A behavioral model to support teachers' self-assessment and improve their LMS mastery

Ibtissem Bennacer, Rémi Venant, Sebastien Iksal

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1st Ibtissem Bennacer
Computer science laboratory
University of Le Mans
Laval, France
Ibtissem.Bennacer@univ-lemans.fr

2nd Remi Venant
Computer science laboratory
University of Le Mans
Laval, France
Remi.Venant@univ-lemans.fr

3rd Sebastien Iksal
Computer science laboratory
University of Le Mans
Laval, France
Sebastien.Iksal@univ-lemans.fr

***Abstract*—While learning management systems have spread for the last decades, many teachers still struggle to fully operate a LMS within their teaching, beyond its role of a simple resources repository. Teachers need to engage themselves as learners of their own environment, to improve their techno-pedagogical skills. To this end, we propose a behavioral model based on teaching analytics to provide teachers with self and social awareness of their own practices on the LMS. The present article focuses on the model we designed on the basis of (i) a qualitative analysis from interviews we had with several instructional designers and (ii) a quantitative analysis we conducted on teachers' LMS activities. We used this model to define three teaching analytics indicators and build a peer recommendation system in order to encourage teachers to improve their skills in the LMS.**

***Index Terms*—Teaching analytics, Learning Management System, Self-assessment, Peer recommendation, Clustering analysis.**

I. Introduction

Learning Management Systems (LMS) are spreading quickly across all areas of education. Despite this growing trend for LMS to facilitate educational activities, the number of teachers using it does not increase as quickly as one might have imagined [1], and many teachers face several difficulties to integrate these platforms into their practices [3]. The main issues they encounter appear to be technical or organizational, mostly due to the lack of support and time devoted to its learning [4]. On the other hand, most universities hire instructional designers (IDs), whose one objective is, to support and train teachers in the LMS use and proper pedagogical fit. However, with only few IDs compared to the number of teachers [2], the former struggle to achieve this goal. For instance, in France, these problems were one of the reasons that led the Ministry of Higher Education to launch the HyPE-13 project[1](Hybridizing and Sharing Teachings) in November 2020. Carried by a consortium of 12 french universities, it aims to provide teachers and students with new learning devices for a better hybrid learning support.

LMS allow the collect of large amounts of traces that depict the behavior of users [5], and thus paves the way for Learning and Teaching Analytics (LA, TA). Learning Analytics relate to the collection and exploitation of traces left by learners to enhance the learning process. Teaching Analytics, which are not explored as much as the former, refer to the methods and tools to help teachers analyzing and improving their pedagogical designs, and more recently, to analyze how teachers deliver their lessons [8]. Hence, we consider TA as a challenging field of research that could bring narrowed support to teachers and IDs for improving LMS use, and eventually have an great impact on technology enhanced learning. In the context of our University, the LMS has been in place for more than ten years, and is considered nowadays as a critical service heavily promoted to teachers. However, the University is facing the same issues we identified previously (LMS use expectations are still not met and 5 IDs only have to carry out requests for more than 600 teachers). Our main objective is then to provide teachers with personal and social awareness [7] of their LMS use, in order to make them engage in learning situations to improve their LMS skills.

To reach this objective, we propose the design and instrumentation of a teachers' model of their LMS use to support their self-assessment. We address here two research questions: (i) How to model the exploitation of a LMS a teacher does and could do in an intelligible way? (ii) What TA indicators can be propose from this model to support self and social awareness and eventually enable feedback and recommendations?

II. Related work

While many efforts have been made to understand student behaviors on LMS, there seem to be a lack of research on teacher's behavior in such platforms [6]. Nevertheless, several studies in TA attempt to understand how teachers deliver their lessons. For instance, [9] proposed the concept of Teaching and Learning Analytics (TLA) as a synergy between TA and LA in order to support the process of teacher inquiry, and [8] used TA to automatically extract teaching actions during face-to-face classrooms (explanation, monitoring, testing, etc.). Furthermore, [15] proposed a Teaching Outcomes Model (TOM) that aims to provide teachers with guidance on how to engage and reflect on teaching data. TOM is a TA life cycle that starts with data collection, followed by their analysis, and then their visualization, where the presentation of the data is achieved with a Teaching Analytics dashboard dedicated to the teacher. In a last step of the cycle, teachers can improve their pedagogical practices thanks to this dashboard.

