Exploring the Relationships between Students' Learning Styles and Social Media Use in Educational Settings

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***Abstract*—With the growing popularity of Web 2.0 tools in educational settings, it becomes important to investigate the influence of students' learning styles on the adoption and use of these emerging tools. Currently, there are only few studies addressing this issue and most of them are based on student self-reported data, e.g., preference, acceptance or attitude toward social media tools, captured by means of questionnaires. This paper explores the relationships between actual students' use of the Web 2.0 tools and their learning styles classified according to Felder-Silverman model. The context of the study is an undergraduate course on Web Applications' Design, with 45 enrolled students. Several machine learning algorithms for classification, association rule induction and feature selection are applied. Results show that learning styles have a limited influence on the students' level of interaction with each of the four Web 2.0 tools considered.**

Keywords—social media, learning styles, machine learning algorithms

I. Introduction

Even if not yet part of the educational technology mainstream, Web 2.0 tools "have reached a high level of maturity and have been increasingly adopted in educational practices worldwide" [7]. This overarching term refers to various applications built on the Web 2.0 infrastructure, such as blog, wiki, social bookmarking tool, social networking service, microblogging tool, media sharing service etc., all of which are also known as social media tools. These technologies can be used to foster communication and collaboration between learners and help create online learning networks.

In this context, it is interesting to investigate the relationship between students' individual differences and their preference and behavior toward the social media tools; this would help identify the success factors of using Web 2.0 tools in educational settings. In particular, in this paper we focus on learning style as one of the individual differences that play an important role in learning, according to educational psychologists [12].

Learning style refers to the individual manner in which a person approaches a learning task. For example, some learners prefer graphical representations and remember best what they see, others prefer audio materials and remember best what they hear, while others prefer text and remember best what they read. There are students who like to be presented first with the definitions followed by examples, while others prefer abstract concepts to be first illustrated by a concrete, practical example. Similarly, some students learn easier when confronted with hands-on experiences, while others prefer traditional lectures and need time to think things through. Some students prefer to work in groups, others learn better alone. These are just a few examples of the many different preferences related to perception modality, processing and organizing information, reasoning, social aspects etc., all of which can be included in the learning style concept [12].

During the last decades, many learning style models have been proposed, which differ in the learning theories they are based on, the number and the description of the dimensions they include. For the current study, we focus on one of the most popular models in technology-enhanced learning [3], namely the Felder-Silverman learning style model (FSLSM) [4]. According to FSLSM, learners are characterized by their preferences on four dimensions: *active* versus *reflective*; *sensing* versus *intuitive*; *visual* versus *verbal*; *sequential* versus *global*. *Active* students learn by trying things out and enjoy collaborative working, while *reflective* students like to think about the material first and prefer working alone. *Sensing* learners have a preference toward facts and details and they tend to be practical and careful, whereas *intuitive* learners prefer abstract material, they like to innovate, to discover possibilities and relationships. *Visual* learners remember best what they see (pictures, diagrams, schemas etc.) while *verbal* learners get more out of words, either spoken or written. *Sequential* learners tend to gain understanding in linear steps, while *global* learners learn in large leaps, being fuzzy about the details of the subject but being able to make rapid connections between subjects. It should be noted that these learning styles are seen as tendencies and not fixed, rigid labels.

The rest of the paper is structured as follows: section II provides an overview of the few related works which explore the relationship between students' learning styles and their preference or behavior toward Web 2.0 tools. Section III describes the context of our study and the approach used for data collection. Section IV details the analysis process: the

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machine learning algorithms applied and the results obtained. Some discussions and conclusions are included in section V.

