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A framework for assessing LMSs e-courses content type compatibility with learning styles dimensions

Dimitrios Kouis, Konstantinos Kyprianos, Parthena Ermidou, Panagiotis Kaimakis, Alexandros Koulouris

University of West Attica, Athens, (Greece)

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Abstract

During the past few decades, it seems that personalizing and adjusting the e-courses' content based on individual learning styles is rather important. Indeed, several studies have been carried out throughout the years regarding the a priori personalization and adjustment of e-courses systems. This way modern LMSs (Learning Management Systems) could identify beforehand the learning styles of the e-course attendants and adjust the lesson content flow and type based on personal learning styles. Nevertheless, little bibliography exists on how to assess the compatibility level between educational content and learning styles dimensions of an LMS, in a real-life environment. With the above thoughts in mind, the current work attempts to introduce and verify an innovative framework for the students' learning styles and e-courses compatibility assessment, based on the content type and volume. The proposed framework is validated through its application at an LMS in a real-life academic environment. Such an approach could be very beneficial for already deployed e-courses on LMSs that aim to differentiate educational content provision based on users' profiles.

KEYWORDS: LMS, E-course, Learning Style, FSLS, Moodle

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1. Introduction

Since the 1970s, the individualisation of learning and teaching methods based on students' diverse learning styles or capabilities has drawn great attention (Coffield et al., 2004; DeJesus et al., 2004). According to Keefe (1988 cited in DeJesus et al., 2004), *learning styles are affective, cognitive and physiologic behaviours, which serve as relatively stable indicators of how students understand, interact and reply to the learning environment*. In practice, the research community developed several models that aim to categorise individuals according to their learning styles (Cassidy, 2004; Graf et al., 2007).

Although each model introduced different ways to show how learning styles can be defined and categorised, all of them conclude that each person follows a different learning approach (Willingham et al., 2015). It seems that the most widespread and easy to implement model is the Felder-Silverman Learning Style (Truong, 2016; Kumar et al., 2017).

Consequently, when it comes to students, it is apparent that their performance and achievement is directly related to the way they react to a learning situation (Cassidy, 2004). Hence, getting information about the students' learning styles is an essential prerequisite for an educational programme's adaptation to serve diverse individual needs. Several studies over the years have revealed that when adaptive tutoring systems, based on individual learning styles are employed (e.g. students with high preference for content with visual characteristics are benefited when they have access to video-based educational material), the students grow more productive, the learning curve and time involved to learn is more efficient and the academic achievements of the learner are improved (Kumar et al., 2017; Yang et al., 2013; Tseng et al., 2008; Adetunji & Ademola, 2014).

Additionally, the advancement of the Internet has allowed educators to embrace LMSs as an alternative teaching tool, available to the students synchronously or asynchronously. Admittedly, most of the universities, nowadays, provide their students with access to e-courses to support their educational processes. Amidst other functions, modern LMSs offer the ability to diversify the educational material per student, for the same e-course, with reference to personal learning styles. In addition, LMSs could offer personalised access to different types of learning activities and educational content, for the same topic, overcoming the limitations of traditional teaching. This way students benefit from engaging in a variety of learning activities and not just those targeted toward their learning styles (Hattie & Yates, 2014). With this in mind, some researchers have employed Moodle platforms and other LMSs to provide personalised learning courses content (or learning objects) for their students (Graf and Kinshuk, 2007; Despotović-Zrakić et al., 2012; Limongelli, Sciarrone and Vaste, 2011). Even the most advanced educational platforms, such as Massive Open Online Courses (MOOCs), focus on the creation of adaptive learning courses (Onah & Sinclair, 2015; Sein-Echaluce et al., 2017) that can support attendees' varying learning styles and needs.

Although several research studies have been done in previous years regarding the a priori personalisation and adjustment of e-courses systems based on the learners' learning styles, limited bibliography exists on how to assess the compatibility level between the educational content and learning styles dimensions of an LMS in a real-life environment. The LMSs content, meaning educational material format (e.g. video, audio, text etc.) and students learning styles compatibility evaluation should be an indispensable part of an academic department performance evaluation, as well as a tool for improving the teaching quality level.

Based on the aforementioned elements, the current work attempts to introduce and verify an innovative framework for the students' learning styles and e-courses compatibility assessment, based on the content type and volume that the latter provide to the students. The proposed framework is validated through its application at the LMS and the students of the Department of Archival, Library and Information Science at the University of West Attica. Such an evaluation process as the one proposed could also prove to be very beneficial as part of the content adaptation and validation process in modern LMSs, in the form of a stand-alone component or add-on.

2. Related work

Over the past decades, various studies regarding the identification of student learning styles for the creation of adaptive learning systems have been done. These studies can be categorized as theoretical and practical. The first category (theoretical studies) aimed mainly to introduce learning models and tools for the identification of individual learning styles. The practical studies concentrated their focus on designing and building adaptive learning systems to facilitate the learning process, based on individual learning styles. Our work is a practical study focusing on evaluating the compatibility of already existing LMSs content in relation to individual learning styles. It is remarkable that the review of all the practical studies carried out reveals that the most common approach for the identification of learning style is the use of the Felder-Silverman Learning Style Model - FSLSM (Silverman & Silverman,1988; Özyurt & Özyurt, 2015).

