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An e-Learning System for Extracting Text Comprehension and Learning Style Characteristics

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ABSTRACT

Technology - mediated learning is very actively and widely researched, with numerous e-learning environments designed for different educational purposes developed during the past few decades. Still, their organization and texts are not structured according to any theory of educational comprehension. Modern education is even more flexible and, thus, demanding, requiring the combination of multiple educational theories for effective results. In this paper we present the combination of two educational theories for text comprehension and learning styles, that are in use by the newly developed Student Diagnosis, Assistance, Evaluation System based on Artificial Intelligence (StuDiAsE) an open learning system for unattended student diagnosis, assistance and evaluation based on artificial intelligence. A trial test about the role of learning styles in student profiling for text comprehension in the educational environment StuDiAsE is described. Research was run with participation of students using the environment for prior knowledge test and text activities. The process revealed remarkable results about the role of learning styles in students' profiles for text comprehension. Three dimensions for learning styles were identified: conceptualization, visualization and progression dimension and were used for profiling. Refinement of profiles incorporates learning styles by decoding student behavior, which reflects student learning styles for text comprehension.

Keywords

E-learning, Learning Methodologies, Educational theories, Student profiles, Learning styles

Introduction

Numerous eLearning systems and open learning environments (OLEs) have been developed, especially after the rapid adoption of ubiquitous internet access with most of the interest coming from higher education foundations for the remote delivery of educational material and advanced courses (McAndrew et al., 2010). Many systems were developed in the same manner as most theoretical educational texts; according to the judgement and writing style of the author and not based on any proven educational theory. In their vast majority, even the systems developed according to known educational theories could only quantitatively assess the educational performance of the learner, usually basing their assessment on just the end numerical result of a test or a series of tests (Restivo et al., 2009). OLEs have been designed more as alternative channels for delivery of educational material rather than an autonomous/active stakeholder in the education environment. Such systems are ineffective for a variety of educational applications and especially for engineering students, where the same end result can be accomplished via several paths. It is understandable that effective learning environments need to be based on known educational theories be adaptive to different learners and capable of providing multivariate feedback and assessment (Ihantola et al., 2010). This is especially true in engineering education, where a one-size-fits-all approach was proven to be highly ineffective, removing the possibilities of adaptation and customization that are critical in engineering education (Hofstein & Lunetta, 2010).

In text comprehension studies, researchers focus on assisting comprehension by improving text coherence (McNamara & Kintsch, 1998), by improving the design of the text form and text activities (Denhiere & Baudet, 1992) or by exploiting a student's prior knowledge on a subject and giving feedback to improve a student's skills (Caillies & Denhière, 2012). Students preferentially take in and process text information in different ways: by seeing and hearing, reflecting and acting, reasoning logically and intuitively, analyzing and visualizing, steadily and in fits and starts (Felder & Brent, 2005; Caillies & Denhière, 2012). Teaching methods also vary. Some instructors lecture, others demonstrate or lead students to self-discovery; some focus on principles and others on applications; some emphasize memory and others comprehension. When mismatches exist between learning styles of most students in a class and the teaching style of the professor, the students may become bored and inattentive in class, do poorly on tests, get discouraged about the courses, the curriculum, and themselves, and in some cases change to other curricula or drop out of school. A learning style model classifies students according to where they fit on a number of scales pertaining to the ways they receive and process information (Felder & Brent, 2005). The Index of Learning Styles (ILS) is an on-line instrument used to assess preferences on four dimensions (active/reflective, sensing/intuitive, visual/verbal, and sequential/global) of a learning style model formulated by Felder and Silverman (1988).

In this paper, we present the StuDiAsE, an advanced OLE developed specifically to cater for the needs of engineering learners. StuDiAsE is based on the text comprehension theory by Denhière and Baudet (1992). This theory, focus on assisting text comprehension by improving the design of the text form and text activities and by exploiting a student's prior knowledge on a subject (Caillies & Denhière, 2012). StuDiAsE is also based on the dialogue theory of Collins and Beranek (1986), which focus on assisting text comprehension using dialogue activities based on dialogue management, strategies, tactics and plans, which promote personalized feedback in learning. Moreover, it is based on the learning styles theory (Felder & Silverman, 1988; Felder & Brent, 2005), which classifies students in learning style according to where they fit on a number of scales pertaining to the ways they receive and process information. By combining these known educational theories across its modules, the StuDiAsE is capable of monitoring the comprehension on behalf of the learners (Collins & Beranek, 1986; Kilpatrick & Turner, 1994; Safer & Fleischman, 2005), assess their prior knowledge, construct individual educational profiles, provide personalized assistance, and provide multivariate assessment. It can also be adjusted to monitor factors that may indicate the motivation of the learner, allowing the delivery of personalized assistance and feedback.

