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RESEARCH ARTICLE

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Are learning styles useful? A new software to analyze correlations with grades and a case study in engineering

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Abstract

Knowing student learning styles represents an effective way to design the most suitable methodology for our students so that performance can improve with less effort for both students and teachers. However, a methodology is usually set in teaching guides according to the previous academic year's information without any knowledge of our current audience. In this work, a new software for learning styles and grade analysis based on the Honey-Alonso Learning Styles Questionnaire has been proposed. This tool proposes the average learning style profiles of a given course by clustering student learning styles and analyzes the possible relation between grades and learning style profiles. By using that program, three different courses from Computer Sciences Engineering degrees during an academic year have been analyzed. The obtained results in our specific context exhibit that possible relation. This information could be useful to understand how students approach learning materials.

KEYWORDS

academic performance, evaluation, grade, learning style, virtual campus

1 | INTRODUCTION

Student assessment is one of the most complicated tasks for teachers. This assessment is affected by different factors, both internal and external. The teaching guide is an example of an internal factor since it can restrict student assessment sometimes. In contrast, different contexts for the same group of students can be found among external factors.

In particular, a factor that can influence student assessment is the learning style that each student seems to use when approaching the learning materials [5, 28, 30, 36]. Student learning styles come from the Learning Style Questionnaire (LSQ) designed by Honey and Mumford [21], which is derived from the Learning Style Inventory (LSI) [29] and it was later adopted by Alonso, Gallego, and Honey to the Spanish educational context [6]. When it comes to the teaching and learning process, we need to take into account that not all students learn in the same way since characteristics, cognitive, affective, and physiological behaviors can influence this knowledge and the competencies acquisition process. In fact, different learning methodologies take into account these specific features to try to understand why students may be approaching the same learning materials differently. For example, adaptive learning focuses on maximizing the learning performance of each student by deploying learning resources adapted to the student's characteristics [7, 32]. Personality is also an important attribute that may impact the learning process [31, 33, 43].

Regarding learning styles, the Honey-Alonso Learning Styles Questionnaire (CHAEA) is a tool designed for identifying learning styles that could be used to understand how a student may be approaching the learning materials at a particular time. We must take into account that, as stated in [36], an appeal of Kolb's Experiential Learning Model is its focus on the experiential learning process rather than on fixed learning traits [49], providing for an acknowledgment and incorporation of personal change and development in the model [20]. Thus, learning styles could be applied in this context in any educational area, both for children and adults. University students are the object of study of many research papers, among which we can find the application of the CHAEA questionnaire in different university fields: sanitary, scientific-technical, humanities, etcetera. [8, 15, 16, 40, 41, 48].

However, in [3] is noted that the LSQ possesses no predictive ability. Duff [13] observed no evidence of construct validity in the LSQ scale, and [14] reported little reliability and validity for the LSQ and its variable dimensional structure. These researchers ultimately conclude that, even after modification, the LSQ is inadequate to assess individual learning styles [36]. Nevertheless, our aim is to assess average learning style profiles and not individual learning styles to establish a possible relation between these average profiles and the student grades. Therefore a novel methodology based on a new tool for the analysis of learning styles and grades has been proposed in this work. The student learning styles belonging to three different courses from Computer Sciences degrees from the University of Malaga during the 2018/2019 academic year are analyzed. Our object of study is to analyze the possible relation between the student assessment and their learning style based on the CHAEA questionnaire. In this way, this information can be used to gain an understanding of how a student may be using a certain methodology for approaching the learning materials. It may be that students can be coached on how they can approach the materials differently with another methodology, and teachers can perhaps use this information to understand why students may be approaching the same learning materials differently. Thus, despite this work cannot provide the exact instructions to achieve a better student assessment, it can provide some guidelines that allow us to act before any course and students, which would have a positive effect on the learning process. Additionally, the code developed in this work is open-access, and it can be found on its website (https://github.com/icai-uma/CHAEA-analysis).

2 | STATE OF THE ART

Many authors have employed the CHAEA questionnaire in their studies over the years. In [46], the objective is to identify differences between the results in the study of the learning styles preferences of teachers and postgraduate students. The CHAEA questionnaire, together with the ACRA scale, are used as potential tools that can be used by a professor tutor to identify the psychoeducational features of tutored students starting college [24]. In [37], a recommendation system of educational strategies based on rules according to the CHAEA questionnaire is proposed. Another study was carried out with engineering university students based on the CHAEA questionnaire, where development, performance, and gender were analyzed [39].

On the other hand, learning styles have also been criticized by communities in the field of education or learning. The review carried out in [42] concludes that there is no strong evidence to incorporate learning-styles assessments into general educational lessons since students have different aptitudes for many ways of thinking and processing information. In another report [45], it is revealed that only a small portion of learning styles studies uses an adequate research design to support the idea that customized instruction based on learning styles produces better learning outcomes than general instruction. Dembo and Howard [12] spreads and advises on the use of learning styles because there is no evidence of improvement or benefits in the learning outcomes.

Nevertheless, the results of the review reported in [11] revealed that despite the fact that many experiments have been carried out to refuse the utility of learning styles, they still are enjoying broad acceptance in practice. The systematic review in [10] reached a set of positive and negative aspects of learning styles. From one side, this methodology could be used as a tool to encourage self-development, not only by diagnosing how people learn, and can be used as a starting point to know better the students. On the other side, there is theoretical incoherence and conceptual confusion in this area that provokes a lack of communication between different research perspectives. Moreover, there are no clear implications for pedagogy. For example, in [27] is stated that learning preference is not always effective learning, and how one studies it can not be classified into a fixed learning style. Another analysis discusses how political and institutional contexts can affect learning and skills methodologies, so the ways that learning styles are applied can be different depending on that context [9]. The testing of the learning styles hypothesis is not completed yet, since most of the works do not provide much formal analysis but at least report use cases where a person's learning style changes with experience, and research in that field is making useful progress [38].

As stated in [11], there have been a handful of empirical studies published since 2009 using experimental-type methods that have found some measure of support for the learning styles hypothesis. These studies could be identified that went beyond simple correlational research and found support for the learning styles hypothesis.

