Personality Questionnaires as a Basis for Improvement of University Courses in Applied Computer Science and Informatics

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Abstract

In this paper, we lay the foundation for an adaptation of the teaching process to the personality traits and academic performance of the university students enrolled in applied computer science and informatics (ACSI). We discuss how such an adaptation could be supported by an analytical software solution and present the initial version of this solution. In the form of a case study, we discuss the scores from a personality questionnaire that was administered to a group of university students enrolled in an introductory programming course at the Faculty of Technical Sciences, University of Novi Sad, Serbia. During a non-mandatory workshop on programming, the participants completed the 48-item short-scale Eysenck Personality Questionnaire–Revised (EPQ–R). By using various exploratory and analytical techniques, we inspect the student EPQ–R scores and elaborate on the specificities of the participating student group. As part of our efforts to understand the broader relevance of different student personality traits in an academic environment, we also discuss how the EPQ–R scores of students could provide information valuable to the process of improving student learning and performance in university courses in ACSI.

Keywords: Academic performance, personality questionnaire, EPQ–R, computer science education.

1. Introduction

Providing a satisfying environment for students that is also conducive to learning represents an important challenge for educators. Higher education, which still seems to retain much of its formal and traditional aura, presents a specific set of educational issues. In a setting that tends to be crowded, competitive, and oriented to specialized knowledge and skills, a student may relatively easily be overshadowed by more prominent peers or even completely overlooked by teachers. This problem is further aggravated by the fact that each area of study in higher education has its own specificities within the educational process. In study programs on applied computer science and informatics (ACSI), there are some special requirements that educators may need to consider.

To organize practical classes and assignments, ACSI departments need laboratories where each enrolled student has a computer at disposal during the class hours. In general, this leads to somewhat smaller capacities of computer laboratories as opposed to traditional classrooms. As a result, class groups in ACSI programs tend to be smaller, which could be beneficial to both students and teachers. In such an environment, a student may get more attention and support from the teacher, while the teacher may get the chance to learn more about the progress of each student in the group and address concrete difficulties that a student faces when learning a new material.

In addition to this, ACSI students are often given project assignments that demand team work, which resembles actual working environments in IT (information technology) industry. This kind of group assignments tends to be effective and popular with ACSI students. However, besides skill mastery that is needed also in individual assignments, team work demands tackling group dynamics, which, if not properly maintained, may lead to negative outcomes.

The two aforementioned specificities of university education in ACSI, i.e., smaller class groups and higher reliance on group projects, provide better opportunities for teachers to understand individual students and adapt the teaching process to the particularities of the class group. At the same time, it is expected that this kind of adaptation would be most natural and effective in smaller student groups and teams.

Besides the information collected in everyday classroom interaction, the teacher may learn much about students from concrete data concerning student academic performance and student personality. For instance, student academic performance in previous assignments or similar courses might be indicative of student results in future. By using this kind of information, the teacher could more precisely identify the struggling students, even well in advance, and provide timely support.

Moreover, formation of teams for project assignments may also be based on academic performance so that there is both diversity within the team with respect to previous academic performance and overall balance between the teams in the same respect.

Understanding personality traits of students could be useful in the tasks of providing support and forming project teams. Personality traits of students might also be indicative of academic success or success in a particular field. Furthermore, by taking into account the personality of a student in the context of group project assignments, the student could be assigned to a team that would allow better collaboration and learning.

As a result of the proliferation of IT resources, the process of storing, retrieving, and analyzing data has become less complicated. The records about student academic performance and personality may be collected and stored within a single data repository. Nowadays, student scores on individual course assignments are usually stored in digital format, which facilitates the process of exporting and merging student data for different assignments and courses. On the other hand, information about personality traits of individual students is not routinely collected and saved for later usage. Nonetheless, by implementing computer-based administration and processing of personality questionnaires, the discovery of personality information becomes a straightforward process whose output, i.e., data about students' personality traits, may be added to the same central repository as in the case of academic performance records.

The goal of the research whose foundations are presented in this paper is to allow for more meaningful teacher intervention and better learning outcomes for students in ACSI by helping university teachers gain data-based insights into their ACSI class groups. This kind of insight could be more easily obtained with the support of an advanced software solution that would feature

- a data repository for collecting and storing data about student academic performance and personality traits and
- a software tool for analyzing the data available in the data repository and providing readable student profiles.

