Adaptive Model for the Selection of Resources and Activities in a Virtual Learning Environment

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Abstract: This paper presents ALPY, an Adaptive System to support Personalized Education in Virtual Learning Environments which favors the selection process of resources and activities for a learning pathway defined by a teacher in a Virtual Learning System. This paper describes the proposed system's architecture, the design of the profiles in ALPY, and the visual prototype. It focuses on the adaptive model ALPY PLUS, and the collection and processing of data or variables such as learning style, personality, and previous knowledge, profiling students for suggested learning resources and activities. This model has been applied in an Systems Engineering introductory course for students in the Tecnológica de Bolívar University.

1 INTRODUCTION

In the educational sector, multiple benefits are achieved for participants using Information and Communication Technologies (ICT) through Virtual Learning Systems (VLS). According to authors such as Hlib et al (Hlib et al., 2019), Foutsitzi et al (Foutsitzi and Caridakis, 2019), and UNESCO (UNESCO, 2017) when using a VLS, a large variety of resources and tools are integrated to improve the performance and practice during the learning process, achieving a comprehensive inclusion of participants regardless of space and time. However, several educational challenges persist. Some of these challenges are related to the fact that each individual learns differently. Resources and activities are for the most part not tailored to students' individual educational necessities, and courses in general do not consider the student's profile,(Rosen et al., 2018), (Karataev and Zadorozhny, 2017), (Iatrellis et al., 2020). There are no tools that allow teachers to personalize resources, (Karataev and Zadorozhny, 2017), (Khosravi et al., 2020), (Kasinathan et al., 2017),(Meacham et al., 2020) and the interfaces are not intuitive to their participants, so the accessibility of learning resources may also be lost (Karataev and Zadorozhny, 2017), (Iatrellis et al., 2020), (Alamri et al., 2018). In order to tackle these challenges, this paper presents ALPY: a technological solution that favors the educational process and offers, through VLS, a personalized education adapted to the student. We emphasize on the adaptive model (ALPY PLUS) used to select resources and activities based on the characteristics of the students and their context.

The remaining of this paper is organized as follows. Section 2 presents and discusses the related works, highlighting their characteristics, advantages, disadvantages, and ICT support in education for VLS. Section 3 presents ALPY, describing the basic and adaptive services, showing its architecture and main design motivations in the context of VLS. Section 4 presents the case study detailing the processes and development of ALPY Section 5 shows ALPY implementation details. The results of this research are analyzed in section 6, and finally, section 7, concludes the paper and presents some pointers for future work.

2 RELATED WORK

This section presents a review of the works related to personalized and adapted education in the VLS. We

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Table 1: Comparison of related works, conventions:✓Includes aspect, ✗Does not include aspect. RO(Rosen et al., 2018), KA(Karataev and Zadorozhny, 2017), IA(Iatrellis et al., 2020), KH(Khosravi et al., 2020), WI(Williams et al., 2016), KS(Kasinathan et al., 2017), AL(Alamri et al., 2018), ME(Meacham et al., 2020).

Criteria		RO	KA	IA	KH	WI	KS	AL	ME
Oriented to	Students	✓	✓	✓	✓	✓	✗	✓	✗
	Teachers	✗	✓	✗	✓	✗	✓	✗	✓
	Tutors	✗	✗	✗	✗	✗	✓	✗	✗
Gamification activities	No evidence	✓	✓	✗	✗	✓	✓	✓	✓
Elements for customization	No evidence	✓	✓	✗	✓	✓	✓	✗	✓
Data for personalization	Previous knowledge	✗	✗	✗	✓	✓	✓	✗	✗
	Past performances	✗	✓	✗	✗	✗	✗	✗	✗
	Learning outcomes	✓	✗	✗	✗	✗	✗	✗	✗
	Student profile	✗	✗	✗	✓	✗	✓	✗	✓
	Student behavior	✓	✗	✗	✗	✗	✗	✗	✗
	Student interaction	✗	✗	✗	✗	✓	✗	✗	✗
	No evidence	✗	✗	✗	✗	✗	✗	✓	✗
Adapted resources	Contents	✓	✓	✓	✗	✓	✓	✓	✓
	Activities	✗	✗	✓	✗	✓	✗	✗	✗
Pathway learning	Implements in the VLS	✓	✗	✓	✗	✓	✗	✗	✓
	No evidence in the VLS	✗	✓	✗	✓	✗	✓	✓	✗
Platform	Web	✓	✓	✓	✓	✗	✗	✓	✓
	Mobile	✗	✓	✗	✗	✗	✗	✗	✗
	Development environment	✗	✗	✗	✗	✓	✗	✗	✗
	No evidence	✗	✗	✗	✗	✗	✓	✗	✗