[1]https://organisation.univ-pau.fr/fr/labels/le-projet-hype-13.html

Beside TA-centered studies, others have explored teacher behaviors in hybrid learning systems (HLS). From that perspective, [10] proposed a theoretical model that identifies four main characteristics of e-learning considered essential to good practice: Dialogue, Involvement, Support and Control. On the other hand, [11] built an empirical framework based on 5 dimensions to describe how teachers cope with techno-pedagogical environment in HLS. These dimensions include modalities of articulation of face-to-face and distant phase, human support, forms of media, mediation and degree of openness. While the last two works propose models to study teacher behavior, they are contextualized for HLS, and are not fully appropriate to analyse how teachers interact with an LMS, which is mostly used as a complement to face-to-face learning. In this context, few researchers were interested in analyzing the behavior of teachers in LMS. [12] proposed a method to automatically certify teachers' competencies from LMS data to help universities make strategic decisions. They identified 6 types of courses at a coarse-grained definition (non active, submission, deposit, communicative, evaluative, balance).

Overall, these works target various purposes: categorizing courses, profiling teachers or analyzing the overall use of LMS. They allow to get relevant insights about what is currently done on the LMS, which may be used to evaluate a teacher. We observed that none of them target teachers' self-assessment of LMS practices through their behaviors analysis, and they all share limits for this purpose. They use student-related data that make comparing a teacher to another difficult since they do not represent the same population in terms of number, grade level, demographic distribution, etc. In addition, the empirical models we reviewed depict current platform usage, with the rejection of unused variables and cannot adapt to future use that is expected.

III. Teacher behavior analysis

A. Methodology

In order to qualify the current and expected teachers' use of the LMS, we applied a quantitatively driven mixed method. In a first step, we carried out a quantitative analysis based on the LMS log data of teachers' actions to infer different profiles of LMS use, and to find clusters of teachers. We performed here a Principal Component Analysis (PCA) and a clustering analysis. In a second step, we conducted semi-structured interviews (i.e. : qualitative interview) with instructional designers (IDs) to collect information and improve the quantitative study. We performed then a second quantitative analysis using the same previous method to address the IDs' comments by adding or modifying some variables. In order to design a behavior model that can handle both present and future expected usages of the LMS, we applied a second analysis on the basis of the first one while selecting different features according to the interviews we did with IDs. Particularly, some of the discussed LMS features are still not used enough to appear in the results of the first quantitative analysis. Moreover, the choice of the model axes (i.e.: the structure, how variables are grouped by axis) is also made from the results of the last PCA analysis, and modified thanks to the qualitative interviews. Finally, this model allowed to design several TA metrics and build a peer recommendation system.

B. Qualitative study

We chose to conduct interviews with IDs because they are always in contact with teachers to help them use the University's LMS, so they have a global insight into the practices used by teachers and the problems they encounter when using the platform. In addition, with the transition to fully online teaching due to COVID19, it was difficult to contact teachers due to their workload unlike IDs. The interviews were conducted separately with 3 female IDs on the same day and each lasted 40 to 50 minutes. All interviews were tape-recorded, transcribed, and analyzed by 2 researchers who compared the different responses by grouping similar ones and detecting particular cases.

The interview guide we prepared includes the different questions classified through several themes: **(i) introduction** (mutual presentation, research objectives, IDs biographies and competencies); **(ii) implementation of pedagogical scenarios (PS) on LMS** (method used by the IDs to implement teachers' practices); **(iii) use of the LMS by teachers** (IDs' perception of the teachers' use, difficulties encountered by teachers for the implementation of their practices, typical teachers' profiles observed, suggested indicators to define and detect these profiles); **(iv) evaluation of the variables used in the first analysis** (opinion about the variables used in the first analysis, discussion about other variables that might be relevant); **(v) evaluation of the groups of teachers obtained** (consistency of the identified groups, and usability of the model); **(vi) tool and expectations** (the vision IDs have of an application for them and expectations for the further development of the research project).

