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Citation for published version

García Solórzano, D.[David], Santamaría Pérez, E. [Eugènia], Morán, J.A. [Jose Antonio], Cobo-Rodríguez, G. [Germán] & Monzo, C. [Carlos].(2018). Personal informatics systems for supporting self-regulation in online learning environments. Computer Applications in Engineering Education, 26(5), 1445-1456. doi: 10.1002/cae.21989

DOI

https://doi.org/10.1002/cae.21989

Handle

http://hdl.handle.net/10609/150888

Document Version

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Personal informatics systems for supporting self-regulation in online learning environments

David García-Solórzano | Eugènia Santamaría | José Antonio Morán | Germán Cobo | Carlos Monzo | Universitat Oberta de Catalunya, Barcelona, Spain

Correspondence: David García-Solórzano, Universitat Oberta de Catalunya, Rambla del Poblenou, 156, Barcelona, 08018, Spain. Email: dgarciaso@uoc.edu

A B S T R A C T

Personal informatics (PI) systems have emerged as powerful tools for helping people to be aware of their behaviors in diverse domains. Nevertheless, little attention has been devoted to educational scenarios. For this reason, this paper presents an educational PI system called Glance and, moreover, evaluates its usefulness in two fully online undergraduate courses.

K E Y W O R D S

Personal informatics systems, self-regulated learning, information visualization, learning analytics, e-learning

1 | INTRODUCTION

One of the features of online education is the separation between students and instructors throughout the teaching-learning process [28]. In addition, the Internet and mobile devices allow each student to learn at her convenience, i.e. anywhere and at any time [7]. Such separation and flexibility give students the control of their own learning process, so that they can adapt it to their personal situation. As a result, a student-centered approach is promoted in online courses, in which the teacher is no longer a transmitter of knowledge, but a facilitator who constantly guides each student through her learning process and arranges meaningful learner-centered experiences [32]. Hence, such an approach requires students to assume primary responsibility for their learning process [8]. Consequently, learners must have a lot of self-discipline and initiative to finish an online course successfully [18]. In other words, online learners should be autonomous, i.e. be self-regulated. For this reason, it is not surprising that research studies have demonstrated a strong relationship between online students' academic success and the use of self-regulated learning strategies [39, 40, 31, 2]. Unfortunately, there are also many works [42, 1] which state that most students are not skilled at self-regulating their learning process. The lack of such skills, together with other factors, may lead to a high dropout rate.

To help online students become self-regulated, learning analytics (LA) can be a valuable tool to support awareness and promote reflection on one's own performance [6]. Due to the large amount of information obtained by LA tools, it is essential to convey it effectively. For this reason, information visualization (IV) techniques, as a subset of LA, are becoming more and more relevant. In this regard, we suggest the use of a new class of systems called personal informatics (PI) for supporting self-regulated learning in online settings. Such tools join the gathering and processing of data with the use of visual cues –in the form of a dashboard– for providing students with relevant information about their own performance in an effective way. More specifically, the contributions of this paper are:

- Section 2 presents the conceptual framework of this research. We first explain what *self-regulated learning* is and their implications in online education (Subsection 2.1). Furthermore, a review of student monitoring tools and learning dashboards based on IV techniques, which may be regarded as the predecessors of educational PI systems, is presented in Subsection 2.2. In Subsection 2.3, we provide a definition of what *personal informatics (PI) systems* are and explain their main features as well as how they can be useful for supporting online students during their learning process.
- Due to the surprisingly little research on educational PI systems, we conduct a literature review on the most relevant educational PI systems which have been proposed so far (see Section 3).

- In Section 4, we introduce a prototype of an educational PI system called Glance which simultaneously provided students with both a fine-grained (i.e. each individual course) and a coarse-grained vision (i.e. the overview of all the courses).
- There is a scarcity of long-term evaluations of educational PI systems. Moreover, the current research evaluations have not been conducted on fully online learning settings. For this reason, we evaluated the usefulness of educational PI systems via two versions of Glance over a long period of time, namely one semester, and in two fully online courses at the Universitat Oberta de Catalunya. Section 5 details the research methodology that we used. The results obtained from testing Glance are shown in Section 6.
- We discuss the findings of the educational PI systems presented in the literature review that, along with our results, provide evidence of the usefulness and potential of PI systems in an educational context (see Section 7).
- Finally, some remarks on further work conclude the article (see Section 8).

2 | CONCEPTUAL FRAMEWORK

2.1 | Self-regulated learning

Due to the nature of the online learning, the teaching-learning process undergoes significant changes compared to that of the traditional F2F instruction. The most important one is the fact that online education is mainly based on a self-regulated learning. Pintrich [29] defined *self-regulated learning* as *"an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features in the environment"*. Generally speaking, it is a process that consists of three cyclical phases [42]:

1. **Forethought**: it involves the student in setting goals, planning a strategy to achieve such objectives, and measuring her own competence to complete tasks and reach goals.

2. **Performance**: it deploys the specific tasks that are part of the strategy defined in the forethought phase. This step is guided by a self-monitoring process whereby the student tracks what she is learning, e.g. to self-record the time that she spends on studying a unit.
3. **Self-reflection**: it focuses on comparing self-monitored data with a standard or goal. This includes tasks such as assessing academic success and adjusting future learning strategies. Hence, in this phase, the student should be aware of her learning process.

As seen, online learners, who are also self-regulated students, should do many and varied actions to be successful. In this regard, self-regulated learning works best when students exactly self-assess their progress and use that information to define strategies, goals, tasks, etc.

