The Effect of Personality and Learning Styles on Individual and Collaborative Learning

Obtaining Criteria for Adaptation

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***Abstract*—The aim of this work is to obtain useful criteria for both individual adaptation and dynamic group formation in adaptive collaborative learning systems. We present the results obtained when analyzing data from students of Computer Science from the Universidad Autonoma de Madrid. We have considered their personality and intelligence, the way they group themselves and their results when working individually and collaboratively, in order to find out relationships between their features, the group composition and their achievements. In this context, we have found that some features related to the student personality, intelligence and learning styles (such as neuroticism, spatial abilities, openness to experience, or sensing learning style) seem to influence their performance. This information can be useful in scenarios of face-to-face learning, blended learning or e-learning. In the context of e-learning, we find this information particularly useful for two purposes. Firstly, it allows the detection of potential students or groups with risk to fail when trying to achieve academic objectives and, therefore, makes it possible to prevent them from failing, by offering them personalized assistance in advance. Secondly, specific grouping criteria can be set for dynamic group formation, trying to lead the students to successful collaborative experiences.**

Keywords— user modeling; collaborative learning; personality; learning styles; criteria for group formation; CSCL; adaptive e-learning

I. Introduction

During the last decades, the Internet has been widely used to support both individual and collaborative learning. New ways of learning have arisen. Teacher and student roles, as well as the ways of discovering, constructing and acquiring knowledge, have changed. In the context of learning, each student's cognitive abilities, personality, affective state, learning style, goals, preferences or context, can determine the way in which he accesses to resources, processes the information, faces practical work, chooses mates, relates with teachers and, in summary, takes part in the learning process. In face-to-face contexts, it is not easy for the teacher to get and take into consideration all that information about every student in order to adapt the activities or resources accordingly. However, it is possible to develop adaptive e-learning systems to guide each student at runtime according to that information [1]. With such purpose, it is necessary to build adaptation mechanisms as well as to collect and store the students' data in what is called the user model [2]. Some systems support collaborative learning (CSCL) [3]. A number of them are able to form workgroups at runtime and to generate collaboration workspaces on the fly [4]. In this case, it is necessary to manage information about students and groups. The use of adaptation methods and techniques makes it possible to support personalized individual or collaborative learning, i.e., to provide adaptive guidance to each student or group dynamically.

When dealing with collaborative work, especially in the context of CSCL, one of the main difficulties relates to the creation of workgroups, since each student learns at his own pace and may not know the others. One of the main goals of an adaptive CSCL system is to propose the most suitable activities to be carried out by each group at each time. Moreover, if the system supports dynamic group formation, it would be expected to propose groups in which the combination of individual features leads to the best possible group performance.

Numerous studies deal with the relationship between academic performance and intelligence. General and specific cognitive abilities would explain between 16 and 54 per cent of the academic performance variance [5]. According to [6], psychometric intelligence can be used to predict future achievements, whilst performance has no impact on future psychometric intelligence. Likewise, there exist works analyzing the influence of personality on the way the students get knowledge or uses it in practical applications. In [7] a relationship between neuroticism and low academic performance is established. According to [8], conscientiousness (in a positive way) and extraversion (in negative terms) are clearly related to achievement. Not only intelligence but also personality and motivation are relevant factors influencing academic performance [9]. Other researchers have investigated the influence of personality on CSCL. For example, [10] proposes to consider the potential influence of personality (on student communication, engagement, and interaction) as part of CSCL system design.

In this direction, the main aim of this study is to get information about the influence of personal traits such as personality and intelligence on the results obtained by students and groups when accomplishing individual and collaborative activities. The impact of learning styles on student grouping for collaborative learning has already been studied [11]. In this work we want to know whether the students' personality and intelligence do influence the way the students group themselves, the way they work together and their achievements when tackling activities individually. Obtaining conclusions regarding the influence of these traits on the learning process would make it possible to consider them for the creation of better e-learning systems, able to guide individuals and groups during the learning process accordingly. In particular, the analysis done has the following goals:

- Getting information about personality and intelligence traits that tend to lead to individual learning failure, to be able to predict, in the context of e-learning, which students are in risk of failing, with the aim of preventing them as much as possible from this, by offering them personalized assistance.
- Determining which combinations of students in groups (regarding their personality and intelligence) lead to better results. This information is expected to serve as grouping criteria for CSCL. In addition, getting information about the combination of traits in groups that normally lead to bad results makes it possible to predict group failure at runtime (in the case that the students group themselves) as well as to take actions in advance in order to avoid it.