From the common data repository, student data may be manually or even automatically accessed, combined, and used to create individual student profiles. These profiles would be both academic and psychological in their nature. Owing to their wider scope, it may be expected that the overall value of these profiles for both the teacher and the students would be higher than for the case in which a structurally simpler profile is considered. Moreover, the construction of these profiles could be based both on the general relationships between personality and academic performance that have been reported in the scientific literature, as well as on the patterns that could be extracted from the repository in a data analysis process.

In this paper, we focus on the following important aspects of the supporting software solution:

- the technical aspect, i.e., the nature and structure of the central data repository and the analytical tool, and
- the conceptual aspect, i.e., the feasibility of including personality information in the process of making inferences about future academic performance and behavior of students.

With respect to the technical aspect of the software solution, we briefly present a data warehouse, which is used as the central data repository in the software solution, and the analytical tool. As an illustration of the conceptual aspect of the software solution, we provide a case study in which some of the basic insights that may be gained from data are reported. The personality data for the case study were collected during a programming workshop for students who were at the time enrolled in one of the two selected ACSI study programs at the Faculty of Technical Sciences,

University of Novi Sad, Serbia. The short version of the Eysenck Personality Questionnaire–Revised (EPQ–R), which is a popular and widely used personality questionnaire, was administered during the workshop.

In addition to Introduction and Conclusion, this paper contains three more sections. Section 2 is devoted to personality questionnaires and their usage, as well as potential relationships between academic performance and personality traits, mostly with respect to the Eysenck Personality

Questionnaire and its common versions. In Section 3, there is an overview of the software solution, which comprises the data warehouse and the analytical tool, while Section 4 covers the conducted case study.

2. Related work

As an important personality theorist and researcher, Hans Eysenck is widely recognized for his selection of main personality dimensions that consists of psychoticism, extraversion, and neuroticism (Revelle, 2016; Zuckerman & Glicksohn, 2016). The revised and improved versions of personality questionnaires built around these dimensions, named the Eysenck Personality

Questionnaire–Revised (EPQ–R), may be found in (Eysenck et al., 1985), where both the regular questionnaire (100-item) and the short questionnaire (48-item) are available.

Eysenck personality questionnaires have been thoroughly evaluated and widely used around the world. There are examples of their usage for large English-speaking countries (Francis et al., 1991), but there are also translations of these and other related questionnaires into many languages, including Spanish (Aluja et al., 2003), Italian (Dazzi, 2011; San Martini et al., 1996), Greek (Alexopoulos & Kalaitzidis, 2004), Finnish (Lajunen & Scherler, 1999), Turkish (Lajunen & Scherler, 1999), Urdu (Lewis & Musharraf, 2014), and Hindi (Tiwari et al, 2009). A large number of EPQ-related studies have been methodically conducted across various countries (Eysenck & Barrett, 2013).

In a large systematic literature review and meta-analysis of studies on correlates of academic performance (Richardson et al., 2012), numerous significant constructs were identified, including various personality traits, motivational factors, and learning approaches. Many researchers have investigated and uncovered relationships between student personality and academic behavior and performance. There are examples for such research for university seminars (Furnham & Medhurst, 1995), as well as for common academic practice (Chamorro-Premuzic & Furnham, 2003). Some of the more recent findings also indicate that there is a relationship between certain personality traits, intelligence, and personal success in education (Boyle et al., 2016). Moreover, there is some evidence supporting the existence of a relationship between personality and learning styles (Furnham, 1992).

3. Software solution

There are two main components in the present software solution: a data warehouse for storing collected data and an analytical software tool. The analytical tool is tightly related to the data warehouse and tailored primarily for exploration and analysis of data contained therein.

The data warehouse contains collected data about student academic performance and personality traits. We opted for a data warehouse because its typical schema design is organized in terms of facts and dimensions, which is especially suited for data querying and analysis. We formed the present data warehouse schema by following a constellation schema design, which was necessary as we identified two regular fact tables, one for student results in course assessments and the other for student scores on a particular personality questionnaire.

We identified the following dimensions for student performance on academic assessments: time, place, institution, study program, study program progress, course, assessment type, assessment measurement unit, administrator (i.e., responsible teacher), and student. In the context of personality traits data, we selected the following dimensions: time, place, institution, study program, personality questionnaire, personality questionnaire scale, personality questionnaire language, personality questionnaire administrator, student, and session. All dimensions were denormalized, which resulted in having one table per dimension. Surrogate keys were formed for each dimension table and each fact table separately. For the purpose of tracking changes in dimension tables, journaling tables were added to the data warehouse.