In [2], Felder's LSI was used to determine whether learning style had an effect on the learning behavior of undergraduate medical students in Saudi Arabia. These students were classified into the active and reflective styles categories. After incorporating four competencies into the teaching methods, obtained results revealed that there were differences in the learning behaviors both in the active and reflective categories. In fact, active learners used multiple activities to improve their learning, communicated more during group work, and formulated a greater variety of novel solutions in problem-solving activities. On the contrary, reflective learners relied on multiple types of reading materials that they studied on their own, listened more intently to others, and tended to draw more on previously acquired information. Despite the fact that this work found differences in the behavior of these two groups during the learning activities, no differences were found during assessments of course content.

According to the field of educational technology, Popescu [44] created a learning style assessment using a web-based learning system. This learning style assessment combined the constructs from many different learning styles questionnaires: visual versus verbal, abstract versus concrete, field dependence versus field independence, deductive versus inductive reasoning, synthesis versus analysis, motivation, persistence, pacing, social aspects, and affectivity versus thinking. In this work, the undergraduate students were divided into two groups: one that learned via instruction intended to match the students' learning styles and one that learned via instruction that was mismatched to the students' learning styles [44]. This separation into two groups improved learning efficiency in terms of time and necessary resources but did not produce increased gains in achievement. Academic assessments were not taken into account.

Another learning style model used in the past [17] is based on five different dimensions: processing, perception, input, understanding, and organization. The study done by Hung [23] focuses only on two of these styles, input, and perception, due to the bad performance of students with these two styles. For the first one, a diagram-based instructional method was used, while for the second, an analogy-based instructional method was preferred. A total of 98 students were divided into three groups, the two mentioned above, and the third group with unmatched styles. They were tested five times during the semester to analyze the correlation between styles and grades. The results showed a significant improvement in the students' scores that received diagram or analogy instructions with respect to those who did not. The best performance was shown by the perception style group, although its broad nature does not allow for establishing a strong link with the analogy-based instruction. However, the methodology employed by the authors was unclear, seeming that students may have received instructions not according to their learning style. This, added to the existence of a third mixed group, does not allow to have a clear validity of their findings.

An interesting study [22] used Felder and Soloman's Index of Learning Styles [18], dividing the 39 Taiwanese fifth-grade students into two categories: active or reflexive. Two classes with the same teacher were analyzed through both pretests and posttests. After a single lesson, the active class did a 15-min brainstorm, while the reflective received instructions and prompts for 10 min and then questions for 5 min. The results showed strong interrater reliability for the two tests. Students improved their knowledge when a reflective or active instructional method was employed compared to students without these matched styles. The authors then concluded that they should take into account learning styles in the course. Nevertheless, the methodology was not strong enough to support the validity of the findings: 39 students and only 1h lesson. The study should have lasted longer, and it should have been composed of multiple lessons. In addition, the final effect is not significant enough for the effort they made in terms of time and specific materials for each learning style (Table 1).

The VAK (Visual, Auditory and Kinaesthetic) model [47], which is the most widely used assessment in schools, was utilized in [35], where a 39-item assessment that was made up of 13 items for each of the three learning modalities were selected to test students' sensitivity to sensory cues, not academic learning.

TABLE 1 Summary of the recent state-of-the-art works on learning styles

References	Positive aspects	Negative aspects
Alghasham [2]	- Divided into active and reflective styles	- No differences were found during assessments of course content
	- Differences in learning behavior were found	
Popescu [44]	- Created a web-based learning system combining several LSQs	- Not produce increased gains in achievement
	- Improved learning efficiency in terms of time and resources	- Academic assessments were not taken into account
Hung [23]	- Big group analyzed with several tests	- Focuses only on 2 of 5 learning styles
	- Scored improvement with specific instructional methods	- Methodology employed was unclear to validate findings
Hsieh et al. [22]	- Active or reflexive students tested	- Essay with 39 students and only 1h lesson
	- Strong inter-reliability for the two tests	- Not significant effect for the effort they made
Mahdjoubi and Akplotsyi [35]	- VAK model used for learning styles	- The aim was not presenting the subject matter in a different way
	- Results showed specific style-based instruction motivates students	
Hassan et al. [19]	- Proposes an adaptative e-learning framework to identify learning styles	- Student grades are not analyzed
	- The motivation increased, and drop-out ratio reduced	
Kaczmarek et al. [25]	- Learning styles assessed by the Index of Learning Styles	- Slight mark differences, insignificant effects
	- Provides helpful information for teachers	
Almeida et al. [4]	- Aims to create a learning methods focused on concepts	- Only 8 students, not generalizable
Akbar and Nasution [1]	- Analyzes correlation between VARK learning styles and marks	- Results are not presented in deep
	- Reasonable difference between each learning style on marks	

Elementary school students from four schools in the United Kingdom were assessed on their learning style, and then all of them were given the same three tasks to complete, which were designed to address the three different learning styles. These three tasks were completing a photo safari, participating in small discussion groups, and exploring the outdoor environment around the school wearing GPS loggers for 2 days, for the visual, auditory, and kinesthetic conditions, respectively.

The results showed that visual learners took more photographs and selected more pictures than locations, auditory learners spoke more in discussion groups, and kinesthetic learners were the most active during the free outdoor exploration time. Although academic learning was not measured in this study, it suggests that the VAK learning styles are related to learning choices and may have some real implications. These implications are not in the direction of presenting the subject matter in a different way depending on the students' learning styles, but they are related to assisting students in choosing academic courses or occupational tracks according to their interests.

Learning styles have been employed recently in higher education with positive results. In particular, e-learning has benefited [26]. For example, [19] proposes a framework to identify the learning style of students based on their interactions with the system. Using that extracted information, the proposal provides an adaptive gamification experience related to their identified learning styles. The experimental results that the authors obtained from this research reveal that the students' motivation was increased, and the drop-out ratio was reduced.