2.2 | Student monitoring tools and learning dashboards based on IV techniques

Learning analytics (LA) applies different methods to detect patterns hidden in educational data sets. One of them is information visualization (IV). Card, Mackinlay and Shneiderman [4] defined IV as *"the use of computer-supported, interactive, visual representations of abstract data to amplify cognition"*. Thus, IV encompasses a set of techniques that transform data into effective graphical representations by taking properties of human visual perception into account. Such visual representations reveal facts and trends that allow users to infer unknown information by combining the visual inputs with their knowledge of data.

For some time now, several student monitoring tools based on IV techniques have been proposed. Generally speaking, such tools obtain students' tracking data from a learning management system (LMS), transform them into a form convenient for processing and generate graphical representations that can be explored by instructors. Two of the most well-known student tracking systems are CourseVis [24] and, its successor, GISMO [25], which allow teachers to examine social, cognitive and behavioral aspects of their learners. In the same way, France et al. [12] supply the teacher with a system that enables them to navigate between complementary visualization tools that give information on the whole classroom, an activity of a particular exercise or the status of a specific student. Zhang et al. [41] designed a plug-in for Moodle called Moodog which, in addition to displaying student tracking data, also sends automatic reminder e-mails to learners. Scheuer and Zinn [36], in turn, created Student Inspector, a system that analyzes log data from LMS and shows the results to teachers by means of multiple views which encapsulate a functionality, e.g. overall group performance, student performance along topics, etc. Likewise, Hardy et al. [15] constructed graphs that display the route taken and the length of time spent by one student through the course material during a work session. Hijón-Neira and Velázquez-Iturbide [16] used an interactive graph for students' grades and a data mountain for access. Juan et al. [17] used scatter plots and line charts to track group activity. Finally, CAMera [37] tries to support self-regulation in personal learning environments (PLE). This is made up of several components like a visual overview on the resources used by the student and an interactive graph that shows learner's social network.

All the previous proposals are valuable tools, but they have a major drawback. They each are a set of views/pages based on different visualizations that all together display different aspects of the teaching-learning process. Due to this fact, looking all the data a student tracking tool provides –by switching among various views/pages– can be a time-consuming and tedious task. As a result, dashboards have been suggested in recent years. The difference with student tracking tools is that a dashboard is *"a visual display of the most important information needed to achieve one or more objectives, consolidated and arranged on a single screen so that the information can be monitored at a glance"* [11]. The fact that a dashboard is a single screen with multiple indicators makes the detection of trends and potential problems easier and faster.

In general, most of the learning dashboards have been addressed to faculty so that they can adapt instruction to the needs of learners and provide them with just-in-time assistance, e.g. [30, 20, 22, 5, 23]. However, as the success of the student primarily depends on herself –especially in online settings–, there has been a shift so that students are also provided with a dashboard that displays information on their performance and learning behavior over time [38].

2.3 | Personal informatics systems

We are convinced that providing a learning dashboard to online students is beneficial to self-reflection. Nevertheless, since many online students are not skilled at regulating their learning, we also think that such dashboards should not only display data collected automatically, but also allow users to add personal data manually. This means evolving the dashboard from a visual tool into a system that combines personal data collection with data visualization, that is to say, we suggest replacing dashboards with a new class of tools called personal informatics (PI) systems. As said in [21], a PI system distinguishes from other tools (e.g. dashboards) by considering the parts of collection and reflection as a whole process. Since the data must be about the user and the user must reflect on that data, the user in a PI system is involved in both collection of and reflection on the data. Specifically, we believe the main benefits that students can get from using PI systems during the learning process are:

- **Self-awareness**: to be self-regulated, learners need information about themselves. In this regard, the fact that the students have to collect personal data manually may be a good way to make them aware of their learning process. Likewise the graphics provided by educational PI systems can be devised so that they show relevant information that many students may probably overlook. Besides the student's personal information, such tools can give information about the class, what allows a learner to make judgments about her own skills by evaluating her progress in comparison with her classmates. As Duval points out, such tools can help to realize a more learner-driven approach [10].
- **Motivational**: PI systems can be very useful for developing and maintaining motivation. Learning, like other personal activities such as losing weight, requires us to get and stay motivated. In this regard, educational PI systems can take a pro-active role, e.g. send messages to learners in order to set new goals, show progress, inquire why they have stopped doing activities, ask whether they need to redefine goals and plans, and so on. Hence, a PI system in an educational context can work as a virtual coach or assistant.

But, *what exactly are personal informatics (PI) systems?* Li, Dey and Forlizzi [21] defined *personal informatics systems* as *“those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge”*. In other words, these systems focus on making people aware of themselves by giving feedback based on personal data.

In recent years, there has been significant work done in the area of personal informatics. As a result, a diverse set of PI systems in different formats (website, app, etc.) and domains have emerged, such as: (1): Exercise: RunKeeper, Nike+, etc.; (2) Health: SocialDiabetes, Mood Panda, etc.; (3) Productivity: Wakoopa, RescueTime, etc.; and (4) Social: Twitalyzer, Klout, etc. Although their domains are different, the previous tools share the same goal: to promote positive behaviors on users by helping them to collect and reflect on personal data to gain a better understanding of their behavior. To this end, such tools are composed of 5 stages [21]:

1. **Preparation**: it focuses on determining what data to collect and how to capture them. Regarding what data to record, in an educational context, it is essential to collect any learning trace. This includes those data that are related to activities performed outside computer-aided learning platforms like LMS or PLE. Some of such data are, for instance, the time spent on reading a book or searching information in the library.

