking with 1-9 scale when they intend to utilize the methods. Obviously, it is difficult for students to do the comparing business as they are not experienced enough to make sensible decisions. These two methods [3, 5] are mainly for dealing with the selection of a thesis supervisor. They are effective to make decisions among a finite number of choices. In addition, several researchers adapt the MCDM approach and design a strategic method to facilitate supervisor selections [4]. However, it merely pays attention on supervisor-sided quality evaluation but neglects some other important factors, such as the similarity degree of students’ potential research interests and supervisors’ research expertise. Furthermore, some authors apply the generic algorithm to deal with the selection problem [18]. They map the task of student-supervisor assignment as an optimization problem. They consider demographic features, academic resume, skills and characteristics such as team working. However, the proposed method ignores the
importance of personality matching between a student and a supervisor. Furthermore, it merely considers the relevance-related and quality-related criteria, but neglects social connections. Subjective characteristics, such as personality styles, play a crucial role in interactions between two persons [6]. In the research study of Sojen, et al. [6], the authors find that subjective criteria such as personality and attitude are important for the communication process among patients and doctors. Therefore, the authors consider the subjective criteria in their healthcare recommendation systems. It is observed that the personality matching is important for individuals’ interactive communications. The existing studies show that ‘meeting of minds’ between two persons can facilitate their effective communications [20]. Oppositely, the mismatching of personalities may cause miscommunication between two individuals. The student-supervisor relationship is a specific collaboration relationship. The relationship is not short-lived and it lasts for a period of time. The personality matching between a student and a supervisor is significantly crucial, which should not be neglected during selection processes. Previous studies pay more attention on objective measurements, while not pay enough attention on subjective personality matching. To fill the research gap discussed above, we focus on designing a personality matching-aided recommendation approach. The details of our proposed method are presented in the next section.

3. Personality matching-aided recommendation approach

The framework of our proposed method is shown in Figure 1. There are two main aspects in our method. The first aspect is called as objective measurements which are consisted of relevance dimension, connectivity dimension, and quality dimension [21]. Meanwhile, the second aspect is called as subjective personality matching which is measured by a typical questionnaire named Mini-International Personality Item Pool (Mini-IPIP) [22]. Then, the respective scores from different dimensions are integrated in order to obtain a final ranking list. A Q&A interaction process is designed to extract users’ different perceived importance towards different dimensional information. Thus, the obtained preferences are leveraged in the process of aggregation. Subsequent sections present the approach further in details.
3.1. Objective measurements: research analytics framework

In our previous work, we define and formalize a research analytics framework (RAF) [21, 23] to profile researchers on a research social networking website named ScholarMate. The RAF consists of three dimensions: relevance, connectivity and quality. Firstly, the relevance analysis plays a role in filtering out irrelevant candidates based on discipline-supervised semantic relevance matching. Secondly, the obtained candidates are analyzed by the connectivity measurement as well. The connectivity analysis calculates their common links (common friends and groups) on virtual social networks. Meanwhile, the candidates are measured by the quality analysis. The quality measurements estimate the candidates’ research outputs. Thus, three dimensional scores are received through the analyses of the research analytics framework. The details in every dimensions are described in the following subsections.

Researchers’ profiles can be constructed by self-claimed information and extracted information from related research activities [24]. The self-claimed information is declared by researchers themselves, such as self-claimed research interests, and self-claimed research expertise. Usually, they are represented by structured keywords. However, we do also consider the extracted information from research activities in order to promise the accuracy of users’ profiles. In research field, teaching courses, publishing papers and applying for projects are three main research activities for all teachers. They are main evidences to recognize a researcher’s expertise. Therefore, we utilize a researcher’s historical taught courses, publications and funded projects to represent his profile. For students, we also construct their profiles through two parts: self-claimed information such as declared research interests, and extracted information from related research activities such as majors, passed courses and interested references.