II. Related Work

Paper [16] reports on one of the first studies which explore the correlations between students' learning style and their preferences toward Web 2.0 tools. FSLSM was used and the associated Index of Learning Styles (ILS) questionnaire [19] was applied at the beginning of the course in order to identify students' styles. Learners' preferences toward Web 2.0 tools were elicited by means of another dedicated questionnaire; students were asked to rate various tools (including blog, wiki, podcast, vodcast but also email and Blackboard LMS) on a scale from 1 to 5, for various learning activities (e.g., reviewing lectures, submitting group projects, having group discussions, etc.). 89 students enrolled in a Web programming course responded to both questionnaires and were included in the study. Pearson correlation was applied and a few significant relationships were discovered: i) *intuitive* learners (who, according to FSLSM, prefer discovering possibilities and relationships and are always ready to try out new things) preferred blogs; ii) *sensing* learners preferred email (a more traditional communication tool, in line with their more careful and detail-oriented nature); iii) *visual* learners preferred vodcasts (not surprisingly, taking into account their preference toward pictures, diagrams, flow charts etc.); iv) *sequential* learners preferred podcasts (since they tend to gain understanding in linear steps and follow logical stepwise paths, so they could run the sequence of lectures at their own pace over and over again to get a better understanding of the course content). No correlations were found for the *active/reflective* dimension.

The authors performed also a second study [17], in which they analyzed the effects of cognitive style (*adaptors* versus *innovators*) [8] on learner acceptance of blogs and podcasts. The context of study was again the Web programming course, in which they included blogs and podcasts as support tools. Kirton's Adaption-Innovation inventory was used to identify students' cognitive style and a dedicated questionnaire was used to elicit students' perceptions regarding ease-of-use and usefulness of the Web 2.0 tools. 187 students filled in the two questionnaires and were included in the study. The results showed that *innovator* students are more likely to perceive blogs and podcasts as useful and easy-to-use as compared to *adaptor* students. Furthermore, *innovators* perceive podcasts as more useful, but less easy-to-use than blogs.

Paper [3] investigates the effects of learning style on the blogging behavior of students in an undergraduate course on software architectures and web technologies. 77 students were enrolled in the course but only 74 of them filled in the ILS questionnaire (for identifying learners' FSLSM dimensions) and were included in the study. Students were asked to use blogs as a kind of personal journal, including insights and remarks on the tasks, problems encountered and solutions found, reflections on the project and teamwork, etc.; however, the blogging activity did not count toward students' grade. The blogging activities were integrated into the course learning management system and various student actions were recorded in a log file. Rank correlation analysis was used in order to find relationships between students' learning style and these blogging actions. No significant results were found regarding: i) the number of visits to the blogging environment; ii) the frequency of reading others' blogs; iii) the preference for using links from the 20 recent blog postings. Some significant correlations were found for the *active/reflective* dimension: i) *active* students tend to post more frequently to their blogs than *reflective* students; ii) *reflective* students' ratio of reading other blog postings vs. posting to their own blogs is significantly higher than that of *active* students; iii) *active* students use charts displaying the number of postings and peer rating more often than *reflective* students. One significant correlation was found for the *sequential/global* dimension as well: *sequential* learners tend to write longer posts than *global* learners. Overall, results show that the blogging behavior is only slightly influenced by learning style, at least from a quantitative point of view; the blog content needs to be further analyzed in order to take into account the quality of students' contributions as well.

Paper [10] analyzes the influence of learning style and competence level on students' perceptions regarding the utility of various e-learning services, tools and content. VAK learning style model is used, categorizing students as *visual*, *auditory* or *kinesthetic* (or a combination thereof). The learning style was identified by means of a dedicated inventory, while students' opinions were gauged by means of a Likert-style survey. 31 students participated in the study and filled in both questionnaires. While the opinion survey addressed a variety of issues (e.g., knowledge acquisition services, communication services, performance assessment services, content media type and instructional role), here we summarize only the findings related to Web 2.0 tools. *Visual* and *auditory* students rated wikis as highly useful services, regardless of their competence level; *auditory* students with lower knowledge level also perceived blogs as useful, while *kinesthetic* students favored media sharing services for their online video tutorials. Social networking systems (such as Facebook) were among the top rated communication services for all students, regardless of their learning style. However, it should be mentioned that the paper only provides descriptive results and the statistical significance of the findings is not addressed.