TABLE 2 Summary of the number of enrolled students (Attd.) and the participants in the survey (Resp.) among the three subjects

Subject	Attd.	Resp.	Degree	Course
CTSI	60	28	BSc in Software Engineering	3°
IS	48	24	BSc in Health Engineering	3°
TAFL	138	55	BSc in Computer Science	2°
			BSc in Computer Engineering	

Focusing on the relationship between learning styles and grades, this correlation has also been studied previously. Regardless, the number of scientific papers about this topic is significantly limited, and their context is entirely particular.

A similar investigation was performed by Kaczmarek et al. [25]. They analyzed the results of 80 dental students: in particular, their marks and the learning styles assessed by the questionnaire Index of Learning Styles, according to Felder and Soloman [18]. Their results showed that students with the highest and lowest grades correspond to specific learning styles; however, the mark differences were very slight. They concluded that this kind of information might be helpful for teachers' and students' support purposes. Nevertheless, this knowledge had an insignificant effect on students' abilities evaluation and did not predict any results. Compared with our study, our results demonstrate a higher correlation between grades and learning styles among a more significant number of students and a broader context. Additionally, our results are not independently based on each learning style as a unidimensional variable; they are composed of profiles. This information also provides the average student profile of the given courses, which may be helpful.

In Almeida et al. [4], a more specific study was assessed among eight selected students with better marks in a given chemistry course. Their proposal aims to create a learning environment focused on conceptual understanding in chemistry grades and how students can enhance their interest in learning using varied and suitable strategies. However, as the authors of this research indicated in their work, it is not possible to generalize the results because of their specific context and the reduced number of students.

More recent research was conducted by Akbar and Nasution [1] to analyze the correlation between learning styles using the VARK (visual-aural-read/write-kinesthetic) questionnaire and marks in the 4th year of a Medicine course (80 students). According to their results, they concluded that there is a relationship between the learning style and the grade, and the difference in effect between each learning style on marks is reasonable. Despite that, the study does not deepen in their results, and their authors indicated the need for further discussion.

3 | CONTEXT

The University of Malaga offers a wide range of degrees from every branch of knowledge, having 59 bachelor's degrees, 53 master's degrees, and 35,000 students. Therefore, diversity is not only present speaking of degrees but also in academic years and courses.

In this work, the information from three courses has been gathered, trying to cover a wide variety. This information is given in Table 2. Courses from the first years of a degree have been avoided since there can be an important bias in the results since many students do not be clear about which degree want to study. Likewise, a sample formed by three different courses from different degrees that belong to the Computer Sciences engineering branch has been used to perform a complete analysis.

On the other hand, it would be advisable to contextualize the assessment methodologies of each analyzed course briefly. The Intelligent Systems (IS) course consists of 11 laboratory practices, a midterm exam, and a final exam. The submission of practices is mandatory, and all of them must be passed to pass this course. The midterm exam is not used to remove contents from the final exam, but it allows for adding additional points to the final grade. Regarding the Theory of Automata and Formal Languages (TAFL) course, it is one of the more theoretical courses from the computer science point of view and also has sizeable mathematical content. The TAFL assessment consists of four independent midterm exams that can remove contents from the final exam. The midterm exams have a unique test about the course contents with penalization for failed questions. Students must pass all the midterm exams to pass this course. The third analyzed course is Computational Techniques in Software Engineering (CTSI), whose assessment is formed by 13 laboratory practices, two midterm exams that can remove contents, and a final exam.

In Table 3, the distribution of marks obtained by the students for each subject is shown. Categorically, the grades were classified in the Spanish style: fail, sufficient, good, and very good. Besides, the average and standard deviation grades of the overall group are presented. As it can be extracted, one of the subjects, CTSI, has outstanding qualifications since it was easy for the students. That is because its evaluation is based on practices

TABLE 3 Mark distribution of the attending students

Subject	Attending					Participants	Nonparticipants
	Fail	Sufficient	Good	Very Good	Avg. (std) mark	Avg. (std) mark	Avg. (std) mark
CTSI	0	6	38	16	8.04 ± 1.13	8.17 ± 0.98	7.93 ± 1.24
IS	5	16	15	12	7.31 ± 2.38	8.43 ± 2.12	6.20 ± 2.12
TAFL	56	39	36	7	5.43 ± 2.68	6.35 ± 2.30	4.82 ± 2.75

without the need to pass a final exam. On the other hand, TAFL is a complex theoretical subject that many students fail in it. Actually, only seven students were able to reach the maximum grade. In the middle is situated IS, where the marks were quite distributed.

4 | METHODOLOGY

The LSQ was developed from Kolb's LSI, which was later adapted by Alonso, Gallego, and Honey to the Spanish educational context and named Honey-Alonso Learning Styles Questionnaire (CHAEA). According to [5, 6], learning styles are classified in four categories:

- Activist style: an agile style where dynamism and participation of open-minded and team students prevail.
- Reflector style: a reasoning style where observation and result analysis from the carried out experiences predominate.
- Theorist style: a speculation style where observation in the theory field is more preponderated than in the practice field.
- Pragmatist style: an order style where practice and application of ideas are more predominant than theory.

The CHAEA questionnaire [5, 6] consists of 80 items regarding the four learning styles (20 items per each style: activist, reflector, pragmatist, and theorist) and answers are based on the agreement or disagreement degree of each question. The answer options are given on a Likert-type scale from 0 to 5 (from nothing/never up to much/always). There are no right or wrong answers. The final result could reflect the tendency towards the predominant learning style of the student at that time in that context, taking into account that there are no pure learning styles.

Once the students from a specific course fulfill the CHAEA questionnaire, a detailed profile from each student will be obtained. However, this involves many different learning style profiles in each course. To achieve our initial objectives more accessible, a general approximation of the average profile/s (or prototype/s) of the student learning styles from a particular course is proposed.

Moreover, an interesting aspect to consider is the possibility of analyzing the student assessment according to the prototypes of learning styles. This way, teachers could use this information to analyze the impact of the used student assessment for each prototype and, therefore, for the entire course. For this reason, the option of providing grades to the students to determine the average mark for each prototype has been added to our developed system.

