REPRESENTATIVE CHARACTERISTICS OF FELDER-SILVERMAN LEARNING STYLES: AN EMPIRICAL MODEL *

Sabine Graf
Women's Postgraduate College for Internet Technologies
Vienna University of Technology, Vienna, Austria
graf@wit.tuwien.ac.at

Silvia Rita Viola
Dip. Ingegneria Informatica, Gestionale e dell' Automazione "Maurizio Panti"
Universita' Politecnica delle Marche, Ancona, Italy
sr.viola@gmail.com

Kinshuk
School of Computing and Information Systems
Athabasca University, Athabasca, Canada
kinshuk@ieee.org

Tommaso Leo
Dip. Ingegneria Informatica, Gestionale e dell' Automazione "Maurizio Panti"
Universita' Politecnica delle Marche, Ancona, Italy
tommaso.leo@univpm.it

ABSTRACT

Learning styles are more and more incorporated in technology enhanced learning and a lot of research work is done in this area. For example, systems are developed which provide adaptivity according to the learning styles of students; relationships to students' performance and other characteristics of students such as cognitive traits are investigated, and techniques are designed to derive the learning styles from the behaviour of students during an online course. The more information about learning styles is available and the more detailed the description of learning styles is, the better such approaches can work and can be investigated. The aim of this paper is to analyse data about learning styles with respect to the Felder-Silverman learning style model (FSLSM), in order to provide a more detailed description of the learning style dimensions. Therefore, we used linear discriminant analysis in order to detect the most representative characteristics of learning styles as represented in the gathered data. Furthermore, we analysed how representative these characteristics are for the specific learning style dimensions. For cross-validation, we conducted empirical frequencies analysis as well as correlation analysis. As a result, we provide a more detailed description of the learning style dimensions of FSLSM. This description is especially important when learning styles are incorporated in technology enhanced learning.

KEYWORDS

Learning styles, Felder-Silverman learning style model, data mining, student models

1. INTRODUCTION

Many researchers agree that learning styles play an important role in education. For example, Felder points out that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style (Felder and Silverman, 1988; Felder and Spurlin,

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2005). Bajraktarevic, Hall, and Fullick (2003) confirmed this by a study showing that students attending an online course that matches with their preferred learning style (either sequential or global) achieved significantly better results than those who got delivered a course that did not match their learning style. To improve the learning progress of students and to make learning easier for them, learning styles are considered more and more in technology enhanced learning systems. CS383 (Carver et al., 1999), IDEAL (Shang et al., 2001), and MAS-PLANG (Peña et al., 2002) are some examples for systems that incorporate learning styles and provide courses that fit to the learning style of the students.

A lot of research work deals with learning styles in online environments. Mostly, learning style models for traditional learning were used for such investigations. When incorporating learning style models developed for traditional learning in online environments, it has to be considered that not all characteristics of the learning style model (such as the preference for spoken language, the preference for group work and so on) can be mapped to each online environment.

In this study, we focus on Felder-Silverman learning style model (FSLSM) (Felder and Silverman 1988), a learning style model that is often used in technology enhanced learning but is designed for traditional learning. The aim of this study is to analyse data based on FSLSM to provide a more detailed description of its learning styles. Therefore, we aim at identifying characteristics of each of the four dimensions of FSLSM in order to be able to make a more gradual distinction within the learning style dimensions. Furthermore, we analyse how representative each characteristic is for each learning style dimension.

Such detailed information is beneficial in many ways. In general, if an online environment supports a learning style only partially, this has to be considered when analysing the output of the system and drawing conclusions. For example, when using information about learning styles to provide adaptivity, a detailed description of learning styles can improve the adaptation process. If a system supports only some characteristics of a learning style, then a student model that includes information about exactly these characteristics is important to provide suitable adaptivity rather then using information about the overall learning style. Another example for the use of such detailed information about learning styles is the derivation of learning styles from the behaviour of students during an online course. Since such an approach has been investigated for different systems (Cha et al., 2006, García et al., 2006, Graf and Kinshuk, 2006) and different systems support different characteristics of learning styles, it is important to be aware of the relevance of the supported characteristics for the learning styles. This leads to a better estimation of the results and hence, to a more meaningful application of the identified information. Also for identifying relationships between learning styles and, for instance, the performance of students in an online course (for an overview see Hayes and Allinson, 1996) or other characteristics of students such as cognitive traits (Graf et al., 2005) detailed information about the learning styles is beneficial in order to be able to build a more accurate relationship.