Our hypothesis is that the students' intelligence and personality have an effect on the results of the tasks accomplished by them, both individually and collaboratively. The goal of this study is to test this hypothesis, as well as to get specific information about that effect, if any, to use it within e-learning systems.

The rest of the paper is organized as follows. Section II presents the case of study analyzed. Section III describes the results obtained. Section IV shows specific applications of the results in the context of adaptive e-learning. Finally, section V presents the conclusions and future work.

II. A Case Study

A. Collecting Personality, Intelligence and Learning Styles

In order to collect the data needed to test the hypothesis, and harvest information about the student personality, intelligence and learning styles, specialized tests were developed. These tests were included within three already existing e-courses specifically developed to support online learning for three different subjects. We will focus on two of them: Information and Data Structures I and Operating Systems I (undergraduate courses of Computer Engineering studies). Through these web-based courses, students access to detailed theoretical explanations, samples, pseudo-codes and solved exercises. In addition, these websites include collaborative activities and self-assessment exercises with detailed feedback. The links to personality, intelligence and learning style tests were included in the top frame of the courses, so that the students can access to them whenever they want. Each student log in by using his official account, and all their interactions within the website are stored in log files.

With the aim of getting information about personality, we chose the NEO Five Factor Inventory (NEO-FFI) test [12]. It is a shortened version of NEO PI-R and it gives quick, reliable and valid measures of the five traits of adult personality: extraversion, neuroticism, conscientiousness, openness to experience and agreeableness. It consists of sixty statements related to human ways of being and behaviors, which have to be rated on a five point scale.

The test set chosen to get information about the students' intelligence was Primary Mental Abilities (PMA) [13]. This set includes one test per each category and ability (verbal, spatial, and general reasoning). It offers a whole evaluation of intelligence basic factors, giving one score for each ability. The PMA-Verbal test assesses the ability to understand and express ideas in words. It consists of fifty questions regarding word meaning, with four possible answers each. The maximum time to complete this test is 4 minutes. PMA-Spatial test measures the ability to imagine and conceive objects in two and three dimensions, and includes twenty questions with six possible answers each. The maximum time to complete the test is 5 minutes. Finally, PMA-General-Reasoning evaluates the ability to solve logical problems, general understanding and planning. This test consists of thirty series to complete. The maximum time to fill in the test is 6 minutes.

Finally, regarding learning styles, we used the Felder-Silverman model [14]. It consists of five dimensions, although, as the authors state, for pedagogical reasons, only four of them are considered: perception (sensing/intuitive), processing (active/reflective), input (visual/verbal) and understanding (sequential/global). We use the corresponding questionnaire from Felder and Soloman's [15], which consists of 44 questions with two possible answers, grouped in four categories, each of them corresponding to a dimension.

We chose these specific tests because of having proved reliability and being used worldwide. We have implemented all of them in a similar way: Firstly, a webpage contains the instructions explaining how to complete the test and includes some samples of solved questions, information about the maximum available time (if any) and the start button. Once the user completes the test (or when the corresponding time runs out, if it is the case), a program calculates the score and generates the feedback page for the user. This feedback includes the score obtained in the test as well as the explanation about its meaning. The rates given by the user for each item, as well as the final score for each test, are stored in XML files.

B. Subject Description and Student Performance

In Information and Data Structures I, the students work in pairs on four practical tasks of increasing difficulty. They can group themselves in pairs as they prefer to do this work. The students have face-to-face sessions with the teacher two hours per week in the laboratory, and can complete their work at any other time, if needed. During the sessions, they can work on their assignments, make questions to the teacher, or be evaluated. They can interact through the e-course available too. The potential marks for the first two practical works were: NA (unapproved), A- (approved, but needs to improve), A (approved) and A+ (approved, very well done). These marks give the students an idea about their ongoing work and knowledge, but are not used to calculate their final mark regarding practical performance. From the third practical work on, they get a numeric mark between 0 and 10, which is used to calculate their final score. In Operating Systems I, there are three practices to be done in pairs. The students are also allowed to choose their partner. They have face-to-face sessions with the teacher two hours per week in the laboratory and they can work on their assignments and make questions to the teacher during this time. In this case, they can also complete the assignment afterwards, if needed, and marks for each task go from 0 to 10 too.