consider works regarding ICT, supporting tools, and basic strategies including adaptation, and ludic activities. There are some learner-oriented systems such as ALOSI (Rosen et al., 2018), SALT (Karataev and Zadorozhny, 2017), EDUC8 (Iatrellis et al., 2020), RIPPLE (Khosravi et al., 2020), TOPOLOR (Alamri et al., 2018), AXIS (Williams et al., 2016). There are others VLS for teaching like: Kasinathan et al (Kasinathan et al., 2017) that features Smart Sparrow tutor system, Adaptive VLE (Meacham et al., 2020).

Table 1 details the strategies and tools used in VLS to apply Personalized Education to these related works. The symbol ✓specifies whether it is or not a strategy or a tool, and the symbol ✗that describes the absence of the aspect. It is important to notice that most of the works are oriented towards students, followed by teachers, and in few occasions tutors. Regarding strategies, most works do not use gamification and ludification elements. Additionally, most works do not evidence changes in the presentation and functionality of the visual interface. Concerning the personalization strategy, most works highlight aspects such as previous knowledge, past performance, student profile, student behavior in the course, and student interaction in the system. The resource most commonly adapted for the students is the educational content followed by the activities. Although a study plan or learning path is defined, most of these works do not suggest any personalized contents and activities concerning the study plan. Lastly, these systems are developed on platforms (web, development environment, and mobile). Each of these related works demonstrates the feasibility of creating a technology solution to support personalized education. Nevertheless, few characteristics of the learner and their context are considered in the works reviewed having only ALOSI(Rosen et al., 2018) considering it as future work. With this in mind, we believe that there is a necessity for a system that includes basic individual characteristics, preferences, context, teacher, course, content, and activities to generate an adaptable and personalized learning experience for each student in a VLS.

3 ALPY

This section describes ALPY (an acronym for Adapted Learning Pathway), an adaptive support system for personalized education in virtual environ-

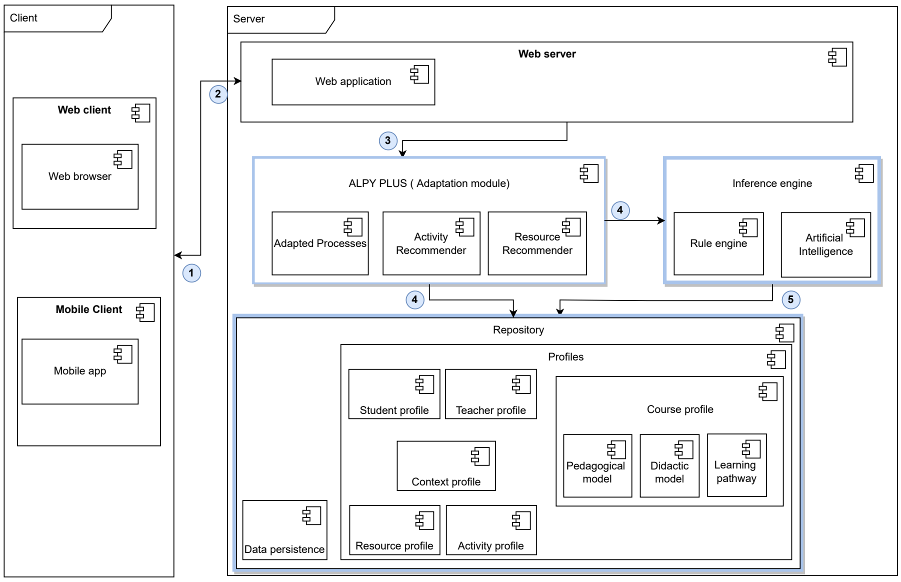

Figure 1: ALPY Architecture.