Throughout the interviews, we did not observe any contradictory statements , and there was a consensus on most of the conclusions. Regarding the implementation of pedagogical scenarios, they mentioned not using any predefined formalism but rather adapt to the teacher's choice. With respect to the LMS usage, they indicated it is underutilized to its potential. One ID specified that most of the LMS activity is located in science faculty where people are "not afraid of computers" and that globally, its use is very variable from one teacher to another. The difficulties experienced by these IDs are considered mainly due to insufficient knowledge of the platform and to the lack of time for learning. According to them, the different activities used in the LMS are resource repository, communication, evaluation, and feedback. More recently they have noticed a demand for more entertaining and attractive activities. Eventually, they proposed some indicators to assess these profiles based on students' frequency of consultation, use of links, and individual or collective resources and quizzes.

With respect to the first analysis we have done (detailed in the following section), they encouraged us to correct some variables calculation. Furthermore, they suggested to include

in our model some activities that were not observed at the time such as the game-type ones. They also emphasized the importance of including feedback activities, which were removed for the preprocessing phase due to their low variance. On the other hand, they expressed, once they saw the teacher groups, (i) their interest in getting to know the very active teachers to get their feedback and (ii) the necessity to have elements to better support teachers without being overwhelmed by numerous indicators.

C. Quantitative study

The LMS adopted by our University is used by most teachers and students. We recovered traces of teachers' activities from June 2016 to July 2018 and from October 2019 to November 2020 (an IT failure on the University's LMS caused the loss of data between the two periods). We present here the study we made following the qualitative study that takes into account the IDs' remarks. Data were preprocessed from the Moodle Database and the LDAP server to store them into a Learning Record Store following the xApi [2] convention: each action is represented as a standalone document that provides a view of the related course, the activity (if any) and the details of the user at the time of the action. From that LRS, 30 variables have been identified and 974 teachers did at least one action related to these features.

We first applied a preprocessing phase with an analysis of variance which consists of removing variables with low variances. The second step aimed to eliminate "ghost teachers" who are considered as course editors but have only performed very few actions on the course, and finally we removed variables highly correlated to each other. The resulting dataset is composed of 585 instances and 13 variables described in table I.

TABLE I
DESCRIPTION OF THE FINAL DATASET VARIABLES.

Variable	**Description** : The avg. number of	**Mean**	**Std dev.**
grade	teacher's creations/editions of grades.	1.40	3.86
quiz	teacher's creations/editions of quizzes.	0.34	1.21
assignment	teacher's creations/editions of assignments.	0.36	0.77
calendar	teacher's use of calendar.	1.86	4.91
chat_msg	teacher's chat messages sent.	0.61	3.84
forum_post	teacher's publications of posts in the forums.	2.41	21.44
forum	teacher's creations of forums.	0.32	0.99
img	teacher's use of images included in the course sections.	0.19	1.00
all_links	teacher's use of links in sections, labels or URL.	4.01	10.40
url	teacher's use of the URL resource.	1.46	4.44
file	teacher's use of the file resource.	5.82	10.31
folder	teacher's use of the folder resource.	0.99	2.55
page	teacher's use of the file resource.	0.66	1.90

We conducted a PCA analysis to detect typologies of LMS uses by teachers. The PCA analysis allows to investigate the diversity of the dataset in a reduced set of variables (components) that we used to define different axes of LMS use by teachers. Using the criterion of eigenvalue [13], the best model explains 72% of the total inertia (i.e.: the information contained in the dataset) through 5 components. The first component expresses 33.97% of the total variance (TV), and represents the global usage of the platform with a consistent use of most platform tools. In other words, all variables are involved with the same polarity and regardless of the type of activities exploited. The second component, which explains 11.56% of the TV, highlights the management of evaluation within the LMS. It gathers tools to manage assignments and submissions (*grade, quiz, assignment*), as well as the use of calendars which is mainly intended to manage deadlines for assignments and assessments. The third component concerns exclusively the use of forums (*forum, forum_posts*) and expresses 10.42% of the TV. The fourth component represents essentially the use of chat activities and the exploitation of images in course sections, and it explains 8.61% of TV. Based on the fact we have no theoretical support nor empirical insight to consider such odd association, we consider that this component which relates chats to images is coincidental. The last component expresses 7.18% of the TV and it is based on course structure. It brings together tools used on LMS to organize and personalize lessons like *pages* and *folders*.

