Journal of Universal Computer Science, vol. 21, no. 1 (2015), 7-22
submitted: 16/5/14, accepted: 1/10/14, appeared: 1/1/15 © *J.UCS*

The Procrastination Related Indicators in e-Learning Platforms

María del Puerto Paule-Ruiz
(University of Oviedo, Oviedo, Spain
paule@uniovi.es)

Moises Riestra-González
(Accenture Analytics, Barcelona, Spain
moi.riestra@gmail.com)

Miguel Sánchez-Santillán
(University of Oviedo, Oviedo, Spain
mel.me85@gmail.com)

Juan Ramón Pérez-Pérez
(University of Oviedo, Oviedo, Spain
jrpp@uniovi.es)

Abstract: In general, research confirms that learning is more effective when students obtain feedback regarding their learning progress. Currently, new versions of e-learning platforms include indicators that provide some static feedback mechanisms and help both learners and educators in planning their learning strategies. This paper explains the usage of indicators in current e-learning systems, generates a taxonomy for their classification, and studies their influence on student performance. Also, it provides a study which is based on the combination of a user-based evaluation process that facilitates data collection and data mining algorithms to infer association rules between learning variables and performance. The results highlight how procrastination influences negative learning performance and how time-related indicators are tightly coupled with students' performance in e-learning platforms.

Keywords: Learning analytics, feedback, educational data mining, procrastination
Categories: K.3.1, H.2.8, H.5.2

1 Introduction

Internet use is widespread in everyday life; it is used in scenarios such as work and communications, and in the way we learn or teach new content. Education has been largely influenced by increased Internet use, resulting in the emergence of virtual learning environments (VLEs) which offer holistic environments for delivering and managing educational experiences [Dagger, 07].

Information and communications technology (ICT) provides a motivational component to assist learning. However, learning in a VLE requires self-regulated processes, which are an important part of the learning cycle [Azevedo, 11][Quintana, 05]. In various approaches to self-regulated learning (SRL) [Barak, 10][Butler, 95][Valle, 10], motivation and feedback play an important role. Research generally confirms that learning is more effective when the learners receive feedback [Bangert-Drowns, 91][Meyer, 86], and successful e-learning initiatives [Johnson, 08] require practice, feedback, and interaction with multiple stakeholders [Welsh, 03].

Studies into feedback in educational settings have focused on information provided to students by external sources; for instance, a teacher or a computer [Butler, 95]. In face-to-face classrooms, learners can obtain feedback from the instructor directly, but communication between learners and instructors in an online learning setting is mediated through subsystems (e.g., e-mail, discussion forums, chat) embedded or integrated within the learning environment. E-learning platforms already include static feedback mechanisms based on learners' interaction with the system [Govindasamy, 01], but there are many scenarios where learners need custom feedback that suits their contexts [Romero, 13] or real-time feedback (RF) to achieve effective learning [Omoda-Onyait, 12].

The visual support of different feedback strategies [Narciss, 14] makes teachers' decisions easier, helps students to monitor their goals, and guides and stimulates reflexion upon the learning process and the skills acquired [Glahn, 08]. According to the literature, there are two different kinds of feedback in an e-learning system [Van Seters, 12]: local feedback provided after completion of an activity, and global feedback related to the status of the learning process. Local feedback is included in most common learning management systems (LMSs); global feedback is represented by simple statistical analysis, or low level information about the interaction between the learner and the platform [Ali, 13].

More recent research specifically comments on the importance of providing visual support to enhance understanding of the learning process, and to enable self-regulated learning [Duval, 11]. Studies about students' self-regulation in the online learning process demonstrate the importance of feedback [Ley, 01][Mory, 04][Orange, 99] and its visualisation [Nussbaumer, 08]. Learning processes require information feedback in order to monitor the progress of learning activities. The basis for this type of information is sometimes referred to as 'indicators' [Glahn, 08], and is related to the process and analysis of learning analytics. Learning analytics is a concept which is closely related to web analytics [Croll, 09] and educational data mining [Romero, 10], and it provides a framework in which students' awareness about their interaction with an e-learning platform can be collected, analysed, and represented, so as to help to make decisions and to improve the learning process.

