Perfect Match: Facilitating Study Partner Matching

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ABSTRACT

With the massive growth of online learning, there has been a decrease in students' face-to-face interactions, leading to rising feelings of isolation. This in turn contributes to several issues such as motivation loss, increased course attrition rates and poor learning experiences. Strong Online Learning Communities (OLCs) have been suggested as a means to help improve the situation, however the formation of OLCs is strongly influenced by learners' individual characteristics and their preferences regarding how and with whom they would want to form study groups. Taking students as its focus, this research attempts to develop a learning partner recommender system (LPRS) to facilitate finding compatible study peers in order to promote informal learning communities among students. From a synthesis of related literature and using data from a study of the student' preferences, a collection of learners' individual characteristics has been identified as a set of matching criteria in our LPRS model. A proof of concept based on the conceptual model has been developed and evaluated with a small group of target users. Results of the investigation showed positive feedback from participants and good prospects of the recommender system.

CCS CONCEPTS

• **Social and professional topics → Computing education**;

KEYWORDS

Online Learning Communities, Learning Partners, Recommender Systems

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1 INTRODUCTION

An innate feature of online learning is the reduced availability of face-to-face interactions and communication through which a sense of learning community is created, which in turn is often responsible for students feeling isolated. It is unsurprising that students feel isolated in fully online courses. However, in the higher education context with an increased reliance on blended learning a feeling of disconnectedness is not uncommon [38, 46]. The issues emerging from disconnected students are many, including a loss of motivation, poor academic performance, and higher drop out rates. In such a context, supporting Online Learning Communities (OLCs) has become a more significant issue [6].

Students' individual characteristics are asserted to have significant impact on the formation of OLCs [4]. Therefore, finding peers compatible with these characteristics is a key factor for having a safe and supportive OLC emerge. In online learning environments, Learning Analytics (LA) data and processes have the potential for facilitating the collection and analysis of data about students' characteristics and preferences regarding those with whom they would want to do their study.

With an ambition of promoting informal online learning communities among learners through stimulation of positive interactions, the research describes the design and implementation of a recommender system (Learning Partner Recommender System - LPRS) which provides students with suggestions on learning partners based on their individual characteristics, what they look for in peers, and preferences in learning partners. A conceptual model of the system was developed with criteria used for generation of recommendations. These criteria were collated from previous literature on Collaboration Learning (CL), Learning Communities (LCs), and Group Formation (GF). This was combined with data on students' perspectives on appropriate matching criteria. A proof of concept of the system was then developed and preliminary user acceptance testing has been conducted. Results of the initial testing have shown that the LPRS is considered to have the potential to facilitate students to overcome some existing obstacles in order to find suitable learning partners and improve their learning experiences.

2 BACKGROUND AND CONTEXT

This section provides an overview of the importance of online learning communities, factors influencing group formation and the use of Learning Analytics to support Recommender Systems.

2.1 Online learning communities

Feelings of isolation are common in fully online courses and MOOCs [5, 24]. In higher education (HE) there is an increasing adoption of blended learning (referring to the integration of online learning activities into the traditional classroom) and therefore on-campus attendance has been declining. This trend is closely related to a major challenge, students' feeling that they are disconnected from their peers [38, 46]. In this context, OLCs have been asserted to play a significant role in improving issues highly associated with students' feelings of isolation, such as low course retention rates, loss of motivation and poor learning experiences.

Although different approaches to encourage OLCs in HE have been studied, the majority of studies have focused on issues such as syllabus design, the instructor's role and behaviour, and strategies to encourage students' interaction [6, 45]. However, the interactions encouraged tend to be centred around subject content in formal learning contexts with an emphasis mainly on cognitive processes [25, 51]. Little attention has been placed on affective social-emotional interactions among students and their role in facilitating OLCs.

2.2 Group formation

Group formation has been a critical task in facilitating collaborative learning (CL) in HE since negative effects might emerge if there is lack of careful consideration in the process of grouping students into teams working together [9]. Being derived from best pedagogical practices, grouping criteria are typically highly associated with learning aspects of students such as their understanding level on a given topic [26] or the collaborative goals set by the teachers such as forming groups of students with heterogeneity in marks or learning styles [34].