Several other authors investigated the correlations between learning style and self-reported preference for social media tools used for educational purposes, with various results, e.g.:

- paper [18] reports no significant relationships between students' *field-dependent/field-independent* style [20] and their attitude toward blogs
- paper [2] reports that *intuitive* students (according to FSLSM) were willing to deliver their knowledge and experience through blogs, as opposed to the students with *visual* preference.

Overall, the reported findings are somewhat contradictory; a few correlations have been found, but they are not consistent throughout the studies. It should be mentioned however that various learning style models were involved and different experimental settings were employed. Also, most of the studies were based on student self-reported data, e.g., preference, acceptance or attitude toward social media tools, captured by means of questionnaires. Paper [3] is a notable exception, relying on actual student performance and analysis of behavioral patterns. Our study also explores the relationships between actual student interaction with the Web 2.0 tools and the FSLSM dimensions. As far as analysis techniques are concerned, statistical correlation tests were the main methods employed in the above studies; in contrast, our approach is based on machine learning algorithms for classification, association rule induction and feature selection. More details regarding the experimental settings are presented in the following section.

III. Context of Study

The context of our study is a course on "Web Applications' Design" (WAD), delivered to 4th year undergraduate students in Computer Science from the University of Craiova, Romania. 45 students were enrolled in the course, being split in 11 teams; each team had to develop a relatively complex Web application, over the course of one semester. The instructional scenario used was *project-based learning* (PBL), which was implemented in a blended mode: weekly face-to-face meetings between each team and the instructor alternated with online collaborative work, supported by social media tools. Four such tools were used:

1. Blogger - for documenting the progress of the project (i.e., a kind of "learning diary" - reporting each accomplished activity, describing problems encountered and asking for help, reflecting on their learning experience); publishing ideas, thoughts, interesting findings (project-related); communicating with the peers, providing solutions for peers' problems, critical and constructive feedback, interacting with other teams

2. MediaWiki - for collaborative writing tasks among the members of a team; gathering and organizing their knowledge and resources regarding the project theme; clearly documenting each stage of the project as well as the final product

3. Delicious - for storing links to resources of interest for the project (i.e., a kind of "personal knowledge management tool"); sharing discovered bookmarks with peers; tagging and rating the collected resources; checking the resources shared by peers (and especially by own team members)

4. Twitter - for staying connected with peers and posting short news, announcements, questions, status updates regarding the project.

More details regarding the PBL scenario can be found in [13].

All student actions on the four social media tools were monitored and recorded by means of a dedicated platform called eMUSE. The platform gathers learner actions from each of the disparate tools, stores them in a local database for further processing (together with a description and an associated timestamp) and presents them to the instructor in suggestive graphical formats. The whole range of functionalities provided by eMUSE can be found in [14]. The technical solution adopted for learner tracking and data collection is accessing the Web 2.0 tools by means of open APIs or Atom/RSS feeds in order to retrieve students' actions. This integration of content from several external sources to create a new Web application, with added value for the user, is known as *mashup* technique - which is reflected also in the platform name (eMUSE - **e**mpowering **M**ash**U**ps for **S**ocial **E**-learning).

The number of actions performed on each tool was computed for each student after the course, as a quantitative measure of the level of involvement of the student with the Web 2.0 tools. Overall, at the end of the semester about 1700 student actions were stored in the platform database.

While the students' actions were automatically collected by the eMUSE platform, their learning styles were elicited by means of a dedicated inventory, the Index of Learning Styles questionnaire (ILS) [19]. ILS consists of 44 questions, each with two possible answers. As a result of the test, the learning style of the student is described on a scale between -11 and +11 (with a step of +/-2) for each FSLSM dimension; e.g., a score of +9 on the *visual/verbal* dimension implies a strong *visual* preference, while a score of -3 implies a mild *verbal* preference. ILS was applied at the beginning of the semester; 42 students filled it in and were therefore included in the analysis, as described next.