Gathering this information can be tedious. However, thanks to the use of technology, this process can be more efficient. In this work, the virtual campus of the University of Malaga has been used for performing the CHAEA questionnaire and gathering then, the provided students' information. Since this virtual campus is based on the free and open-source learning management system called Moodle, the CHAEA questionnaire has been adapted to be used in Moodle. In fact, there are Moodle modules that can manage CHAEA questionnaires, such as LSTest (http://innova.cicei.com/course/view.php?id=24). However, many Moodle system administrators from big institutions or companies do not trust the installation of new packages since they can have compatibility problems with other installed modules, specific versions of Moodle, etcetera. Hence, a new system that can be integrated with Moodle without installing it in Moodle has been developed. This way, any teacher using a Moodle-based virtual campus could use the CHAEA questionnaire for their students in a fast and straightforward way. Therefore, our proposed system developed for Moodle can be beneficial for the global teaching community.

The proposed system has been divided into three different parts:

- **Manager**. Subsystem used by the teacher. This subsystem corresponds to the native modules from Moodle "Question bank" and "Quiz." By using this subsystem, the teacher can design the CHAEA questionnaire, get students to fulfill it, and extract their answers for analyzing them.

- **Viewer**. Subsystem used by the student. This subsystem is a plugin written in Javascript for the Chrome browser, so the student must have this browser installed to add this plugin. With the Viewer, students can see their learning styles after fulfilling the CHAEA questionnaire. This subsystem was developed since the settings of the Quiz module can be difficult to provide students with information about their learning styles after fulfilling the CHAEA questionnaire. For this reason, the Viewer is an alternative to show students their learning styles to prevent teachers from setting the Quiz module.
- **Analyzer**. Subsystem used by the teacher. This subsystem is written in Matlab, and teachers need to install it on their computers. Thanks to the provided data by the Manager, this subsystem can determine the average profiles of the student learning styles. Also, it can provide the student grades so that different statistics about the student assessment for each detected learning style can be given.

Figure 1 depicts the workflow that the teacher may follow to determine the average learning style profiles of the student body of the selected subject. The workflow is as follows:

1. First, the teacher must access its Moodle platform and design the CHAEA questionnaire by adding some questions. To avoid adding questions one by one, an XML file containing the questions from the CHAEA questionnaire is given by the Manager. These questions must be stored in the Question Bank to be available for every teaching course. This process is just made once.
2. Second, the teacher enables in Moodle the CHAEA questionnaire to be fulfilled by the students belonging to a certain course. Detailed instructions step by step are provided by the Manager to make easy the elaboration of this stage by the teacher.
3. Third, students must fulfill the designed questionnaire. Students can use the Viewer to obtain clearer information about their learning style results.
4. Once the student answers are obtained, the teacher can export them in an XLSX file. Again, further instructions are given step by step by the Manager.
5. If the teacher has the student's grades, they can also be exported in an XLSX file, and the Manager can offer detailed instructions again.
6. Then, the Analyzer is fed with the exported file of answers or grades.
7. After executing the Analyzer, the average profiles of the student learning styles are obtained. If the student grades are also fed to the Analyzer, grades for each average profile will be given.
8. By analyzing this information, the teacher could propose modifications to different aspects of the course, such as methodology or student assessment, to improve student performance. This way, by analyzing the performance based on course modifications, the characteristics that offer a better performance could be determined.

4.1 | Analyzer considerations

Once the operation of the proposed methodology is shown and the course students fulfill the CHAEA questionnaire, several considerations can arise, such as what the ideal number of average profiles in a course is, how these profiles are determined, how each student corresponds to each of these profiles, etcetera.

In this work, a widely used data clustering technique known as K-means has been proposed [34]. This technique consists of the partition of a data set into K clusters in which each input sample belongs to the cluster with the nearest mean (cluster center or cluster centroid), which is the prototype of the cluster. In our case, the data set corresponds to students that fulfilled the CHAEA questionnaire of a course.

To select the parameter K (number of clusters), we need to take into account that if a low number of clusters K is chosen, part of the students could not be associated with a prototype similar to their individualized results. On the other hand, a large number of clusters K will yield too many clusters that can complicate getting the prototype of the student learning style. In this work, a case study for values of $K = \{2, 3, 4\}$ has been performed so that different student groups can be analyzed more precisely.

5 | RESULTS

Table 4 reflects the numerical output of the Analyzer for each group of students with a specific learning style pattern, which is generated by the K-means classification algorithm. For each value of K, the average marks of the students that fall into one group are computed. Also, the average and standard deviation marks of the survey respondents are shown. Complementarily, Figures 2–4 depict the spider maps and pie plots of the generated groups to visualize better the learning styles of each group and their distributions (in percentages). In addition to this, each learning style has been analyzed