In the next section, we describe FSLSM in detail. Afterwards, we focus on our case study describing the ILS questionnaire, on which the study is based, as well as the different kinds of analyses we conducted and their results. Section 4 concludes our work.

2. FELDER-SILVERMAN LEARNING STYLE MODEL

There are several different learning style models in literature such as by Kolb (1984), Honey and Mumford (1986) as well as Felder and Silverman (1988), each proposing different descriptions and classifications of learning types. In our work, we are focusing on the Felder-Silverman learning style model (FSLSM). Most other learning style models classify learners in few groups, whereas Felder and Silverman describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions. Another main issue is that FSLSM is based on tendencies, saying that learners with a high preference for certain behaviour can also act sometimes differently. According to Carver et al. (1999), “the Felder Model is most appropriate for hypermedia courseware” and it can also be seen that FSLSM is used very often in research related to learning styles in advanced learning technologies.

In the following discussion, the four dimensions of FSLSM are described. Each learner is characterized by a specific preference for each of these dimensions.

The first dimension distinguishes between an active and a reflective way of processing information. Active learners learn best by working actively with the learning material by applying the material and trying things out. Furthermore, they tend to be more interested in communication with others and prefer to learn by working in groups where they can discuss about the learned material. In contrast, reflective learners prefer to think about and reflect on the material. Regarding communication, they prefer to work alone or maybe in a small group together with one good friend.

The second dimension covers sensing versus intuitive learning. Learners who prefer a sensing learning style like to learn facts and concrete learning material. They like to solve problems with standard approaches and also tend to be more patient with details. Furthermore, sensing learners are considered as more realistic and sensible; they tend to be more practical than intuitive learners and like to relate the learned material to the real world. In contrast, intuitive learners prefer to learn abstract learning material, such as theories and their underlying meanings. They like to discover possibilities and relationships and tend to be more innovative and creative than sensing learners.

The third, visual-verbal dimension differentiates learners who remember best what they have seen, e.g. pictures, diagrams and flow-charts, and learners who get more out of textual representations, regardless of the fact whether they are written or spoken.

In the fourth dimension, the learners are characterized according to their understanding. Sequential learners learn in small incremental steps and therefore have a linear learning progress. They tend to follow logical stepwise paths in finding solutions. In contrast, global learners use a holistic thinking process and learn in large leaps. They tend to absorb learning material almost randomly without seeing connections but after they have learned enough material they suddenly get the whole picture. Then they are able to solve complex problems, find connections between different areas, and put things together in novel ways but they have difficulties in explaining how they did it. Because the whole picture is important for global learners, they tend to be more interested in overviews and a broad knowledge whereas sequential learners are more interested in details.

3. CASE STUDY

In order to investigate the learning style of students we performed a case study where 207 students participated. 122 students are from Massey University of New Zealand and 85 from Vienna University of Technology in Austria. To measure the learning styles of the students, they completed a questionnaire developed by Felder and Soloman (1997). In the following section, this questionnaire is briefly introduced and afterwards the results of our study are presented.

3.1 Index of Learning Styles

The Index of Learning Styles (ILS), developed by Felder and Soloman, is a 44-item questionnaire for identifying the learning styles according to FSLSM.

As mentioned earlier, each learner has a personal preference for each dimension. These preferences are expressed with values between +11 to -11 per dimension. This range comes from the 11 questions that are posed for each dimension. When answering a question, for instance, with an active preference, +1 is added to the value of the active/reflective dimension whereas an answer for a reflective preference decreases the value by 1. Therefore, each question is answered either with a value of +1 (answer a) or -1 (answer b).

The ILS is an often used and well investigated instrument to identify the learning styles. Felder and Spurlin (2005) provide an overview of studies dealing with analysing the response data of ILS regarding the distribution of preferences for each dimension as well as with verifying the reliability and validity of the instrument. While these studies seem to support the argument that ILS is reliable, valid and suitable, also some open issues arose which need further investigations (e.g. Viola et al., 2006).