A data warehouse for academic performance data that was presented in (Ivančević et al., 2011) served as a starting point in the formation of the present data warehouse. The initial version of the data warehouse underwent various changes and was extended to encompass personality data. In Figure 1, we give a graphical overview of a schema segment covering data about student scores on scales of personality questionnaires. In this graphical overview, primary keys are denoted by the key symbol and foreign keys by the rhombus symbol, while the role of tables may be discerned by the prefix in the table name, i.e., the *Dim* prefix denotes a dimension, while the *Fac* prefix denotes a fact. The extract, transform, and load (ETL) process, which is responsible for populating the data warehouse with clean records, was designed for comma-separated values (CSV) files (Shafranovich, 2005) as primary data sources. To this end, we wrote an auxiliary program in the Java programming language that extracts data from CSV files and prepares the data for loading into the data warehouse. The design of the data warehouse, which includes formation of the presented schema, was carried out using MySQL Workbench 6.3 Community Edition (MySQL, n.d.), an integrated tools environment for the MySQL database management system (DBMS), while the implementation was performed using MySQL Server 5.7 Community Edition (MySQL, n.d.), a relational DBMS.

The analytical tool, which is also part of the software solution, is a web application that retrieves data from the data warehouse or external CSV files matching the required structure and allows analysts to perform exploration and analysis of data concerning student performance and personality. It is organized into various modules, each supporting one principal exploratory or analytical task.

The analytical tool was built using the Shiny framework (Shiny, n.d.), a framework for building analytical web applications based on the R environment for statistical computing (R, n.d.). As there is a large growing collection of packages for R, there is a solid basis for extension of the analytical tool with latest or still experimental analytical procedures.