   As for how to capture data, they can be collected by the user manually (e.g. logbook or adding the information into the system explicitly) and/or automatically stored by the application by means of a device/service (e.g. bracelet, app, etc.). In a learning context, many data have to be collected manually, i.e. students must report them. Actually, this explicit data collection done by the student is one of the key differences between a learning dashboard and an educational PI system, since the latter provides learners with some mechanism for storing data on activities that are performed outside the online scenario.
2. **Collection**: this stage addresses how often to gather the data. The frequency of collection can vary from one type to other. Most of the data recorded automatically are associated with an event, i.e. when an event occurs, the system stores the related data. As for the data

reported manually, their collection faces several barriers. Some problems occur because of the user, e.g. she lacked time/motivation or she does not remember to collect information.

3. **Integration**: data can come from many different sources and have multiple formats, e.g. numeric, text, audio, etc. Hence, data should be cleaned, prepared, transformed and made available for use. This is just the goal of this phase.
4. **Reflection**: one of the principal goals of PI systems is to aid people to gain insights into their own behaviors. To this end, the representation of the data as well as the interaction with them become key aspects. This stage concerns how to visualize data in an understandable way for the user so that she can infer reliable latent information only observing and manipulating the graphics and making use of their own knowledge. In this regard, PI systems, instead of using a set of views/pages in which each of them shows different graphs, opt for dashboards that display, in a single page, a set of indicators by using different visualization techniques. At this point, an important aspect to consider in learning settings is the students' educational level (i.e. university, secondary school, etc.) [38], since some visualizations can require some extra knowledge to be understood by learners.
5. **Action**: as seen, IV techniques do not suggest actions, but they only give the users enough information to make decisions and perform the consequent actions. In contrast, there exist other methods, known as data analysis techniques (e.g. data mining), which are capable of detecting some latent information after processing the data by using artificial intelligence algorithms. Such information is usually in the form of patterns that can be transformed into recommendations, predictions, etc., e.g. "*Students like you who had not accessed to the classroom for 2 weeks during the last semester dropped out! Visit your classroom!*". Hence, a PI system that uses data analysis techniques becomes a pro-active tool that suggests actions to the users. The only two drawbacks of such techniques are that the users rely on the accuracy of the information proposed by the tool and its high cost of development.

3 | RELATED WORK: EDUCATIONAL PERSONAL INFORMATICS SYSTEMS

In this section we review the most relevant educational PI systems that have been proposed so far. At this point it should be noted that most of them are identified as learning dashboards in the literature. For this reason, we delimit which of these tools are PI systems as follows: educational PI systems are those tools that target students, mainly give information about the individual user, their visual appearance is in the form of a dashboard and, at the same time, allows learners to store either data on the learning process that is performed outside the learning platforms (i.e. offline) or data that are based on the reflection on her own performance.

Taking the previous definition of educational PI systems into account, it should be noted that, although PI systems have proved to be useful for helping users to be self-regulated in different domains, limited research exists on such tools in learning scenarios, whether online or not. Furthermore, as it is an emerging area of research, the few proposals that exist focus on different issues and settings, though the main goal is always to help students be self-regulated.

CALMsystem [19] could be considered as one of the first educational PI systems. This asks students for providing self-assessment ratings on how they perceive their current knowledge on different topics. With this information, CALMsystem is able to provide a student with her learner model via a simple dashboard in the form of a table that is made up of a text and an emoticon for each topic. This visualization offers the student the opportunity to compare her own assessment of her with that inferred by the system. Thanks to CALMsystem, students are encouraged to reflect on their knowledge so they can be helped to develop autonomy over their learning and improve the metacognitive skills that lead to enhanced self-assessment.

As seen, the previous PI system attaches great importance to the data analysis (i.e. the inference), being the visualization very simple. In contrast, the Student Activity Monitor (SAM) [14] goes a step further in terms of data visualization. More specifically, SAM displays a dashboard with 3 areas with different visualizations: (1) a chart pane that allows the learner to switch the chart to compare, simultaneously, the students of a course in terms of the time expenditure and document usage; (2) statistics based on global course data; and (3) a recommendation pane that enables graphical navigation through the most used documents and those on which the most time has been spent. Besides using data generated by the PLE, SAM uses data stored by the students explicitly. More specifically, learners send Twitter a message with hashtags to identify it as time tracking message and a description of the task and duration.

Similarly, StepUp!, in its first version [33], was a system that empowered second year engineering students to reflect on their own activity and that of their peers in a course in which the learners developed software in Java. Thus, StepUp! 1.0 provided students with data about the time spent with different tools, such as Eclipse IDE documents. The time spent was tracked by RescueTime and the Rabbit Eclipse plug-in. Both tools had to be installed and run by the students in their computers. Later, a general-purpose version, StepUp! 2.0, was launched [35]. This new release did not focus on monitoring a set of tools related to Java programming, but it tried to give general information about any course by using different learning traces, such as time spent on the course (by forcing student to use the time tracker Toggl); wiki, blog and Twitter use; etc. Its interface also changed from a set of widgets to a big table.

Finally, Michel et al. [26] proposed DDART, an educational PI system for project-based learning that provides learners with high-level personalization functions that allow them to choose the traces, the calculation mode and the visualization associated to their indicators. The indicators are based on the combination of activity and reporting traces. The former correspond to users' actions stored automatically by the LMS, while the latter are reported by the learners themselves to explain how they have performed their activities out of the learning environment.

4 | GLANCE: AN EDUCATIONAL PI SYSTEM

We developed two versions of an educational PI prototype called Glance to know to what extent online students perceived such systems useful for helping them to be self-regulated. Next, we explain how Glance was designed by using the five-stage model detailed in Subsection 2.3.

4.1 | Preparation

The following student data were stored: (1) finished and delayed activities; (2) grade of each continuous assessment assignment (CAA); (3) number of unread, read, posted and replied messages; and (4) dates in which learners logged in, finished an activity and read/posted/replied a message. The collection of such data by the system was principally non-intrusive and required no user intervention, except for: 1) the completion of an activity, which was marked by the students manually, and 2) the grades of the CAAs, which were put by the teachers. Hence, Glance combined data that were automatically stored by the online learning platform and data recorded by the students, what distinguishes it from a learning dashboard.