To start with, Cha et al. (2006) proposed a methodology to identify the learning style of the individual based on the FSLSM with the employment of an intelligent learning environment. The learning styles are identified through the interaction with the system and the intelligent learning environment customises the interfaces accordingly (e.g. text vs pictorial navigation buttons to the content). In a similar approach, Garcia et al. (2007) employed Bayesian networks (BN) precision to detect student learning styles. More specifically, they employed a BN where the input is the student's interactions with the web-based educational system. The BN results were evaluated through the comparison with the results of a corresponding questionnaire. The results were promising, but some mismatches occurred due to the fact that some students were not familiar enough with the system. Finally, Yang, Hwang and Yang (2013) developed an adaptive learning system by considering not only learning styles, but also cognitive styles. The evaluation showed that their adaptive learning system could improve the learning achievements of the students. Finally, Labib, Canós & Penades (2017) decided to adopt an ontology, based on the creation of interconnections between the different learning style model dimensions (such as Kolb and Felder-Silverman models) and learning styles with the relevant learner's characteristics. Their aim was to cover the heterogeneity that exists in different learning style model dimensions and to handle customization effectively.

The following three research efforts focus on implementing e-learning systems that diversify e-course content based on students' learning styles. More specifically, Radenkovic et al. (2009), Klašnja-Milićević et al. (2011) and Ocepek et al. (2013) distributed questionnaires in order to classify learners in specific learning styles, employing the FSLSM framework. Based on the results of the questionnaires, the authors proposed adaptive e-learning systems corresponding to the preferred learning style of each individual and the preferred types of multimedia materials.

On the contrary, Adetunji and Ademola (2014) propose an Automatic Adaptive E-Learning System (AAELS) that adapts to e-course participants' learning styles automatically. The system does not require the user/learner to perform any preliminary activity before it gets information about their adaptive needs; the system does this automatically when a user/learner navigates their way through the e-learning platform.

Finally, two recent studies show that the identification of the students' learning style is still in use in some disciplines and plays a crucial role at the educational environment. More specifically, Crockett et al. (2017) proposed a method for the prediction of learning style in conversational intelligent tutoring systems with the employment of fuzzy decision trees. The results showed that their approach augmented the prediction of the individual's learning style. In another study, McKenna et al. (2018) tried to identify the learning style of the post-graduate pre-registration nursing students using a very "traditional" research approach based on questionnaires.

The following works focus on Moodle as an LMS in order to provide to students e-courses content based on their individual learning style. More specifically, Graf and Kinshuk (2007) and Limongelli et al. (2011) proposed add-ons to Moodle that provide adaptation capabilities. They both identified the learning styles based on the FSLSM. The results proved that teaching is more effective and learning results are better when e-courses' content is fitted to the students' learning styles (e.g. adaptation features related to differentiation on content type / volume and/or content sequence).

Next, via a more generalised approach, Despotovi-Zraki et al. (2012) conducted a survey where they aimed to measure if the adapted e-courses can benefit the students. The described e-course adaptation method utilises data mining techniques to classify students into clusters with regards to FSLSM and activities in Moodle. Research results proved that teaching resources and activities adapted to learning styles led to significant improvement in learning results.

The following research works have a different approach in identifying the learning style of the individuals. Specifically, they do not use the "traditional" questionnaires proposed by many authors but they try to find the learning style by the employment of other activities. In particular, the studies focus on other activities, such as video-based multimedia material (Chen & Sun, 2012), literature-based methods (Ahmad et al., 2013), game-based problem-solving activities (Hung, Chang & Lin, 2016) and computational intelligence algorithms (Bernard et al., 2017). They all pinpoint the importance of the discovery of the individual's learning style and they all conclude that the students were greatly benefited when they were presented with material based on their specific learning style.

Considering the popularity of e-courses, especially with the advancement of Massive Open Online Courses; automated tools for content compatibility assessment, in conjunction with students' learning styles could be useful both for educators, as well as for quality evaluation purposes. The usefulness of such automated tools, that would provide the ability to continuously assess content compatibility level, in relation to students' needs, could prove significant for educators, as well as higher level decision makers. Consequently, the following sections present an innovative methodology and application of it in an actual academic department LMS.

3. Methodology

3.1 E-course content and learning style compatibility assessment framework

The need for introducing a framework for LMS content quality assessment is an essential part of the evaluation process of a higher education department. Since the Department of Archives, Library and Information Studies (University of West Attica, Greece) relies heavily on the use of an LMS (with more than 50 undergraduate and postgraduate e-courses) a formal evaluation was performed, and its results presented in Zervos et al. (2013). The results of the previously mentioned evaluation highlight mainly the students' favorite activities and behavior patterns when studying, in relation to LMS offered functions. Although useful remarks were obtained, there was no information about the e-courses content compatibility with the specific requirements of students' learning styles. In this sense, an easy to implement evaluation framework, comprising of five phases, which are briefly described below and depicted in Figure 1, was formulated for the department's e-courses content characteristics evaluation, as provided through its LMS.