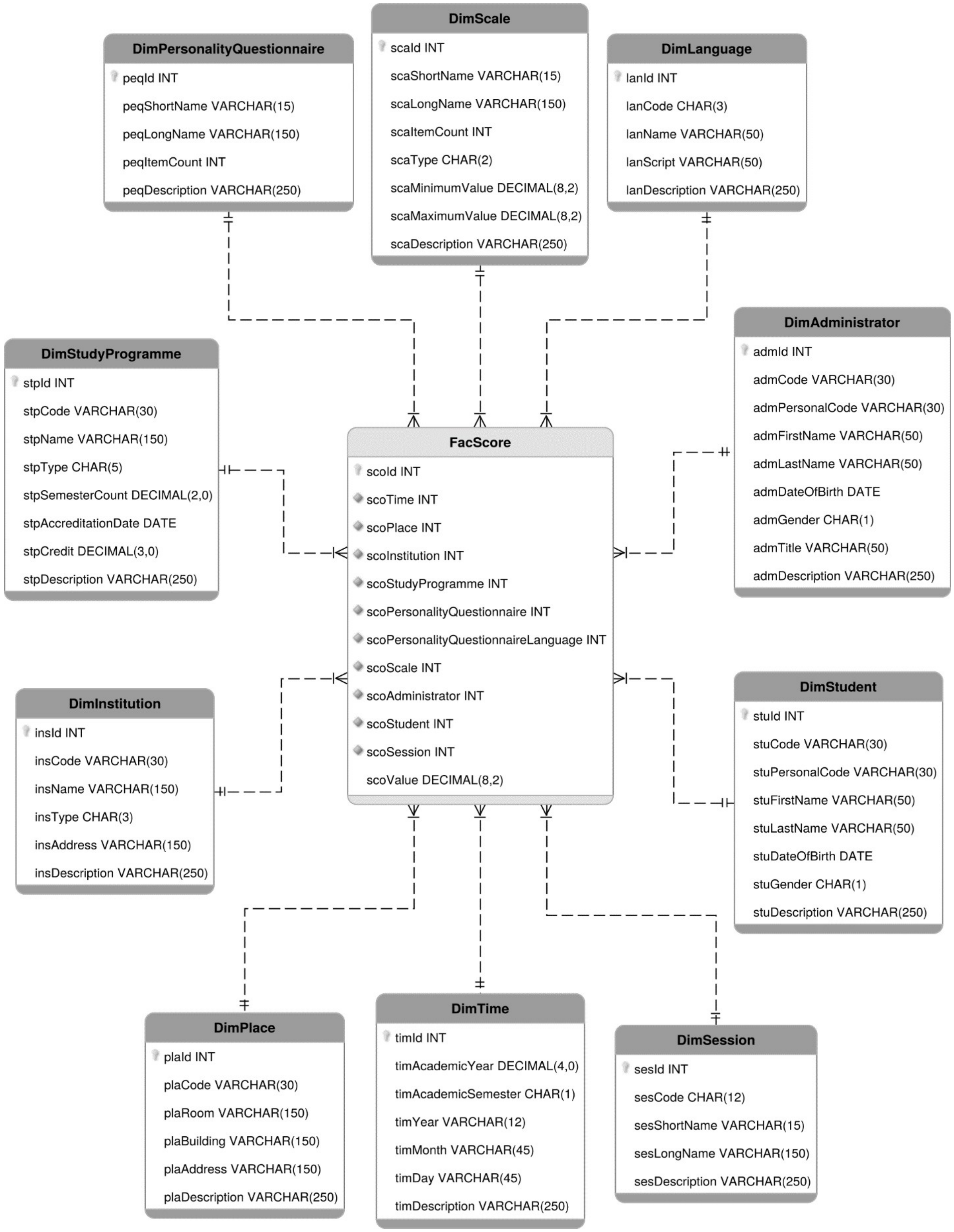

Figure 1. A data warehouse schema segment for scores of university students on scales of personality questionnaires

The Shiny framework further facilitates the development and extension process as it allows developers to leverage the analytical capabilities of the R environment and focus on building analytical functionalities. For these reasons, new features may be regularly added to the analytical tool. At present, various common statistical summaries and visualizations may be created by using the analytical tool, but there is also support for other techniques, some of which are illustrated in Section 4.

4. Case study

In 2014, after the end of the winter semester, the Valentine's Day workshop on the C programming language was organized at the Faculty of Technical Sciences, University of Novi Sad, Serbia. The undergraduate students who had just completed the regular classes in *Programming Languages and Data Structures (PLDS)*, an introductory first-year course on programming, were invited to participate in the workshop. This invitation was addressed to the students of two ACSI-related undergraduate study programs: *Computing and Control (CC)* and *Power Software Engineering (PSE)*. In total, 24 students (19 males and 5 females) aged 19 to 20 responded and fully participated in the workshop. During the workshop, participating students could learn more about certain topics on C programming that had not been covered during the PLDS course and complete a test on the material covered in the workshop. They were also given the 48-item short-scale EPQ–R (Eysenck et al. 1995), which contained 12 items for each of the four contained scales: Psychoticism (P), Extraversion (E), Neuroticism (N), and Lie (L).

The EPQ–R data from the workshop were processed and loaded into the data warehouse. Overall EPQ–R scores of students are given in table 1. When interpreting these scores, participant self-selection should be considered as the participating students voluntarily responded to a general invitation to the workshop. Moreover, the size of the sample should also be taken into account, especially for the female group of participants. For these reasons, the reported scores should be carefully interpreted when attempting to form conclusions about overall personality traits for the whole population of PLDS students or ACSI students in general. Nonetheless, the male/female ratio and the CC/PSE ratio that are observed for all the CC and PSE students then enrolled in the PLDS course appeared to be relatively well preserved in the sample of participating students.

The results in table 1 are arranged into five groups: a group covering all participants, a group pair organized by gender (Male vs. Female), and a group pair organized by study program (CC vs. PSE). For each group-scale combination, the mean score and the standard deviation (SD) were calculated. Although both the group pair for gender and the group pair for study program are imbalanced in terms of group size (19 males vs. 5 females and 18 CC students vs. 6 PSE students), the overall difference in scores across the four EPQ–R scales is greater between the students of different gender.

Table 1. EPQ–R scores of students by group and scale

Group	N	P		E		N		L	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
Male	19	4.05	1.72	6.74	3.45	3.11	2.33	5.53	2.20
Female	5	2.20	0.45	9.80	2.17	4.80	3.63	7.20	4.27
CC	18	3.67	1.50	6.72	3.58	3.50	1.92	5.78	2.44
PSE	6	3.67	2.42	9.33	2.07	3.33	4.46	6.17	3.71
Total	24	3.67	1.71	7.38	3.42	3.46	2.65	5.88	2.72

The higher P scores for males and the higher N scores for females generally correspond to the overall differences between the genders that were reported in the original EPQ–R paper (Eysenck et al., 1985). Nonetheless, the relatively small differences between the genders in their E scores and L scores in the original study appear to be more pronounced in the present study.