In the following chapters, we will discuss the basic architecture of the system and present how its modules make use of the known educational theories to provide higher quality education to both new and advanced learners. In StuDiAsE, learning styles reflect upon the profile and result from decoding monitored elements of student navigation and are used for the refinement of the profile. In order to refine the profile we translate the monitored elements which represent the students' learning styles for text comprehension. A research study, aiming to perform evaluation tests of the system to improve profiles for better educational effectiveness, is presented.

The state of the art

In the state of the art a number of Adaptive Educational Hypermedia (AEH) systems and Open Learner Environments (OLE) utilize learning style as a basis of the text comprehension and the user modelling (Felder & Spurlin, 2005). Existing evaluation studies are summarized by Brown et al. (2009) and include quantitative evaluation for adaptation and navigation techniques. Examples include AES-CS, INSPIRE, ARTHUR, MANIC and EDUCE (see Table 1).

*Table 1.*Comparison of learning environments: educational theories and learning style theories for learner modelling

Educational environment & author(s)	Learning style model & author(s)	Learner model	Educational theory / approach
AES-CS, Triantafilou et al. (2002)	Witkin & Goodenough, (1997)	Questionnaire. Learner directly modifies learner model	Learners can switch between different instructional strategies
ARTHUR, Gilbert & Han (2002)	Witkin & Goodenough, (1997)	Alternative styles of instruction differ in the type of media they use	Mastery learning – dynamically adapts the instructional style according to learner's performance
INSPIRE, Papanikolaou et al. (2003)	Honey & Mumford (1992)	Questionnaire. Direct manipulation of learner model	Adapt method and order of presentation of multiple types of educational recourses
MANIC, Stern & Wolf, (2000)	(Model not specified)	System adapts learner model	Presentation of content objects using *stretchtext* -allows certain parts of a page to be opened or closed
EDUCE, Tangney (2006)	Gardner, (1983)	System dynamically models learning characteristics	Multiple Intelligence - Instructional material is matched and mismatched with learning preferences

Researchers (Matera & Costabile, 2002; Brown et al., 2009) provide case studies to model quantitative evaluation of learning-style-adapted e-learning environments for personalized learning. What these systems mentioned in table 1 have in common is that the learning styles are used to form an important part of the learner profile and the learning style preferences are used for adaptation. The weakness of these systems is that there is no any theory of text comprehension, which is systematically used, to be combined with the learning style. This combination we implement could strengthen and enrich the system in the construction of a more effective learner profile and personalized learning.

Adapted educational theories

Denhière and Baudet (1992) argue that text comprehension implies the understanding of fundamental cognitive categories. When a student attempts to comprehend a text, constructs a symbolic structure in an attempt to understand the world described by the text. The key role in this illustration lies on cognitive categories which are: the person, the situation, events, acts, as well as the temporal, causal relations and hierarchy of part-whole relationships that connect these symbolic structures. The organization and structure of symbolic structure is also examined on micro and macro-levels. The theory of Collins and Beranek (1986) is related to the objectives and dialogue strategies used by teachers for reflection and scientific thinking when students ask questions for learning of a subject matter. The dialogue is used to serve both of these two purposes of learning. The teachers are not trying to teach concepts, but put them within the context of the theory of a subject.

Based on these two theories, the modules of StuDiAsE perform diagnostic and dialogue sections. Diagnosing the cognitive profile of the learner is crucial for the development of adaptive systems, making the monitoring and evaluation of the learners a critical research subject regarding OLEs (Franca et al., 2012). During the diagnostic section, StuDiAsE provides the student with a series of questions meant to assess general prior knowledge (diagnostic tests) in a specific subject. After reading the text and answering the questions, the student enters the interactive part of the education and is asked to engage in dialogue with the system, in an attempt to revise the student's discrepancies or incorrect answers. The student is then guided through the construction of more coherent arguments in text comprehension. It should be noted the students are given the freedom to access or skip any of the educational steps at any point of time; however, should a student wishes not to follow the recommended path, the assessment and feedback capabilities of the system may become heavily limited, or the system may even be unable to provide any personalized feedback and assessment.