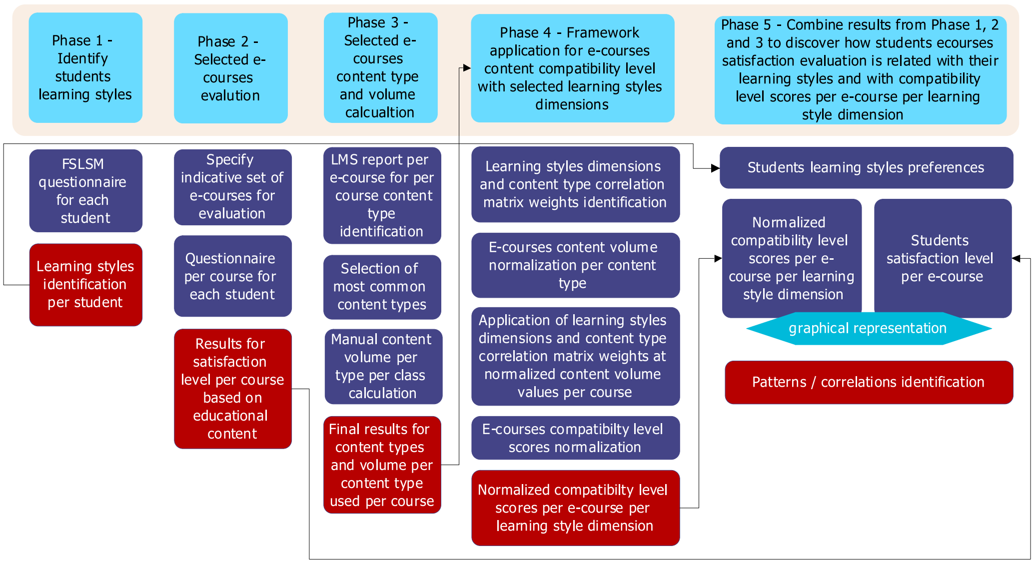


Figure 1 - Methodology phases overview

The first phase of the proposed evaluation framework concerns the identification of students' learning styles via the use of the FSLSM questionnaire. This phase aims to determine for each student, as well as at departmental level, the score for all FSLSM learning styles scales. In the second phase, students were asked to state their satisfaction level about the usefulness of the content, meaning comprehension support and achievement of pass mark during final exams, for a representative set of e-courses (per semester and per course type, e.g. lecture course only, or lecture and lab course). It is noted that the under-evaluation e-courses were part of the students' major degree program. Specifically, the questions asked concerned the degree to which the content promoted students' course learning outputs understanding, as well as if they achieved satisfactory marks during the exams. Their satisfaction level was measured via a four-level grading scheme. At the next phase (phase three), for each selected e-course the content types (e.g. text, presentations, assignments, quizzes etc.) and the volume per type (e.g. number of files, presentations etc.) were identified. The types of content per course and the volume were retrieved from LMS reporting system, while in some cases content volume was calculated manually (text pages, PowerPoint slides etc.). Content types selected (see Table 2) are corresponding only to those that used by the e-courses that participated in the evaluation. Next, at phase four, a correlation matrix which provided a mathematical tool for quantifying the e-course level of compatibility with the two (out of four) more appropriate FSLSM learning style scales, in conjunction with the volume per type content, was introduced. Before applying the weights depicted in the correlation matrix, the content volume values per course, were normalized using the min-max scaling. After, by multiplying the correlation matrix weights, with each e-course volume normalized value per content type data, the compatibility level score per learning style scale was calculated. Again, for allowing comparison between e-courses a normalization process was implemented. At the last phase (phase five), the results from the phase one, two and four were combined. Specifically, a graphical representation of normalized compatibility level scores per learning style and students' satisfaction level per e-course, participating in the sample, enables the identification of useful correlations and patterns. The results from phase 5 provides significant evidences about whether e-course compatibility levels, with specific learning style scales dimensions, are related to students' satisfaction levels and/or their learning styles.

3.2 Felder-Silverman Learning Style Model

The decision to select the FSLSM was based on the fact that it is the most wide-spread model for analyzing the individual's learning style (Graf, Kinshuk and Ives, 2010). FSLSM can describe the learning style in much detail compared to other methods (Graf et al., 2007). Additionally, the Felder model is more appropriate for e-learning and web-based learning systems (Kuljis and Liu, 2005). According to the FSLSM, the learners are divided into four two-dimensional scales, based on the Index of Learning Styles – ILS (Graf et al., 2007) as they are presented in detail in Table 1.

Learners style scales and their dimensions	Description per dimension
Scale 1 *Active vs Reflective* (Act / Ref) Processing	Active learners tend to understand information better by doing something active with it. They prefer exercises and group participation. They learn by doing something. On the other hand, reflective learners prefer to take their time and think about it quietly. They prefer to study alone and to do individual exercises.
Scale 2 Sensing vs Intuitive (Sen / Int) Perception	Sensing learners prefer to learn through examples from the real world. They tend to be patient with details and good at memorizing facts. They are more practical and careful than intuitive learners. On the other hand, intuitive learners prefer innovation and they dislike repetition. They can better grasp new concepts and are more comfortable with abstractions and mathematical formulations in comparison to sensing learners.
Scale 3 Visual vs Verbal (Vis / Ver) Representation	Visual learners prefer to learn through pictures, diagrams, flowcharts, videos, etc. However, verbal learners prefer to learn from words, whether spoken or written. They tend to communicate and discuss with other people.
Scale 4 Sequential vs Global (Seq / Glo) Understanding	Sequential learners tend to learn gradually, step by step from the individual information give, to the general meaning. Whereas global learners tend to perceive the general meaning, understanding afterwards the specific details. They can solve complex problems quickly.

Table 1 - Felder-Silverman learners style scales and dimensions (Klašnja-Milićević et al., 2011; Adetunji and Ademola, 2014; Felder and Soloman, 2017)

The determination of the learning style score per scale is made through the employment of a questionnaire, which contains 44 questions with two available responses (a or b), which aims to detect the individuals' preferences through each scale's dimensions, as Felder and Silverman defined them. For each scale, 11 questions are posed. For example, assume that for the 11 questions of the "active" vs "reflective" scale, a learner scored 9 answers with the "a" and 2 with the "b". The score for this scale is calculated by subtracting the smaller number of answers (based on the letter) from the larger one and by adding the letter (a or b) for which the answers where the majority. For our example, the final score for the scale "active" vs "reflective" is 7a (9-2=7 plus the letter "a"). Figure 2 depicts how scores per scale are interpreted in relation to the dimensions of the FSLSM. More specifically, a score between 11 to 9 either for "a" or "b" expresses a very strong preference for one of the dimensions of the scale. Accordingly, scores between 7-5 indicate a moderate preference for a dimension, while the score from 3 to 1 expresses a rather well-balanced attitude to both scale dimensions.