3.1.1. Relevance dimension: discipline-supervised semantic relevance matching. In the process of the relevance analysis, we follow the principle of the discipline-supervised semantic relevance matching. Firstly, the hierarchy of disciplines is constructed according to the discipline category from the Chinese Ministry of Education (MOE) (www.moe.gov.cn). Thus, we can calculate the similarity of a supervisor’s department and a student’s major by making use of the category tree method [25]. The discipline similarity of a supervisor $s_i$ and a student $t_j$ can be obtained by the following equation.

$$\text{sim}(c_i', c_j') = 2 \cdot \frac{d(LCS(c_i', c_j'))}{d(c_i') + d(c_j')}$$ (1)

Where, $c_i'$ (resp. $c_j'$) represents a student’s major (resp. a supervisor’s department), $d(x)$ measures the length from the root to the target concept. Furthermore, $LCS(c_i', c_j')$ denotes the least common subsume between $c_i'$ and $c_j'$.

Next, we employ a semantic keyword matching method [26, 27] to calculate the matching degree on relevance dimension. Firstly, a keyword-document (KD) matrix is constructed. It is a $n_k \times n_d$ matrix whose $n_k$ is the number of keywords and $n_d$ is the number of documents. It represents the association between keywords and documents. Keyword correlation matrix is constructed based on a mutual reinforcement principle method [26] which is an iterative process to measure similarities. The similarity between two objects is based on the similarity values which are computed in the previous iteration. As described in a previous study [26], the mutual reinforcement factor assigns higher relevance to the keywords which represent the very same documents and the documents which are represented by the very same keywords. A student’s profile is expanded with five most relevant keywords. The enriched profile facilitates the further process of matching. Thus, the Equation (2) shows the semantic keyword similarity between a student’s profile and a supervisor’s profile. Finally, the discipline-supervised semantic keyword similarity between a student and a supervisor is aggregated by multiplying the two parts, which is shown in the Equation (3).

$$MD_k(s_i, t_j) = \sum_{m=1}^{n_d} TF_{u_i}(m) \cdot TF_{v_j}(m) \cdot \text{sim}(m)$$ (2)

$$R(s_i, t_j) = \text{sim}(c_i', c_j') \cdot MD_k(s_i, t_j)$$ (3)

Where, $s_i$ represents a student and $t_j$ represents a supervisor. $TF_{u_i}(m)$ (resp. $TF_{v_j}(m)$) denotes the
frequency score of keyword $m$ in the student’s profile (resp. the supervisor’s profile); $sim(m)$ shows whether keyword $m$ is an original keyword or an expanded keyword. If it is the original keyword, $sim(m) = 1$. Otherwise, $sim(m)$ is the value in the keyword correlation matrix. $R(s, t_i)$ is the final score in the relevance dimension.

3.1.2. Connectivity dimension. The online interactions between students and supervisors are also mined from virtual social networks and are considered in our proposed methods. The acceptance probability of a student towards a recommended supervisor will be higher when they share more common links (such as friends, participated groups etc.) than others [28]. Expression (4) respectively represents every student’s and supervisor’s friend networks. Meanwhile, Expression (5) respectively shows their participated groups. The connectivity value is calculated by Expression (6). It should be normalized by the sum of all the candidates’ values on this dimension.

$$<s, f_1', f_2', f_3', ..., > <t, f_1', f_2', f_3', ..., >$$  \hspace{1cm} (4)

$$<s, g_1', g_2', g_3', ..., > <t, g_1', g_2', g_3', ..., >$$  \hspace{1cm} (5)

$$C(s, t_i) = \sum_{j=1}^{n_{friend}} x_{ij}y_{ij} + \sum_{j=1}^{n_{group}} x_{ij}y_{ij}$$  \hspace{1cm} (6)

Where, $s_i$ represents a student and $t_j$ represents a supervisor. $n_{friend}$ is the total number of $s_i$’s and $t_j$’s friends. $x_{ij}y_{ij}$ is equal to 1 when a user is a common friend of $s_i$ and $t_j$. Meanwhile, $x_{ij}y_{ij}$ is equal to 1 when a group is a common one which both the student $s_i$ and the supervisor $t_j$ participate in.

3.1.3. Quality dimension. In terms of quality dimension, we consider the quality and quantity of a supervisor’s publications and the quantity of his funded projects. Based on the involved journals’ impact factors, we divide them into three levels and set different weights to them according to parameter experiments. Thus, the score of “publication” ($Pub_j$) is measured by Expression (7). The number of a supervisor’s projects is taken into account and it is presented by $Pro_j$.

$$Q(s, t_i) = \alpha n_{pub}Pub_j + \beta n_{proj}Pro_j$$  \hspace{1cm} (8)

Where, $Pub_j$ and $Pro_j$ should be normalized firstly. $\alpha$ and $\beta$ represent the weights of candidate’s publications and projects. Furthermore, $\alpha + \beta = 1$. In the present study, they are set equally and both of them are equal to 0.5.