For this purpose, the educational material of the system is formatted according to Denhière and Baudet’s (1992) theory of text comprehension, which suggests three versions of each text: S-text, M-text, and T-text with questions accompanied by alternative answers (Sorenson & Macfadyen, 2010; Samarakou et al., 2015). The three versions of text with questions which each module should include are:

- S-text (Relational) and S-type questions describe a document with focus on simple descriptions of the hierarchy of part-whole relations of the system described in the document, as well as on descriptions of the processes, event and system status on micro-level.
- M-text (Transformative) and M-type questions designate a document with focus on descriptions of the sequence of events and the state to state transitions of the system.
- T-text (Teleological) and T-type questions describe a document with focus on detailed descriptions of the objectives and sub-objectives for which the system has been constructed or of the changes within the system from an initial to a final state due to events in order to achieve the objectives on macro-level.

As such, after the student gets involved in the educational process and as diagnostic and interactive parts are being completed, the modules explore the comprehension of the student on each type of text. The monitoring and logging modules store information that is being assessed by the modelling and profiling modules, initially identifying the comprehension of each student over a specific type of educational text. By default, the system is programmed to attempt and increase the comprehension of the student on relational texts, which is considered to be the easiest type. Once the system asserts that the comprehension of the student on relational texts is sufficient, it proceeds to improve comprehension on transformative texts. Similarly, when the comprehension of transformative texts appears to be sufficient, the system proceeds to teleological texts.

The question that we will try to answer in this Section is whether the involvement of the students in the e-learning scenario can provide some indication towards their categorization according to Felder criteria (Felder & Silverman, 1988). In particular we investigate whether the attributes related to the way students are processing the material, the challenges they take and the results of their efforts can lead us to estimations related to their learning styles. In general such an endeavor should be based only upon the data related to the overall performance of the student as well as the selections and results in individual questions; i.e., the typical data that come from a testing activity. In the case of StuDiAsE, we begin from the fact that the researchers have administrative access to the e-learning platform and we can enrich this activity with various data coming from the overall student activity.

In terms of the conceptualization, we have considered two sets of questions oriented at intuitive and at sensing students. The former set includes questions mostly theoretical related to concepts, usage scenarios of system and interaction. The latter are related to the formulation of concrete facts and definition of procedures as well as identification of logical gaps in workflows. In terms of off-channel data, the sequential attempts of a student towards the successful completion of a question and the gradual approach of the result indicate a sensing approach. The capability of generalization and extension of results to situations different from those examined in the syllabus material indicate intuitive potential.

The evaluation of the visualization potential has also been initially performed through the creation of different types of situations. One set based on syllabus presented using figures and visual representation and the other based on dense text and verbal procedure descriptions and explanations. Visual learners perform better in the former set, while verbal learners prefer the latter. Regarding the off-channel data, we have been evaluating the way the students are navigating in the application (a) either leveraging the individual visual artifacts and pages, handling efficiently the graphical user interface, (b) or based upon the instructions and frequently consulting the written documentation related to the functionality and operations supported of the application.

To determine the collaboration dimension we consider the interaction among the students. For certain time periods, a collaboration tool among the students is enabled and it is upon the student whether they can use it in order to collaborate with the other students. Their behaviour both from the active point of view (whether they initiate communications attempts) and the passive point of view (how they react to inbound communications attempts) can discriminate them to active learners who typically work with others to the reflective learners who learn by themselves in an individualized manner. In terms of off-channel data the exchange of results (when applicable and allowed) as well as the similarity of the responses can provide indication towards collaborative and active attitude. It is not infrequent that student who study together, when evaluated provide similar results in their tests.

The progression dimension discriminates the students into the sequential learners who typically progress in small incremental steps to the global learners who are holistic, systems thinkers and learn in large leaps. This is evaluated by the way the students split larger tasks and attempt (or not) to decompose the tasks in smaller more manageable one or delve into the overall task at once. This dimension can also be is related to the approach of the student, either an iterative (and more global) approach where "easy" or acquainted questions are preferred or the waterfall approach where the full set of questions is approached. This information is extracted when we ask the student to divide the available time into specific tasks.