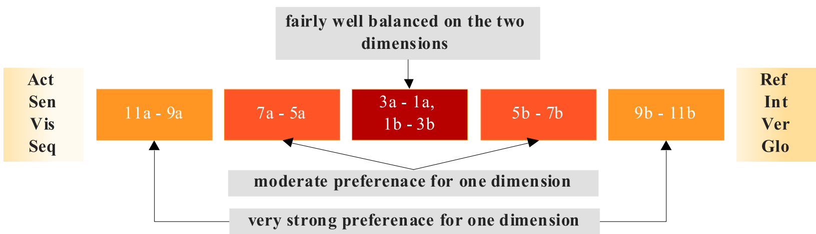


Figure 2 - FSLSM dimensions scoring interpretation

3.3 Educational content according to learning styles – Correlation matrix

Based on the aforementioned types of learners, the teachers must create the corresponding content in the form of learning objects that reflects the learning style of each student. The LMSs such as Moodle provide a great variety of learning objects (Graf, Kinshuk and Ives, 2010; Zervos et al., 2013) such as content objects (e.g. text files, presentations, videos etc.) and interactive objects (e.g. tests, quizzes, assignments, forums, thesaurus, databases etc.).

Having the above thoughts in mind, Mendez, Morales and Vicari (2016) tried to relate learning objects to learning styles based on the FSLSM. Such a study facilitates and gives guidelines to the teachers to create the corresponding learning objects and materials by taking into consideration the individual's learning style. Following their example, the table below quantifies via a weighting vector for FSLSM scale 1 and 3 dimensions (Active vs. Reflective and Visual vs. Verbal), the relation to specific content types such as presentation files, text files (pdf, word etc.), assignment/projects activities, quizzes/interactive modules, video/audio files, external links to reference material and computer files (source code, XML files etc.). Weighting is useful because it presents the results as a single score and keeps the complexity of the evaluation framework low (for communication purposes). It is worth mentioning that the content types selection was based on their popularity among department teachers of the evaluated LMS. Also, only FSLSM scale 1 and 3 are related to content types as they are more affected by the content format and the presence of activity modules. Subsequently, scales 2 and 4 were not used for the proposed compatibility assessment framework as they are associated more with the content itself and the teaching model, followed by the instructor.

Content type and activity modules / weighting factor per dimension	Scale 1 – Processing		Scale 3 - Representation	
	Active	Reflective	Visual	Verbal
Presentation files	0	0.4	0.1	0.2
Text files	0	0.5	0	0.6
Assignments / projects	0.3	0	0.1	0.1
Quiz/Interactive modules	0.3	0	0.3	0
Video/Audio	0.2	0	0.3	0
External material (links to articles, books, reference material etc.)	0	0.1	0	0.1
Other computer files (source code, xml files, rdf examples, bibliographic records, etc.)	0.2	0	0.2	0
Total	1	1	1	1

Table 2 - FSLSM dimensions and e-courses content types correlation matrix

As reflected in the correlation matrix weighting values, dimensions such as "*active*" and "*visual*" are better served by content type such as video, audio clips, PowerPoint presentations (for the "*visual*" dimension) and activity modules such as assignments, quizzes and other computer-oriented files (source code, XML files, RDF examples, bibliographic records, etc.). However, text files, presentations and other types of reference material are more suitable for improving the educational process of students who prefer readings, narratives, diagrams and presentation (reflective and verbal). Moreover, the weighting values are considered balanced and aligned with the content types or activity modules with the most volume or population. In more detail, the weighting factors presented in Table 2 were obtained though testing, intending to give greater values to more "compatible" content type in relation to a certain learning style dimension and less value (or even zero) to types of content that are not relevant or don't fit to the educational process based on students' learning characteristics. The results and conclusions for the specific set of e-courses are not significantly influenced when weighting values with minor differences are used.

3.4 LMS e-courses compatibility level calculation

After presenting the correlation matrix, a set of 21 e-courses were selected to be assessed concerning their compatibility with 1 and 3 dimensions of the FSLSM scales and students' learning styles. The e-courses information and thus compatibility levels were normalized by applying the min-max normalization during the assessment process. This option was intentionally adopted as it allowed for the obtaining of comparative results about e-courses that could encourage the spirit of competition between faculty members.

Next, an example of how the compatibility level per e-course is calculated**,** is described. In the second column of Table 3, the volume of the most common types of content, as well as the number of activity modules used (following the correlation matrix types), were measured, per e-course. By taking into account content volume of educational resources (e.g. number of slides in presentation files, number of assignments etc.), that are included in the e-course material, a more precise indication of their gravity and importance, during the educational process, is obtained, compared to considering content type only. For better understanding, the chosen e-courses for evaluation, were ranked in descending order by content type, volume and number of activity modules (presented in the third column of Table 3). The e-course picked as an example, had the highest volume of text content with more than 2.700 pages. As stated in the methodology section, all content values per type and per e-course were normalized using min-max scaling (see the last column of Table 3).

Content types &activity modules	e-course material volume	e-courses order by volume per content type / module number	normalized values
Presentation files	342 slides	9th	0.36
Text files	**2736 pages**	**1st**	**1.0**
Assignments / projects	6	11th	0.20
Quiz/Interactive modules	0	-	0.00
Video/Audio	0	-	0.00
External material (links to articles, books, reference material etc.)	21	5th	0.68
Other computer files (source code, XML files, RDF examples, bibliographic records, etc)	1	6th	0.06

Table 3 - e-course example - normalised values based on content type – activity module /volume – number of instances

E-course score computation for FSLSM scales 1, and 3 dimensions entails multiplying the normalised values for each of the content type and activity modules with the weighting factors of the correlation matrix (see Table 4, row 1 for the example e-course). The weighted results that occur are again normalised using the min-max rescaling process (see Table 4, row 2) for the set of e-courses under assessment.