We consider indicators as a tool to help instructors and learners in their planning and development of learning strategies while also providing support to information systems for the generation of recommendations and decisions, thus improving the learning process. By enhancing the learning process, students not only get better results, but also improve how they learn in the system. Based on this premise, we analysed the use of indicators and learning analytics in actual e-learning platforms in previous literature, giving special attention to journal papers and conference papers such as LAK ('Learning Analytics and Knowledge'), EC-TEL ('European Conference on Technology Enhanced Learning'), and the International Conference on Educational Data Mining (EDM). We also examined articles and book chapters published between 2000 and 2014 on the databases of the Educational Resources Information Centre (ERIC), the Social Science Citation Index (SSCI), and the Science Citation Index (SCI).

From this analysis, we obtained a view of which, how, where, and when indicators are being used in e-learning platforms, and we designed a study to discover time-related variables. Our study allows us to gain a wide understanding of the use of these types of indicators and the influence of academic procrastination in the learning performance.

2 Related Work

Educational research shows that monitoring students' learning is 'one of the major factors differentiating effective schools and teachers from ineffective ones' [Cotton, 88]. This is essential in e-learning systems, where physical interaction between teachers and students often disappears, only to be replaced by online interaction tools such as forums or chat rooms. Most e-learning environments collect large amounts of data in logs about students' interactions and activities within their system [Romero, 10], and usually provide some monitoring features to enable teachers and learners to view some aspects of this data; e.g., history of pages visited. In [García, 07], the authors explain how the LMSs keep detailed logs of all activities that students perform. Not only every click that students make for navigational purposes are stored, but also test scores, elapsed time, etc. However, student tracking data is complex and is usually organised in some tabular format, which in most cases is difficult to follow and inappropriate for the instructor's need [Mazza, 04], such as being made aware of what is happening in distance learning or identifying students that are at risk of dropping out [Clow, 12].

In the last few years, there has been an increased interest in applying big-data techniques and data mining to educational systems; in doing so, it has established educational data mining (EDM) [Romero, 09]. EDM is a discipline concerned with developing methods for exploring the unique types of data obtained from different types of educational contexts (for example, learning environments). Extracted knowledge can be represented by visual and conceptual models, and it can be used by teachers and learners in formative and summative assessments.

An important objective of educational data mining [Castro, 07] is the development of feedback applications for both actors in the learning process: the student and the teacher. These applications allow actors to obtain interesting and unknown information from logs, so as to generate relevant feedback to the users. Indicators provide mechanisms for visualising different data sets, and are aimed at helping teachers assess learning processes, as well as encouraging students to reflect on feedback, or verify or modify their actions during the accomplishment of a learning activity. Most of these indicators implement a static approach to providing information for learners' support in learning interaction cycles [Garries, 02], whereas others consider the educational context, evolving through time and according to students' learning paces. Together with indicators, the contextual information of the learning process has been proven to be a significant support for understanding students' actions in learning environments [Glahn, 08].

Learning analytics proposes a framework [Solar, 11][Greller, 12] for studying how contextual information about students' interaction with e-learning systems can be measured, collected, analysed, interpreted, and represented in order to provide teachers and students with support in decision-making, as well as to enhance teaching and learning activities. In this case, data visualisation is represented not as individual indicators, but as overall learning information panels (learning dashboards) in which the different interaction indicators are all grouped together. The main value of this model is the attention given – otherwise known as the 'awareness' [Govaerts, 10] – to the learning process, rather than to learning itself. However, this approach does not precisely determine the amount and nature of the factors that should be measured during the learning process.

2.1 Academic Procrastination and Learning Analytics

Shraw and colleagues [Shraw, 07] define academic procrastination as 'intentionally delaying or deferring work that must be completed'. Procrastination adversely affects academic progress because it limits both the quality and quantity of student work and it leads to a number of negative results [Rakes, 10]. However, not all forms of procrastination lead to negative consequences [Chu, 05]. Chu and Choi (2005) differentiate between passive procrastination and active procrastination. While passive procrastinators allow the negative, indecisive behaviour to paralyse them, active procrastinators make deliberate decisions to procrastinate because they prefer to work under pressure. And in [Steel, 07], the author discusses the use of the term procrastination to describe positive behaviour.