3.2. Subjective personality matching

Personality matching plays an important role in enhancing interactions among people. Evidence shows that appropriate personality matching can facilitate effective communications [20]. The personality matching will be measured by the Mini-International Personality Item Pool (Mini-IPIP) scale consisting of 20 items [22]. Supervisors and students are requested to complete a personality scale in order to recognize their personality types. The Mini-IPIP scale is short of the typical international personality item pool used for Five-Factor Model scale which is a dominant measure in trait psychology [29-31]. The appropriate psychometric properties of the Mini-IPIP scale is verified in previous studies [22]. There are five aspects: extraversion, agreeableness, conscientiousness, neuroticism, and imagination [22]. Every individual aspect in the Mini-IPIP is measured by four items which is a practical minimum number for scale length [22].

The five aspects are clearly defined in previous studies [22, 29, 31]. Firstly, extraversion represents the propensity to be sociable, assertive, active, talkative, and directive [32]. The opposite of the extraversion is introversion which stands for being shy, quiet and reserved. Secondly, agreeableness stands for being cooperative, courteous, and tolerant [32]. The opposite side is disagreeable, short-tempered, and uncooperative. The ones with low score in this aspect are not prefer to defer to others. Thirdly, conscientiousness shows the tendency to be responsible, dependable, and persevering [32]. Those who get low scores in this aspect tend to be careless, disorganized and unreliable. Fourthly, neuroticism stands for being emotional, nervous, and insecure [32]. Persons with low neuroticism share high ability to endure stress. Fifthly, imagination refers to the tendency to be creative, imaginative, flexible, and broadminded. Individuals with low score in this aspect tend to be conventional and close-minded [32]. Therefore, the five aspects are utilized to represent persons’ different types of personalities.

Initially, all students and supervisors are requested to finish the Mini-IPIP scale. Every aspect is represented by the average scores of four items. The personality styles of every person are expressed
as a five-dimensional vector. The differences between two individuals are measured by the distance of two five-dimensional vectors, as shown in Equation (9), if the student prefer a supervisor with similar personality styles. It is an ideal situation when two persons are similar in every aspect. Therefore, we calculated the matching degree by adapting the algorithm of geometric means [33] following the principle of ‘the more similar in every aspect, the better’. In order to facilitate the calculation process, we set the initial value as 1. Furthermore, we calculate the reciprocal values based on the principle of ‘the least, the best’.

\[ d_{s, t}(x, y) = \frac{1}{\prod_{i=1}^{n} \left( x_i^v - y_i^v \right)^2 + 1} \]  

(9)

Where, \( s \) represents a student and \( t \) represents a supervisor. \( d_{s, t}(x, y) \) denotes the value of the matching degree of personalities between a student \( s \) and a supervisor \( t \). Furthermore, \( x_i \) represents the value of student \( s \) in \( k \)th aspect of personalities. \( y_i \) shows the respective values of supervisor \( t \). \( n \) is the number of aspects, and here it is equal to 5.

In our proposed method, we pay attention to users’ different preferences of personality matching. Therefore, we design a Q&A process (table 2) for students to express their preferences. Different ranking strategies are applied in the calculation process for different students. For the ones who prefer similar personality matching, we adopt the principle of ‘the least, the best’ during the ranking process according to the values obtained by Equation (9). Meanwhile, for the ones who prefer complementary personality matching, we adopt another principle of ‘the largest, the best’ during the ranking process. Therefore, the \( d_{s, t}(x, y) \) is calculated without conducting the reciprocal process. Furthermore, for the ones who do not care about the personality matching, the matching degree is not considered during the calculation process.

3.3. Final aggregation

Firstly, we design a Q&A process to extract students’ implicit preferences towards different dimensional information. A previous empirical study shows that recommendation system based quizzes can understand users more and better than that of rating-based recommendation system [34]. As the information in different dimensions means different significances to users, it is an attempt to design an explicit Q&A process to extract users’ preferences.