ments. ALPY uses a learning pathway or study plan as input and then it selects the educational contents and activities, taking into account the individual characteristics of the participant in the educational process. To achieve this, ALPY contains three main components. (see Figure 1).

- A database (DB) in which the information of the participants in the VLS is stored through profiles. These profiles contain the users' individual characteristics and the course's particular characteristics in the system.
- An adaptive module called ALPY PLUS used to offer adjustable services in the VLS based on the particular characteristics of the students. It is also used to suggest educational resources to the VLS teachers, so they can be facilitators in the particular learning process of their students through the learning pathway.
- An inference engine based on machine learning (AI) techniques, which recalculates rules in the VLS based on established components and adapts according to the information and behavior of the participants.

3.1 ALPY Architecture

The proposed architecture for ALPY is detailed in Figure 1 where the three components mentioned earlier are depicted. It is worth mentioning that the paper (Henriquez-Nunez et al., 2022) explained the initial architecture of the ALPY model; however, through the case studies, an update was developed and presented for this paper. Below we present the list of services provided by ALPY:

- Generate a learning pathway defined by the teacher (teacher user).
- Consult the learning pathway (student user).
- Consult the level of academic progress (teacher and student user).
- Assess activities (student user).
- Evaluate activities (teacher user).

In accordance with the ALPY architecture Figure 1, the service's invocation starts with the access of a user from any client (1), either web or mobile, to the VLS, thus requesting the VLS login service. Then, the VLS responds with the interface adapted to the type of client but without the services adapted to the user (2). To enrich the service with adaptation characteristics, ALPY PLUS, takes into account the user's data entered and data acquired in the database (such as basic data, academic experience, learning style, likes and interests of the student, and her/his environmental context), analyzes the data to identify the student (3), characterize her/him wiht the inference engine (4), and subsequently group the data into a profile (5). At the same time, the decision rules and AI modules defined in the inference engine are activated. In addition to this, 5 could request information from the repository. Considering each of these steps in the interaction path, with the defined architecture it is possible to offer the mentioned services. Also, with these steps, it is possible to offer new enriched services to the students that allow them to continue favoring their learning, for example, by supporting monitoring according

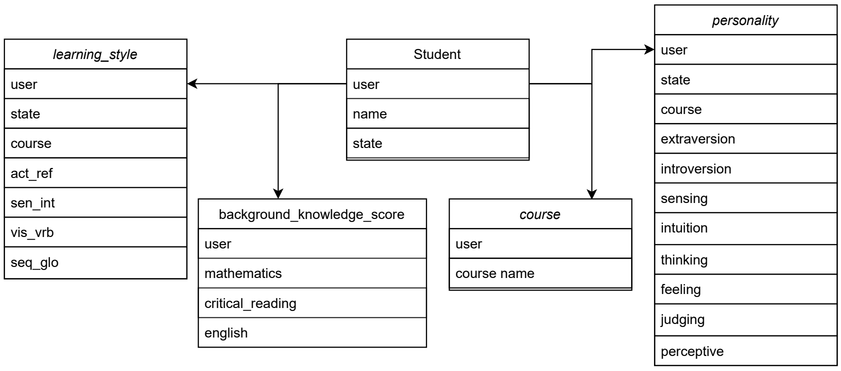

Figure 2: Class Diagram Student Profile.

to their peers who have completed one of the topics of the course or keeping in mind the nearby location of the students to manage a convenient schedule of course advising.