3.2 General analysis

First, we analyzed the distribution of preferences for each dimension. As a result, 57% of the students in our study were found to have an active preference, 58% a sensing preference, 87% a visual preference, and 56% a global preference. Table 1 shows a more detailed description, classifying the preferences of learners in strong/moderated (values from 5 to 11 in the ILS) and balanced (values from +3 to -3 in the ILS). Looking at the overview of similar studies given by Felder and Spurlin (2005), our results are mainly in agreement with the results of these studies. Some small differences can be seen in the sensing/intuitive dimension, where slightly more intuitive learners have attended our study, as well as in the sequential/global dimension where more global learners have participated.

Table1. Strength of preferences (distinguishing between strong/moderate and balanced preferences)

str./mod. active	Bal-anced	str./mod. reflective	str./mod. sensing	Bal-anced	Str./mod. intuitive	str./mod. visual	bal-anced	str./mod. verbal	str./mod. sequent.	bal-anced	Str./mod. global
24%	61%	15%	29%	53%	17%	64%	33%	3%	16%	68%	16%

According to the distribution of the preferences, it can be seen that the results of our study are in agreement with the results of already performed studies. This indicates that our sample is representative and can act as basis for further analysis.

3.3 Grouping of questions

Looking at FSLSM, it can be seen that each learning style (e.g. active, reflective, sensing, and so on) is described by different characteristics. Based on the description of FSLSM (Felder and Silverman, 1988), the questions in ILS were manually grouped according to the similarity of semantics. The following table provides the semantic groups of learning styles as well as the questions belonging to these groups. A question may appear twice in the table, if the answer to the question points to two different semantic groups.

Table 2: Semantic groups associated with the ILS questions

Style	Semantic group	ILS questions (answer a)	Style	Semantic group	ILS questions (answer b)
Active	trying something out social oriented	1, 17, 25, 29 5, 9, 13, 21, 33, 37, 41	Reflective	think about material impersonal oriented	1, 5, 17, 25, 29 9, 13, 21, 33, 41, 37
Sensing	existing ways concrete material careful with details	2, 30, 34 6, 10, 14, 18, 26, 38 22, 42	Intuitive	new ways abstract material not carefule with details	2, 14, 22, 26, 30, 34 6, 10, 18, 38 42
Visual	pictures	3, 7, 11, 15, 19, 23, 27, 31, 35, 39, 43	Verbal	spoken words written words difficulty with visual style	3, 7, 15, 19, 27, 35 3, 7, 11, 23, 31, 39 43
Sequential	detail oriented sequential progress from parts to the whole	4, 28, 40 20, 24, 32, 36, 44 8, 12, 16	Global	overall picture non-sequential progress relations/connections	4, 8, 12, 16, 28, 40 24, 32 20, 36, 44

3.4. Analyses of semantic groups

According to the classification provided in table 2, some analyses were performed in order to detect the most representative groups of each learning style. The analyses were performed based on the data from ILS questionnaire, using a hybrid approach.

In order to find the most representative semantic groups of each dimension, Fisher linear discriminant analysis (e.g. Duda et al., 2000), a well known multivariate methods for linear optimal separating dimensionality reduction, was conducted. Then the model given by linear discriminant analysis was compared with some empirical results regarding both frequencies analysis and correlation analysis in order to cross-validate it.

3.4.1 Detecting characteristics of the learning style dimensions

In order to apply consistently statistical methods, data were transformed in frequencies, i.e. on absolute scale, as follows. Let Q be the 207x44 matrix containing in rows individuals and in column the answer to each ILS question. For each question q_i, Q=44, two numerical variables, namely the two answers to each questions, $a_1 = 1$ if $q_i = 1$ (otherwise 0) and $a_2 = 1$ if $q_i = -1$ (otherwise 0) were obtained.

Let A be the 207 x 88 matrix containing in rows individuals and in columns the a_i, i=1,…,88. The matrix A has rank 44 by construction, since two columns are constrained to sum up to 1 in rows. Fisher linear discriminant analysis (LDA) was then performed on the whole matrix A of learners' answers to ILS.

This method, a well known multivariate method for dimensionality reduction, is able to find the optimal linear direction of separation. It was used in order to find a vector of weighting coefficients able to indicate the most important ILS questions for the discrimination between each ILS dimension and the highest absolute values of coefficients corresponding to answers.