When examining the results of a particular group, a comparison with another group is usually performed. By using the new analytical tool, it is possible to inspect and analyze the collected personality data, which includes comparison of two data samples by scores on common scales. However, comparison of personality data is a delicate task. Measuring instruments should be reliable and standardized (Eysenck & Barrett, 2013), while cross-cultural applicability of the used questionnaire needs to be checked before making a comparison across different cultural contexts (Alexopoulos & Kalaitzidis, 2004).

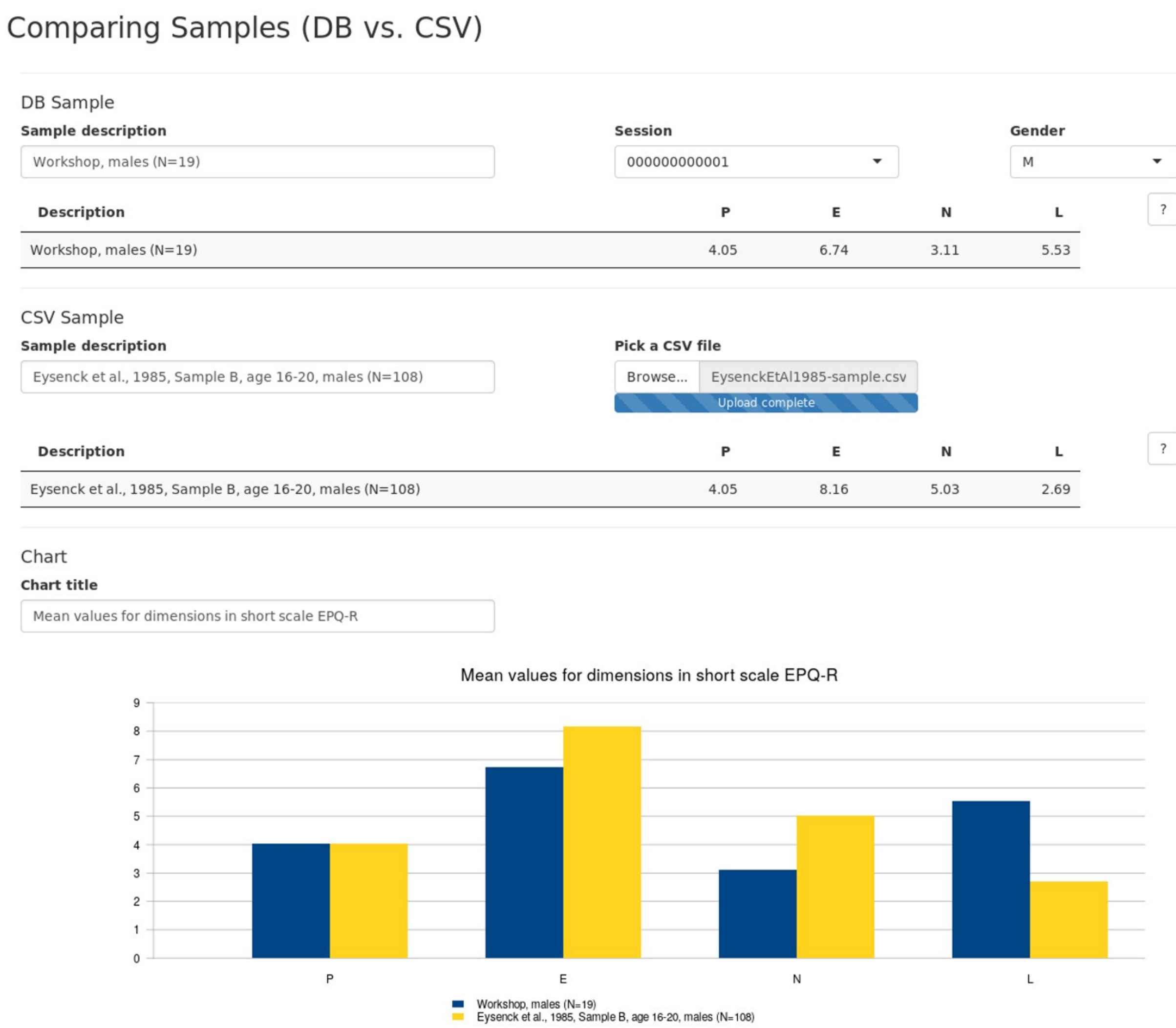

Figure 2. Comparison of mean scores on the EPQ–R scales between the male students who participated in the workshop and a male group of similar age from the original EPQ–R study (Eysenck et al., 1985), as shown in the analytical tool