Furthermore, the effectiveness of the quiz process is verified in the preliminary evaluation section. As shown in table 2, the details of the Q&A process are specifically demonstrated. There are five questions for every student to answer. It includes users’ preferences towards different types of personality matching, and different weights towards the relevance dimension, the connectivity dimension, the quality dimension, and the personality matching dimension. Users can show the degree of importance of their own preferences on corresponding measurements. Then, the students’ preferences are extracted from their answers. These extracted preferences play significant roles in designing the weights of different dimensions in the respective algorithms.

<table>
<thead>
<tr>
<th>Table 2. Q&amp;A process</th>
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</thead>
<tbody>
<tr>
<td>1. In terms of personality, which kind of supervisors do you prefer?</td>
</tr>
<tr>
<td>☐ the ones with similar personality with you</td>
</tr>
<tr>
<td>☐ the ones with complementary personality</td>
</tr>
<tr>
<td>☐ both will be OK</td>
</tr>
</tbody>
</table>

2. In terms of personality matching, how important is it to you when you select a supervisor?

☐ not important ☐ a little important ☐ important ☐ very important

3. In terms of relevance (knowledge expertise etc.), how important is it to you when you select a supervisor?

☐ not important ☐ a little important ☐ important ☐ very important

4. In terms of social connectivity on RSNs, how important is it to you when you select a supervisor?

☐ not important ☐ a little important ☐ important ☐ very important

5. In terms of quality, how important is it to you when you select a supervisor?

☐ not important ☐ a little important ☐ important ☐ very important

The ‘not important, a little important, important, and very important’ will be represented as the respective values 0, 1, 2 and 3. If a user expresses that a certain aspect is ‘not important’ to him, we set 0 weight to this aspect during the calculation process. Every user assign different importance toward different aspects. Assume \( w_i \) is the importance a user assigned to one aspect, it should be normalized by the sum of the values \( \sum_{i=1}^{4} w_i \) which he shows to all the aspects.

After we get the scores from the relevance dimension, the connectivity dimension, the quality dimension, and the personality dimension, we need to aggregate them in order to obtain a final ranking list. Thus, \( FS(s, t) \) represents the final score between a student \( s \) and a supervisor \( t \), and it can be aggregated by the Equation (10).

\[ FS(s, t) = w_dis, pub_{s,t} + w_{dis, pro_{s,t}} + w_{dis, d_{s, t}}(x, y) \]  

(10)
For example, if a student’s preferences on Relevance, Connectivity, Quality, and Personality are very important, a little important, important, and important, the respective values are presented as (3, 1, 2, 2). Then, the \( \sum_{i=1}^{4} w_i \) is equal to 8. Therefore, the normalized weights are (0.375, 0.125, 0.25, 0.25).

4. Preliminary evaluation

4.1. System implementation

The proposed supervisor recommendation approach is applied on ScholarMate which is developed by our team members. ScholarMate is an online research social network community and it aims to foster researchers to research and innovate smarter. Furthermore, the platform automatically collects users’ publications from multiple resources, such as CNKI, Scopus, and ISI. Researchers on the platform can connect other researchers by adding them as friends. They can not only self-organize but also participate in groups in terms of their specific interests. In the research social network, they can share papers, like others’ works and comment on them simultaneously. The system collects and mines the relevant information from users’ homepages, smart research CVs, related research activities and so on. Furthermore, the authenticity of researchers’ published papers and funded projects are verified on ScholarMate. Figure 2 shows the interfaces of a user’s homepage and the supervisor recommendation service.

![Figure 2. Interfaces of homepage and supervisor recommendation service on ScholarMate](image)

4.2. Preliminary experiment design

We design a preliminary user study to verify the effectiveness of our proposed method named as RAF-P. The results from our method are compared with the ones from three baseline methods. Firstly, previous studies on supervisor-selection usually leverage the relevance analysis and the quality analysis. Therefore, we compare the results from our proposed method with that from the method based on relevance and quality (named as R&Q-based method). Secondly, in order to verify the effectiveness of Q&A interaction-based aggregation method, we compares with the ones from RAF with traditional aggregation method (named as TraA). Thirdly, in order to verify the effectiveness of personality matching, we compare our results with the ones from pure objective measurements with Q&A-based aggregation method (named as NewA).