This section will present the profiles proposed in the ALPY architecture. According to the works analyzed in section 2, in order to allow the VLS to personalize the student's learning process, a user profile must be developed including basic data such as name, identity document, and gender. In addition to the basic data, we must also consider the individual characteristics of each user like learning domain, learning style, likes, preferences, and interests, among other data. The ALPY model integrates all these characteristics inside its learner profile. For this adaptive model, is crucial consider other profiles, such as those of the course, teacher, content, activities, and context or interaction of the system with the learner, which, in contrast to the other profiles, include data related to space-time, environment, social skills, and technology. These characteristics will allow the learning system to personalize and adapt the support resources, improve the basic services, and include new adaptive services, making the learning process more personalized.

By detailing these profiles, it is possible to implement specific adaptive services and offer new ones. For example, with the student profile, if there is data about her/his learning style, it is possible to offer educational resources taylored to her/his style. Similarly, having preferences data such as the way of studying or study habits and frequency, we can provide the student with monitoring services in the course. Data related to location or the use of the schedule, could define a tutoring service for the course. Finally, other data could be technological like taking into account the device, type of operating system, or resolution, enable ALPY to offer adapted educational resources.

4 CASE STUDY

This section presents the ALPY prototype developed for the introductory course of Computer Science at Tecnológica de Bolívar University, hence implementing student profiling to allows us to suggest personalized content and activities for the student. For our experimentation we have a set of first-semester students at the faculty of engineering who are taking the first-semester fundamental subject in their area of study using the MOODLE platform. In particular, we have two groups that combined represent an audience of 73 people.

4.1 Data Capture

Once the profiles are built, the implementation is developed in the VLS, in this case, MOODLE (Moodle, 2022). The students are profiled according to Figure 2. The student profile contemplates not only the basic data including the user identification number and full name in the VLS, but also, other data such as basic knowledge, learning style, personality, and the enrolled course. To obtain data like personality and learning style, it was necessary to create two test-type modules in the VLS, developed in languages including HTML, CSS, and PHP and linked to MOODLE libraries. The information about the student's previous knowledge is currently shared by the university through an institutional database that was queried to obtain a comma separated value CSV file. By collecting all the information, it is possible to visualize it globally see Figure 3. It should be noted that the data called "state" allows for a follow-up on whether or not the student has developed the tests through which enrichment information is obtained.

For the analysis of the students' personality during in the course, the Myers Briggs Test (MBTI) (Felder

course	state	user	E	I	S	N	T	F	J	P	act_ref	sen_int	vis_vrb	seq_glo	critical_reading	english	maths
40513	1	Student_N1	4	5	3	1	**7**	5	3	3	**7a**	5a	5a	1a	75.00	87.00	72.00
40513	1	Student_N2	7	**9**	7	8	9	8	9	9	1a	1a	**7a**	1a	65.00	56.00	54.00
40513	1	Student_N3	7	9	9	9	9	9	**9**	9	7a	3a	1a	**9a**	55.00	67.00	58.00
40513	1	Student_N4	**7**	3	5	7	7	6	4	6	3a	5a	**5b**	3a	52.00	47.00	58.00
40513	1	Student_N5	7	9	9	9	9	9	9	**9**	3a	3b	5b	**7b**	60.00	55.00	53.00
40513	1	Student_N6	6	**9**	**9**	9	9	7	9	9	1b	**5a**	**5a**	1a	60.00	52.00	52.00

Figure 3: Data collected from students.

et al., 2002). was used, which measures personal preferences or inclinations in the way of relating, processing information, making decisions, or organizing their lives, corresponding to four dichotomies, with two extremes each one: Extraversion (E)/Introversion (I), Sensing (S)/ Intuition (N), Thinking (T)/ Feeling (F), Judging (J)/ Perceptive (P). When creating the module in the VLS, we continued with the model that proposes 72 situations, where the student must select only those that reflect some aspect of her/his personality. Each 9 of these 72 situations corresponds to an extreme of the personality. Once the personality is defined, the MBTI model presents how this type of personality thinks and behaves, suggesting activities and processes that help her/his personal growth. Figure 3 shows that the letter with the highest score determines the student's personality inclination.