In web-based courses, procrastination has been correlated with lower grades [Tuckman, 02] and has been negatively correlated with exam scores. Rakes and Dunn [Rakes, 10] consider that the tendency to procrastinate increases in the online environment and is prevalent and detrimental to student learning and performance. Because procrastination can lead to decreased academic performance, and because the most basic of learning data in virtual learning environments for learning analytics is the interaction [Agudo-Peregrina, 14], it is important to determinate which variables of the interaction are relevant for procrastination.

2.2 Learning Management Systems and Indicators

In [Macfadyen, 10] [Wang, 02], the authors propose that data on students' online activity in LMSs, such as BlackBoard or Desire2Learn, may provide an early indicator of students' academic performance. LMSs usually provide rather basic analytics such as simple statistics on technology usage or low-level data on a student's interaction with the learning content. This kind of visualisation (Figure 1: Number of submissions shown by BlackBoard Analytics) (Figure 2: Percentage of time of study shown in Moodle using the plugin 'Analytics and Recommendations') prevents teachers from generating relevant and suitable feedback according to the students' needs [Nicol, 06].

There are many indicators and several different approaches to visualising them, but currently one of the most important problems is deciding which of these indicators is suitable for supporting learners' awareness and self-reflection. Duval [Duval, 13] proposes a categorisation of indicators that identifies the type of data that learners are shown, including effort (time spent), resources used (visited URLs), communication (social media), artefacts, and quality (ratings). Paule-Ruiz and colleagues [Paule-Ruiz, 13] consider usability and didactic effectiveness parameters to support the assessment of multichannel interactive learning solutions, as self-regulation could be affected by environmental satisfaction (e.g., perceived satisfaction and perceived usefulness) [Liaw, 13]. There are also examples in the scientific literature of applications or frameworks that provide learner indicators, such as the operation framework model for context-aware applications [Zimmermann, 05], which describes the information processing of interaction footprints of learners in a learning environment. Other software, such as SAM [Govaerts, 12] or CAM [Wolpers, 07], analyses user interactions to extract indicators of time spent by learners on learning activities, and uses different visualisation techniques to enable more detailed analysis. Attending to LMS, the Moodog plug-in [Zhang, 09] visualises metrics of activity logs in Moodle using bar charts; and CourseVis [Mazza, 07] utilises information visualisation and graphical representation techniques to display web log data generated by the WebCT.

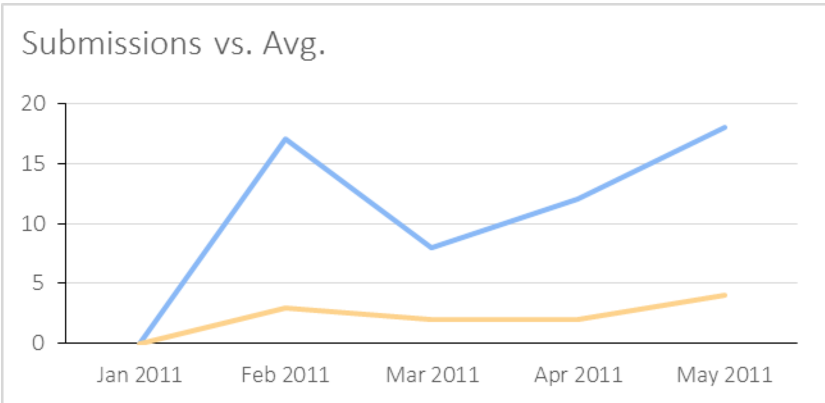

Figure 1: Number of submissions shown by BlackBoard Analytics, comparing student submissions (dark) versus major submission rate (light)

	Assignments	Chats	Choices	Databases
Student1	13.33%	11.25%	8.57%	10.26%
Student2	8.89%	8.75%	11.43%	7.69%
Student3	24.44%	18.75%	11.43%	15.38%

Figure 2: Percentage of time of study shown in Moodle using the plugin "Analytics and Recommendations'.