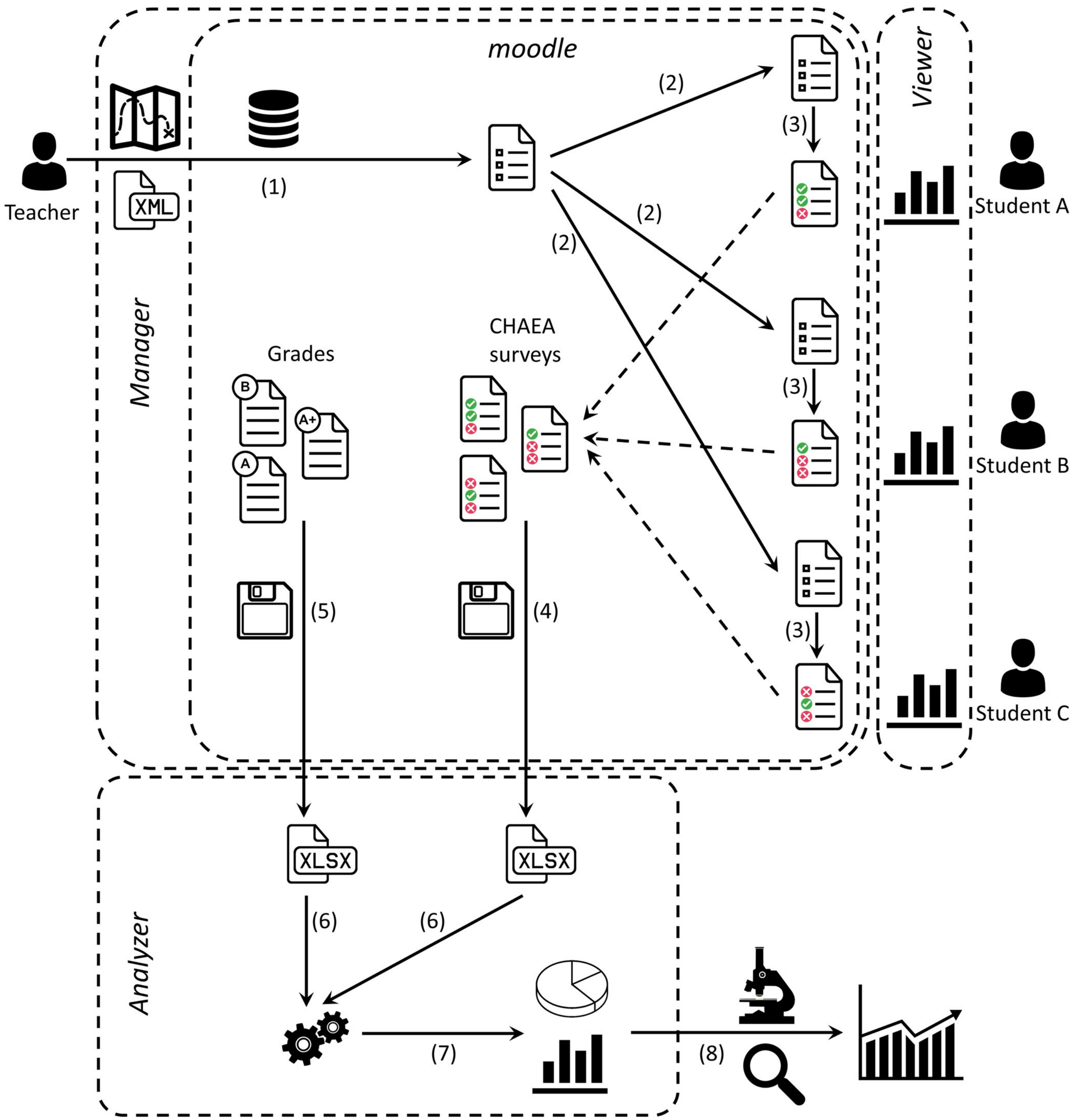

FIGURE 1 Workflow of the proposed methodology

TABLE 4 Average marks within each student cluster generated by the survey and average (std.) mark of all the surveyed students

	$K = 2$		$K = 3$			$K = 4$				
Subject	Group 1	Group 2	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3	Group 4	Average (std) Mark
CTSI	8.21	8.11	7.65	8.64	8.28	7.73	8.83	8.32	8.00	8.17 ± 0.98
IS	8.53	8.31	8.53	8.59	7.08	8.51	8.80	7.91	7.08	8.43 ± 2.12
TAFL	6.08	6.69	5.87	6.70	6.57	5.75	6.78	6.48	6.81	6.35 ± 2.30