In order to identify the learning style study, we use Felder and Soloman's Test (Felder and Soloman, 1993), which proposes four bipolar categories of learning styles, simplifying them as follows: Sensitive(sen) / Intuitive(int), Visual(vis) / Verbal(vrb), Active(act) / Reflective(ref) and Sequential(seq) / Global(glo). When developing the module in the VLS, the model was maintained and proposed 44 situations, 11 for each bipolar category, and with two possible answers called a or b. Once the learning style is identified, a specific teaching technique is proposed to meet the needs of most or all students in a given class. Figure 3 shows the levels of preference and the letter corresponding to only one of the bipolar categories in the learning style, where 1 to 3 shows a low level, 5 to 7 is a moderate level, and 9 to 11 is a strong level.

Once the learning style is identified, the specific teaching technique is proposed to address and thus meet the needs of most or all students in any given class.

Concerning the students' prior knowledge, this study takes into account as information the results of the Colombian State exams in Secondary Education called Saber 11 tests (Instituto Colombiano para la Evaluación de la Educación - Portal ICFES, 2020). These tests show the development of essential capabilities obtained by students in fundamental areas such as Critical Reading, Mathematics, Citizenship capabilities, Natural Sciences, and English; for this, the state defines a performance scale classified into four levels of performance that qualitatively describes the skills and knowledge of the evaluated and quantitatively has a score, where level 1 (insufficient) starts from 0 to 35, level 2 (minimum) from 36 to 50, level 3 (satisfactory) from 51 to 65 and level 4 (advanced) has a score from 66 to 100. In this study, only the areas of Critical Reading, Mathematics and English are considered at performance levels 3 and 4 as presented in Figure 3, taking into account that most of our group study focuses on these subjects.

Once the student's information has been obtained, that is to say, once we have complete information about learning style, personality, and data from the Colombian state exam, ALPY characterizes and integrates the data into a set of profiles (see Figure 4). It is important to note that ALPY has an initial profile, for scenarios when information about learning style, personality, or data from the Colombian state exam are not available for the suggestion of resources and activities. This initial profile can be classified into four cases with their respective suggestions:

- Case 1.There is no information about the learning style, but there is information about their personality and data from the state exams. According to this information, a default activity is suggested.
- Case 2. There is no information about personality, but there is information about learning style and data from the state exams. According to this information, a default resource is suggested.
- Case 3. There is no information corresponding to the data of the state exams; however, there is information about learning style and personality. According to this information, a default resource and activities are suggested.
- Case 4. No information is available; nothing is suggested, but general learning resources are presented.

Complete information about the students will make it much more effective to suggest resources and activities.
According to the Figure 4, only one profile out of nine possible is highlighted in blue. More specifically, if