As seen, all the collected data were linked to the learning process regardless of the tools or services, such as Moodle, Twitter, etc. This allows Glance to be a general-purpose PI system whose usage and results may become widespread across the whole educational community.

4.2 | Collection

The data that were automatically stored by the system (e.g. number of read messages) were captured in real time. The frequency of collection of the rest of data depended on either the learner (for activity's completion) or the teacher (for the grades of the CAAs).

4.3 | Integration

The data used in Glance were stored and extracted from the relational database of the tool. This fact made the use of the data easier. In fact, this phase was practically non-existent.

4.4 | Reflection

Glance (see Figure 1) was a web-based PI system that looked like a dashboard and used information visualization (IV) techniques to provide students with useful information. Such a design is in line with the recommendation of Duval [10].

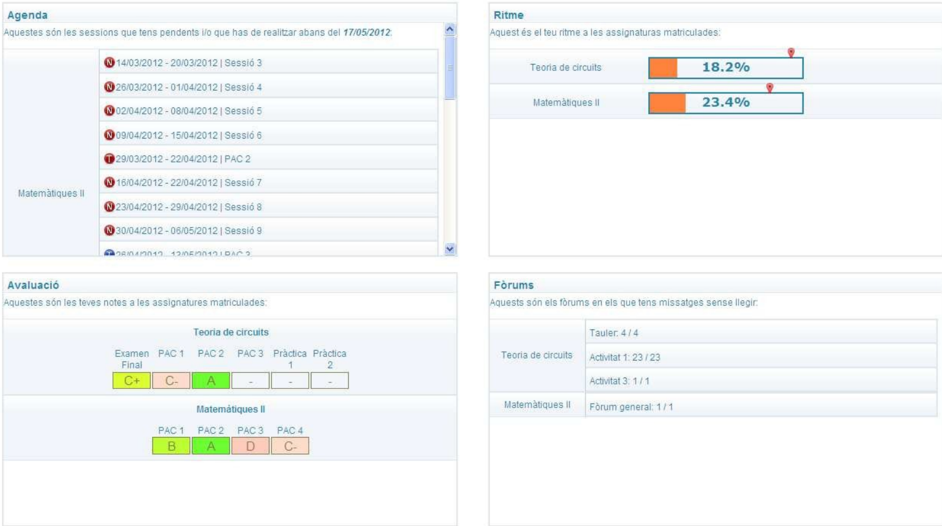

Figure 1. Glance's information areas (left to right, top to bottom): schedule, pace, assessment, and forums.

In contrast to other proposals, Glance did not only focus on giving a student awareness of each of the courses in which she was enrolled individually, but it also provided an overview of the learner's status in all her courses. As a result, the student simultaneously had both a fine-grained (i.e. each individual course) and a coarse-grained vision (i.e. the overview of all the courses). To this end, Glance consisted of four areas which summarized different types of information: 1) schedule, 2) pace, 3) assessment, and 4) forums. They are explained below. As it will be seen, Glance avoided using charts and graphics that could be complex to students. In fact, it did not use bar and line charts or large tables or network graphs which, according to [3, 38], are the most frequently employed visualizations in dashboards. Instead, Glance prioritized the use of simpler mnemonic symbols and visual inputs, e.g. colors and letters.

4.4.1 | Schedule

This area (top left in Figure 1) showed the sessions (similar to an F2F lecture with one or more activities) that had to be performed in the next 15 days and the ones that were already delayed.

All sessions were ordered by the deadline ascendingly, regardless of the course to which the sessions belonged. Moreover, each session was colored according to its status as follows:

- **Green**: the student had completed all the tasks related to that session.
- **Blue**: the session had not been completed yet and moreover the current date was previous to the session's finish date.
- **Red**: the session was not complete and its deadline was prior to the current date.

Besides the colors, three letters were used to indicate the assessment type of the sessions:

- **Letter *T***: a totally graded session, i.e. all its activities belonged to some CAA.
- **Letter *P***: the session was partially graded, i.e. it included normal and graded activities.
- **Letter *N***: the session was normal/no graded, i.e. it only had normal activities.

When a session was clicked, the platform displayed all the activities related to it. Each activity also had a status color and an assessment letter (T or N). The completion of a session/activity was marked by the students manually. Likewise, the sessions were automatically marked as complete when all their activities were finished and vice versa.

This area aimed to help learners become more organized. Thanks to the information provided, learners could develop a better personal study plan by taking the status of their learning process (i.e. sessions' status) and the time they had available into consideration.

4.4.2 | Pace

This information area (top right in Figure 1) compared, for each course, the learner's studying pace (in orange) with the course pace (predefined by instructors and indicated by a red marker). This allowed the students to be aware of whether they were on time, behind or ahead of the ideal pace. This area was related to the functionality of marking a session/activity as finished.

4.4.3 | Assessment

For each subject, this area (bottom left in Figure 1) displayed its CAAs and the grades that the student had obtained. Each grade had a color to easily show the assessment progress in each course. Thus, the best grade (i.e. A) was green, while the worst one (i.e. D) was colored in red.

4.4.4 | Forums

This part (bottom right in Figure 1) –only available in the second prototype, i.e. Glance 2.0– was devoted to showing the unread messages of the discussion forums of each subject. If a forum was clicked, then its content was displayed in a pop-up window.

4.5 | Action

Glance did not use any data analysis method and, therefore, it did not suggest any action. However, some visual cues gave insights into the learning process that had an implicit action to perform. For instance, a task in red suggested doing that delayed activity as soon as possible.