During the whole semester, the students have the corresponding e-courses available and they can interact with them whenever they want. The two subjects include two main exams during the course, one in the middle of the semester and another one at the end. The students can take an extra one after the end of the semester voluntarily. All the end-term exams contain two parts: one related to the work done plus the knowledge acquired during the lectures, and the other one related to laboratory work. The students take these exams individually.

The students accessed to the e-courses since their publication. Filling the tests was not compulsory. The involvement of the students increased during the course. The number of collected tests was 96 in Information and Data Structures I and 119 in Operating Systems I. The information obtained about each student's personality and intelligence (verbal, spatial and general reasoning dimensions) was analyzed, together with information about group formation and individual and group performance, with the purpose of getting hints about the impact of these values on both group performance and individual achievements.

Regarding the students' performance, the results obtained when carrying out individual and collaborative activities during the course were analyzed, including their results on individual exams (regarding both theoretical concepts and practical work) and their results when working together in laboratories. All the data representing their interactions within the websites were available too.

C. *Data Harvesting and Analysis*

The completion of the tests gave rise to a set of XML files, each of them including information about the student id, the type of test taken, the answers given, the score obtained according to the corresponding scale and the percentile in relation to different categories (graduates, engineers, and directors). This last information constitutes an additional encouraging element for the students to take the tests. Since it is possible to establish those comparisons, we incorporated that information along with the corresponding scores. The teachers passed us the marks obtained by the students in the theoretical examinations and the scores assigned to their practical work, including both the group mark and the result of individual examinations. They also gave us information about group (pair) formation. With these data, it was possible to start the analysis of correlations between student personal traits and their performance in individual examinations, in terms of individual learning, and between student personal traits, group formation and performance in collaborative practices, analyzing the influence of these traits on the outcome of the collaboration.

Several statistical techniques have supported the data analysis, carried out using SPSS [16]. Apart from the basic descriptive statistics, we used correlations, regression models, stepwise regression models and discriminant function analysis. The results obtained are presented next.

III. Results Obtained

In this section, we present the results obtained for each course, as well as those obtained when analyzing all the data together. Firstly, a summary of these results is presented. Table I sums up the relevant results obtained in the analysis of individuals. IDS stands for Information and Data Structures I, OS means Operating Systems I and the symbols mean the following:

++ : positive influence, statistically significant.

\+ : positive influence, not statistically significant.

\- : negative influence, not statistically significant.

-- : negative influence, statistically significant.

TABLE I. Relevant Influences After Data Analysis (Individuals)

	IDS (theory)	IDS (practices)	OS (theory)	OS (practices)
Intelligence (verbal abilities)	+	+	++	
Intelligence (spatial abilities)		++		
Intelligence (general reasoning)	+			
Personality (neuroticism)	--			
Personality (openness to experience)	+	++		
Personality (agreeableness)	+			
Personality (conscientiousness)			+	++
Learning style (sensing)		++		

Table II shows, in a similar way, the results of the analysis of pairs regarding the influence of group homogeneity/heterogeneity. In Information and Data Structures I, data from 96 students is available. 52 of them have filled in the personality tests, 40 the learning styles test, 47 the verbal abilities test (intelligence), 33 the spatial abilities test (intelligence) and 31 the general reasoning test (intelligence). The average mark in the theoretical exams is 6.41 (SD = 1.9) and that in the practical works is 8.42 (SD = 1.6).

The correlation analysis showed us that certain traits seem to affect the marks the students obtain both in the theoretical exams and in the practical works. With an acceptable level of significance (0.036) we saw that neuroticism influences the marks obtained by the students in the theoretical exams; this personality trait affects negatively to the performance (Pearson Correlation Coefficient = -0.323). Neuroticism relates to anxiety, so it could be reasonable that this is a relevant feature in the context of examinations, especially during the first year of the students at the university.

In the case of the practical works carried out during that course, the personality trait openness to experience has certain influence on the student results (0.387). This can be due to the fact that practical work requires more involvement, and the capacity of getting involved in tasks is related to openness to experience. In the fourth practice, related to tree data structures, spatial abilities (one of the intelligence factors) also influence on a significant way (0.42 with significance of 0.018 in one of the practical works). It is interesting to see that students with no enough spatial abilities perform worse when working with the practical assignment related to "trees", which sounds quite reasonable.