Dimensions	Active	Reflective	Visual	Verbal
e-course score per dimension	0.07	0.71	0.07	0.76
normalized score	0.13	1.00	0.10	1.00

Table 4 - Course example - Applying FSLSM dimensions weighting matrix on content normalised values

As expected, due to the excessive volume of text content for the e-course used as an example, the scores for dimensions such as reflective and verbal were the highest (equal to 1) among all other e-courses. However, the e-course in question scores low for dimensions "active" and "visual" due to the lack of compatible educational material. Concluding, it is evident that the e-course example would best support students with strong preference for reflective and verbal dimensions.

In more detail, the majority of the respondents (73%) were between 18 to 23 years old, while one out of ten was between 24 to 26 (students who had put their studies on hold in the past, or delayed their graduation). It is notable that 17% of the respondents were more than 27 years old, which may seem unusual for a 4-year study academic department.

4. Results and data analysis

As stated before, the framework was validated through its application in an academic department's LMS. The results included the responses collected from more than 150 students via an online questionnaire with two parts. Part 1: the Index of Learning Styles (ILS) test, developed by Richard M. Felder and Barbara A. Soloman (44 questions), and Part 2: the evaluation score for the 21 e-courses content (21 questions one per e-course that participated in the evaluation process). Before presenting the analytical results of the responses, the demographic and academic characteristics of the responders are presented (Figure 3), plus details on the e-course selection learning style profile, based on the FSLSM dimensions.

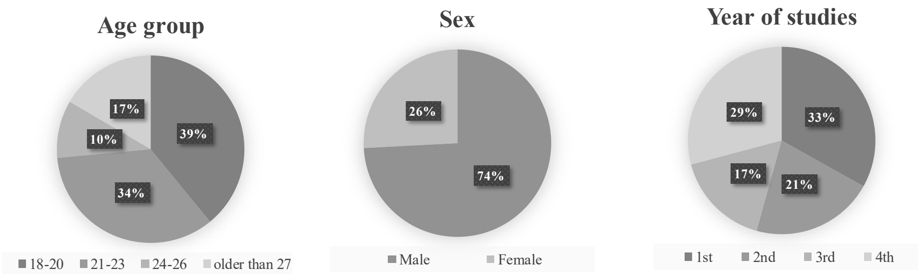


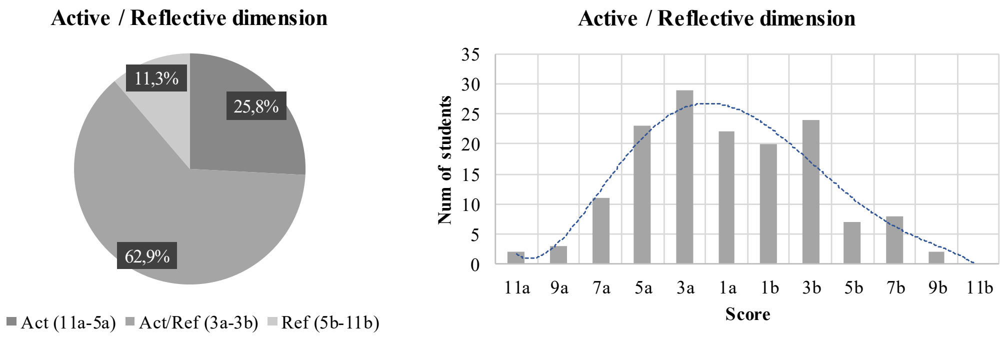
Figure 3 - Students demographic and academic characteristics

Those respondents are mainly school teachers, lawyers, computer scientists etc. working towards a career change or professional development, by obtaining a second degree. The majority of the respondents were female (74%) which was expected as this reflects the gender ratio of the department's students. Finally, the distribution of respondents among the year of studies was balanced (1st year 17%, 2nd year 21%, 3rd year 33% and 4th year 29%).

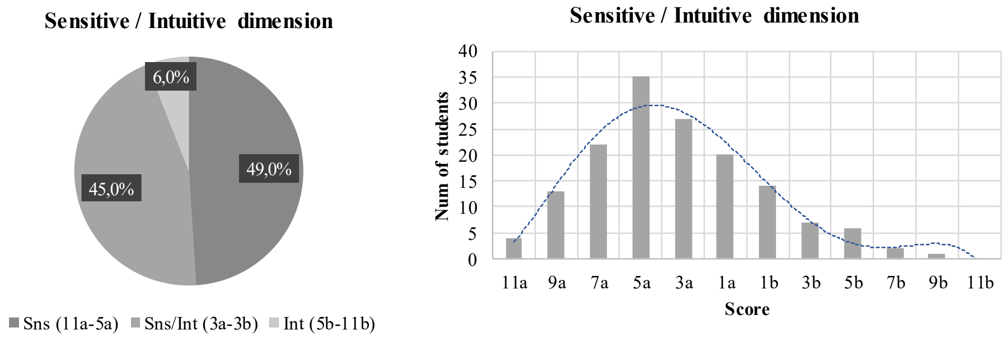
Also, the department's LMS (http://ecourses.alis.uniwa.gr) hosts more than 44 undergraduate e-courses, distributed in 7 semesters. As the ILS test comprised of 44 questions, it was decided to narrow the number of under evaluation e-courses per semester, to 3 in order to reduce "survey taking fatigue". In this way the entire number of e-courses selected was 21. It is noted here that 14 e-courses were linked to lecture and lab courses, while the remaining 7 e-courses related to lecture-only courses, while all of them belong to the "core courses category" (required courses), where students enrolment is obligatory.