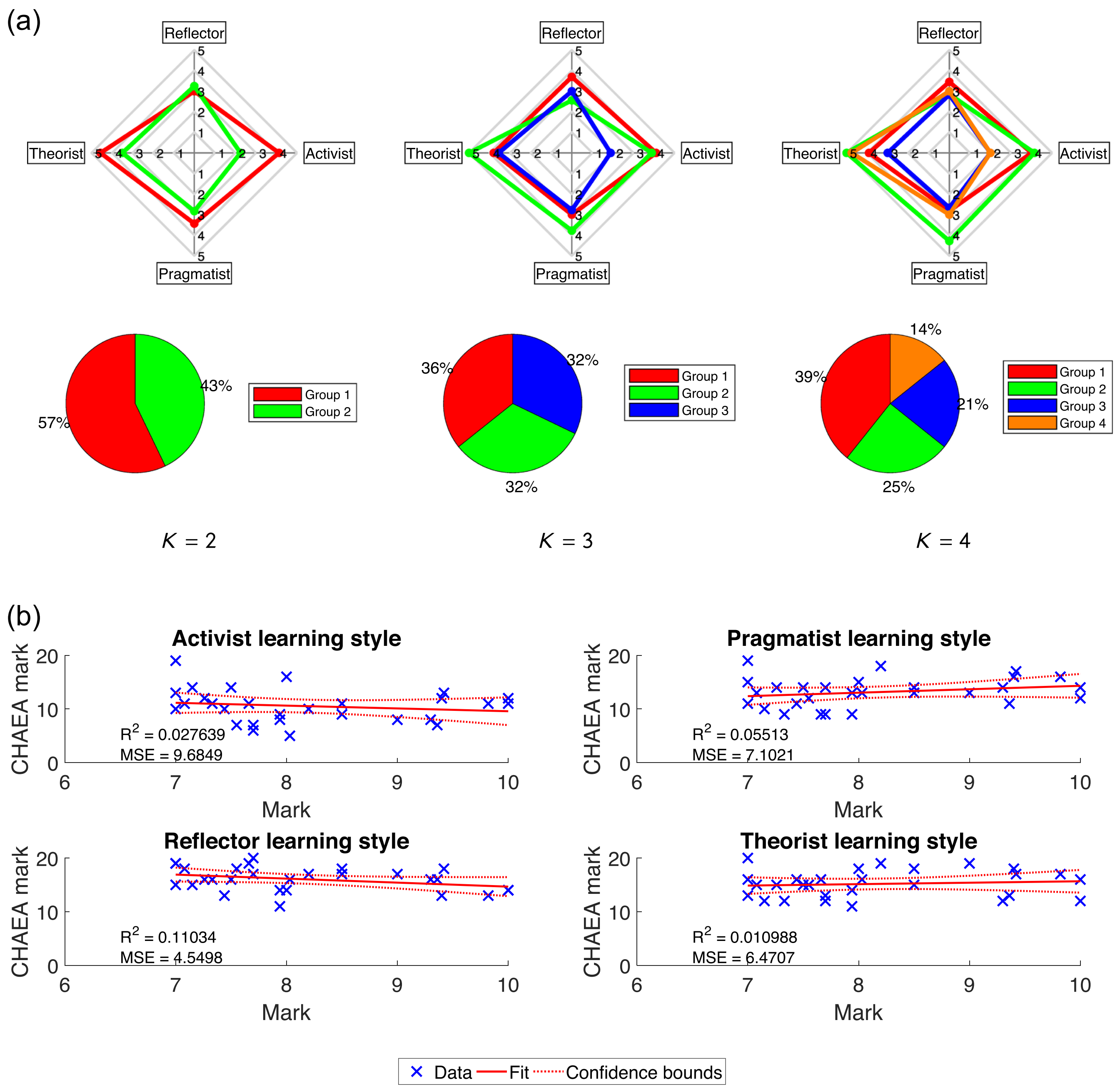

FIGURE 2 Group and mark correlation analyses of the subject CTSI. Classification of the CHAEA results has been done for $K = 2, 3, 4$. In addition, for each learning style, the subject grades, and the CHAEA marks of all participants have been analyzed with a linear regression model (a) Average learning style profiles for different K values, (b) Mark correlation analysis.

separately, comparing the CHAEA marks and the students' grades obtained in the course.

In the subject CTSI, the differences between marks are very slight. However, there are two, or even three groups within the class with different learning styles, as can be seen in Figure 2. One of them represents a quite theorist and activist profile, while the other represents a medium profile. When three groups are considered, the class is equally distributed, and the new third group stands out for its low level of activism profile. If $K = 4$ is used, the outcomes are quite similar, which may indicate that this division is not very relevant. The posterior regression analysis reveals that most of the best students are associated with a profile with high levels of pragmatism, reflectivism, and theorizing. In general, the student body is not very active.

The subject IS (Figure 3) is more subject to divisions, in special for $K = 3$ and $K = 4$. The division into two groups yields similar group sizes with two clear sheds, which represent a theorist and activist profile. However,

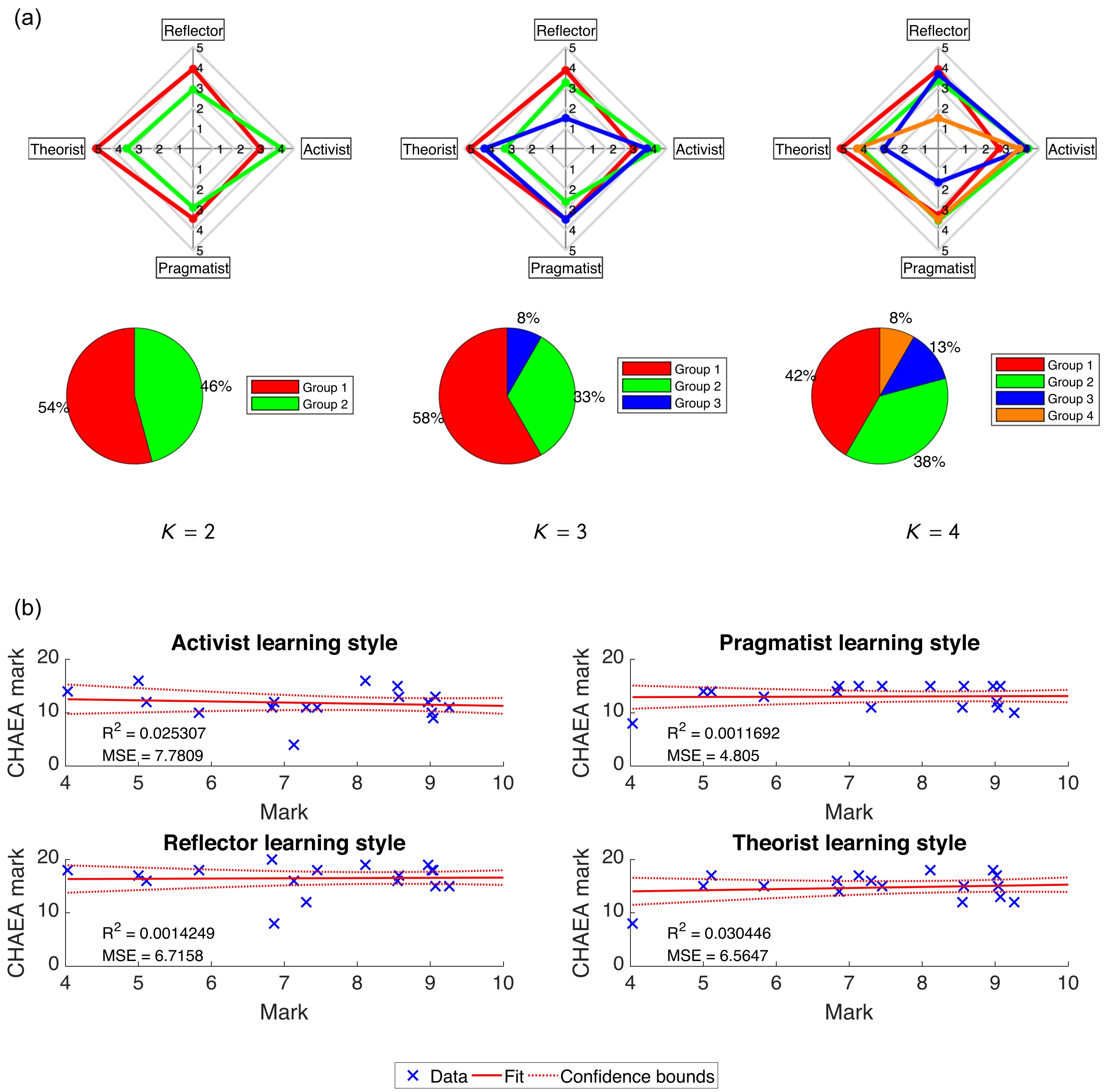

FIGURE 3 Group and mark correlation analyses of the subject IS. Classification of the CHAEA results has been done for $K = 2, 3, 4$. In addition, for each learning style, the subject grades, and the CHAEA marks of all participants have been analyzed with a linear regression model (a) Average learning style profiles for different K values, (b) Mark correlation analysis.