IV. MODEL DEFINITION AND EXPLOITATION

A. Model

We defined a comprehensive behavioral model that describes within six axes how teachers make use of the LMS, with respect to previously discovered components from the PCA analysis, and to the results of the semi-structured interviews we had with the IDs. With these explainable dimensions, this model allows to evaluate weaknesses and strengths of teachers in terms of LMS mastery. Thanks to the mixed method we applied, this model includes not only features that represent the current situation, but also features that depicts LMS activities that are not yet fully exploited by teachers and that may be of importance in the future. The 6 dimensions are detailed below:

A.1 Evaluation: this axis represents the different tools used by the teacher to assess his/her students. It reflects the second component of the PCA and with respect to the results of the qualitative analysis, this axis aims at evaluating how the teacher benefits from the digital environment to organise and implement students' assessment. It includes: *quiz*, *assignment*, *grade*, *calendar* and *attendance*.

A.2 Reflection: it concerns the LMS features that can provide teachers with a way to get feedback from students on their teaching and the digital resources they use. It includes both variable *survey* and *choice*.

A.3 Communication: this axis is devoted to the different means of communication used by the teacher to facilitate the transfer of information to the students and to improve the sharing between them. It also brings together the third and

[2]https://xapi.com/developer-overview/

the fourth component of the PCA (*forum, forum_discussion, forum_posts, chat, chat_messages*).

A.4 Resources: this axis refers to the diversity of resources the teacher provides to students, and include then the *file, book, folder, page, glossary and url* variables. Based on the *comp5* of the PCA analysis, other variables mentioned were added thanks to interviews with IDs.

A.5 Collaboration: this axis concerns the promotion of collaboration between students with different LMS features. It includes the *workshop, wiki, via, choice and data* variables.

A.6 Interactivity and gamification: it gathers the interactive or playful activities used by teachers to animate their courses and make them more attractive. It was identified on the basis of qualitative analysis with *lesson, course_format, img, gallery, game and lti* variables.

B. Teaching Analytics indicators

Based on the teachers' behavior model derived from the quantitative and qualitative analysis, we designed three TA metrics for awareness and self-assessment.

a) LMS usage trends

In order to determine a TA indicator to support social awareness, we provide teachers with a current view of their position relative to the others. We propose here and for each axis a clustering model in order to distinguish groups of teachers based on their current behavior. Thus for each of the axes, we applied the same preprocessing steps we used in our quantitative analysis then we tested several clustering algorithms (K-Means, Dbscan, Agglomerative clustering and Gaussian Mixture). The results are exposed in Table II, with S the mean silhouette score (a high value indicates that the teacher is well matched to its own cluster), N the number of clusters and O the number of outliers for Dbscan.

TABLE II
RESULTS OF THE CLUSTERING ANALYSIS

Axis	Kmeans	Dbscan	Hierarchical Clust.	Gaussian mixt.
A.1	S=0.81, N=2	**S=0.85, N=1, O=3**	S=0.84, N=2	S=0.2, N=2
A.2	**S=0.91, N=13**	S=0.68, N=1, O=11	S=0.81, N=6	S=0.89, N=15
A.3	S=0.84, N=2	**S=0.92, N=1, O=2**	S=0.77, N=2	S=0.7, N=2
A.4	S=0.83, N=2	**S=0.91, N=1, O=1**	S=0.85, N=2	S=0.59, N=2
A.5	S=0.76, N=2	**S=0.81, N=1, O=1**	S=0.76, N=2	S=0.34, N=2
A.6	**S=0.98, N=2**	**S=0.98, N=1, O=3**	**S=0.98, N=2**	S=0.87, N=2

For each axis, the models converge towards a detection of particular teachers (active teachers and non-active teachers), and not towards a regular or homogeneous classification. This result is consistent with other studies in literacy so far [14]. The best silhouette scores are obtained by the Dbscan algorithm, except for the second axis which was Kmeans. We therefore chose the DBscan algorithm because it is capable of detecting specific instances of the platform usage.

b) Usage scores

The previous metric gives an insight about the present degree of teachers' mastery with respect to the group. However, the clustering method discards some of the features (due to the required preprocessing steps), and only provides an overall view of the skills related to other teachers. Here we propose two complementary indicators to measure how the teacher profits from the LMS, based on the complete model.