We performed two comparisons of samples by scores on the EPQ–R scales, but, because the compared samples originate from different spatial, temporal, and demographic contexts, the results and their interpretation should not be regarded as definitive. Nonetheless, the examples presented in this case study are indicative of some characteristics of the analyzed group, while also serving as an illustration of the capabilities of the analytical tool and depicting its intended role in the improvement of ACSI courses.

In the first comparison by scores on scales, we used the analytical tool to compare the personality data of male participants from the workshop to the reported summary data from the original EPQ–R study (Eysenck et al., 1985) that were obtained for the short-scale EPQ–R and a sample of males aged 16-20 which is part of Sample B from the original EPQ–R study. The comparison results are given in Figure 2 in the form in which they appear within the analytical tool.

The data for the workshop participants were loaded from the data warehouse, while the summary data from the original EPQ–R study were loaded from a CSV file. The bar chart featured in Figure 2 shows mean scores on the EPQ–R scales for the selected workshop participants (denoted by blue bars) and the selected participants of the original EPQ–R study (denoted by yellow bars). The mean scores on the P scale agree between the two samples, but the overall scores for the other scales vary.

In the second comparison by scores on scales, we compared the personality data from the workshop to more recent personality data collected in Serbia. In a psychology-related study about gastrointestinal disorders (Filipović et al., 2013), the authors assessed personality traits for a control group of 60 individuals by using what seems to be the same or at least a similar type of questionnaire as in the present study, i.e., a questionnaire of 48 items distributed equally between the psychoticism, neuroticism, lie, and extraversion scales. When the mean scores for all the participants of the workshop are contrasted with the mean scores for the control group in the other study (Filipović et al., 2013), a good match may be observed for the P and E scales (3.67 vs. 3.73 and 7.38 vs. 7.43, respectively), but there is still some variation for the N scale and especially the L scale (3.46 vs. 4.43 and 5.88 vs. 2.23, respectively).

In both comparisons, largest differences were observed with respect to the L scale. The L scores for the workshop sample are considerably higher than the corresponding values for the other two samples considered. However, a sound discussion of the underlying causes would require additional investigation.

In general, tables might not be the most fitting presentation technique when many values need to be shown. In the case of multiple dimensions, i.e., scales, which are common for personality questionnaires, even bar charts lose some of their usefulness. Radial axes and visualization of individual instances within a radial coordinate system, e.g., by applying the RadViz method (Radial Coordinate visualization) (Nováková, 2009), may be used to form an overview of a sample across multiple dimensions. We used an implementation of the RadViz method from the *svdvis* package for R (Chung, 2015) to create a radial visualization for EPQ–R scores of all the participating students, which is shown in Figure 3.

The radial visualization in Figure 3 depicts each participating student as a dot whose color indicates the gender of the student, blue for male students (M) and red for female students (F). The position of a dot in the visualization is determined by the scores of the associated student on the four EPQ–R scales. The radial overview may provide a much clearer outline of clustering within the analyzed group. Although there are only five female students, they are concentrated in a relatively narrow area within the radial coordinate system.

On the other hand, the division of data points by gender might not be the only useful strategy when visually inspecting the analyzed sample in a coordinate system. Numerous clustering algorithms may be used to determine which data points share similar scores across the EPQ–R scales, i.e., which data points belong to the same cluster of similar entities based on their corresponding EPQ–R scores. A radial visualization in which data points were organized into three clusters is given in Figure 4. Each cluster is marked by a different color: cluster 1 by red, cluster 2 by green, and cluster 3 by blue.