LDA is aimed at finding a direction *w*, usually one-dimensional, that maximizes the intra-class separation of the higher dimensional instances projected onto it. More formally, being X an *m*-by-*n* matrix, let $w'm_i^{(1)}$ and $w'm_i^{(2)}$, *i*=1,…,*n*, be the *d*-dimensional sample means of the projected points according to the classes of individuals, and (1/m) $(s1^2 + s2^2)$ an estimate of the whole variance of the pooled data, where

$$sc^2 = \sum_{x \in C_i} w'x_i - w'm_i^{(c)} \qquad (1)$$

and $c \in C = \{1,...,k\}$ indicates the class; LDA is aimed at finding a vector *w* that maximizes the criterion function

$$J(w) = \frac{\left| w'm_i^{(1)} - w'm_i^{(2)} \right|^2}{s1^2 + s2^2} \qquad (2)$$

The outcome of the method is a new geometrical representation that maximizes the separation between two sets of points obtained by a projection on a lower dimensional space (usually 1-dimensional). In the vector of coefficients *w*, that in this case has dimensions (88, 1) weights associated to each variable are arranged according to the contribution in separating the sets along the direction given by *w*. For all the four couples of styles both the relative direction and the coefficients were detected.

Due to the rank deficiency and to the redundancy of the matrix *A*, the outcome of LDA showed a vector in which the coefficients associated with each answer were equal in absolute values, but opposite in signs according to the association with each style inside each of the four ILS dimensions.

In order to detect the importance of each semantic group within the learning style dimensions, the coefficients of *w* associated with each answer were investigated using a synthetic index of the importance of each semantic group of questions according to each learning style dimension, calculated as the average of the absolute values of the coefficients related to each answer in table 2. Table 3 summarizes the results.

Table 3: The relevance of the semantic groups on the learning style dimensions (values > 0.5 are highlighted)

Styles	Semantic groups	Act/ Ref	Sen/Int	Vis/Ver	Seq/Glo
Active	try something out	**0.639**	0.113	**0.536**	0.211
	Social oriented	0.452	0.146	0.190	0.180
Reflective	think about material	**0.597**	0.122	0.486	0.217
	impersonal oriented	**0.698**	0.143	0.175	0.170
Sensing	existing ways	0.237	**0.568**	0.301	0.174
	concrete materials	0.178	**0.777**	0.380	0.245
	careful with details	0.147	0.409	0.329	0.456
Intuitive	new ways	0.193	**0.678**	0.309	0.237
	abstract material	0.225	**0.715**	0.453	0.173
	not careful with details	0.008	**0.699**	0.026	0.151
Visual	pictures	0.238	0.227	**0.944**	0.167
Verbal	spoken words	0.202	0.189	**0.648**	0.171
	written words	0.171	0.199	**1.086**	0.258
	difficulty with visual style	0.297	0.388	**0.789**	0.078
Sequential	detail oriented	0.224	0.218	0.290	**0.800**
	sequential progress	0.100	0.237	0.432	**0.686**
	from parts to the whole	0.123	0.154	0.113	**0.839**
Global	overall picture	0.174	0.186	0.202	**0.819**
	non-sequential progress	0.140	0.175	**0.520**	**0.715**
	relations/connections	0.074	0.278	0.375	**0.869**

Since a high value indicates a strong impact of the semantic group for the respective learning style, it can be seen that for an active learning style the preference for trying something out has more impact than the preference for social orientation, e.g. for discussing and explaining learning material to each other or working in groups. On the other hand, for a reflective learning style, the social behaviour is more relevant than the preference to think/reflect about learning material. That means that for supporting students with a reflective learning style, it is important to give them also the opportunity to work individually. Regarding the sensing/intuitive dimension it can be seen that the preference for concrete learning material seems to be most important for learners with a sensing learning style. In opposite, the preference for abstract material is most relevant for intuitive learners. While for sensing learners, the carefulness with details seems to be less representative, the tendency for being not patient and not careful with details is characteristic for intuitive learners. While for the visual learning style only one semantic group exists, which is also highly representative, for the verbal learning style the most representative semantic group is the preference for written words. But also spoken words and the difficulty with visual style seems to play a relevant role. Interesting is that the results of the visual/verbal dimension show additionally an impact regarding the preference of trying something out and a non-sequential learning progress. Since these relations are not described in FSLSM, further investigations are necessary. Regarding the sequential/global dimension, all expected semantic groups show high relevance for the respective learning styles. Most important is the preference for relations and connections to other areas for global learners and for sequential learners the ability to infer from parts to the whole solution is most relevant. The groups for a sequential or non-sequential way of learning achieved for both learning styles the lowest value, but are still representative.