IV. Analysis and Results

Our goal was to investigate whether there are dependencies and connections between the actions of the students on the four Web 2.0 tools (as recorded by eMUSE), and their learning styles. To this end, we used typical machine learning algorithms for classification, association rule induction (*Apriori* [1]) and feature selection (*ReliefF* [9]). We aimed at determining a symbolic, explicit model that can be easily interpreted. It was also important to use algorithms that belong to different classification paradigms, which can provide different perspectives about the problem at hand. Therefore, we chose a decision tree inducer, *C4.5* [15], and a generalized instance-based method, *NNGE* [11]. From the implementation point of view, we used *Weka* [6], a popular collection of machine learning algorithms.

The case studies focused on 2 scenarios: the analysis of the number of actions in a category (i.e., with each social media tool) and the temporal evolution of the number of actions and their category.

A. Scenario 1. The Number of Actions

In this scenario, we considered only the total number of actions which a certain student performs on each of the 4 tools. We investigated whether it is possible to predict a student's learning style based on the Web 2.0 tools he/she uses for communication, collaboration and learning support.

We constructed a dataset with each of the 4 descriptors (*sequential/global - SG, active/reflective - AR, sensing /intuitive - SI, visual/verbal - VV*) as the class and the number of actions for each tool as the inputs.

The learning styles were discretized into 6 categories, based on the scores obtained on the ILS questionnaire: *BigNegative (-11 and -9)*, *Negative (-7 and -5)*, *SmallNegative (-3 and -1)*, *SmallPositive (+1 and +3)*, *Positive (+5 and +7)*, *BigPositive* (+9 and +11). For example, for the *SG* dimension, a positive value indicates a tendency toward the *sequential* style, while a negative value indicates a *global* style. The number of actions was discretized into 5 categories (*VeryLow, Low, Medium, High, VeryHigh*).

A part of the decision tree induced by *C4.5* for the *SG* style is presented next. In parentheses, the number of correctly classified and incorrectly classified instances are noted, respectively. Thus, a resulting rule, although inexact (14 correctly classified instances and 9 exceptions) is, e.g.: "If the number of *Wiki* actions is *VeryLow* and the number of *Delicious* actions is *VeryLow* and the number of *Twitter* actions is *VeryLow*, then *SG* is *SmallPositive*."

```
Wiki = VeryLow
|   Delicious = VeryLow
|   |   Twitter = VeryLow ⇒ SG = SmallPositive (14/9)
|   |   Twitter = Low ⇒ SG = SmallNegative (2/1)
|   |   Twitter = Medium ⇒ SG = SmallNegative (1)
...
Wiki = Low ⇒ SG = SmallPositive (4/2)
Wiki = Medium ⇒ SG = SmallNegative (4/2)
Wiki = High ⇒ SG = BigPositive (1)
Wiki = VeryHigh ⇒ SG = SmallNegative (2/1)
```

As *C4.5* uses the information gain criterion to split data, and *Wiki* (i.e., the number of actions performed on the wiki) corresponds to the first split, it implies that *Wiki* is the most important factor to describe the *SG* model.

The rules (generalized exemplars) provided by *NNGE* are of the following form (in parentheses, at the end, the number of instances covered by that rule is indicated):

```
Blogger in {VeryLow} and Delicious in {VeryLow} and Twitter in {VeryLow}
and Wiki in {VeryLow,Low} ⇒ SG = SmallPositive (3)
```

The algorithms were also applied for the other learning style dimensions. The resulting decision trees are quite large, which shows that there are no compact rules to describe the learning style depending on the discretized number of actions.

Also, there are many rules provided by *NNGE*, with many single instances which cannot be included into a generalized exemplar.