5 | METHODOLOGY

In terms of evaluation, most of the proposals described in Section 3 were exploratory and thus the scarcity of long-term evaluations is noteworthy. Moreover, they were not deployed in online learning courses. For this reason, this research aimed to evaluate the usefulness of educational PI systems via two versions of Glance over a long period of time, namely one semester, and in two fully online courses. Next, the research methodology that was used is detailed.

5.1 | Research question

This study mainly addressed one research question: do online students perceive personal informatics systems useful for helping them to be self-regulated?

5.2 | Research design

In order to address the aforementioned research question, each version of Glance was tested in two half-yearly fully online undergraduate courses offered at the Universitat Oberta de Catalunya (UOC) for one semester (i.e. 5 months approx.). Since two tests were conducted, we tried to control, as much as possible, those factors that could change from test to test and, hence, could influence the results. To this end, we performed the following actions:

- The teachers in charge of the two courses attempted that both their attitudes and the difficulty of the CAAs and exams were similar to those of the previous test/semester.
- Each teacher was monitored daily so that we could ensure that the behaviors of the different instructors were practically identical.

Likewise, the use of Glance was mandatory for all the students during the two tests. As a result, the participants had used the platform in depth and, hence, their opinions were well-founded. At this point, it should be emphasized that the evaluations performed by many related works (see Section 3) were based on specific sessions in which students used the PI system for the first time for a short period of time (i.e. 10-30 minutes) by performing different tasks. For example, DDART [26] and SAM [14] were evaluated in one and two evaluation sessions, respectively, whereas StepUp! 1.0 [33] was evaluated by the students after using it for only 10 minutes. Likewise, CALMSystem [19] was used during 60-minute sessions over a period of 2 weeks, while StepUp! 2.0 was deployed for one month [34] or six weeks [35] at most. Moreover, in some works the use of the PI system was not mandatory (e.g. the first case study of StepUp! 2.0 [35]) or the students interacted with simulated data (e.g. StepUp! 1.0 [33] and DDART [26]).

5.3 | Instruments

At the end of each test, a web-based self-administered questionnaire was sent to the students. Most of the questions used a 5-point Likert scale, but also there were some open text questions.

5.4 | Participants

Participants were undergraduate students recruited from the following two half-yearly fully online undergraduate courses offered at the Universitat Oberta de Catalunya (UOC):

- **Electric Circuit Analysis**: this subject taught concepts related to electric circuits, e.g. Ohm's law. Regarding the assessment, three optional CAAs were suggested by the teacher. In order to pass the course, students had to take an on-site final exam.
- **Mathematics II**: this focused on continuous-time and discrete-time Fourier transforms. Students were free to do 4 CAAs, but they had to take a mandatory final exam on site.

As for the two tests, 42 and 44 students filled out the questionnaire, which meant a response rate of 36.5% and 38.3%, respectively. Both response rates are greater than the average response rate for online surveys, which is about 33% [27]. Hence, the response rates for the two tests can be considered as good. Moreover, the number of respondents for each test is higher than the one in other related works. For example, SAM [14] and DDART [26] were evaluated by 12 students each, while CALMsystem [19] and StepUp! 1.0 [33] were evaluated by 30 and 36 learners, respectively. Likewise, the total number of respondents for Glance was 86.

Since the present research focused on the usefulness of PI systems in fully educational online environments, we had to guarantee that the participants were an acceptable and representative sample of all online students. In this regard, considering the archetype of online learner described by the literature [9], we can state that the profiles of the respondents and the target population were practically identical, i.e. older than 25 (92.9% in the first test and 88.6% in the second one) and with online learning experience (92.9% and 84.1% enrolled in the UOC at least 3 semesters, respectively). The only exception was that most of the respondents were men (95.2% and 86.4%, respectively), what is not surprising if we consider that the two courses belonged to a STEM degree in which there are usually more men than women.

5.5 | Data analysis

Due to the nature of data, these were considered as nonparametric. Likewise, as each version of Glance was evaluated by two groups/courses, a Mann-Whitney (MW) test was conducted for each aspect that was asked to find whether the two groups disagreed. In general, the results showed the groups of each test had a similar opinion.

6 | RESULTS

Next we present the results from the questionnaires. These are divided into three parts: (1) Glance as a whole, (2) the information areas, and (3) some visual inputs.

6.1 | Overall evaluation of Glance

When the students of both versions of Glance were asked for assessing the tool as a whole, 82.9% in the first version and 81.8% in the second one rated it 3 (*fair*) or greater (see Table 1). As shown in the box plots of Figures 2 and 3, the distribution of the responses was left-skewed, its variability was low (IQR=1.25 and 1, respectively) and the respondents who rated it 1 (*very poor*, Glance 1.0: 7.3%; Glance 2.0: 4.5%) were outliers in the two tests (i.e. $q < Q_1 - 1.5 \cdot IQR$). This means that the mass of the distribution was concentrated on the higher values. In fact,