Curiosity score: this score indicates the teacher's degree of curiosity according to each axis. Counting the number of non null variables over all the teacher's courses, it aims to encourage to discover other LMS features within the axis. This score is formalized by the next equation:

$$curiosity_a(t) = |\{\sum_{c=1}^{C_t} x_{t,i,c},\ x_{t,i} > 0\ \forall i \in [1; m_a]\}| \quad (1)$$

With $x_{t,i,c}$ the value of the feature $i \in [1, m_a]$ (m_a the num. of features for the axis a) for the teacher t in the course $c \in [1, C_t]$ and C_t the number of courses where the teacher t has at least one non null variable.

Regularity score: this score considers how often a teacher exploit the features related to an axis with respect to their courses. In other terms, it helps validating a skill based on the repetition of practice. It is calculated by the following formula (using the previous symbols):

$$regularity_a(t) = \frac{\sum_{i=1}^{m_a} |\{x_{t,i,c},\ x_{t,i,c} > 0\ \forall c \in [1; C_t]\}|}{m_a \cdot C_t} \quad (2)$$

Regarding our university, the two usage scores confirm the low use of the LMS by teachers (figure 1). The majority of teachers (between 789 and 971 depending on the axis) have scores below 40%, whereas few of them (between 1 and 120 depending on the axis) have values above 60%. Knowing that the best scores are identified in the resources and then evaluation axis. Moreover, the results show that the values of the curiosity score are higher than those of the regularity score, which means that not all teachers use the platform in the same way to implement all their courses, and this can also be explained by the fact that, in general, it is the main teacher of a course who is in charge of creating the course environment.

C. Peer recommendation

With the purpose of helping teachers improve their scores and overall use of the LMS, we provide them with automatic peer recommendations. Thus, when the teacher obtains low scores in an axis, if there is a close peer with better metric values for that axis, the system invites the current user to contact that peer, giving an example of one of their relevant courses so that the teacher can get inspiration from the colleague's course. To do this, we built a content-based filtering model [16] based on the TA indicators we designed and taking into account the proximity between teachers.

The figure 2 explains the way we have exploited the model and the metrics defined above.

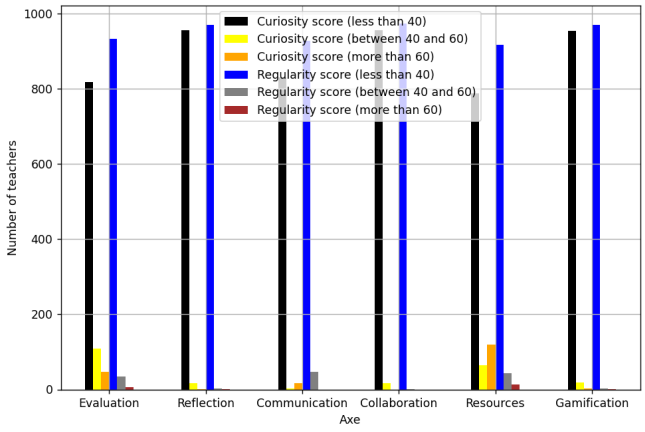

Fig. 1. Analysis of university teachers' scores

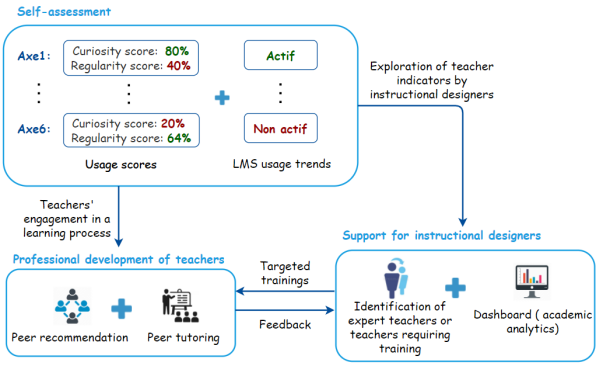

Fig. 2. General scheme of the approach

V. Conclusion and Perspectives

In this paper, we designed a behavioral model of teachers based on a qualitative and a quantitative analysis. This model describes teachers' practices through six major axes of mastery and allowed us to design several TA indicators that allow the teacher to engage in a learning process. Then, to help teachers improve their use of the platform, we provide them with automatic peer recommendations. On the other hand, the different TA metrics we propose can be used by the IDs to detect teachers with particular needs for a particular axis, in order to offer them a specific and precise help. In addition, the IDs seek feedback from the teachers considered as experts by our system, in order to benefit from their experiences and better organize the tutoring for the newcomers. However, our approach has some limitations. Many teachers use other technologies to manage their teaching, that we do not have access to. Moreover, our study does not take into account what happens in a class, outside the technological environment. Furthermore, We consider all teachers in the same way regardless of context.