Many of students' individual characteristics and preferences have been used as grouping criteria in previous research including personality [22, 28], learning styles [31], topic-specific knowledge level [52], demographic traits [34], communication skills [33], and topic preferences [48]. However, each study investigated an individual characteristic or a small set of factors; and most of the time considered learning performance (grades) as the ultimate goal of encouraging collaborative activities. Also, previous work has mainly focused on supporting teachers assigning students into short-term groups primarily based on topic- or project-specific requirements rather than for the formation of more generic task-free and longer lasting informal study groups.

Nevertheless, research in this area has strongly suggested that students' characteristics and preferences play an important part in grouping them into a team. These factors are even more vital when it comes to attempts to promote informal learning communities. The present project aims to create an accessible platform where learners can find peers with compatible characteristics which fit their preferences in order for a comfortable and trusting atmosphere to be created, which is the key for a learning community to emerge.

2.3 Recommender systems for study partners

In education contexts, recommender systems play an important role in the effort to improve learning experiences, with a focus on generating recommendations for learning materials or courses content to access. Recently, there has been an increased interest in research to develop systems to support students to find study partners, emphasising the reciprocal nature of recommendation requirements [37]. Different factors have been used to generate recommendations such as knowledge level, availability, preferences [23], demographics, interests [40], or on an ad-hoc basis in cases where students need help with specific problems [11, 12]. These studies have brought valuable contributions to research in the field and showed the potential for improving learners' experience through suggesting suitable peers. However, factors used in those studies for recommendation generation are based on researchers' rationale or academics' requirements. The students' attitudes and perspectives have not been explored. Evaluation approaches used to assess these systems have often employed synthetic data, focusing mainly on technical aspects such as scalability, coverage, precision and recall [23, 40]. Again, students' experience and satisfaction have not been investigated.

Moreover, in the context of remarkable growth of online learning, Learning Analytics (LA) has the potential to collect data about students' characteristics and preferences in an objective manner. Thus, LA can serve as one of the primary data sources for such a recommender system. However, in the context of this paper, establishment of the system has the highest priority in order for the matching process to be investigated. Therefore, integration of LA data from external sources will be deferred to further research.

3 METHODOLOGY

Considering the identified research problem, that forming a meaningful informal learning community in higher education contexts can be challenging, this paper presents a learning partner recommender system where students are provided with suggestions on peers who might learn well with them based on compatible characteristics and preferences.The research questions are:

> RQ1: What are the characteristics of students which can be used as matching criteria?
> RQ2: How to design and implement the proposed LPRS?

In order to tackle these research questions, two phases of the study have been established employing a mixed method. Phase 1 focuses on identifying a set of students' characteristics which can be used as matching criteria in the system. In this stage, studies in relevant areas have been reviewed to compile a collection of students' characteristics conducive to OLCs which can be used as study partner matching criteria. Then data collection was carried out with IT students to explore their perspectives on the collated characteristics and potential of the proposed LPRS. Next, Phase 2 of the research aimed at implementing the proposed learning partner recommender system. A working proof of concept of the recommender system has been designed, implemented and investigated with a focus group.

4 ANALYSIS AND RESULTS

By reviewing literature on areas including Collaborative Learning (CL), Online Learning Communities (OLCs) and Group Formation (GF), a collection of students' individual characteristics which are considered as influential factors in their participation in collaborative activities, and in the formation of a learning community in online environments, was collated.

The identified characteristics were classified into two categories: (1) Academic factors: motivation, self-efficacy, skills, learning styles, learning patterns, academic interests and education level; and (2) Socio-psychological factors: personality, willingness to communicate (WTC), self-perception of being connected, hobbies, demographics, and preferred communication channels. Table 4 gives a summary of the important students' characteristics from literature conductive to collaborative learning, knowledge sharing, and the development of OLCs.