<table>
<tr><th rowspan="2"></th><th colspan="6">Version 1.0</th><th colspan="6">Version 2.0</th><th colspan="6">Total</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>N</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>N</th><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>N</th></tr>
<tr><td rowspan="2">Glance</td><td>3</td><td>4</td><td>11</td><td>13</td><td>10</td><td>1</td><td>2</td><td>6</td><td>13</td><td>15</td><td>8</td><td>0</td><td rowspan="2">5</td><td rowspan="2">10</td><td rowspan="2">24</td><td rowspan="2">28</td><td rowspan="2">18</td><td rowspan="2">1</td></tr>
<tr><td colspan="6">U = 161.5, Z = -1.237, p = .216</td><td colspan="6">U = 203, Z = -.940, p = .347</td></tr>
<tr><td rowspan="2">Schedule area</td><td>4</td><td>4</td><td>10</td><td>12</td><td>9</td><td>3</td><td>4</td><td>9</td><td>11</td><td>8</td><td>12</td><td>0</td><td rowspan="2">8</td><td rowspan="2">13</td><td rowspan="2">21</td><td rowspan="2">20</td><td rowspan="2">21</td><td rowspan="2">3</td></tr>
<tr><td colspan="6">U = 141, Z = -1.266, p = .205</td><td colspan="6">U = 213.5, Z = -.675, p = .500</td></tr>
<tr><td rowspan="2">Pace area</td><td>2</td><td>3</td><td>9</td><td>14</td><td>12</td><td>2</td><td>5</td><td>8</td><td>12</td><td>8</td><td>10</td><td>1</td><td rowspan="2">7</td><td rowspan="2">11</td><td rowspan="2">21</td><td rowspan="2">22</td><td rowspan="2">22</td><td rowspan="2">3</td></tr>
<tr><td colspan="6">U = 149.5, Z = -1.313, p = .189</td><td colspan="6">U = 175, Z = -1.395, p = .163</td></tr>
<tr><td rowspan="2">Assessment area</td><td>3</td><td>2</td><td>9</td><td>15</td><td>11</td><td>2</td><td>1</td><td>3</td><td>17</td><td>13</td><td>10</td><td>0</td><td rowspan="2">4</td><td rowspan="2">5</td><td rowspan="2">26</td><td rowspan="2">28</td><td rowspan="2">21</td><td rowspan="2">2</td></tr>
<tr><td colspan="6">U = 190, Z = -.157, p = .875</td><td colspan="6">U = 188, Z = -1.321, p = .186</td></tr>
<tr><td rowspan="2">Forum area</td><td colspan="6" rowspan="2">Not evaluated</td><td>1</td><td>7</td><td>10</td><td>10</td><td>16</td><td>0</td><td rowspan="2">1</td><td rowspan="2">7</td><td rowspan="2">10</td><td rowspan="2">10</td><td rowspan="2">16</td><td rowspan="2">0</td></tr>
<tr><td colspan="6">U = 212.5, Z = -.709, p = .479</td></tr>
</table>

Answers were provided in a 5-point Likert scale (1-very poor, 5-very good).
The column *N* indicates the number of “no response” answers.
The mode is in bold type.

Table 1. Evaluation of Glance by the students in the two tests along with the results of the Mann-Whitney tests.

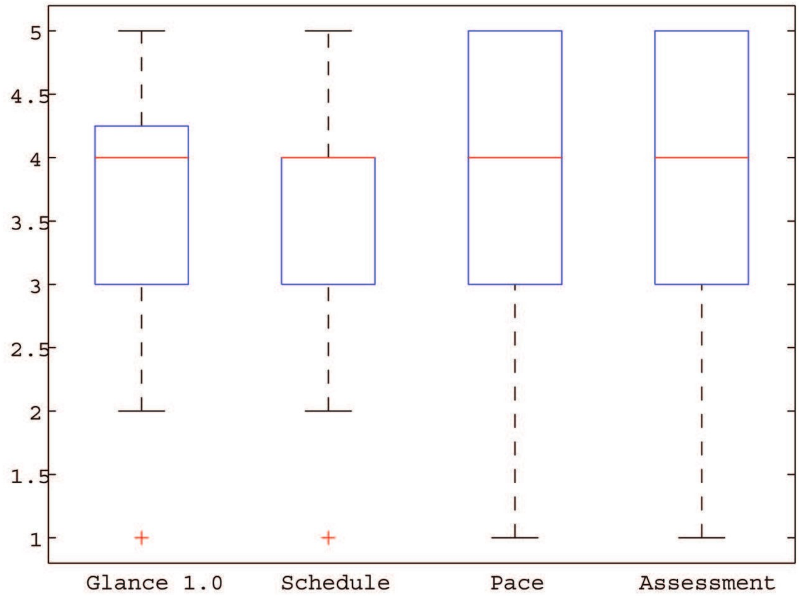

Figure 2. Box plots of the evaluation of Glance 1.0 by the students.

56.1% for Glance 1.0 and 52.3% for Glance 2.0 rated it 4 (*good*, 31.7% and 34.1%) or 5 (*very good*, 24.4% and 18.2%), being the median and the mode equal to 4 (*good*) in both prototypes.

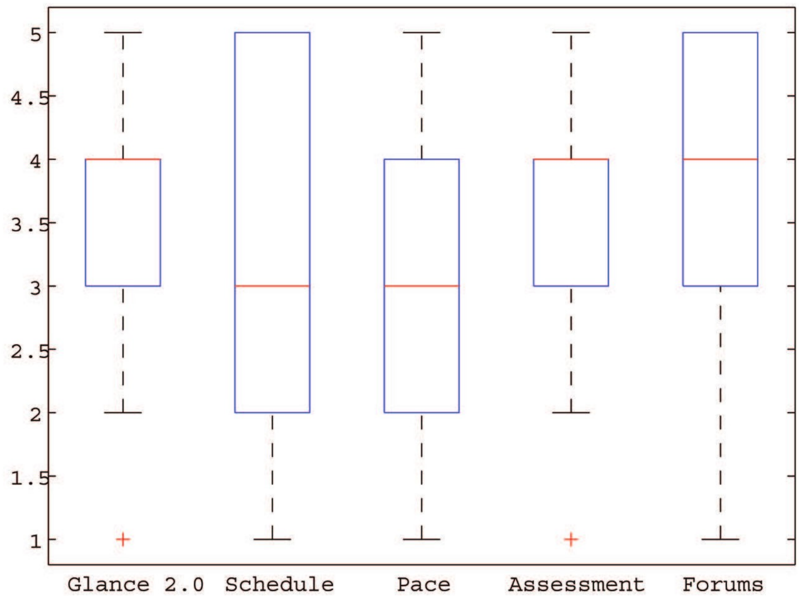

Figure 3. Box plots of the evaluation of Glance 2.0 by the students

v_i	n_i	p_i	P_i
1 – Nothing	2	4.5%	4.5%
2 – Little	4	9.1%	13.6%
3 – Normal	8	18.2%	31.8%
4 – Quite a lot	**19**	**43.2%**	75%
5 – A great deal	11	25%	100%
	n = 44	$\sum p_i = 100\%$	

The mode is in bold type.