2.3 Indicator Classification: A Suggested Taxonomy

We consider two approaches to classify the indicators (Figure 3). In [Glahn, 08], the authors define the smart indicators as those parts of the system that present the interaction footprints [Farzan, 05] to the learners. Therefore, they often depend directly on the system in which they are used. More recently, Verbert and colleagues

[Verbert, 13] have proposed that user interaction data can be processed in such a way that it can be visualised by indicators, enabling the teacher or learner, rather than the software, to make sense of them. In the second approach, visualisation techniques [Card, 99][Spence, 00] are used to assist both instructors and students with self-reflection and awareness of what and how they are doing [Govaerts, 12][Soller, 05].

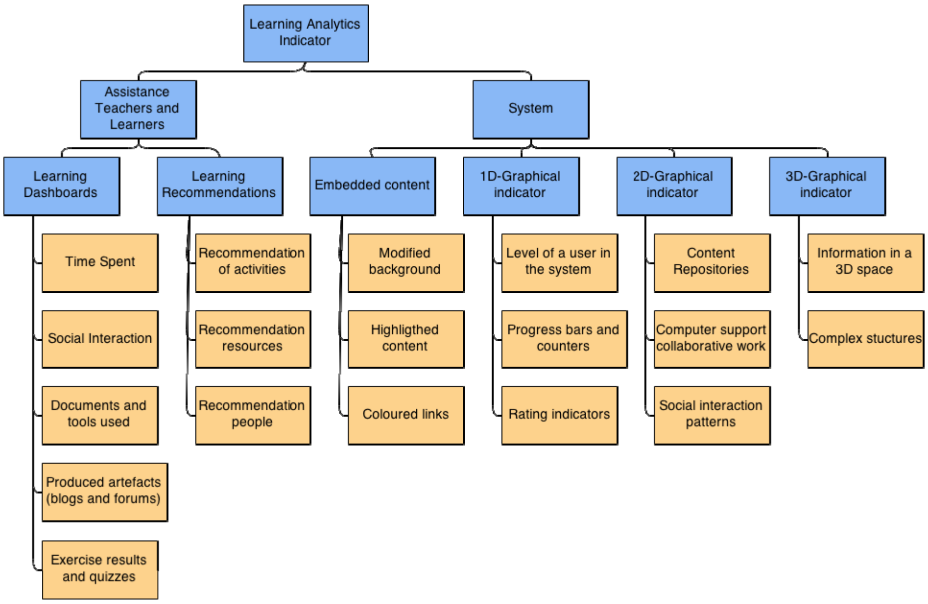

Figure 3: Indicator classification

3 Our e-Learning Study

Our main objective is to analyse and obtain conclusions about the relationship between the usage of procrastination related indicators in learning management systems and the final marks or performance obtained by the student, using performance as the characterised variable. Firstly, we describe how and from where the input data is obtained; then the procedure is explained for transforming this input data into experimental results for students and teachers, applying association rule mining; and finally, we analyse the variables included in several of these rules with the aim of a better understanding of the influence of time related indicators on the students' performance.

3.1 Instruments and Participants

We used students' data from the Moodle system, which is one of the most widely used e-learning platforms in Spanish universities [Álvarez García, 10]. The study used information corresponding to 33 students, 20 male and 13 female, enrolled in the fourth year of a geomantic and topography engineering degree of a university in the north of Spain. This course was taught from September 2012 to April 2013, and was organised into three main units with the same structure: mandatory and recommended resources, assignments, and evaluations. To complete the course, each student had to complete a test, and submit one or more assignments per unit in the platform to ensure they had been assessed with continuous evaluation.

All students were notified that their interaction with the platform was tracked and stored on a database table [Slade, 13][Fournier, 11], and that these records were being analysed by us to obtain results for our study. All of the students consented to our using their data for educational and research purposes.

3.2 Procedure and Data Analysis

The main objective of this analysis is to find variables that may be used as indicators in e-learning platforms, with special attention to the variables related with predictors of procrastination such as task delay [Steel, 07], among others. Each indicator should provide feedback to both students and teachers. Students need real-time feedback to achieve self-reflection and awareness of their learning process; the teachers, meanwhile, require global feedback after the subject has finished, so as to encourage the use of indicators that could provide better performances in the future.