the average grades were similar. Thus, combined with the fact that there is dispersion in the marks distribution (see the last column of Table 4) may denote that exists a third group of students with a specific learning style profile. Therefore, if $K = 3$ is analyzed, one can come across the existence of a minority group representing a thoughtless profile (8% of the total number of students). Group 3 has the lowest marks, with a difference of around 1.5 points, which means that special attention could be paid to the learning and evaluation methodology used in this group. If now the division is done into four groups, a group with a nonpragmatist profile appears (Group 3) with marks also below 8 points. Group 4 represents a reflector group, and Groups 1 and 2 are quite similar, so it may indicate the division into three is the best selection. The thoughtful learning style profile is predominant based on the regression analysis. However, most of the students with marks over seven

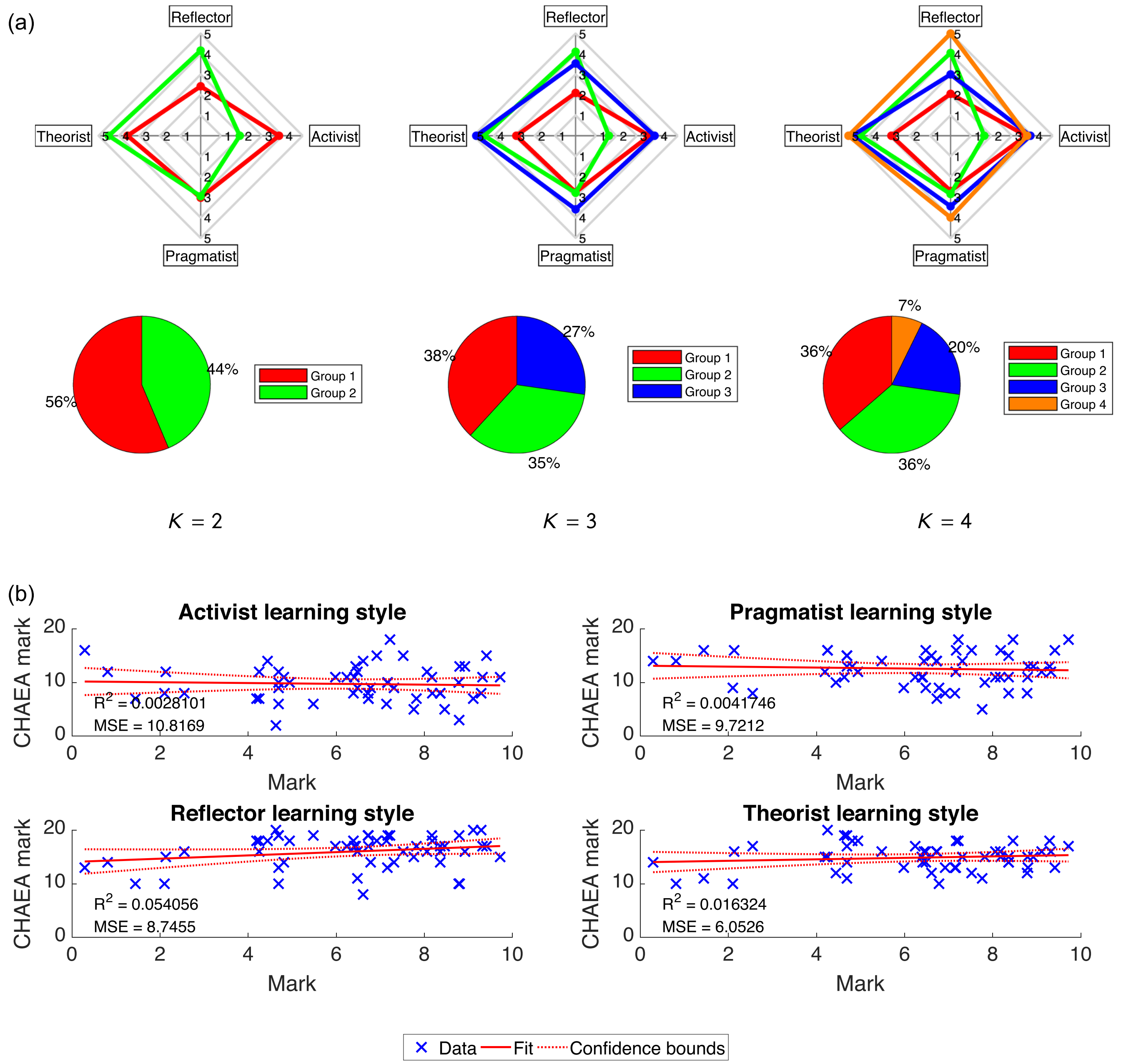

FIGURE 4 Group and mark correlation analyses of the subject TAFL. Classification of the CHAEA results has been done for $K = 2, 3, 4$. In addition, for each learning style, the subject grades, and the CHAEA marks of all participants have been analyzed with a linear regression model (a) Average learning style profiles for different K values, (b) Mark correlation analysis.

points, achieved higher CHAEA marks in the theoretical and pragmatic learning style.