TABLE II. RELEVANT INFLUENCES AFTER DATA ANALYSIS (PAIRS)

	OS	All pairs
Heterogeneity in conscientiousness		++
Homogeneity in verbal abilities		+
Heterogeneity in general reasoning	+	

Regarding learning styles, students with a sensing profile, contrary to those intuitive, seem to obtain better marks in the practical tasks (0.391). This could be because the resolution of these practical tasks most of the times involves the application of resolution methods, or the implementation of available pseudo-codes, being intuition less relevant here.

The construction of regression models for the data available has shown that verbal intelligence, openness to experience and agreeableness are the most influential factors regarding the marks obtained in theoretical examinations, although the results in this case are not statistically significant (significance = 0.906). On the other hand, openness to experience (significant) is the trait that most affects the marks obtained in practical works, with a weight of 0.637 (standardized beta coefficient) in a stepwise model.

Regarding the analysis of data about pairs working together, the main results when looking for correlations between, on one hand, differences in trait values and, on the other hand, the marks obtained, are not statistically significant, but indicate a tendency to get homogeneous groups regarding general reasoning, extraversion and openness to experience (correlation values: 0.98, 0.58 and 0.49, respectively), and heterogeneous with respect to agreeableness and neuroticism (values of -0.41 and -0.33).

In Operating Systems I, the correlation analysis has shown a little but statistically significant positive influence of the verbal abilities on the theoretical exam marks (0.22), as well as certain influence of conscientiousness (in a positive way) on the practical task marks (0.325). The regression analysis also indicates a significant influence of verbal abilities on theoretical exam marks (standardized beta coefficient of 0.489) and a slight but statistically significant relation between personality traits and practical work marks, being again the conscientiousness the factor with more weight in the prediction (standardized beta coefficient: 0.22).

The first result made the teachers of the course think about both the course contents and the corresponding evaluation. The way in which an operating system works must be comprehended. Therefore, the teachers normally provide deep and reasoned explanations, and students are required to give very well-reasoned explanations in the exams. So, could it be the case that the evaluation method favor students with high verbal abilities? Does the nature of the subject determine the way in which teachers explain it and evaluate the students? In any case, information about the influence of verbal abilities on learning performance can be used, e.g., to help students with less verbal abilities.

Regarding the practical work, practices of Operating Systems I are less "guided" than those of Information and Data Structures I, where the students received detailed explanations of every single issue and pass a weekly "control" from teachers, who normally help them to organize to deliver the work on time. Therefore, it makes sense that conscientiousness is more relevant in Operating Systems, in which practical work tend to be a complex task and teachers do not give students detailed advice about the expected progress (therefore, the students need to be more responsible to achieve good results). Consequently, it can be said that students with less conscientiousness run a higher risk of getting worse results when learning Operating Systems. Therefore, they can be a specific challenge for adaptive e-learning systems to overcome this limitation. After analyzing the pairs of Operating Systems I, the only conclusion obtained suggests a positive influence of heterogeneity regarding general reasoning (intelligence feature) on the final marks of the pair.

Finally, the analysis of all the pairs together (from the three courses) shows a statistically significant tendency to form homogeneous groups regarding conscientiousness. It is observed with a significance level of 0.0489 and a Pearson Correlation Coefficient of 0.313 when considering the values of both members of the pair regarding this factor. This can be beneficial for pairs with high conscientiousness (according to the relationship between it and performance, as observed in [8] and in our own results), while disadvantageous for the others. The analysis of pairs also shows certain positive influence of the homogeneity regarding verbal abilities (R square = 0.384, standardized beta coefficient = -0.43), although it is not statistically significant (significance = 0.167).

IV. APPLICATION IN ADAPTIVE E-LEARNING SYSTEMS

The results of this work can be applied in different scenarios, including face-to-face learning, blended learning or e-learning. We are especially interested on their use in adaptive e-learning systems that support individual personalized assistance and collaborative work, including dynamic group formation, such as CoMoLE (Context-based adaptive Mobile Learning Environments) [17].

CoMoLE supports the design and dynamic generation of e-learning environments able to:

- Recommend Web-based individual or collaborative activities to be carried out by each student or group, according to each one's features (e.g., personality), preferences (e.g., learning style), needs, previous actions or context at each time (location, available time, device, emotional state), among others.
- Generate individual and collaborative workspaces to support the realization of each activity at each time. It generates them on the fly, according to the activity to be carried out as well as to the user/group features. It selects the most suitable content versions and individual/collaborative tools for each case, and generates the corresponding workspace accordingly.