4.1 Learning styles identification

The figures that follow (Figure 4a, b, c, and d) depict the aggregated ILS test scores from all the participants, in an attempt to determine the department's students learning style profile, based on the FSLSM dimensions. The analysis of the results points out that the department's students have a strong/moderate preference for "*sensitive*" and "*visual*" learning style dimensions. In particular, 49% of the respondents' scores for scale 2 ("*sensitive*" vs "*intuitive*" dimensions, see Figure 4b) are between 11a and 5a, exhibiting a strong/moderate preference for the "*sensitive*" dimension. A well-balanced attitude for both dimensions of scale 2 shows that 45% of the respondents score from 3a to 3b and only the 6% of the students score between 5b and 11b, suggesting a strong/moderate preference for the "*intuitive*" dimension. Similar results apply to scale 3 ("*visual*" vs "*verbal*" dimensions, see Figure 4c). In detail, 38.4% of the respondents' scores are between 11a and 5a, suggesting a strong/moderate preference for the "*visual*" dimension, 53% of the responders present a well-balanced attitude for both dimensions (scores from 3a to 3b) and only 8.6% are in favour of "*verbal*" dimension. As far as concerns scale 1 ("*active*" vs "*reflective*" dimensions, see Figure 4a) and scale 4 ("*sequential*" vs "*global*" dimensions, see Figure 4d) students exhibit a rather well-balanced attitude for both dimensions with 62.9% and 71.5% of them scoring between 3a and 3b. It is notable that 1 out of 4 (25.8%) seem to have a moderate preference for the "*active*" dimension.



(a)



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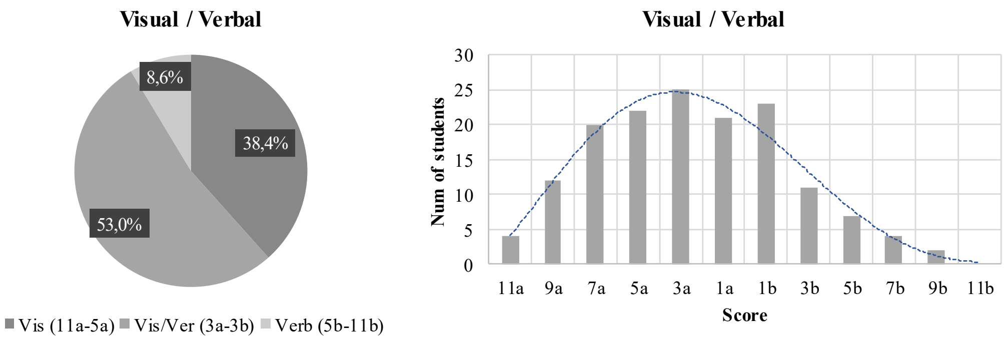

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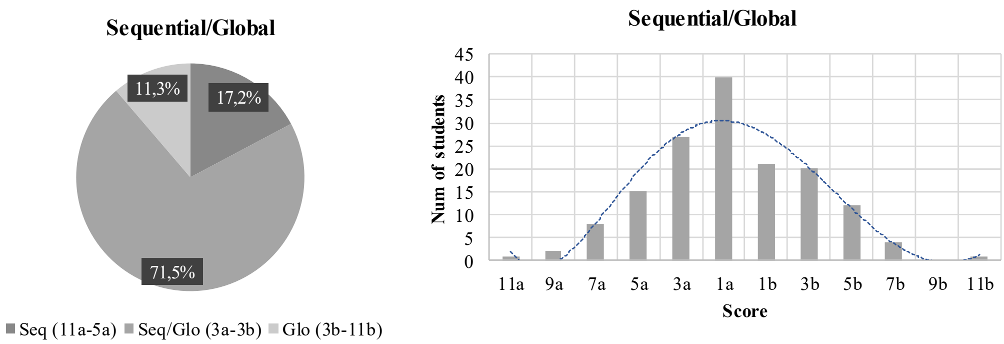
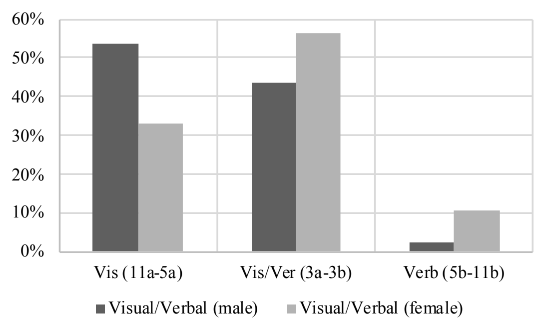


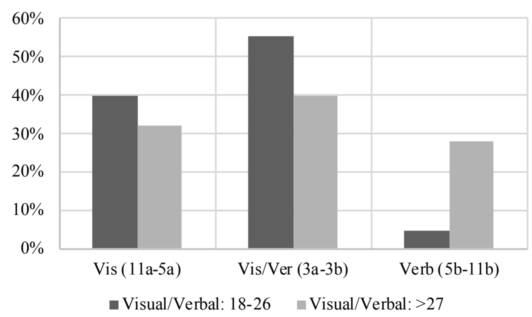
(d)

Figure 4 - FSLSM dimensions results per scale: (a) Scale 1 results – Act/Ref, (b) Scale 2 results – Sen/Int, (c) Scale 3 results – Vis/Ver, (d) Scale 4 results – Seq/Glo