The complete profiling, modelling and evaluation of the learners is being performed through the use of artificial intelligence and, specifically, fuzzy logic (Caillies et al., 2002). The artificial engine decides on real time the current comprehension of each student on a specific educational text type, as well as actively works to classify the user according to Felder's theory. This is done in order to provide useful, practical and effective educational feedback, maximizing educational performance. Finally, at the completion of the educational process, the student is presented with both the initial and final educational profiles, with clear indications on the improvements and weaknesses. The process of building a cognitive profile of a student is based on several characteristics, such as the student's prior knowledge on the particular subject, knowledge gaps, contradictive answers and actions, even from the student's attitude during the exercise and his/her willingness to participate. As such, it also is a requirement of the monitoring module to attempt and motivate the students, ideally by adapting to their educational profile, and particularly into engaging in the diagnostic process, which will be providing both the current educational status of the student before the procedure and the final cognitive profile (Grossman, 2009).

Architecture

StuDiAsE is capable of monitoring a student's text comprehension, assess their prior knowledge, build an individual student profile, provide personalized assistance feedback and evaluate a student's performance both quantitatively and qualitatively through artificial intelligence mechanisms (Nicol & McFarlane-Dick, 2006; Bull & Kay, 2010; França et al., 2012). Cognitive profile represents student's text comprehension style over a thematic topic. The initial profile represents a student's prior knowledge concerning the thematic topic. Student's special features, identified in the prior knowledge test involve his inactive concepts, misconceptions, conflicts, knowledge gap or contradictions in his arguments. Moreover, other features such as his motivation for participation in activities and his learning style are identified and monitored, option which is utilized for offering the most appropriate text activities for the personal preferences of each student. The text activity, which is given to the student as personalized feedback acts as a motivational factor for further involvement in text comprehension activity. Such feedback can be given in the form of help, advice, suggestion and guidance and may drive students to the process of reflecting to their thoughts. After this activity the system infers the final profile of each student which represents the revised profile after reflection. The student profiling process takes into account the initial and the final profile, as well as the changes which happen with student's active participation through reflective thinking. StuDiAsE is divided into three modules: the monitoring, the logging, the profiling, the modeling and the evaluation module.

The monitoring module

This module observes and monitors the student's answers to questions while the student participates in: (a) in prior knowledge test, and (b) in text activities. For each of its subjects StuDiAsE provides a prior knowledge diagnostic test in order to identify and recognize a student's prior knowledge concerning the subject. Prior knowledge test consist of a number of general or specific questions with alternative answers about the subject (Tsaganou & Grigoriadou, 2011). By monitoring the student's answers to questions regarding a specific subject, the system takes note of the student's educational needs. Moreover, monitoring facilitates analysis, editing and codification of a student's arguments process, which contribute in the formulation of student's initial cognitive profile. For each subject StuDiAsE provides appropriate text activities: text with questions accompanied by alternative answers. Activities help the student build, during the comprehension process, symbolic representations of the information contained in the text. According to the different educational needs of each student, the system provides the appropriate text activity which stands as individualized feedback to promote reflection and scientific thinking. The module for monitoring the student's answers to questions within the educational environment is designed so as to satisfy specifications in order to record: (a) the student's name (for registered students), (b) the thematic subject code (c) the thematic prior knowledge test code, (d) the total number of questions included in the prior knowledge test, (e) the total number of alternative answers to each question of the test, (f) the kind of questions: multiple choice, position & justification, question-pairs with alternative answers, categorizing entities, classifying events or operations, completion of event or operations missing in a sequence, (g) the type of each question, (h) the number of questions for each type and (i) the level of difficulty of each question.