3.4.2 Cross validation

In order to cross-validate results, both Pearson’s correlations and empirical frequencies were used. In the empirical frequencies analysis, we compare how often students with, e.g. active and reflective learning style, answer a specific question with a specific (e.g. active) preference. If a question is highly representative for, e.g. the active/reflective dimension, then students with an active learning style answer significantly more often with an active preference than students with a reflective learning style.

To prove that questions for the respective dimensions are representative, the percentage of, e.g. active learners, answering a question with, e.g. active preference, is compared with the percentage of reflective learners answering the question with an active preference. The difference of these percentage values acts as a measure indicating how representative a question is for a specific dimension. 7 questions of the active/reflective dimension, 10 of the sensing/intuitive dimension, 9 of the visual/verbal dimension, and 5 of the sequential/global dimension achieved a difference of 30% or more. All these questions except one belong to the respective dimension. The one exception indicated a sequential/global learning style but seems to be representative for the sensing/intuitive dimension as well as for the sequential/global dimension. This can be explained by the existing correlation between the sensing/intuitive and sequential/global dimension (reported in Felder and Spurlin, 2005 as well as identified by the performed correlation analysis). Overall, this analysis shows that almost all of the questions are highly representative for their dimensions.

In order to identify the most representative questions for each dimension, the questions were ranked according to the above introduced criterion. The five most representative questions for each dimension are shown in table 4.

Regarding the active/reflective dimension it can be seen that the first, third and fifth ranked questions deal with social oriented behaviour asking whether students are considered as outgoing, gotten to know many other students in a class, and liked to work in groups. In contrast, the second and fourth ranked questions are

Table 4: The 5 most representative questions for each dimension of the ILS according to frequencies analysis

	Rank	Question No.	Question
Active / Reflective	1	37	I am more likely to be considered (a) outgoing. (b) reserved.
	2	1	I understand something better after I (a) try it out. (b) think it through.
	3	13	In classes I have taken (a) I have usually gotten to know many of the students. (b) I have rarely gotten to know many of the students.
	4	25	I would rather first (a) try things out. (b) think about how I'm going to do it.
	5	21	I prefer to study (a) in a study group. (b) alone.
Sensing / Intuitive	1	6	If I were a teacher, I would rather teach a course (a) that deals with facts and real life situations. (b) that deals with ideas and theories.
	2	38	I prefer courses that emphasize (a) concrete material (facts, data). (b) abstract material (concepts, theories).
	3	18	I prefer the idea of (a) certainty. (b) theory.
	4	10	I find it easier (a) to learn facts. (b) to learn concepts.
	5	2	I would rather be considered (a) realistic. (b) innovative.
Visual / Verbal	1	31	When someone is showing me data, I prefer (a) charts or graphs. (b) text summarizing the results.
	2	11	In a book with lots of pictures and charts, I am likely to (a) look over the pictures and charts carefully. (b) focus on the written text.
	3	7	I prefer to get new information in (a) pictures, diagrams, graphs, or maps. (b) written directions or verbal information.
	4	19	I remember best (a) what I see. (b) what I hear.
	5	3	When I think about what I did yesterday, I am most likely to get (a) a picture. (b) words.
Sequential / Global	1	36	When I am learning a new subject, I prefer to (a) stay focused on that subject, learning as much about it as I can. (b) try to make connections between that subject and related subjects.
	2	20	It is more important to me that an instructor (a) lay out the material in clear sequential steps. (b) give me an overall picture and relate the material to other subjects.
	3	8	Once I understand (a) all the parts, I understand the whole thing. (b) the whole thing, I see how the parts fit.
	4	44	When solving problems in a group, I would be more likely to (a) think of the steps in the solution process. (b) think of possible consequences or applications of the solution in a wide range of areas.
	5	4	I tend to (a) understand details of a subject but may be fuzzy about its overall structure. (b) understand the overall structure but may be fuzzy about details.

about whether students tend to try things out or think the learned material through. These two characteristics were identified in the previous section as well. As a result of both analyses, it can be seen that social behaviour as well as the preference for trying things out or thinking things through are important for the active/reflective dimension. Since discriminant analysis is more accurate for distinguish relevant aspects, the difference of the impact of social behaviour for active learners and reflective learners can not be seen here.