Characteristics	Research Base	Data Source
Education Level	[4]	LA
Learning Styles	[1, 31]	Felder-Silverman questionnaire
Learning Patterns	[15, 50]	LA
Academic Interests	[10, 26, 52]	LA & Self-report data
Motivation	[18, 43]	MSLQ Quiz (Motivation subscale)
Self-efficacy	[10, 18]	MSLQ Quiz (Self-efficacy subscale)
Skills & Experiences	[10, 15, 31, 32, 48]	LA & Self-report data
Willingness to Communicate (WTC)	[8]	WTC Questionnaire
Personality Traits	[18, 48, 49]	Personality Questionnaire
Self-perception of being connected / separated	[4, 44]	Self-report data
Demographics	[4, 21, 34]	LA (profile data) or Self-report data
Preferred Communication Media	[4, 47]	Self-report data
Hobbies	[27]	Self-report data
Students' Preferences	[17, 48, 49]	Self-report data & Interaction data

*** Blue = academic factors. Pink = socio-psychological factors.**

Table 1: Students' characteristics conductive to OLCs

4.1 Phase 1: Confirming Preferences

Since the proposed LPRS is student focused, aiming to match peers with compatible characteristics and preferences, it is essential to explore; (1) students' perspectives on factors they consider important when looking for study mates, and (2) their attitudes towards the proposed recommender system. An online survey and semi-structured interviews with undergraduate IT students of Monash University were carried out to obtain these insights.

The online survey instrument was designed based on the types of LCs [42] and Sense of Community [30] factors. The focus was on students' experience on three forms of Learning Communities, including: Knowledge-based, Practice-based and Task-based LCs [42]. Also examined were the perceived benefits of being a part of an LC, difficulties when working/learning with others, and factors which they find important in peers when working in a group. Follow-up interviews were conducted to obtain deeper insight into factors covered in the survey. From April to June 2017 when the online survey was available, 35 students responded (24 males and 11 females). Out of the 35 survey respondents, ten students (7 males and 3 females) agreed to take part in the follow-up interview session.

Findings from the Phase 1 data collection (both online survey and interviews) are presented below. First of all, among the three forms of LCs, informal learning communities (Practice-based) received more negative remarks compared to the other forms. Students tended to feel less comfortable and valued this form of LC least. An insight regarding this trend relates to how the three forms of LCs take place in the current learning environment. For Task-based learning activities, group members usually have a clear idea of what they have to do, which tasks to accomplish and a suitable manner to collaborate together. Therefore, while conflicts regarding how to work together towards a common goal might occur, students would tend to make efforts in resolving collaboration issues emerging so that the collective work would not be jeopardised and harmfully affect learning outcomes (such as grades). In terms of Knowledge-based LCs, participants share common interests in a particular area. Also, they do not have the pressure of completing a task/project towards a deadline. Consequently, Knowledge-based LC members are likely to feel less tense and more relaxed working with each other. This is in contrast to Practice-based LCs. Here, students have to figure out how to collaboratively work and learn together mostly by themselves outside of classroom and beyond the initial instruction period. This is where students might best develop their self-regulated and collaborative learning, but also where difficulties would emerge in respect of how to effectively collaborate with others, how to juggle lectures, tutorials, self-study and outside classroom learning activities, and how to benefit from participating in this form of LCs. This is an area where the present research has the potential to make significant impact.

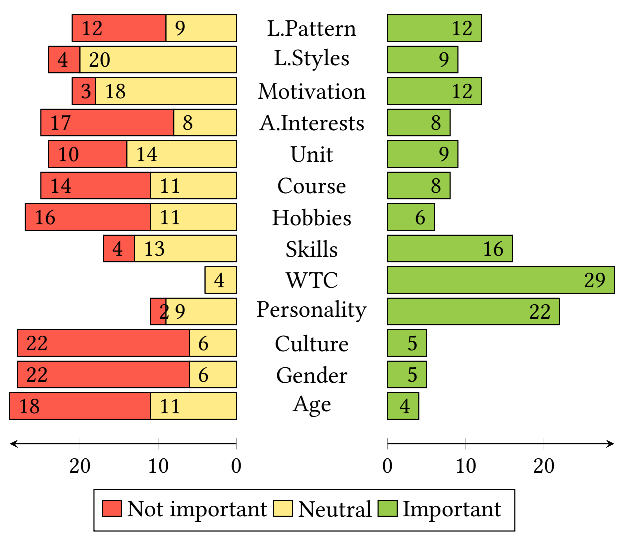

Figure 1: Students' perceived importance of different characteristics (N=33)