Variable	Description	Discretised Values
Resources (R)	No. of clicks in mandatory resources	LOW/MEDIUM/HIGH
RecommendedResources (RR)	No. of clicks in recommended resources	LOW/MEDIUM/HIGH
Assignment (Discarded)	No. of submitted assignments	LOW/HIGH
Quizzes (Q)	Time spent until completed quizzes	LOW/MEDIUM/HIGH
Timetoresources (TTR)	Time until first click on a mandatory resource	LOW/MEDIUM/HIGH
Timetorecommended (TTRR)	Time until first click on a recommended resource	LOW/MEDIUM/HIGH
Timetoassignments (TTA)	Time until first submission of an assignment	LOW/MEDIUM/HIGH
Timetoquizzes (TTQ)	Time until first attempt in the evaluation test	LOW/MEDIUM/HIGH
Timetofirstaction (TTFA)	Time until first action in the unit	LOW/MEDIUM/HIGH
Performance	Student grade	FAIL/PASS/GOOD

Table 1: Variables used in the study with their abbreviations, descriptions, and discretised values

To analyse the data in both ways – for students and teachers – we obtained the logs from Moodle. All data were then classified into four files: one per unit, and a final one comprising all the information. From these generated files, we got the variables related to our objective (Table 1). We discretised their values using the ‘equal-width’ method, excluding the ‘performance’ variable, where we chose the ‘manual method’ to establish manually the cut-off points to obtain the groups. The performance variable is the grade of a student, assessed as the sum of grades of quizzes and assignments. Finally, we discarded the 'assignment' variable because the 'equal width' method generates discretisation into two classes, one of which contained 32 of the 33 elements in the study, which could obstruct a correct analysis of the data.

Variables shown in the previous table (Table 1) can be classified into three groups: the first group includes all variables which are counted such as Resources, RecommendResources, or Assignment, and they are measured as the sum of clicks or the number of submitted assignments; the second group contains all variables that are related with the time a student spends in completing a task in a course (i.e., Quizzes); the last group encloses the procrastination variables, named with the prefix 'Timeto', and is measured as the time from the beginning of a course or subject until the student performs a specific action.

Previous studies [Romero, 10] demonstrate how association rule mining is useful for obtaining feedback. In our study, the rules were obtained using Weka [Hall, 09], which includes the Apriori algorithm [Agrawal, 94] and Predictive Apriori [Mutter, 05] implementations, extracting only those rules that relate 'performance' with all other variables.

3.3 Students: Experimental Results and Discussion

As mentioned previously, in our study we obtained association rules per unit which may allow generating new time-related indicators that could provide 'real-time' feedback to the students.

3.3.1 Obtaining Association Rules

First, to obtain the association rules related to performance, we used the Apriori algorithm, with an accuracy greater than 0.95, and the Predictive Apriori algorithm, with a support greater than 0.95. This process was run with each unit file to get the rules per unit; this resulted in 189 rules (Table 2).

With the rules detailed in Table 2, we then generated a bar chart (Figure 4) to better understand which variables are more significant for student performance. This chart summarises the distribution of the variables into the rules. All variables are ordered according to the percentage of appearances. To identify each variable, we used its abbreviation (Table 1) to make a simpler chart.

Analysed Unit	Apriori	Predictive Apriori
Unit 1	12	47
Unit 2	6	52
Unit 3	19	53

Table 2: Number of rules obtained per unit and algorithm

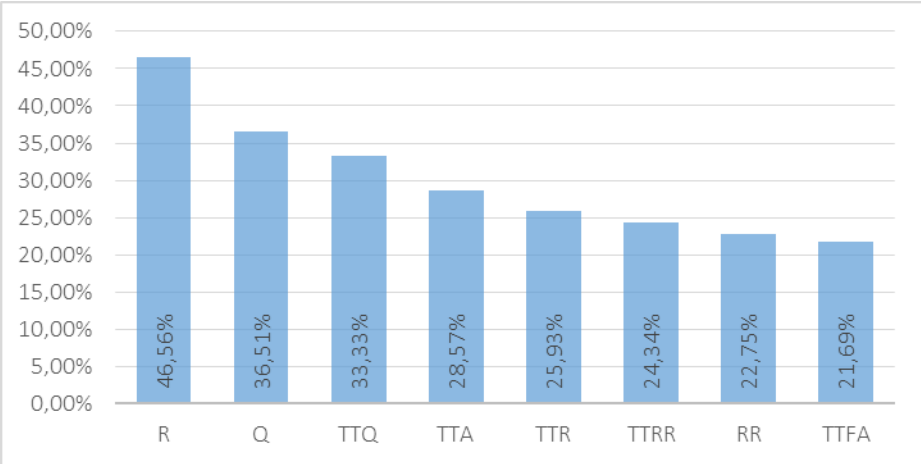

Figure 4: Distribution of rules into variables after student analysis in percentage