The logging module

The logging module monitors student's movements during activities, which reflect their behavior (Samarakou et al., 2013b). Students have agreed to be monitored but they do not have control over this process. The type of inputs available for monitoring students depends upon the educational settings. The input monitored refers (a) to the responses of the user to the structured questions and (b) complementary information including help invocations, movements within the text etc. Student movements include the selection of answers to questions of different types and seeking assistance using the on-line help. The system monitors the number of hits per page, pages visited and order of steps taken by the student. As a result the monitoring system keeps a complete history of the time each student spent on each subject content page, as well as the time intervals between activities. The system monitors how many times a question has been visited and how many times the answer has been changed. Moreover, the system monitors the student's logical mistakes/errors or unnecessary steps. Finally, the system also monitors the activities the student chooses to partake, the number of times he makes a mistake of the same or different type, as well as any other information connected to student behaviour during interfacing with the environment.

The profiling module

The initial profile represents a student's prior knowledge concerning a thematic subject (França et al., 2012; Samarakou et al., 2013a). To specify a student's special features, the diagnostic module exploits, as a starting point, the results recorded in the prior knowledge test which embodies appropriate questions with alternative answers about a particular thematic subject. Student's special features to be identified in the text activity involve his misconceptions, conflicts, inactive concepts, knowledge gap or contradictions in his arguments. This option is utilized for offering the most appropriate text activities for the individual needs of each student. The text activity which is given to the student as individualized feedback acts as a motivational factor for further involvement in text comprehension activity. Such motivation may drive students to the process of internally reflecting to their thoughts. Moreover, feedback can be given in the form of help, advice, suggestion and guidance, or even in the form of solved problems-examples, which can engage student in the reflective process. After the activity, the system assesses the student's final cognitive profile.

The modelling module

The student diagnostic module in StuDiAsE deduces the cognitive profile of a student. A student's model represents his or her cognitive profile for text comprehension over a thematic subject and his learning style. The process of student profiling takes into account the initial cognitive profile and the final cognitive profile, as well as the changes which happen with student's active participation through reflective thinking (Figure 1). Specifications for composing a student's model are: (a) description of the rules applied for deducing a student's initial cognitive profile, (b) artificial intelligence techniques used for the diagnostic process such as case based reasoning, fuzzy logic or neural networks, (c) description of the layout of the student features such as descriptive characterization (high, medium or low level profile) or numeral (33%, 66% or 100% performance), (d) decision making techniques for supplying each student with the appropriate text activity after the diagnostic process, (e) preferences on three dimensions of a learning style model and (f) description of the structure and the content of the cognitive profile and the student model.

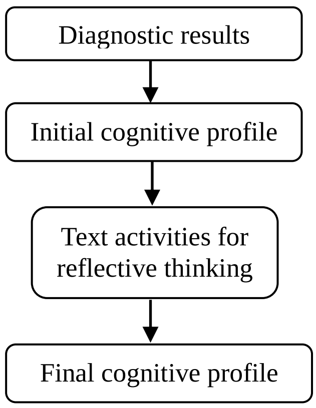

Figure 1. The modelling module

The evaluation module

The involvement of students throughout the entire process depends on individual decisions, from answers and movements, the willingness to participate, from the compliance with instructions and encouragement offered by the system in various phases. If the student insists on wrong or flawed responses, the artificial intelligence system should be designed to achieve the minimization of conflicts and focus on trying to change the reasoning of the student. The minimization will be possible when the learner alone removes the contradiction and thus becomes able to construct a more coherent argument (reflection) (Samarakou et al., 2009). The evaluation module has as its core the student model. By using artificial intelligence techniques, it is possible to evaluate the details of the initial and final cognitive profile. While the output of the system is the cognitive profile of the student, as inputs were used the following items:

- Recorded data of student involvement during modeling: Elements indicating the engagement of the student in the diagnostic process (informing the student for initial cognitive profile), in the process of creating a cognitive profile and model (the number of times that the cognitive profile characterization has changed), the student's decision to reconsider contradictory answers to questions / errors, etc., indicating the engagement of the student in the improvement of his cognitive model (steps leading to a change in thinking and changes in the model),
- Recorded data of system navigation elements.

Trial test

The trial test aimed to perform test of the system for possible improvement of learning profiles, to monitor student movements which reflect students' learning styles and to make students participate in the refinement of their learning profile. The objective was twofold: to test educational effectiveness and consistency. This test was conducted with participation of 28 students studying Informatics (Informatics Sector) in the 2nd EPAL Amarousiou, (Vocational Lyceum). The knowledge domain was that of telecommunication networks, a thematic subject included in StuDiAsE system. Participants were 16 students from the third grade and 12 students from the second grade Informatics course. Students of the third grade had prior knowledge about main concepts acquired during a relevant course they attended the previous year. The students of the second class had prior knowledge only about very basic concepts.