In the short term, we aim to find the appropriate methods to instrument the behavioral model in order to precipitate any eventual changes in the application that we will be developing and increase its chances of being accepted and used by both teachers and IDs. Furthermore, we intend to experiment this application at the University level, once the first version is operational, in order to evaluate its usability and the interest that the teachers will have in it as well as the satisfaction of the IDs. At a longer term, we intend to conduct an experiment on the impact that this tool can have on teachers' practices.

References

[1] Wang, W. T., and Wang, C. C. (2009). "An empirical study of instructor adoption of web-based learning systems". Computers and Education, 53(3), 761-774.

[2] Daele, A. (2014). "La formation en ligne". Les conseillers et ingénieurs pédagogiques. Distances et médiations des savoirs. Distance and Mediation of Knowledge, 2(7).

[3] Nashed, N. N., Lahoud, C., Abel, M. H. (2022). Educational Resources Recommender System for Teachers: Why and How?. In Advances in Deep Learning, Artificial Intelligence and Robotics (pp. 71-80). Springer, Cham.

[4] Douali, L., Selmaoui, S., Bouab, W. (2022). Using Learning Management System in Distance Teaching: Thoughts of Future Teachers. International Journal of Research in Engineering, Science and Management, 5(1), 18-23.

[5] Heathcote, E., and Dawson, S. (2005, October)." Data mining for evaluation, benchmarking and reflective practice in a LMS". In E-Learn: World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education (pp. 326-333). Association for the Advancement of Computing in Education (AACE).

[6] Albó, L., Barria-Pineda, J., Brusilovsky, P., and Hernández-Leo, D. (2019, September)." Concept-level design analytics for blended courses". In European Conference on Technology Enhanced Learning (pp. 541-554). Springer, Cham

[7] Gutwin, C., Stark, G., and Greenberg, S. (1995). "Support for workspace awareness in educational groupware".

[8] Prieto, L. P., Sharma, K., Dillenbourg, P., and Jesús, M. (2016, April). "Teaching analytics: towards automatic extraction of orchestration graphs using wearable sensors". In Proceedings of the sixth international conference on learning analytics & knowledge (pp. 148-157).

[9] Sergis, S., and Sampson, D. G. (2017). "Teaching and learning analytics to support teacher inquiry: A systematic literature review". Learning analytics: Fundaments, applications, and trends, 25-63.

[10] Coomey, M., and Stephenson, J. (2018). "Online learning: It is all about dialogue, involvement, support and control—according to the research". In Teaching & learning online (pp. 37-52). Routledge.

[11] Peraya, D. (2014). "Distances, absence, proximités et présences: des concepts en déplacement". Distances et médiations des savoirs. Distance and Mediation of Knowledge, 2(8).

[12] Regueras, L. M., Verdú, M. J., De Castro, J. P., and Verdú, E. (2019). "Clustering analysis for automatic certification of LMS strategies in a university virtual campus". IEEE Access, 7, 137680-137690.

[13] Tamura, M., and Tsujita, S. (2007). "A study on the number of principal components and sensitivity of fault detection using PCA". Computers & Chemical Engineering, 31(9), 1035-1046.

[14] Yuen, A. H., and Ma, W. W. (2008). "Exploring teacher acceptance of e-learning technology". Asia-Pacific Journal of Teacher Education, 36(3), 229-243.

[15] Ndukwe, I. G., and Daniel, B. K. (2020). "Teaching analytics, value and tools for teacher data literacy: A systematic and tripartite approach". International Journal of Educational Technology in Higher Education, 17(1), 1-31.

[16] Wang, D., Liang, Y., Xu, D., Feng, X., and Guan, R. (2018). "A content-based recommender system for computer science publications". Knowledge-Based Systems, 157, 1-9.