The learning styles results presented are aligned with the overall profile of the department's students and results from other similar research activities (Shuib and Azizan, 2015; Thomas et al., 2002; Murphy et al, 2004; D'Amore, James and Mitchell, 2012). The majority of the students that follow archival, library and information studies have a theoretical background, providing some justification for the "*sensing*" dimension**,** strong/moderate preference and the rather balanced attitude to both scales 1 and 4 of the FSLSM test. Also, after an in-depth analysis of the results, two more interesting findings were revealed about the "*visual* vs *verbal*" dimensions. Those findings are depicted in Figure 5a and b. As can be observed from this figure, there is a relationship between the "*visual*" and "*verbal*" learning style dimensions, with gender and age factors. 53.8% of the male students present a strong/moderate preference for the "*visual*" dimension (score 11a to 5a), while for females the percentage drops to 33%. It is also interesting that almost 28% of students with an age greater than 27 years old present a strong/moderate preference for the "*verbal*" dimension (score 5b to 11b), while for younger students the percentage drops to 4.8%.



(a)



(b)

Figure 5 - FSLSM dimensions results deviations based on gender and age

4.2 Compatibility level scores per learning style dimension vs students' satisfaction levels per e-course

Figure 6 and figure 7 present the 21 e-courses FSLSM scales 1 and 3 scores as they derived from the computation procedure presented previously. The order of the e-courses is based on the results from the students' satisfaction survey (dotted line).

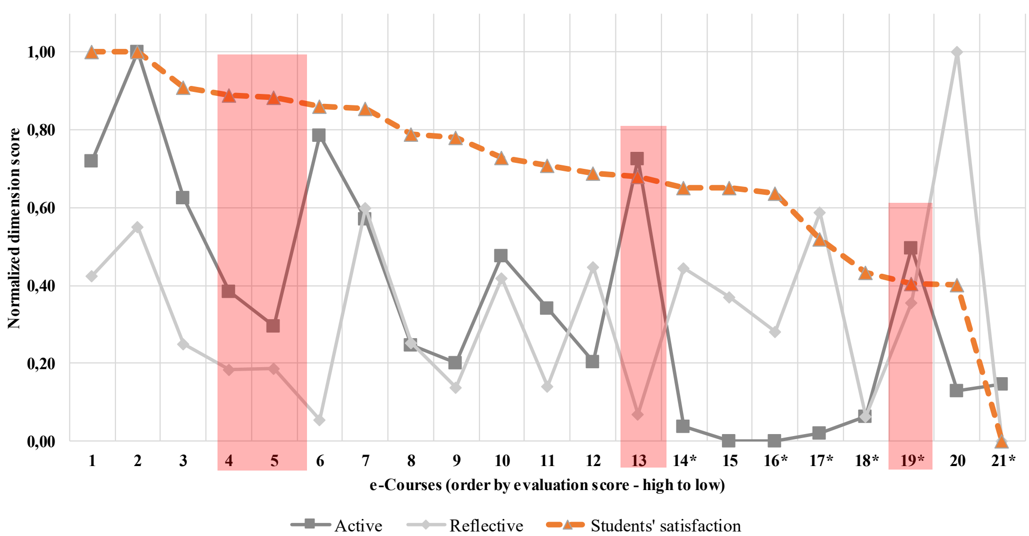


Figure 6 - E-courses compatibility levels for FSLSM scale 1 – Students' satisfaction level

As depicted in Figure 6, it can be seen that in general, e-courses that their content present high compatibility levels with the "*active*" learning style dimension are also receiving high scores reference student satisfaction. Whereas, e-courses with the "*active*" learning style dimension show a low compatibility level and are receiving low student satisfaction scores. As can be seen in Figure 6 (see e-courses with id 4, 5, 13 and 19), there are some exceptions to the general trend. Specifically, e-courses with ids 4 and 5 present high student satisfaction scores, while the compatibility level indicator for the "*active*" dimension is considered low. On the other hand, the situation for e-courses with ids 13 and 19 is reversed, as they present low student satisfaction scores and a rather high compatibility level indicator for the "*active*" dimension.

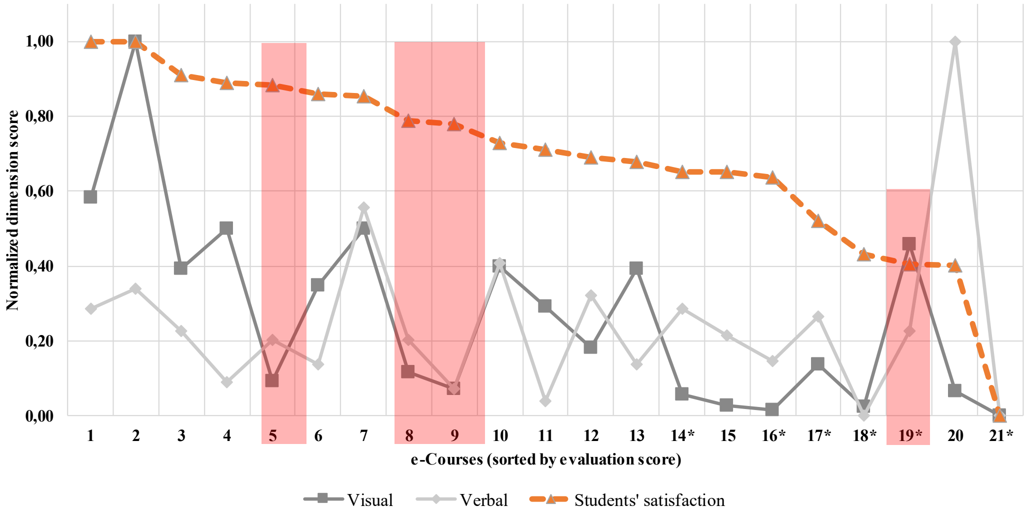


Figure 7 - E-courses compatibility levels for FSLSM scale 3 – Students' satisfaction level

The results for the "visual-verbal" dimensions are similar. As depicted in the figure above (Figure 7), it can be seen that e-courses that are scoring better on the "visual" learning style dimension are receiving high satisfaction grades. This conclusion is also supported by the fact that the specific group of students had a strong preference for visual dimension. On the contrary, e-courses that exhibit low compatibility level with "visual" dimension are graded with low scores from students. As expected, there are some deviations from the general trend. Specifically, e-courses with ids 5, 8 and 9 present high student satisfaction scores, while the compatibility level indicator for the "visual" dimension is considered low. Whereas the situation for e-course with id 19 is reversed, as it presents low student satisfaction scores and a rather high compatibility level indicator for "visual" dimension.