Table I presents the error rates and some descriptors of each model. The unpruned version of the *C4.5* algorithm was used, because it consistently provided better results for our learning problems. For the decision trees, the number of leaves was used as an indicator of the tree complexity. In terms of the number of rules given by *NNGE*, the number of generalized exemplars or hyper-rectangles (*H*) and the number of individual instances or singles (*S*) are mentioned.

The *ReliefF* feature selection algorithm was applied to identify the most relevant attributes for each classification problem. The results refer only to the algorithm performance on the training sets. Since these errors are very large, there is no point in further applying cross-validation to test the generalization capability. It is clear that the models do not capture the data well.

TABLE I. CLASSIFICATION PERFORMANCE FOR THE LEARNING STYLES AS A FUNCTION OF THE DISCRETIZED NUMBER OF ACTIONS

	SG	AR	SI	VV
C4.5 error	47.61 %	47.62 %	35.71 %	33.33 %
C4.5 no. leaves	17	17	17	21
NNGE error	23.81 %	26.19 %	28.57 %	33.33 %
NNGE no. rules	9H / 9S	8H / 11S	6H / 9S	3H / 18S
Most relevant attribute	Wiki	Delicious	Twitter	Wiki

Beside classification, the *Apriori* algorithm was applied to find association rules. First, we analyzed only the relationships between the number of actions. In the brackets, the confidence of the rule is indicated. The rule $A \Rightarrow B$ has confidence c if $c\%$ of the transactions in the dataset that contain A also contain B. The first 3 high-confidence rules found are the following:

```
Twitter=Low ⇒ Wiki=VeryLow (1)
Blogger=VeryLow, Twitter=Low ⇒ Wiki=VeryLow (1)
Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow (0.94)
```

For example, one can interpret the first rule as: "When the number of *Twitter* actions is *Low*, the number of *Wiki* actions is always *Low*."

Then, the dataset with the number of actions and the learning styles was analyzed. The first 5 high-confidence rules are in this case:

```
Delicious=VeryLow, SI=BigPositive ⇒ Twitter=VeryLow (1)
Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow (0.94)
Delicious=VeryLow, Twitter=VeryLow ⇒ Blogger=VeryLow (0.94)
Delicious=VeryLow, Twitter=VeryLow, Wiki=VeryLow ⇒ Blogger=VeryLow
(0.93)
Blogger=VeryLow, VV=BigPositive ⇒ Wiki=VeryLow (0.92)
```

However, it seems that these rules do not provide any clear, useful causal relationships. We could only infer that students with a low level of activity on one tool tend to have a weak performance on other tools as well.

Beside the investigations above, the following ones were also attempted: i) the percentages of actions out of the total number of actions, for a student, instead of the actual number of actions; ii) discretization with 3 classes instead of 5; and iii) the comparison of learning styles within student teams. The results were not better than before.

The high errors on the training set in case of classification can be explained, in part, by the discretization process, where the equal-width interval method may not have captured the trends in the data in a flexible enough manner. However, it is possible to apply *C4.5* and *NNGE* on the unprocessed numerical inputs as well. We performed the same analysis on numerical data, where the inputs were the number of actions for each tool, as percentages out of the total number of actions of a student. Since no information is lost in the inputs, the training set errors are much lower, as shown in Table II.

By performing 10-fold cross-validation, the error rates become very high. Even if the algorithms, especially the instance-based *NNGE*, can exactly capture the data, the models do not generalize well.

TABLE II. CLASSIFICATION PERFORMANCE FOR THE LEARNING STYLES AS A FUNCTION OF THE RELATIVE NUMBER OF ACTIONS

	SG	AR	SI	VV
C4.5 error (TS)	17.64 %	29.41 %	14.71 %	17.65 %
C4.5 no. leaves (TS)	9	8	9	8
C4.5 error (CV)	64.71 %	91.18 %	61.76 %	70.59 %
NNGE error (TS)	0 %	0 %	0 %	0 %
NNGE no. rules (TS)	9H / 6S	9H / 11S	9H / 5S	9H / 5S
NNGE error (CV)	76.47 %	85.29 %	61.76 %	58.82 %
Most relevant attribute	Blogger	Delicious	Twitter	Twitter