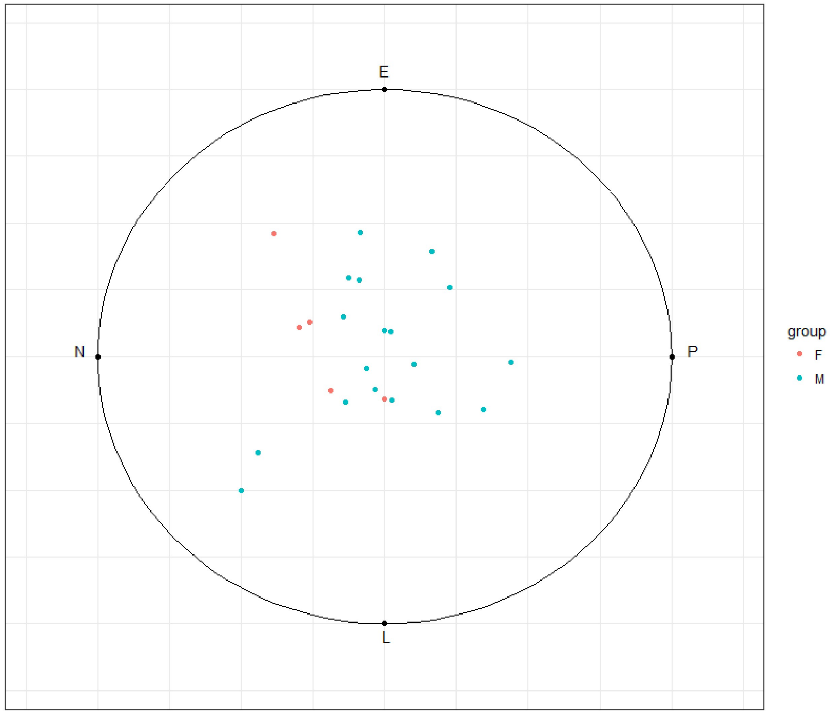

Figure 3. Radial visualization of scores across the EPQ–R scales for the male and female participants

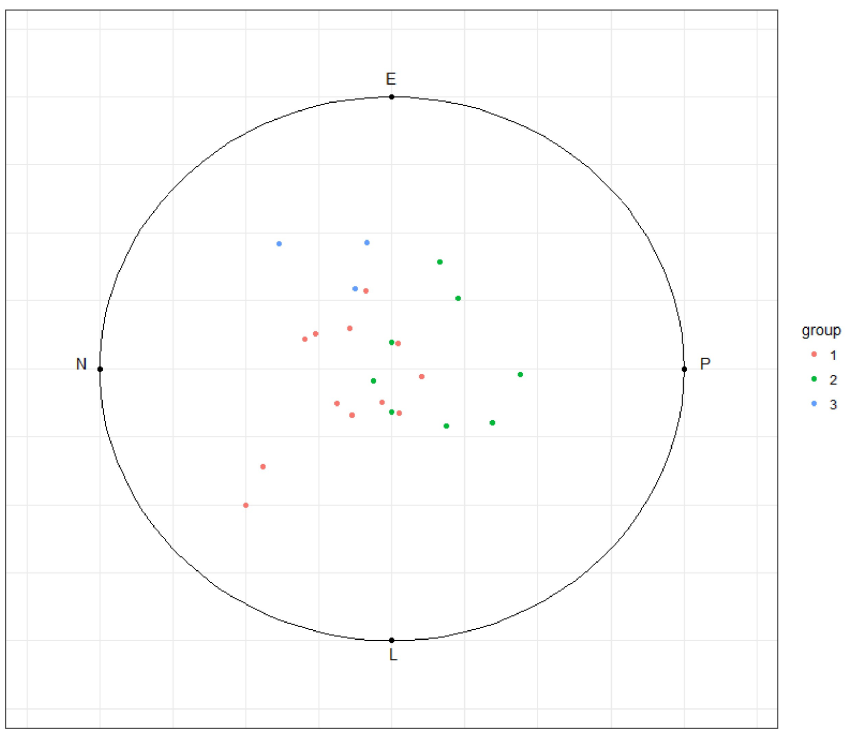

Figure 4. Radial visualization of scores across the EPQ–R scales for clustered data about all the participants

The clusters were generated using an implementation of a hierarchical clustering algorithm available in the R environment (R, n.d.). The top three clusters were extracted from a hierarchical cluster tree shown in Figure 5, while the color of data points in the visualization shown in figure 4 was determined based on cluster labels. Hierarchical clusters could be used when investigating which students in the analyzed sample share similar personality traits. This could be especially useful for smaller student groups as the teacher may manually inspect the cluster tree and its leaves, which designate individual students. For instance, there are three students in cluster 3, who are represented within the tree in Figure 5 by identifiers 14, 22, and 24. The students with identifiers 14 and 22 are more closely linked and more similar to each other than to the student with identifier 24.