The new postgraduates who have not selected supervisors are targeted in this present research. We randomly invite 40 students majoring in business administration to participate in our user study. Meanwhile, we construct a candidate supervisor set which includes 34 researchers with professor titles on ScholarMate. Every student receives a recommended list which includes at most 12 candidates from four methods. The results are randomly mixed before sending to the students for satisfaction assessments. The target students are invited to express their satisfactions with 1-7 Likert scale [35] towards the recommended candidate supervisors according to their personalized profiles. The higher satisfaction score reflects better recommended results. In the end, there are 22 valid respond results. The respond rate is 55%.

The supervisors’ profiles are constructed through online related information on ScholarMate and they are complemented with information collections through e-mail. The related information on ScholareMate contain research interests, publications, projects, title, taken/taught courses, preferred references, social activities and so on. As the questionnaire of Mini-IPIP and Q&A interaction process are not designed on the website currently and they are still in the test phase, we have to collect this information by sending e-mails to the users. We randomly send emails to 50 supervisors requesting them to complete the Mini-IPIP scale. There are 34 valid responds. Meanwhile, the students’ profiles are constructed offline as we design an offline user study at this stage. In the data collection stage, they are requested to provide their objective information and complete the Mini-IPIP scale. They are invited to show their different preferences through the Q&A interaction process as well. Thus, we employ our proposed method and three baseline methods to do the supervisor recommendations for the target students. At the satisfaction feedback stage, the
students are requested to show their satisfactions towards the mixed recommended results.

### 4.3. Evaluation metrics

According to the final ranking list, we recommend top-3 supervisors from every methods (our proposed method and three baseline methods) for every target student. Meanwhile, we ask the targeted students to rank the mixed recommended results with 1-7 point scale.

To verify the effectiveness of proposed recommendation approach, we make an advantage of the Average Rating (AR) metric and the Normalized Discounted Cumulative Gain (NDCG) metric [36]. The details of the algorithms are showed as follows:

\[
AR@n = \frac{1}{n} \sum_i r_{ij}
\]

\[
NDCG@n = \frac{1}{n} \sum_i \frac{DCG_i@n}{\max DCG_i@n} \tag{12}
\]

Where, \(DCG_i@n = \sum_{j=1}^{k}[2^j - 1]/\log(1+j)\) \(\text{max DCG}_i@n\) is an ideal \(DCG\), when the order of all recommended items is perfect.

### 4.4. Preliminary results and analyses

In this section, we present and analyze the results from our preliminary user study. Firstly, although the Mini-IPIP scale is proved to be valid and reliable in previous studies [22], we make use of SPSS Statistics 20.0 to test the reliability and validity of our sample data from the personality questionnaire. The sample size is 56 (22 from the students and 34 from the supervisors). The details are shown in the Table 3. Secondly, the detailed results in terms of the AR metric and the NDCG metric are presented in the Table 4. Thirdly, we conduct the paired t-tests by the SPSS in order to guarantee that the results from our method are significantly different with that from the other respective methods. The results are presented in the Table 5.

The left part of the Table 3 shows the values of factor loadings and cross-loadings. All of the factor loadings exceed 0.8 which is higher than the threshold value of 0.7. Therefore, it demonstrates that all of the items possess acceptable measurement properties. Furthermore, the assessment of construct reliabilities is conducted as well. The results are presented in the right part of the Table 3. All the Cronbach’s alphas are higher than 0.9 which is over than the threshold value of 0.8. In terms of the values of convergent validity showed in the last column in the Table 3, we can observe that all of the values are greater than 0.7 which is over the recommended threshold of 0.5. Overall, the measures of personalities by the Mini-IPIP scale are reliable and valid.