In the sensing/intuitive dimension it can be seen clearly that the first four questions are dealing with whether students prefer concrete material like facts and data or abstract material such as concepts and theories. Therefore this characteristic seems to be the most representative one for this dimension. This is also confirmed by the results of the discriminant analysis. The fifth question is about whether a student considers himself/herself as realistic or innovative and belongs to the semantic group of existing ways/new ways, which can be seen as the second important characteristic according to discriminant analysis.

Regarding the visual/verbal dimension it is interesting to see that the first two questions from the verbal point of view are about written text, question three and five consider written and spoken words and only the fourth question is about spoken words. While there are more questions about written words than about spoken ones, the results nevertheless indicates that for verbal learners both, written and spoken language is important. For visual learners, there is only one characteristic namely to learn best from what they see. These results are in agreement with the results from the discriminant analysis.

In the sequential/global dimension, the first, second, and fourth question deal with whether students prefer a sequential way of learning (from the viewpoint of a sequential style) or whether relationships and connections to other areas are more important for them (from the viewpoint of a global style). The other questions are about the other two semantic groups respectively for a sequential and global learning style. According to the results from discriminant analysis, all relevant semantic groups are covered by the 5 most relevant questions from table 4. While for the global style the order of relevance is in agreement of both analyses, for the sequential style the preference for a sequential learning progress seems to be less relevant according the discriminant analysis.

Looking at correlations inside frequencies of the answers according to each of the eight learning styles, interesting features emerged. Correlations were calculated over the total number of positive answers to each of the 88 answers allowed by ILS (2 possible answers for each question), transforming then data from a binary scale to an equivalent numeral one, for coherence and consistency with the applications of Pearson's correlation coefficients and related p values.

Many high (greater than 0.7) values were found; related p values are very small ($p < 0.05$), indicating a significance. In particular, a great number of high absolute values of correlation coefficients involve questions belonging to all semantic groups associated with active/reflective dimension and cross dimension correlations between these groups; questions belonging to all semantic groups associated with sequential/global dimension and cross correlation questions between these groups, and questions belonging to the semantic groups associated with visual/verbal dimension (pictures/spoken and written words).

This led to hypothesize that linear discriminant analysis was able to give a more synthetic view of representative characteristics with respect to the difference of empirical frequencies that present at the first positions of rank variables that in most cases achieve high correlations.

Eventually, it looks like, looking at the results, that some correlations between dimensions of learning styles are likely. This hypothesis needs a deeper and dedicated investigation both of the analyses presented by literature (e.g. Felder and Spurlin, 2005) and the statistical analyses performed on this dataset in order to be tested and explained.

4. CONCLUSION AND FUTURE WORK

In this paper, we provided an in depth analysis of Felder-Silverman learning style model (FSLSM) based on data from the ILS questionnaire in order to get more information for a better application of learning styles in technology enhanced environments. Therefore, we associated each dimension of FSLSM with semantic groups (such as the preference for spoken language or the preference for concrete learning material), and analysed the impact of each group for each learning style. A hybrid approach was used for detecting interesting features both from research and from application viewpoint.

The results show a more accurate description of FSLSM, pointing out relevant characteristics within the dimensions. Especially for the use of learning styles in technology enhanced learning, such an accurate description is important for relating the learning style model with the features of the online environment. In recent years, technology enhanced learning has put great attention on learning style models in order to improve adaptivity in e-learning systems. Incorporating not only learning style dimensions but also the different characteristics within these dimensions lead to a more accurate representation of student's learning styles and therefore enhance the potentials of adaptive learning environments. Moreover, the in-depth investigation of learning style characteristics could improve also pedagogical models, supporting a more effective and personalized learning.

Future work will include additional statistical analyses in order to confirm our results. Moreover, future work will deal with facilitating the concrete applications of the results by providing a list of features in online environments that addresses the identified semantic groups. An extension of the results of the ILS questionnaire might be a meaningful aim for future work as well, in order to provide not only information about the learning style dimension but also about their semantic groups. Furthermore, we plan to use the additional information of semantic groups for providing adaptivity, detecting learning styles from the behaviour of students in online courses, and investigating relationships between learning styles and, for instance, performance or characteristics of students such as cognitive traits.

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