This kind of cluster forming and representation would be suitable for teachers who need to split a group of students into an arbitrary number of distinct subgroups. The differences between these subgroups with respect to gender, personality, performance, or some other factor could then serve as a basis for forming diverse project teams in ACSI courses.

As indicated in recommendations for collaborative group work, a heterogeneous group should have four students and exhibit variety in academic ability, gender composition, and international membership (Lawrie et al., 2014). Moreover, it seems that some diversity in a student project team, e.g., diversity in gender, or certain patterns in representation of particular learning styles within the team may be linked to better team performance (Lau et al., 2012). Nonetheless, the effects and importance of different types of diversity in a team may change with time (Harrison et al., 2002), so careful consideration of multiple criteria is needed when attempting to direct the team formation process.

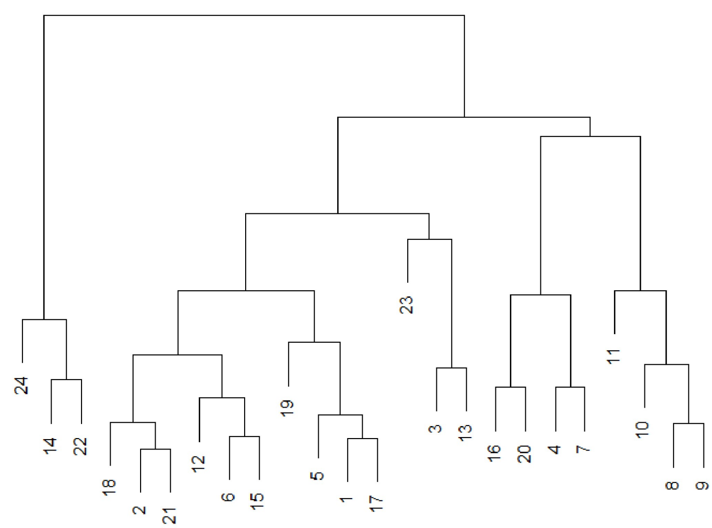

Figure 5. Hierarchical clustering by scores across the EPQ–R scales for data about all the participants

5. Conclusion

In this paper, we discuss how personality questionnaires may be used to collect data about personality traits of students and how these data, together with data about academic performance of students, may allow the teacher to better understand the student population. This improved understanding is necessary to perform some adaptations of the teaching process and potentially increase student learning and performance in university-level ACSI courses. We provide an overview of the initial version of a software solution for collection and analysis of data about student academic performance and personality traits. We also present a case study in which we applied the software solution and provided examples of using various data analysis techniques.

These examples represent various usage scenarios whose purpose is to provide different insights about the analyzed student population. By using the software solution, the teacher may inspect student data and perform analyses designed specifically for the domains of education and psychology. The discovered patterns could be used to tailor student collaboration and teaching in small groups of students to certain psychological characteristics of individual students.

There are many research directions for future work. In order to support additional features, e.g., extensive data visualizations or predictive performance models, we may utilize latest analytical procedures and extend the software solution on a regular basis. We intend to organize new workshops to collect larger data samples that better represent the overall student population and experiment with different personality questionnaires to identify which questionnaires and scales should be used to get data for reliable prediction of student performance and behavior in ACSI courses. An integrated set of data about student personality and performance could be a basis for generation of new research ideas and hypotheses. Personality data for students from similar study programs or even other study areas could be used in new comparisons of samples to learn more about the students involved. Novel learning methods that could be beneficial for students in ACSI courses, e.g., micro-learning (Jomah et al., 2016), may be evaluated with the help of the software solution. Data from experiments about such methods could be first stored and then analyzed using the software solution to check for improvements in student learning. We also plan to do research concerning creation and comparison of causal models that link teaching practices and student personality and learning styles with learning outcomes and student academic performance. The goal is to provide teachers with a unified software solution for student profiling that could issue early warnings for struggling students and offer teaching recommendations based on the available data.

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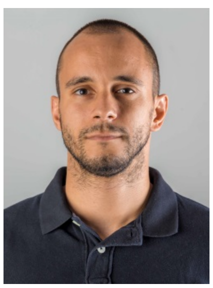

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