The students worked on the thematic subject of “Local Networks” in StuDiAsE environment following the instructions of their teachers. The process was consisted of three phases:

- At the beginning each student answered the initial diagnostic test D1 consisted of questions with alternative answers from which the student’s initial profile was estimated.
- Then in the interactive part, depending on the diagnosis, the student followed the suggestions of the system to deal with the appropriate for him activity (text with questions) S-type, M-type or T-type.
    - S-type activity includes text which describes units that constitute a system (local network) represented by the text, part to whole relations connecting system units (network nodes) and static states of the units (transmission state in the network).
    - M-type activity includes text which describes events and event sequences taking place in the units of the system the text refers to (sending a packet of bits) and which provoke state to state transitions of the system and causal and temporal relations among events and the changes they bring to the state of the system (change the network from “conflict state” to “transmission state” due to repetition of broadcast the right time).
    - T-type activity includes text which describes a tree of goals and sub-goals and how the technical system described by the text changes from an initial to a final state due to events in order to achieve the goals and sub-goals (the technique to overcome conflicts in sending a packet of bits and achieve transmission).
- At the end, student answered the final diagnostic test D2 from which the final profile was estimated.

During this process, students were monitored. Monitoring included student movements, between others: the selection of answers to questions of different types, the use of the on-line help, the number of hits per page, pages visited and order of steps taken by the student, the time each student spent on each subject content page, as well as the time intervals between activities. The system monitored how many times a question has been visited and how many times the answer has been changed. Moreover, the system monitored the student’s logical mistakes/errors or unnecessary steps. Finally, the system also monitored the activities student chooses to partake, the number of times he makes a mistake of the same or different type, as well as any other information connected to student behavior.

The relation between monitored results of student behavior is expected to reflect on their learning styles and is analyzed into three out of four dimensions of Felder and Silverman:

- Conceptualization dimension which includes: (a) intuitive students who like abstract information, have in mind the goals of a technical system and don’t like courses that require memorization, and (b) sensing students who like solving problems and enjoy courses that have more descriptive texts with connections to the real world.
- Visualization dimension which includes: (a) visual students who rarely used the help mechanism of the system and also spent a little time in doing the text comprehension activity, and (b) verbal students who used the help mechanism and get most out of written explanations.
- Progression dimension which includes: (a) sequential students who gained understanding in small steps and showed minor changes in their profile, and (b) global students who learn in large jumps and showed mayor changes in their profile.

Results and discussion

The trial test aimed to test if the presented system StuDiAsE works effectively. In order to assess the system’s effectiveness and consistency we examine both technical and educational point of view. From a technical point of view, the purpose of the test was to study if the monitoring process is made according to the rules and provides the appropriate elements for student profiling and for decoding learning styles. Moreover, the purpose is to test if there are any monitoring mistakes and if the system delivers the appropriate feedback. Moreover, testing the behavior of the system while multiple users have been working simultaneously revealed some technical glitches, such as conflicts in storing data, which have been dealt with. From an educational point of view, the purpose of the test was to study the refinement of profiles to incorporate learning styles by decoding monitored profile features and student behavior for better educational effectiveness. The results which the trial test revealed about the possible connection between text comprehension styles and Felder theory's learning styles were used for initial classification. Table 2 summarizes the results.