Mw test: U = 175.5, Z = -1.637, p = .102

Table 2. Breakdown of to what extent Glance 2.0 helped the students to be aware of their situation in the course.

The students of the second prototype were explicitly asked: *"to what extent did Glance 2.0 help you to be aware of your situation in the course?"*. As shown in Table 2, the mode and median were 4 (*quite a lot*, 43.2%), followed by the values 5 (*a great deal*, 25%) and 3 (*normal*, 18.2%). This meant that 68.2% of the respondents stated that Glance 2.0 had helped them to be aware of their learning process significantly (i.e. scores 4 and 5). Or, in other words, only 13.6% of the respondents thought that Glance 2.0 had not helped them to be self-aware (i.e. values 1 and 2). As shown in the box plot of Figure 4, the first quartile includes scores 1, 2 and some responses equal to 3, whereas the other three quartiles include scores 3, 4 and 5.

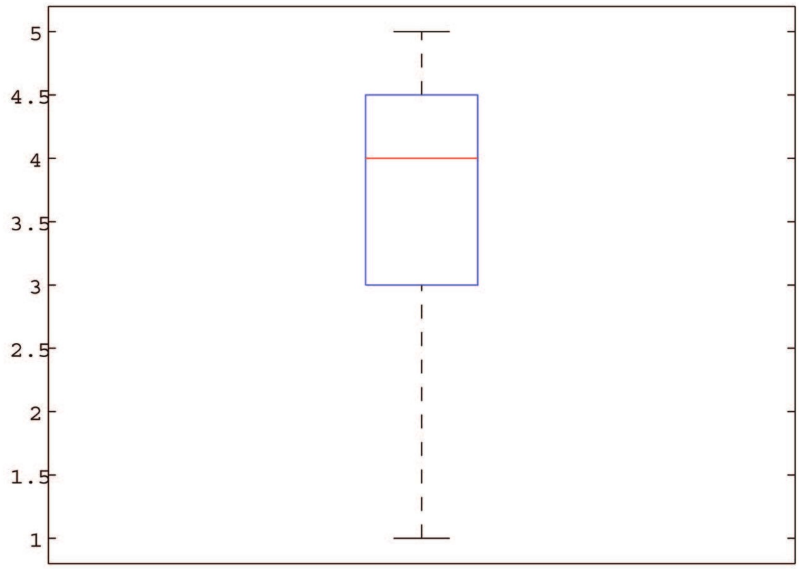

Figure 4. Box plot of to what extent Glance 2.0 helped the students to be aware of their situation in the course

6.2 | Evaluation of Glance's information areas

Besides evaluating Glance as a whole, each of its information areas was also evaluated individually (see Table 1, Figures 2 and 3). As for Glance 1.0, the forum area was not assessed, since it did not exist. In any case, as shown in the results of the Mann-Whitney tests of Table 1, the opinion of the two groups in each test was similar for each of the information areas.

Regarding the schedule area, 79.4% and 70.5% of the respondents in Glance 1.0 and 2.0, respectively, found it *fair* (i.e. score equal to 3) or better. As for Glance 1.0, the mode and the median were 4 (*good*, 30.8%), whereas they were 5 (*very good*, 27.3%) and 3 (*fair*, 25%) for Glance 2.0, respectively. The results were better in Glance 1.0 because those who rated 1 (*very poor*, 10.3%) could be labeled as outliers (see Figure 2). Moreover, there was quite consensus in the answers of Glance 1.0 (IQR = 1) compared to those of Glance 2.0 (IQR = 3).

With regard to the pace area, this had different reception depending on the version of Glance. Regarding the first prototype, 87.5% of the students rated it 3 (*fair*, 22.5%) or higher. However, the evaluation of this area was surprisingly lower in the second version, with 69.8% of the answers equal or greater than 3. From the questionnaire, no explanation could be found.

As for the assessment area, the percentage of answers equal to 3 (*fair*) or higher was 87.5% in Glance 1.0 and 90.9% in Glance 2.0. As seen, this information area got a very good evaluation. In both tests, the median was 4 (*good*, 37.5% and 29.5%, respectively), while the most chosen score was 4 and 3 (*fair*, 38.5%) in Glance 1.0 and 2.0, respectively. The results were better in Glance 2.0, since the scores equal to 1 (*very poor*) were outliers (see Figure 3).

The fourth area, i.e. the one related to the discussion forums, was only evaluated in Glance 2.0 (see Figure 3). It obtained a mode equal to 5 (*very good*, 36.4%) and a median equal to 4 (*good*, 22.7%), being 81.8% of the responses equal or greater than 3 (*fair*, 22.7%).