Second finding was about valued factors in peers. 33 out of 35 students who participated in the online survey responded to a question asking them to specify which characteristics they consider important when looking for study partners. Survey data revealed that characteristics in other peers which were appreciated by most students included willingness to communicate, personality, academic skills/experience, motivation and learning patterns (see Figure 1). Other factors which received varying lower levels of significance by the participants were learning styles, interests, hobbies, demographics and education levels. Similar perception was found in interview results except for learning patterns where students mentioned that one's learning patterns might result from one's degree of self-motivation and personality. Also, it should be noted that self-efficacy was not examined in the initial survey. This factor only emerged during the interviews and was later searched for in previous literature and integrated into the list of important characteristics (Table 4). Importantly, responses showed that there existed a need among learners for finding peers who possess favourable features and to make connections with those peers.

Finally, as for the proposed LPRS, 96% of survey respondents contended that compatible characteristics among learners could help improve (or had possibilities in improving) their learning experience. Also, the majority of interviewees' opinions suggested that students believed such a system could facilitate matching learners with compatible characteristics and fitted individual preferences (such as similar interests and complementary skills).

4.2 LPRS Conceptual Model

Based on the synthesis of literature and results retrieved from the Phase 1 data collection on IT students' perspectives, a model of a partnership recommender system for students is shown in Figure 2. Results from Phase 1 suggested that different characteristics are perceived with varying level of significance by students. That suggested an idea for assigning weights to characteristics in determining the compatibility level of two arbitrary learners.

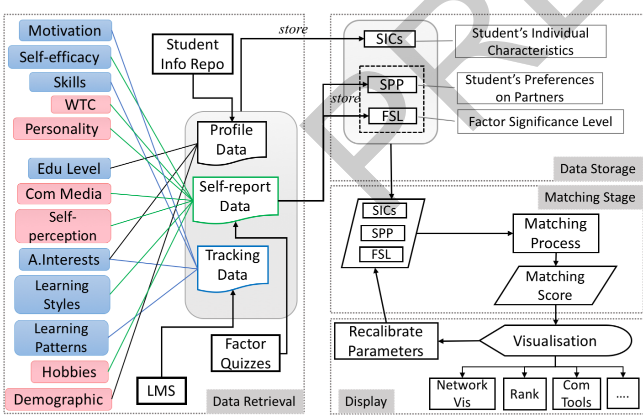

Figure 2: LPRS Conceptual Model

The proposed LPRS model consists of four stages - Data Retrieval, Data Storage, Matching, and Display. In the model, 13 factors (Figure 2 left) are used as matching criteria, the five listed on the top being the ones that either received high perceived significance according to the survey results or emerged from the interviews. The other factors at the bottom (including learning patterns and seven other factors) are those with varying levels of importance as perceived by students who participated in both the survey and interviews. Values of these factors are suggested to be retrieved from three main sources including: profile data, tracking data and self-report data. Profile data involves students' basic information such as demographics, education level, degree, major, year and academic interests. Tracking data, derived from a Learning Management System (LMS), keeps track of students' activity within the online learning environment. Self-reported data refers to data provided by students themselves through explicit indication or completion of characteristic forms. After that, the retrieved data is stored, being categorised into (1) student's profile, data about their own characteristics, and (2) student's preferences, which consist of preferences on learning partners and significance levels of different factors. Next, data is fed into a matching process to generate compatibility scores. An interactive visualisation is suggested to be used to present recommended peers so that students can have a better insight into the displayed results.