Another interesting finding is that e-courses which are linked to lecture only courses (see Figures 6 and 7, e-courses with ids 14, 16, 17, 18, 19 and 21) are getting the lowest scores on both dimensions "active" and "visual" as well as in the students' satisfaction rating. Although there was an expectation that students are more intrigued by courses comprised of lectures and lab exercises, the lack of interactive and visual/multimedia material seems to have a negative impact on the results of students' satisfaction scores.

5. Discussion

At this point it is important to address the criticism on the usefulness and the scientific coherence of learning styles application in relation to educational activities that has been raised lately by research community (Newton, 2015; Newton & Miah, 2017; Kirschner & van Merriënboer, 2013; Kirschner, 2017). More specific, Kirschner (2017) summarizes learning styles major drawbacks in the following: (1) There has been no proof or at least no proof that learners are benefited when they are given different instructions based on their learning styles, (2) the identification of learning style based on questionnaires suffers from fundamental problems. Although, this may be partially accurate for conventional teaching, there is still vigorous research interest for implementing adaptive e-learning environments by utilizing learning styles or cognitive styles models (Özyurt & Özyurt, 2015; Truong, 2016; Kumar, Singh & Jyothi-Ahuja, 2017, McKenna et al., 2018). The computer-based nature of adaptive e-learning environments allowed researchers to acquire empirical evidence of the merits that learning styles and educational content correlation presents (Radenkovic et al., 2009; Klašnja-Milićević et al., 2011; Chen & Sun, 2012; Ocepek et al., 2013; Yang, Hwang, & Yang, 2013; Adetunji & Ademola, 2014) in an attempt to address the first point of the criticism mentioned above. Also, the e-learning environments improved significantly the precision of automatic learning style identification based on students' behaviour in combination with self-report measures techniques (Bernard et al., 2017; Crockett, Latham & Whitton, 2017; García et al., 2007), addressing the second point of criticism. In this sense, learning styles application in relation to educational activities in LMSs, rather than traditional face-to-face teaching, is an important aspect that could support higher engagement thus better satisfaction levels for the students.

Moreover, based also on our findings, the individualisation of learning and teaching methods based on students' diverse learning styles or capabilities, although it is not a new concept, appears to be an attractive add-on feature for modern LMS environments. Usually, before attending an LMS e-course, students' learning styles are identified, so that they can access the most appropriate content. An alternative approach, such as the one presented in this paper, could be a framework for assessing the compatibility level between educational content and students learning styles dimensions per e-course. Educators and learning content creators could redesign the e-course workflows and provide multiple types of material and content according to the assessment results of each student. This alternative approach could be very beneficial for already deployed e-courses and traditional LMSs as they could provide personalised learning activities and educational content, extending the limits of traditional teaching in a classroom.

The sections above presented an innovative methodology for evaluating the compatibility between student learning styles and e-course material. The application of the assessment framework at an academic department was easy and straightforward leading to useful results for educators and the department's quality assurance committee. The results section provided sufficient evidence that an immediate connection between students' learning preferences, their degree of satisfaction and e-courses compatibility levels with particular learning styles dimensions, exists. More specifically, it has been seen that e-courses utilizing content types that better support the "*visual*" and "*active*" learning style dimensions are graded with the highest scores by the students. The same trend appears with the courses that have both theory and lab parts, as expected. Such a result may be attributed to the fact that the courses that have both theory and lab parts are more interactive, in contrast to the courses that have only the theory part and might be more difficult. In addition, the deviations observed between the satisfaction ratings of certain e-courses and the learning style dimensions scores are indications that students' responses are influenced not only by the content type, but also by factors such as the level of difficulty, the instructor's teaching methods, the topics presented etc. Moreover, the presentation of the compatibility assessment and evaluation results in a comparative way had an immediate impact on the department's faculty. Most of them started to reconsider their teaching approach, whilst a guide to good practices during e-course content development is being produced.

6. Conclusion and future developments

Our future work aims to further improve the proposed framework and explore the opportunities for implementing an add-on for Moodle LMS. Clearly it is essential to identify students' satisfaction levels in a multidimensional way, including quantitative and qualitative information about their performance results. Also, it is considered necessary to further automate the content type and volume calculation, as well as to add information referring to their utilization by the students, directly from LMS reporting system. Finally, further effort has to be put into computing different metrics per compatibility assessment case, e.g. for a unique e-course, or for a specific semester's e-courses, or for all e-courses in the LMS.

In conclusion, we believe that the proposed framework is sound, easy to apply and contributes to the improvement of e-courses content. The benefits from the application of the presented framework could be seen during the design and improvement of new and already existing e-courses. Finally, from a technical perspective, our work specifies most of the requirements, the workflows and the details necessary to design and implement an LMS add-on component in order to accommodate the compatibility assessment between students' learning styles and e-course material. Such a function is missing from modern LMSs and is expected to contribute positively to their operation and quality enhancement.

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