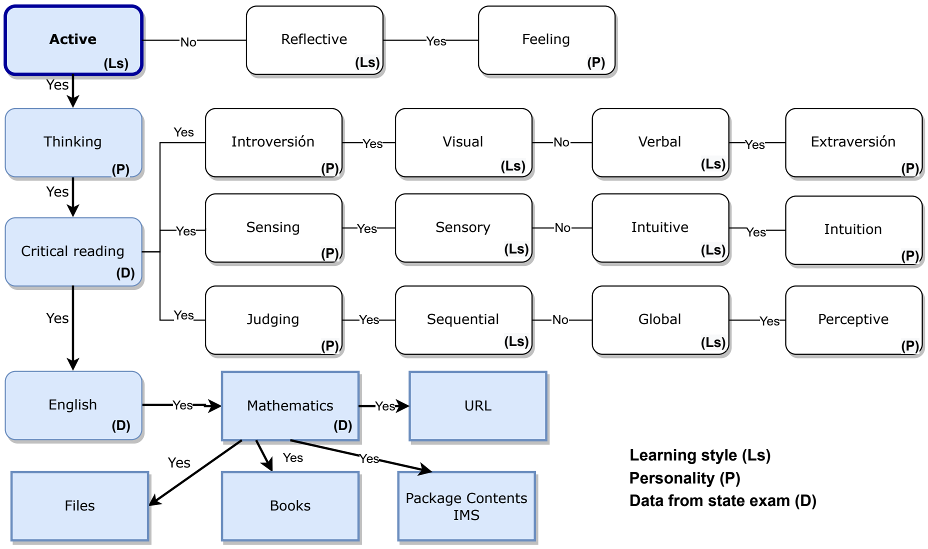

Figure 4: Defined ALPY profiles.

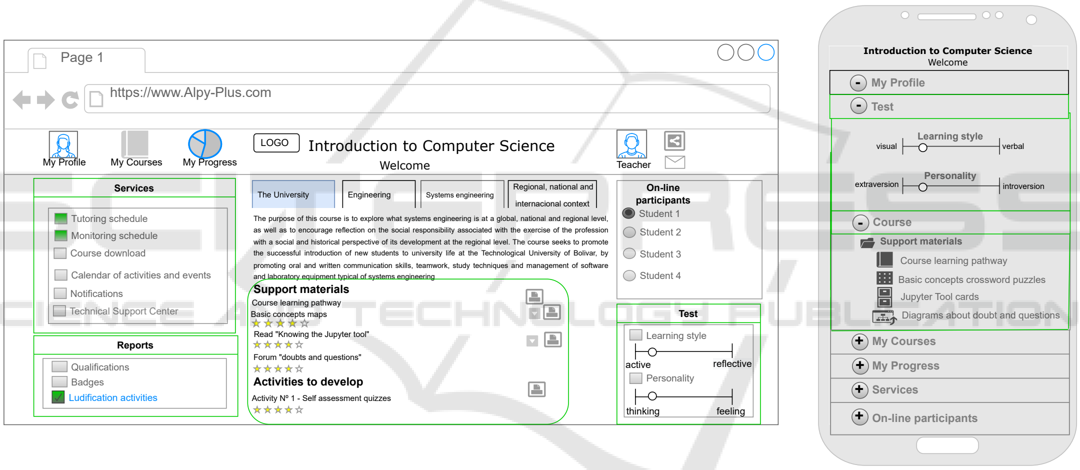

Figure 5: Prototype according to profiles.

the student has an active learning style, thinking personality, and meets the established score at a satisfactory or advanced level in the basic capabilities of Critical Reading, English, and Mathematics, personalized learning resources are suggested.

In order to propose concrete examples with the data of some students in the course, we have three profiles, where the previously described profile relates to students in the first group (group profile Nº1). For this students, learning resources such as: Files, IMS Content Packages, books and URLs, will be suggested. Likewise, the same learning resources will be suggested for students in the group profile Nº2, where they prefer a visual learning style; students in this profile group have personality that tends to introversion and meets the established score at a satisfactory or advanced level in the previous knowledge of the Saber 11 tests. For students in the profile group Nº3, who have the sequential learning style, their personality is judging and meets the established score at a satisfactory or advanced level in the previous knowledge of the Saber 11 tests. In this case, for the suggestion of the learning resource, it is worth noticing that there is the possibility of suggesting the same resources, as in this case for the previous student group profiles, but the defined personality of each group is the one that introduces a change in the presentation of the suggested resource. As mentioned before, students in the group profile Nº1 consume the URL through text, students in the group profile Nº2 uses graphics, and student in the group profile Nº3 interacts with the URL manually through sequences of steps, leading the three students to the reflection of the same topic, with the same resource, but in a different ways of study to match their personalities. Finally, regarding the suggestions of learning activities for each student, it could be the same activity, for instance, presenting a study material, but based on the personality of each student, it will be suggested that students in the first group are presented with the course material organized logically through concept maps, students in the second group through crosswords, diagrams, puzzles, and students in the third group through a case study with step by step instructions with a structure with tasks, objectives, and milestones clearly defined.