One can notice that the most relevant attribute has changed compared to the corresponding value (*Wiki*) for *SG* and *VV* in Table I. The resulting decision tree for *SG* is listed below. The most relevant attribute given by *C4.5*'s information gain criterion (*Twitter*) is now different from the value given by *ReliefF* (*Blogger*). These changes also suggest that there are no stable trends to be identified in the dataset.

```
Twitter <= 3.45
|  Twitter <= 0 ⇒ SG = Negative (3)
|  Twitter > 0 ⇒ SG = BigNegative (2/1)
Twitter > 3.45
|  Delicious <= 10.19
|  |  Delicious <= 0 ⇒ SG = SmallNegative (7/1)
|  |  Delicious > 0
|  |  |  Delicious <= 9.09 ⇒ SG = SmallPositive (2)
|  |  |  Delicious > 9.09 ⇒ SG = SmallNegative (2/1)
|  Delicious > 10.19
|  |  Delicious <= 25.81
|  |  |  Twitter <= 27.78 ⇒ SG = SmallPositive (5)
|  |  |  Twitter > 27.78 ⇒ SG = Negative (3)
|  |  Delicious > 25.81
|  |  |  Twitter <= 15.85 ⇒ SG = SmallNegative (2)
|  |  |  Twitter > 15.85 ⇒ SG = SmallPositive (8/3)
...
```

We present below the hyper-rectangles with the largest number of instances for each learning style, as provided by *NNGE*:

```
4.55<=Blogger<=25 and 0<=Delicious<=10.19 and 12.1<=Twitter<=50 and
25<=Wiki<=77.27 ⇒ SG = SmallNegative (6)
0<=Blogger<=7.32 and 0<=Delicious<=23.33 and 6.67<=Twitter<=18.18
and 70<=Wiki<=77.27 ⇒ AR = SmallNegative (4)
15.09<=Blogger<=55.56 and 8.89<=Delicious<=42.11 and
3.45<=Twitter<=38.64 and 0<=Wiki<=46.55⇒ SI = Positive (6)
4.26<=Blogger<=22.22 and 13.79<=Delicious<=40.91 and
17.58<=Twitter<=44.83 and 0<=Wiki<=60.44⇒ VV = BigPositive (8)
```

Unfortunately, it seems to be difficult to gain specific insights from these rules that are in line with the theoretical assumptions. Even worse results are obtained when considering the direct relation between an individual tool and a learning style. No single preference toward a learning tool is directly correlated to a learning style.

B. Scenario 2. The Evolution in Time

In this scenario, we analyzed the action data taking time explicitly into account. We discretized the period of data collection into 5 equal intervals, we eliminated the students with only two or three actions and we computed: i) the total number of actions in each time interval; and ii) for each tool, the percentage of its total number of actions in that time interval.

Table III shows both the training set and the cross-validation errors, and it is clear that, again, there is no general model to be captured in this way. Similar results were obtained when considering the relations between individual tools and learning styles.

TABLE III. CLASSIFICATION PERFORMANCE FOR THE LEARNING STYLE AS A FUNCTION OF THE NUMBER OF ACTIONS IN THE 5 TIME INTERVALS

	SG	AR	SI	VV
C4.5 error (TS)	23.52 %	26.47 %	11.76 %	17.65 %
C4.5 no. leaves (TS)	8	7	9	7
C4.5 error (CV)	73.53 %	73.53 %	55.88 %	64.71 %
NNGE error (TS)	0 %	0 %	0 %	0 %
NNGE no. rules (TS)	10H / 7S	9H / 6S	8H / 6S	8H / 10S
NNGE error (CV)	76.47 %	73.53 %	55.88 %	55.88 %
Most relevant attribute	I3	I5	I3	I3

Finally, association rules were generated for all the available data: the total number of actions in the five time intervals (*Total1*, *Total2*,..., *Total5*), the number of actions corresponding to the four tools in the five time intervals (*Blogger1*, *Blogger2*,..., *Wiki5*) and the four learning style dimensions.