Starting from $K = 4$ and focusing on the TAFL subject (Figure 4), the four groups are characterized by a decreasing level of a thoughtful profile (Groups 4, 2, 3, and 1, respectively). Curiously, this order matches the decreasing order of the average grades. This fact implies that this learning style profile could have some kind of influence on the evaluation procedure. Besides, Group 2 represents a very passive group, and Group 1 is a mainly active one, and it is present in the average marks, being one of the most considerable differences among groups. They are the most prominent groups in size. This analysis reveals that if $K = 2$ is used, an equally distributed student body will be present with two different profiles. Thus, the evaluation of this subject could consider these two types of profiles. If more precision is needed, a third group representing a thoughtless profile with a size of 8% can be extracted. It is interesting to verify that the average grades and the number of failures of the subject shown in Table 3 are very deficient, even more so since the subject is very theoretical as the observed learning style profile. It should be noted that the mathematical content is quite high, and is contrasted with the group scores shown in Table 4. The scatter plots yields high dispersion in the active and pragmatic learning styles profiles, while the other two yields better linear fits with lower errors. Those are the predominant learning styles obtained for the students that pass the subject.

6 | DISCUSSION

It is well-known that every course and its students are quite different. Even when the same course belongs to different degrees, its context can be different. Therefore, our case study focuses on finding common patterns in the detected learning style profiles for each course.

Technical courses seem to have a large percentage of students that fit into the theorist and methodical learning style profiles. Our results show that students with an activist profile are the most sufferer if the course assessment is only performed by midterm exams. Maybe, more interactive activities could be incorporated during the academic year to measure competence acquisition in the same way as happens in the Intelligent Systems course.

Generally speaking, computer science students are mainly represented by a theorist profile, with a medium level of pragmatism profile and a wide-ranging level of reflectivism and activism profiles. Moreover, $K = 3$ seems to be the most suitable number of clusters, since $K = 4$ can involve too much detailed analysis, whereas $K = 2$ can yield a poor representation of the average learning style profiles. According to $K = 3$, three equally distributed learning profiles for the CTSI and TAFL courses are obtained, of which average profiles are mainly theorists. In the case of CTSI, it presents a theorist and activist profile, a medium pragmatic profile, and a low reflector profile, whereas, for TAFL, approximately similar profiles are obtained. In the case of the IS course, the obtained groups have different sizes, where the most abundant groups present a theorist profile, the second group present a mainly activist profile, and the smallest group presents a low reflector profile.

In principle, the pragmatist learning style profile could be assumed to be associated with Computer Science studies due to its practical nature. Regarding this, it is interesting to observe for $K = 4$ how the groups with the highest pragmatist score (Figures 2–4, subfigure (a)) correspond with the groups with the highest marks (Table 4). The presented study results indicate a correlation, to a greater or lesser extent, between those groups of students with the highest marks in terms of learning styles in the specific context of this work.

The analysis performed here was only focused on the engineering field, but it is also applicable to other degrees. It is expected to find differences between the student learning style profiles present in engineering degrees and in arts degrees. Therefore, the evaluation method could be different in each case. Nevertheless, a kind of guide can be proposed as a result of the application using the proposed tool. First, an initial analysis of the students learning styles can be carried out at the beginning of the course. Depending on the outcomes, the teacher may adapt the standard activities into two or three versions according to the detected prototypes, as the CHAEA group analysis determines. In the middle of the course, a second questionnaire may be passed and combined with the grades of some midterm exams, so the teacher would be able to have feedback on the adaptation, and, therefore, correct it if necessary. Finally, this analysis can be repeated at the end of the course so that a longitudinal study might be useful for successive years.

It is important to remark that CHAEA questionnaires should not be considered a mainstay to organize a course or identify student traits [11]. Many researchers have concluded that CHAEA is not the most adequate tool to assess individual learning styles, so other methodologies may be considered to have a significant study of the learning style of the students. Nevertheless, at this time, and in this context, the proposed tool can be used to understand how a student may be approaching the learning materials, and teachers can perhaps use this information to understand why students may be approaching the same learning materials differently, to coach them on how they can approach those.

Moreover, it must be highlighted how, in general, participant students achieve a higher mark than nonparticipant students, as can be observed in Table 3. It may indicate that participants are more motivated and committed to their studies (or, at least, to the subjects analyzed in this work) than nonparticipants. In our specific context, a questionnaire to detect learning styles (CHAEA) has been used to distinguish between participants and nonparticipants. For future work, it may be interesting to use another kind of voluntary questionnaire to confirm and assess that motivation degree.

Comparing our results with those obtained in most related research papers [1, 4, 25], a high correlation between learning styles and grades may be established. That relationship cannot be generalized to every case, and further research should be carried out, but the information available may help teachers and students to propose changes in the course to enhance the learning process.

7 | CONCLUSION

Knowing the audience's learning style can be useful both for students and teachers since it allows understanding of how a student maybe approach the learning materials, so students could be coached on how they can approach the materials differently (e.g., engage in more reflection) and teachers can perhaps use this information to understand why students may be approaching the same learning materials differently. This would allow for improving learning efficiency, and teachers could analyze which are the necessities of each student according to the methodology used. Moreover, students can be aware of this by identifying and using strategies to face their difficulties. In contrast, teachers could analyze the predominant learning style in their classes to modify some aspects of the methodology, gain a better understanding of their students, improve their learning efficiency, and save time and effort for both.

In this work, a new tool for learning styles analysis has been developed, and it is free and available on its website (https://github.com/icai-uma/CHAEA-analysis). The community can widely use it since it is integrated with Moodle, which is the world's most popular learning management system. This tool can be used in a course to obtain the average profiles of the learning styles of its students. The tool also takes into account the grades of the students. This way, the teacher can establish a relationship between the learning styles prototype of the students and their obtained marks.

A case study in Computer Sciences Engineering has been elaborated to analyze the benefits of the proposed tool. It has been determined that students can be grouped into several learning styles prototypes, and each prototype obtains a different average mark. Thus, actions could be taken along the course to enhance the learning process by adapting the features of exams, exercises, and practices to the learning styles prototypes of the students.

Therefore, future works may allow analyzing the impact of learning styles on the marks of the students that belong to a specific course or degree, not only in Computer Sciences Engineering. In addition, the tool may be integrated into different learning management systems or even mobile applications to be user-friendly to study the real-time evolution of the students within the course.

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DATA AVAILABILITY STATEMENT

The code will be free and available on its website when the paper is published.

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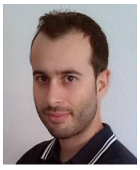

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