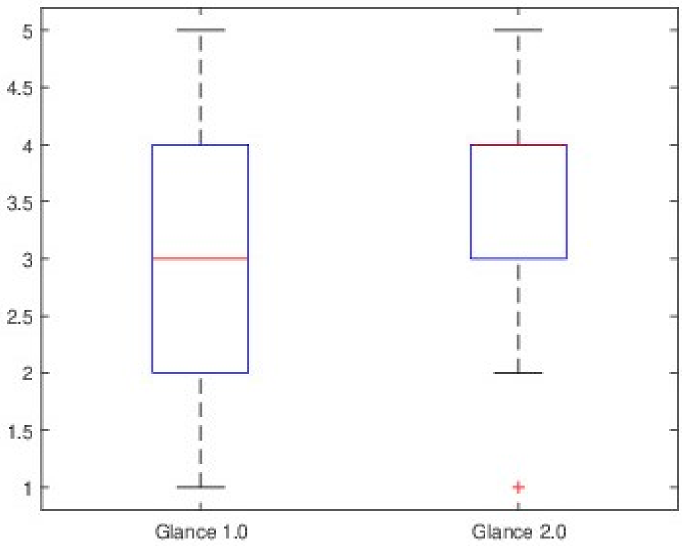

Figure 5. Box plots of the evaluation of the usefulness of the assessment letter in the two versions of Glance by the students

6.3 | Evaluation of several visual inputs

Apart from the information areas, some specific visual inputs were evaluated by the students too. One of them was the status color shown in the schedule area, which indicated if a session (and activity) was on time, behind or ahead of schedule. Over 85% and 93% of the responses were equal or greater than 3 (*neither useful nor useless*) in Glance 1.0 and 2.0, respectively.

Another visual input was the assessment letter. This item achieved a significant better result in Glance 2.0. Specifically, the percentage of responses equal or greater than 3 (*neither useful nor useless*) went from 73.2% in Glance 1.0 to 90% in Glance 2.0. Moreover, the median and mode were 4 (*useful*, 43.2%) for Glance 2.0, whereas they were 3 (28.6%) for Glance 1.0. Furthermore, the score equal to 1 for Glance 2.0 was an outlier (see Figure 5).

7 | DISCUSSION

The learners' opinions shown in the previous section indicate that Glance helped our students to be aware of their situation in the course and, consequently, to self-regulate their learning process better. This finding reinforces the results of other research works which state that PI systems are useful to students. For instance, StepUp! 1.0 [33] was evaluated in a Java course. The researchers first provided 36 students with information about a dummy user and later a subset of 10 students was provided with real data. The results from the questionnaires indicate the respondents found StepUp! 1.0 useful to learn how they were using the tools during the lab sessions. Moreover, they thought that such a tool could help them to achieve goals. Likewise, in StepUp! 2.0 [35], the authors conducted an experiment with 27 students for 6 weeks. The learners expressed that they had been very aware of their own efforts, just a little bit less aware of the efforts of the other members in their group, and less aware of the efforts by the rest.

Since self-reflection is one of the most critical phases of self-regulated learning, it is not surprising that many research studies, such as SAM [13, 14] and StepUp! [33], state that, according to the students' opinion, the main potential use of a PI system is to see how others are performing within the course and compare it with their own work. Hence, learners like to know not only about them but also about their classmates. This conclusion seems rather intuitive, since having information about you and your context helps to make better decisions. In self-regulated learning, making decisions lies in assessing the own academic success in order to adjust the future learning strategies. Consequently, a PI system can be useful for such an assessment. This is CALMsystem's case [19], a PI system which was evaluated by 30 students, aged 8-9 years old, during 60-minute sessions over a period of 2 weeks. The results showed that the system was effective in improving the self-assessment skills.

Lastly, the real impact of educational PI systems has been analyzed too, although this research is still young. For example, Santos et al. [34] concluded that StepUp! 2.0 had higher impact for students working in groups and sharing a topic than learners working individually.

8 | CONCLUSIONS AND FUTURE WORK

We have explained how a PI system can be beneficial to self-regulated learning, especially the online one. Moreover, we have introduced our educational PI system called Glance by using the stage-based model defined in [21]. In contrast to other educational PI systems, Glance was a general-purpose tool which did not show information about the courses enrolled one by one, but it displayed all the data related to all the courses simultaneously. Moreover, although Glance was clearly targeted to online undergraduate students, it used simple visualizations mainly based on colors and letters, instead of charts and more complex graphs. This fact allows Glance to be used, in the future, with learners who have different educational level (i.e. primary, secondary and tertiary education) and study in different learning settings (i.e. online or blended).

We have detailed the research methodology too. Unlike other research works, we tested two versions of Glance in two long-term tests. While the tests of other researches lasted six weeks at most, we conducted each test for one semester. Moreover, the number of respondents for each test was higher than the rest of the related works. Likewise, we have presented the results from testing Glance that, along with those of other research works, have furnished evidence of the usefulness of educational PI systems. However, more research is needed. For instance:

- **Impact**: the research on the effects of educational PI systems is still in its early stages and most of the studies are exploratory or proof-of-concept. In this regard, our results only show the perceived usefulness of an educational PI system, but such usefulness should be measured in terms of the impact that the tool has on students' performance too. This is a limitation of the present research and the related articles. For this reason, we want to conduct a quasi-experiment to compare the learning outcomes of one control group and one test group. The latter would use Glance, whereas the former would not.
- **Motivation**: this is a key aspect during the learning process. In this regard, adding gamification techniques could be a good solution.

- **Customization:** in line with DDART [26], a future research line may be to study how to enable learners to easily customize the indicators while avoiding cognitive overloading.
- **Guidance**: Glance did not give suggestions that guided students, thus it left the conclusions in learners' hands. Hence, we plan to use algorithms that utilize the stored data to infer new information that allows us to give some advice.

As seen, educational PI systems are part of an incipient field which can be very beneficial to students. For this reason, we believe that a sustained research on PI systems is necessary.

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