### Table 3. Statistics for testing the scale’s reliability and validity

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<tr>
<th></th>
<th>E1</th>
<th>A1</th>
<th>C1</th>
<th>N1</th>
<th>I1</th>
<th>Cronbach’s alpha</th>
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<td>.035</td>
<td>.100</td>
<td>.926</td>
<td>.065</td>
<td><strong>0.949</strong></td>
<td><strong>0.830</strong></td>
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<tr>
<td>N2</td>
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<td>.124</td>
<td>.080</td>
<td>.915</td>
<td>.159</td>
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<td></td>
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<tr>
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<td>.121</td>
<td>.074</td>
<td>.905</td>
<td>.157</td>
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<tr>
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<td>.039</td>
<td>.050</td>
<td>.897</td>
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<td></td>
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<tr>
<td>I1</td>
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<td>.148</td>
<td>.142</td>
<td>.260</td>
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<td><strong>0.920</strong></td>
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<td>.259</td>
<td>.173</td>
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<tr>
<td>I4</td>
<td>.129</td>
<td>.172</td>
<td>.101</td>
<td>.094</td>
<td>.883</td>
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</tbody>
</table>

In Table 4, the results of different methods are presented in details. In the last column, it also presents the improvement percentage of our proposed method over the baseline method which achieves the best performance among the three baseline methods.

### Table 4. Detailed results of the methods

<table>
<thead>
<tr>
<th></th>
<th>R&amp;Q-based</th>
<th>Track</th>
<th>NewA</th>
<th>RAF-P</th>
<th>Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
<td>4.000</td>
<td>4.550</td>
<td>4.683</td>
<td>5.117</td>
<td>9.268%</td>
</tr>
<tr>
<td>NDCG</td>
<td>0.736</td>
<td>0.757</td>
<td>0.783</td>
<td>0.891</td>
<td>13.793%</td>
</tr>
</tbody>
</table>

According to both the AR metric and the NDCG metric, our proposed method achieves the best performance comparing with the other three baseline methods.

In terms of the AR metric, the results from our method obtain the average satisfaction of 5.117. The
results from NewA achieves 4.683 and it shows the best performance among the baseline methods. It is 9.268% improvements comparing the results of our proposed method with that of the best baseline method (NewA). Meanwhile, according to the NDCG metric, it is 0.891 of our method and it is 0.783 of the best baseline method (NewA). Therefore, our method achieves 13.193% improvements over the best baseline method.

Base on the values of RAF-P and NewA, it shows that the personality matching-aided method outperforms the approach without considering personality matching. According to the values of TraA and NewA, we can conclude that the method considering users’ different preferences towards different dimensions aggregates the factors better and receives higher users’ satisfactions than the method without considering theses when conducting the aggregation process.

Additionally, we conduct paired t-tests for significance testing of the results of RAF-P over that of all the baseline methods. In Table 5, it presents the p-values of the results in the perspective of both the AR metric and the NDCG metric. We set the confidence interval as 95%. According to the p-values in the Table 5, it can be observed that the results from our proposed method and that of the baseline methods are statistically significant in terms of both the AR metric and the NDCG metric.

<table>
<thead>
<tr>
<th>Paired t-test</th>
<th>RAF-P</th>
<th>RAQ-based</th>
<th>TraA</th>
<th>NewA</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NDCG</td>
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<td></td>
</tr>
</tbody>
</table>

*p-value significant at α≤0.05, **p-value significant at α≤0.01, ***p-value significant at α≤0.001.

5. Conclusion and future work

In China, there are more than 600 thousand new students pursuing postgraduate education in 2013. It is an increase of 3.68% comparing with the number in 2012. In this study, we put forward a personality matching-aided recommendation approach to facilitate the process of supervisor selections. The supervisor selection is crucial for students at the beginning of their research career. However, the widespread mismatching phenomenon triggers us to rethink the importance of appropriate selections. In this paper, it integrates objective measurements (relevance, connectivity and quality) and subjective personality matching which is an important aspect but is not paid enough attention in the existing studies. Furthermore, the proposed approach is carried out to provide the service of supervisor recommendation on ScholarMate, a research social network. A preliminary user study is conducted in order to evaluate the effectiveness and efficiency of our proposed approach.

However, there are several limitations in our current study. Firstly, we evaluate the performance of the proposed approach according to students’ satisfactions. If the realistic data is available, we will intend to conduct the evaluation based on realistic successful rate of establishments of student-supervisor relationships in the future. Secondly, we focus on the keyword similarity when we compare students’ and supervisors’ profiles. In the future, a related domain ontology can be constructed to facilitate the profile matching. Thirdly, we merely conduct a preliminary user study to evaluate the effectiveness of our proposed method. In the future, we will increase our sample size and conduct a comprehensive experiment to verify the proposed approach.

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References