5 ALPY PROTOTYPE

This section presents VLS with and without ALPY, showing the visualization of the course for the defined profiles.

5.1 VLS Without ALPY

The web and mobile interface is presented with the primary services without adaptation, showing the essential services of the course such as: consulting the course plan, teacher and classmate contact information, communicating by internal messaging with classmates and teachers while being online in the course, consulting course progress, activity, and grade reports.

The figure 5 (left) illustrates a prototype of the adapted course for the student using ALPY. The VLS demonstrates the essential services mentioned in the previous section, but addittionally, in green we present the adaptive services. In this case, the Figure presents a web page prototype for the students in the group profile Nº1. The activities, educational resources are selected according to previous knowledge, and we also include the active learning style, and thinking personality in the visualization. In addition, this profile suggests contents including basic conceptual maps, written documents, and activities such as forums, among other ludic activities. Figure 5 (right) illustrates the same web page for the student in the group profile Nº2. In this case, the course is presented as a mobile client, the activities and educational resources are personalized according to the previous basic knowledge, visual learning style, and introversion personality. Additionally, the prototype suggests visual learning content using crosswords for the basic concepts, tool cards about the current topic, and activities with written indications.

6 RESULTS

Once the concept proof was developed in the VLS and considering the data analysis, the following results were obtained. Out of a total of 73 students who participated by answering the learning style module, it can be said that 16 students were classified as art of the visual style, followed by 11 students that tend to be sensitive, 7 sequential, 5 active, 4 present reflective, 2 global and 2 intuitive. It should be noted that the group also presented the characteristic of not being defined in a single learning style; dichotomies and trichotomies can be presented in the learning styles; precisely 26 students had these characteristics.

When analyzing the personality module, those with defined styles coincide with the grouping of profiles proposed in this study. As stated, a student who has a visual style tends to have an introversion personality, and a verbal one tends to have an extroversion personality; another example is a student who has a sensitive learning style tends to have a sensitive personality or if it is her/his intuitive style, her/his personality is intuitive as well. Likewise, for those not in a single learning style, the personality matches the grouping of the profiles. For example, a student with a visual-sequential dichotomy tended to have an introversion-judging personality. However, the results also suggested the possibility of new profiles in this test, further strengthening this research.

7 CONCLUSIONS AND FUTURE WORK

This paper presented the adaptive model of ALPY, an Adaptive System to support personalized education in Virtual Learning Environments. This paper focused on presenting the process of profiling a student in a VLS, obtaining and processing the necessary student-specific data to suggest personalized learning resources and activities for the student. This paper developed several adaptive model tests in an introductory computer science course at Tecnológica de Bolívar University. The tests and results demonstrate an adequate student profiling and grouping of students to suggest resources and activities in two steps, without showing the conflict between the data of the defined profiles. It also offers the possibility of providing new adaptive services according to their educational necessities and preferences. In other words, it is possible to suggest a resource to support the student by considering the student's data, including her/his learning style, personality, and previous knowledge of Critical Reading, Mathematics, and English. The student's personality can guide the personalization of the type of resource and learning activity. It should be noted that when developing these tests, the results suggested the possibility to define more than one learning style; dichotomies and trichotomies have appeared in our 73 student group subject to this study.

For future work, we plan to articulate an inference engine that establishes the decision rules to further strengthen the adaptive services for suggesting resources and activities and integrate into VLS new evaluation mechanisms for teachers and feedback mechanisms for students. We would like to involve new enrichment data such as student capabilities focused on their careers, as well as new modules to measure student motivation, among others, to implement new suggestions in VLS according to content and activities.

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