- According to conceptualization dimension, students who achieved high level in T-type questions in D1 or D2 tests (T-students), who possibly prefer abstract texts, seem to behave as *intuitive* students. Students who achieved high level in M-type questions in D1 or D2 tests (M-students), who prefer descriptive texts, seem to behave as *sensing* students. Students who achieved high level in S-type questions in D1 or D2 tests (S-students), who prefer very descriptive texts, seem to behave as *strong sensing.* Adopting this initial classification, the trial test results were on average: 57.14% *sensing*, 17.85% *strongly sensing* and 25% *intuitive*.
- As for visualization dimension, students who used help text of the system frequently, while they are trying out the initial diagnostic test D1 or D2, (usually spend a lot of time to finish the test) seem to behave as *verbal*. On the other hand, students who rarely used help text in D1 or D2 (spend a little time to finish the test) seem to behave as *visual*. Students who frequently used help in both the initial D1 and the final diagnostic test D2, seem to behave as *strongly verbal*. Similarly, if rarely used help in both D1 & D2 seem to behave as *strongly visual*. Following this classification, the trial test results were on average: 53% *strongly verbal* and 17% *strongly visual.*
- According to progression dimension, for the degree of performance improvement in the profile, two categories of students were identified: those who showed one change in their performance and those who showed two or more changes. Students which achieved one change between profiles D1 and D2 seem to behave as *sequential*. This small step means small improvement in performance. Students which achieve two or three changes between profiles D1 and D2 seem to behave as *global,* whereas more than three changes as *strongly global*. More than one step means great improvement in performance. The trial test results were on average: *sequential* (42.85%) and *global* (28.57%).

Table 2. Total learner profile is structured by text comprehension and learning styles

Dimension	Learning styles	Identified elements in diagnosis tests: D1 (initial)/ D2 (final)	Prevailed text comprehension styles
Conceptualization	Intuitive	High level in t-type questions in D1 or d2	T-students (prefer abstract texts)
	Sensing	High level in M-type questions in D1 or D2	M-students (prefer descriptive texts)
	Strongly intuitive	High level in T-type questions in D1 and D2	T-students (strongly prefer abstract texts)
	Strongly sensing	High level in S-type questions in D1 and D2	S-students (strongly prefer descriptive texts)
Visualization	Visual	Rare use of help (a little time spent)	T-students (fast in using the system)
	Verbal	Frequent use of help (a lot of time spent)	M-students (slow in using the system)
	Strongly visual	Very rare or no use of help (a little time spent)	T-students (very fast in using the system)
	Strongly verbal	Very frequent use of help (a lot of time spent)	S-students (very slow in using the system)
Progression	Sequential	One change / step in the profile	S-students
	Global	Two or three changes / steps in the profile	M-students
	Strongly sequential	No change in the profile	S-students
	Strongly global	More than three changes / steps in the profile	T-students

A large number of students, who scored "high level" in T-type activities, were also classified as *intuitive and visual*. This means that those who preferred abstract texts rarely used the help mechanism and also spent a little time in doing the text comprehension activity. Moreover, they showed important improvement in their profile (two or three steps) as most of them were classified as *global*.

Another remarkable result was the combination of sensing, sequential and visual styles for a significant number of students. This is translated as the case of students who scored “high level” in M-type activities, used the help elements and showed not remarkable improvement in their profile. Based on the above results, discussion has been made regarding the fact that we have an opportunity to personalize instruction not only in terms of content, but also in terms of student learning style. Text comprehension S, M and T types within the StuDiAsE system reflect not only different educational needs but different learning styles. Based on Table 2 results, Table 3 depicts an indicative learner profile of Alice, an M-student.

Table 3. Indicative learner profile

Student name	Alice		
Initial profile D1	M –type (High level)		
	S-type: 0,57	M –type: 0,83 (maximum score)	T –type: 0,14
Average value (AvD1)	0,51		
Final profile D2	M - type (High level)		
	S-type: 0,86	M –type: 1,00 (maximum score)	T –type: 0,86
Average value (AvD2)	0,91		
Change: AvD2-AvD1	+0,40		
Number of changes	2		
Learning style			
Conceptualization decision	Sensing		
Visualization decision	Verbal		
Progression decision	Global		

Conclusion

The monitoring module of StuDiAsE, can observe the sequence of a student’s actions and provide a wealth of information to the educator that can be used to improve instruction and learning within the lines of a course. Educators may adjust their teaching techniques and customize the instruction to match the needs of the student by delivering personalized educational material based on their text comprehension styles and learning styles.

In order to make improvements in the learning environment of StuDiAsE, we have decided the set of monitorable indicators and the types of data which require monitoring. Moreover, we have organized information gathered from monitoring. All available sources of information have been used for a refined and more accurate estimation of the student profile. We explored several queries, which have been discussed, have found their answers and others are going to be the object of future research. A large scale evaluation study may verify the results.

Discussion so far provides clear justification as to why a comprehensive learner profiling system should be set up as an integral part of an e-learning framework.

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