Finally, we established an association between the recurrent rules in each unit. Using the two first units, we can find that six rules are repeated in both; whereas if we use all three units, we can find only two rules repeated in all units. This rules-matching allows us to generalise some rules that define the behaviour of the students regardless of the unit in which they are working (Table 3). Although only two rules are repeated in all units, there are several rules that have a slight difference (such as rules 2 and 3), and these can also be used with repeated rules to obtain common rules per unit. This will help us understand which variables and values can be used to generate new procrastination related indicators into the students' e-learning platform.

ID	Rule	Accuracy	Unit
1	IF resources=high AND timetoquizzes=low THEN performance=good	0.98725	1, 2, 3
2	IF quizzes=medium AND timetoquizzes=low AND timetoresources=low THEN performance=good	0.98224	1, 2
3	IF quizzes=medium AND timetoresources=low AND timetoassignments=low THEN performance=good	0.98224	1, 2
4	IF resources=high AND timetoassignments=low THEN performance=good	0.97058	1, 2, 3
5	IF resources=low AND timetoresources=high AND timetoassignments=low THEN performance=pass	0.97058	1, 2
6	IF resources=high AND timetoquizzes=low THEN performance=good	0.98725	1, 2

Table 3: Rules after analysis for students and unit

3.3.2 Discussion

In analysing the association rules, we can gather some parameters that affect a student's performance. Rule 5 provides information about the relationship between a student's behaviour and his/her performance. In this rule, the 'resources' variable has a low value, and the 'timetoresources' variable has a high value. In contrast, all other rules link behaviour with a high performance, so we can infer that students that access resources several times, spend a medium amount of time on evaluation tests, and start doing tasks in the course early, will probably obtain better results.

In addition to this, all rules contain at least one variable related to the time until students start undertaking an activity on the e-learning platform ('timeto...'); however, the 'timetofirstaction' variable, which is shown by default in Moodle, does not provide relevant feedback about student performance (Figure 4).

3.4 Teachers: Experimental Results and Discussion

To provide global feedback to the teacher, we obtained association rules after the course had finished, in order to obtain variables for creating indicators to teachers that could provide better performances in the future.

3.4.1 Obtaining Association Rules

The process of obtaining association rules was the same as in the case of students: the same algorithms – Apriori and Predictive Apriori rules – were used, with the same margins of accuracy and support. The main difference is that, in this case, we had only one file, which contained all students' interactions over the three units of the course. After applying both algorithms, we obtained 58 rules: 51 from the Apriori algorithm, and seven from the Predictive Apriori algorithm. Following this, we explained the distribution of the variables into the rules in Figure 5. We used the same order as in the students' chart in order to view the main differences. The most relevant rules, using the accuracy to choose these rules, are also shown in Table 4.

ID	Rule	Accuracy
1	IF quizzes=medium AND timetofirstaction=high THEN performance=fail	0.99109
2	IF recommendedresources=low AND quizzes=low THEN performance=fail	0.98884
3	IF timetoresources=high AND timetoassignments=high THEN performance=fail	0.98884
4	IF quizzes=high AND timetoresources=low AND timetoassignments=low THEN performance=good	0.988884
5	IF resources=high AND timetoresources=low THEN performance=good	0.98476