4.3 Phase 2: LPRS Design and Development

Although there are 13 factors suggested to be used as matching criteria in LPRS, as a proof of concept six out of the 13 are used as key matching factors. The five factors which are perceived as important to students include: Willingness to communicate, Personality, Self-efficacy, Motivation, Skills; and the sixth factor - Learning styles - has been employed intensively in group formation area. Factors, such as Demographics, Education level and Academic interests, are used as recommendation filtering conditions. Value of the motivation factor is currently collected in self-rating form, but will potentially be retrieved from an external source (LMS).

4.3.1 Design blocks. The system proof of concept is comprised of four main blocks - Profile, Preference, Recommendation, and Utilisation, as demonstrated in Figure 3. Profile is made up of results from characteristic forms. Preference keeps track of what students look for in preferred learning partners. Recommendation takes care of the presentation of recommended peers generated from the matching process; while Utilisation aims to facilitate initial contact among students as well as future evaluation of the system.

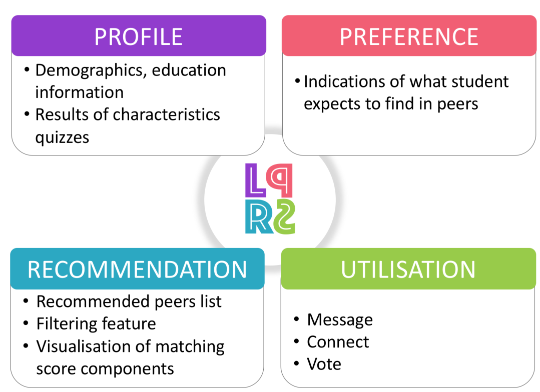

Figure 3: LPRS Design Blocks

4.3.2 Student Profile and choice of characteristic questionnaires. Four characteristics (WTC, Personality, Self-efficacy, Learning styles) are retrieved via questionnaires. The questionnaires employed are those which have been designed and reported on in literature (see Table 2). Although some studies were conducted to automatically identify students' characteristics such as Personality traits [2, 16], or Learning styles [3, 7, 19] based on students' online activities in LMSs, those studies had to resort to corresponding questionnaires to evaluate the automatic approaches' performance and accuracy. Thus, although there is an awareness that users would have to be involved more in data retrieval phase of the system, for the purpose of quality data, self-report questionnaires are the key data sources.

Characteristic	Questionnaire	#Qs
WTC	WTC Scale [29]	12
Personality	BFI-10 [41]	10
Self-efficacy	Self-efficacy subscale from the (MSLQ) for College students [35]	8
Learning Styles	Felder-Silverman questionnaire (Active/Reflective & Global/Sequential) [13, 14]	22

Table 2: Characteristic Questionnaires

4.3.3 Matching approach. The matching approach identified is known as a two-way or reciprocal recommendation [36, 37]. This is distinguishable from common recommender systems where the recommended items are objects and suggested to human users with their individual taste/preference. Suggesting learning partners would not work if a recommendation only satisfies one party. It is essential to take into account characteristics and preferences of both the recommended peer, as well as the one who receives the recommendation.

In reciprocal recommendation, there are two main methods: Content-based and Collaborative Filtering (CF) [36, 37]. The former refers to an approach where a target user is suggested to make connections with people who possess similar attribute values as the ones the target user has connected to. The latter can be either Item-based or User-based. Item-based assumes that if many of A's connections are also connected to B, then A might also like to connect to B too. User-based assumes that similar users might wish to connect with the same people. A Content-based approach is applicable when there is a substantial amount of user interaction data, which is not the case at an early stage of the LPRS [39]. CF is conducted mainly based on similar users' opinions which tend to be more social network oriented. This research focuses on students' more intrinsic characteristics, their preferences and how they impact their participation in learning communities.

Thus, the recommendation approach employed in LPRS has been established: profile-preference matching and content-based. At the start of the process, matching is performed through calculation of the degree to which the profile and preference between two users match. Content-based approach can then be applied once a certain amount of user interactions have occurred.