The high-confidence rules with the highest support are displayed below, including class association rules, where the learning styles are always in the right hand side of the rule:

```
Total3=VeryLow, Blogger1=VeryLow, Blogger3=VeryLow,
Blogger5=VeryLow, Twitter1=VeryLow, Twitter2=VeryLow ⇒
SG=SmallPositive (1)
Twitter2=VeryLow, Twitter5=VeryLow, Wiki3=VeryLow ⇒ AR=Positive (1)
Blogger3=VeryLow, Blogger5=Low ⇒ SI=Positive (1)
Total3=VeryLow, Blogger2=VeryLow, Wiki2=VeryLow ⇒ VV=BigPositive (1)
```

and general association rules:

```
Delicious2=VeryLow ⇒ Total4=VeryLow (1)
Total3=VeryLow ⇒ Total4=VeryLow (1)
Wiki4=VeryLow ⇒ Total4=VeryLow (1)
Wiki4=VeryLow ⇒ Delicious2=VeryLow (1)
Delicious2=VeryLow, Wiki4=VeryLow ⇒ Total4=VeryLow (1)
```

As an overall assessment of the obtained results, the rules are quite complex and hard to interpret, especially when they involve a combination of tools. Also, similar conditions appear for different classes (e.g. *Negative* vs. *Positive*) and different conditions appear for the same class or similar classes (e.g. *SmallPositive* and *Positive*). Some potential causes for these inconclusive results are provided in the next section.

V. DISCUSSION AND CONCLUSION

In this paper we investigated whether there are dependencies and relationships between students' learning style (according to FSLSM) and their preference toward certain Web 2.0 tools used as learning support instruments (according to the number of actions performed on that tool). The results showed that learning styles have a limited influence on the students' level of activity involving each of the four tools (Blogger, MediaWiki, Delicious, Twitter). In what follows, we provide some possible explanations for these results.

We only took into consideration the student actions which involve an active interaction or a contribution to the social media tools (e.g., posting or commenting on a blog, but not reading a blog; adding a bookmark on Delicious, but not browsing peers' bookmarks etc.). Thus we did not completely capture the preference for a certain tool; for example, a *reflective* student may have spent a lot of time reading his/her colleagues' blog posts or analyzing their contributions on the wiki, but this type of interaction was not measured. This limitation comes from the type of student actions that can be collected from the social media tools, as they are provided by means of feeds or APIs.

Also, we did not take into account the content of the students' contributions and the learning tasks they refer to. For example, a *sensing* and an *intuitive* student may have had the same number of actions on the blog, but the former may have posted mainly facts, source code and practical examples, while the latter may have contributed with theoretical aspects and innovative ideas. Furthermore, the recorded actions refer to various types of learning activities: creating content (*blog_post-entry, wiki_revise-page, wiki_upload-file*), social interactions (*delicious_add-friend-to-network*), organizing content (*delicious_post-bookmark*), communication and feedback (*blog_post-comment, twitter_post-tweet*) [14], but in our current analysis we did not discriminate among them; this is a limitation that we plan to address in our future work.

Finally, it may be that learning styles do not influence students' preference and behavior toward the four Web 2.0 tools. This could be explained by students' flexibility to accommodate a wide variety of emerging social media applications into their learning environment, without being limited to a particular tool [16]. This also suggests that our instructional scenario and the tools it relies on are not biased toward any particular learning style. Indeed, these findings are in line with another analysis that we conducted taking into consideration the students' course grades, which showed that FSLSM dimensions have weak or no correlations with the student performance [5].

Nevertheless, further studies are needed to fully understand the relationships between learning style and preference toward social media tools in educational contexts. These will involve additional action types (as described above), more analysis algorithms (including also a qualitative dimension), as well as a larger number of students.

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