Table 4: Rules after analysis for teacher

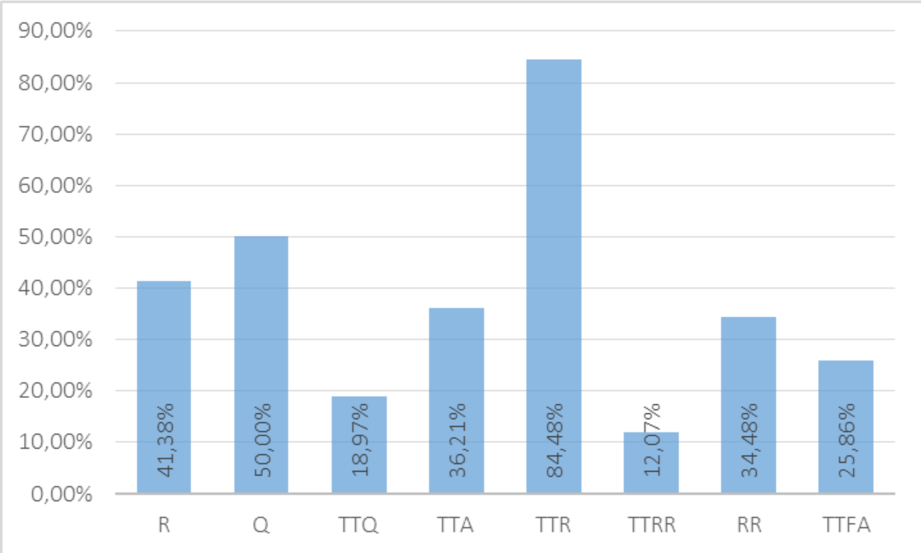

Figure 5: Distribution of rules into variables after teacher analysis in percentage

3.4.2 Discussion

When using the variables related to 'time to', the rules obtained after the teacher analysis are similar to the student analysis ones. However, we detected two different kinds of rules in this experiment: those that relate some variables with a failing performance, and those that link variables with a good performance. All 'time to' variables demonstrate a behaviour that is in opposition to the performance when combined with others: a high 'time to' value has a fail 'performance' value, and when the first value is low, the second one has a good value. For example, 'timetoresources' in rule 3 has a high value and the performance is classed as a fail, whereas in rule 4, the same variable with a low value results in a good performance. According to these rules, we can conclude that students who wait a long time until starting a task in the course will probably obtain a lower performance.

4 Conclusions and Future Work

From an educational point of view, feedback plays a fundamental role in the online learning process, and constitutes an essential area in all approaches to self-regulated learning. Indicators are mechanisms for providing visual feedback in virtual environments; they enhance the understanding of learning processes and enable self-regulated learning. These indicators help teachers assess the learning process, and encourage students to reflect on feedback, or verify or modify their actions during the execution of a learning activity.

This research explores the usage of indicators in e-learning platforms, making a deep study of learning analytics, educational data mining of e-learning log files, and learning indicators. In our paper, we propose a taxonomy based on the assistance of indicators provided to teachers and learners, as well as on the ways in which they are represented.

We also make a study with students enrolled in an e-learning platform, with the main objective being to find procrastination related indicators in LMSs. The results allow us to infer that the information related to the time until starting an activity on the platform (‘time to…’) can be adequate procrastination related indicators for the student and educator, as the students who wait a long time until starting a task in the course could obtain a lower performance.

While the LMSs do not provide indicators to these procrastination variables, we consider it advantageous to complement current indicators in the LMS with ‘time to’ variables, as they are related to negative forms of procrastination, and this has been linked to several negative indicators of learning outcomes [Schouwenburg, 04]. These procrastination indicators also may be represented with the association rules using trees or directed graphs. The trees show the paths students may follow within a specific context, specifying the performance for each of them, or they may even suggest to the students the actions to be taken in order to increase their possibilities of success. This dynamic representation of the learning cycle prompts the learner to use this strategic information to solve the learning task in his/her next trial and feedback experience, according to the Interactive-Tutoring-Feedback (ITF) Model [Narciss, 14].

Although the findings are encouraging and useful, the present study has certain limitations that require further research. These include a deeper study of other educational aspects, such as learning styles or social networking, and the relation between learning efficiency and performance. We believe this future study could help to generate newer and more confident learning indicators, which would provide more accurate self-reflection and awareness to teachers and students. Finally, in order to obtain effective learning, LMSs should add real-time feedback based on indicators that change according to the learners’ contexts or needs.

Acknowledgements

This work has been funded by the Department of Science and Innovation (Spain) under the National Programme for Research, Development and Innovation: project TIN2011-25978 entitled ‘Obtaining Adaptable, Robust and Efficient Software by including Structural Reflection to Statically Typed Programming Languages’.

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