This part presents the matching algorithm used in the system - Profile-preference matching. Data of a user (referred to as user A) in the system is comprised of A's characteristics (which consists of values of the six factors) and A's preferences (which includes (i) A's preferred value of factors in peers, and (ii) A's perceived significance level of characteristics when looking for learning partners). For each pair of two users referred to as users A and B, firstly one-way matching scores $score_{(B \to A)}$ are generated. This indicates how user B's characteristics fit user A's preferences. Then the reverse one-way matching score $score_{(A \to B)}$ is calculated, which indicates how user A's characteristics fit user B's preferences. It is to be noted that the calculation of one-way matching scores takes into account the weight (significance level) of factors which were assigned by the users. The calculation of $score_{(B \to A)}$ can be formulated as:

$$\sum_{i=1}^{N} fit(V_{C_i(B)}, V_{C_i Pref(A)}) * W_{C_i(A)}$$

N is the number of characteristics used as matching criteria ($N = 6$ in this research). $V_{C(B)}$ is user B's values of a specific characteristic C. $V_{C_{Pref}(A)}$ is value of the characteristic C which user A would want to find in learning peers. $W_{C(A)}$ is the weight user A has assigned to the factor C. Then the harmonic mean [37] of the two scores is generated to obtain the compatibility score between the two users. Figure 4 demonstrates a way in which recommendations on peers can be represented. Information includes the peers' user name, compatibility score, education and demographics, their skills, as well as interests. Here, users can filter the recommendations based on these kinds of information.

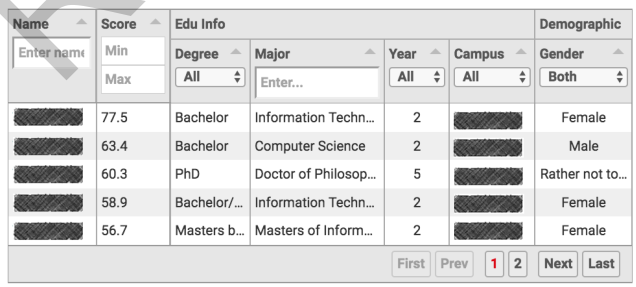

Figure 4: Recommendations with peers' info

4.3.4 Presentation of Recommendations. Inspired by the work of [20] about a visualisation technique which employs bar charts to create an interactive representation of multi-attribute rankings, an inline horizontal stacked bar chart was used to visualise how compatible a target user is with other users in the system.

Recommendation results are presented to a target student in a form of compatibility scores with decomposition of the score components. Figure 5 demonstrates the visualisation of recommendations presented to a target student (called user A). Here, column 1 lists the name of recommended peers, followed by the *Score* column which indicates the compatibility score of user A with a corresponding peer. This compatibility score is made up of components represented in column 3 and 4. Column 3 (*They fit you*) illustrates the extent to which the peers' characteristics fit user A's preferences; while column 4 (*You fit them*) represents the degree to which user A's characteristics suits the peers' preferences. Characteristics are colour-coded and the length of each portion represents the weight which user A has assigned to that characteristics when the user entered their preferences. The order of coloured bars is based on how user A ranked/weighed the importance of the characteristics. As for the shades of a colour, the darker shade of a colour represents how much one's characteristic fits the other's preference regarding that particular matching criterion, While the lighter shade illustrates the unmatched portion.

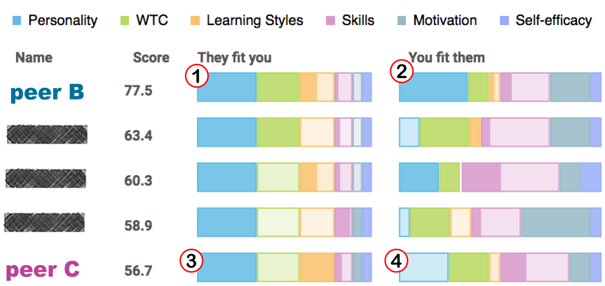

Figure 5: Recommendations with compatibility score decomposed

To illustrate, in Figure 5, user A (the student who receives the recommendations) ranked the characteristics as Personality, WTC, Learning styles, Skills, Motivation and Self-efficacy in descending order of importance. Therefore, stacked bars in both column 3 and 4 are arranged consistently in this order. Regarding individual matching factors (characteristic), user A considers personality as the most important characteristics while looking for learning partners and similar personality is preferred.