Details about the recommendation process carried out by CoMoLE, along with experimental results, are found in [17]. The results of this work constitute an interesting source of information for adaptive and recommender e-learning systems. On one hand, knowing the influence of personality and intelligence on individual achievements allows the identification of student profiles that may have specific needs at particular times. This is useful in face-to-face and blended scenarios too. For example, if neuroticism has proved to affect negatively to performance, and neuroticism is related to anxiety, a teacher or an adaptive e-learning system such as CoMoLE can propose one enjoyable/relaxing activity to a neurotic student right before presenting him an evaluation test.

More specifically, some types of students may have particular needs regarding certain types of courses. For example, we found out that the students with visual (versus verbal) learning style obtained lower marks in one of the subjects. During the last years, this subject has been presented mainly through textual slides, and the evaluation has based on textual explanations (even though the discipline is mostly technical). Different experiences have taken place regarding adaptation to learning styles, with different results [18]. We think that teachers or adaptive e-learning systems such as CoMoLE can consider the student profile along with information about the course nature, in order to offer alternative materials (schemas, pictures, etc., if available) to visual-style students to facilitate their understanding. The teacher in charge of the e-course can even provide different types of problem statements and self-evaluation resources, if feasible, so that the most appropriate ones can be selected at runtime for each student according to their profile.

Another result obtained, dealing with the same subject, suggests the possibility of automatically alerting the students with a lower level of conscientiousness about the need of carrying out the practical work in a continuous manner, when it comes to performing a task of large magnitude. Obviously, teachers can also consider this in face-to-face learning.

With respect to automatic group formation in adaptive e-learning systems, some mechanisms have already been developed [19]. Grouping criteria is essential unless random grouping is preferred. In that sense, the incorporation of the results obtained is immediate in systems like CoMoLE: its grouping mechanism can be fed by the criteria desired. In face-to-face or blended scenarios, those criteria can be used to group the students for collaborative work.

All these applications of the work done are especially useful in the context of courses delivered completely online, since, in many cases, the students have little contact with their teachers. In these cases, providing effective personalized guidance is essential. However, as said before, information about the influence of the students' personality, learning styles and intelligence on learning performance can be used not only as adaptation criteria in e-learning; it is also useful for teachers in face-to-face and blended learning: they can help their students during the learning process accordingly.

V. Conclusions and Future Work

In this work, we have studied the impact of intelligence, personality and learning styles on individual and collaborative student performance. The results obtained have been presented in detail in section III. They shed light on the influence of these factors on the student/group performance during the learning process. This study has been made with groups of two students. Further studies are needed to show whether these results would be the same for bigger groups in different e-learning contexts and whether the fact that filling the tests were not compulsory could have introduced some bias in the analysis.

The final goals, in the context of e-learning, are: to be able to guide each student according to his traits; to detect individuals/groups with high risk of failure and assist them dynamically in order to prevent them for failing; and to obtain information about the combinations of student features that perform better (regarding personality and intelligence), to use it as criteria for automatic group formation. Specific applications of the results obtained in adaptive e-learning systems have been presented in the previous section.

As it has been mentioned above, these results are also useful for teachers in face-to-face learning. In any case, the final aim is to maximize the possibility of student success during the realization of individual and collaborative tasks and, more generally, during the learning process.

Recent works in the area of adaptive systems and user modeling deal with obtaining information about the students in non-intrusive ways. E-learning systems should definitely adapt their contents, activities, workspaces and learning strategies to each user's preferences, needs, personality, learning style, context, emotional states, and so on.

However, the richer the adaptation is, the more information about the student is needed. Getting all this information is not easy. The students can feel overloaded if we ask them to fill in all the corresponding questionnaires. Some steps have been given to shorten Felder's learning style questionnaire, either by adapting the questionnaire on the fly [20] or by monitoring the student mouse movements [21].

Regarding personality, we have taken some steps towards the inference of users' personality from their interactions within Facebook [22]. Finally, the students' emotional state at a time seems to affect their motivation and, therefore, the learning outcome. We have recently successfully investigated the possibility to infer user emotional states starting from what they write in their Facebook walls [23]; changes in their "usual emotional state" are detected too. It would be interesting to study, e.g., how emotional states affect workgroup, and which are the better "emotional" combinations for group formation.

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