Considering the recommended peer in the first row (peer B), the peer has the highest compatibility score of 77.5 (out of 100). At 1, user A's preference regarding Personality is satisfied by peer B's Personality. Similarly, as can be seen at 2, peer B perceives personality as the most important and prefers study partners with similar personality traits. User A and peer B fit quite well in terms of other factor as well. In contrast, peer C - who has the lowest compatibility score in user A's top 5 recommendations - ranks Skills as the most important factor, followed by Personality, WTC, Motivation, Self-efficacy and learning styles. Although peer C's value of Personality fits user A's preference concerning this factor 3, peer C prefers those with different personality traits 4. Similarly, user A's requirement on WTC is not met by peer C. Also peer C's Skills preference is not fully satisfied by user A's experiences. These mismatches all affect the final compatibility score of the two users.

4.4 LPRS User Acceptance Testing

In order to investigate usability of the proposed LPRS and gather its target user's opinions about the system, a second round of data collection involving a focus group (FG) was conducted. Activities in the session involved system interactions (account creation, data inputs, system outputs), group discussion, 8-item usability questionnaire, and seeking user comments. An invitation to the FG was advertised in three units of Faculty of IT, Monash University. Eight students agreed to take part in the FG activities. By the time of the FG commencement (31st May 2018), key system blocks had been preliminarily developed including user profile, preferences, generation and presentation of recommendations.

In FG discussions participants confirmed that there exist difficulties when it comes to looking for peers to learn with due to mismatches of characteristics among peers. Specific characteristics mentioned included work attitude, personality, commitment, learning styles, skill-level, and motivation. One participant stated:

> There's no existing platform which allows students who are strangers to study together [...] Normally you can meet people at lectures and tutorials, but not people from other streams or timetables.

As for system usability, positive feedback was given by the participants. All the students were positive about the potential of the system to facilitate students finding informal learning partners with compatible features. The majority of the participants (7 out of 8) found LPRS simple to use. They managed to become familiar with the system with little effort or detailed instructions. Interestingly, participants also mentioned that the 'characteristics' questionnaires seemed to generate similar results to the ones which they had previously taken, particularly those for personality and learning styles. Also, the students reported that the visualisation of recommendations were interesting and tended to meet their expectations. They reported that the inline bar chart (see Figure 5) could help users make sense of the compatibility scores which indicate the degree to which they and their peers fit.

Importantly, useful suggestions emerged from the FG activities and discussion which have contributed to further refinements being applied to the development of the LPRS. The main points suggested were: (1) using additional matching criteria (such as location, degree, major, interests), (2) changes to make the visualisation of the recommendation easier to understand, (3) features to generate better user experience, such as an improved process for completing the characteristic forms, and (4) supporting users' decision making, such as providing more relevant information about connected peers. These minor changes will be implemented before further usability testing and deployment of the system at large scale.

5 CONCLUSION AND FURTHER RESEARCH

This paper describes the model of LPRS and the process in which its proof of concept was developed employing a collection of students' characteristics as matching criteria. The identification of the characteristic set (to address RQ1) involved (1) literature view on relevant areas, and (2) investigation of students' perspectives on LCs and preferences for a partner recommender system. A working system was implemented (to address RQ2) with different components including system data retrieval, matching approach and implementation, recommendation presentation implementation, and integration of utilisation tools. An initial user acceptance test has been conducted. Results have shown interest from students as the target user of the system, and good prospects of the LPRS to facilitating finding peers with compatible characteristics to form informal learning communities.

The next steps in refining the LPRS include: system modifications based on student feedback from the FG, additional user testing prior to wide scale deployment, combination of both qualitative and measurable quantitative approaches in evaluation, and integration of data retrieved from LMS systems to incorporate LA on their online activity.

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