A Dashboard for Learning Paths Visualization in Distance Education.

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Abstract: In Distance Education, Virtual Learning Environments (VLEs) usually collect and store rich datasets of students' interactions with the learning environment. However, most reports offered by these tools do not offer teachers a detailed and easy-to-understand representation of the paths students take during their learning processes. This work proposes a dashboard to help teachers working in Distance Education explore students' learning paths in an easy and intuitive way. The tool was developed using an iterative design process and evaluated with real data in a usability study involving teachers from a public school which offers online secondary courses. The results show that teachers could obtain several types of insights from the dashboard and also devise possible data-informed pedagogical interventions. Also, results from the EFLA perceived usefulness questionnaire suggest that the tool can be useful to teachers working in Distance Education.

Keywords: dashboards, distance education, data visualization, learning paths.

Um Dashboard para Visualização de Trajetórias de Aprendizagem em Cursos à Distância.

Resumo: Na Educação a Distância (EaD), os Ambientes Virtuais de Aprendizagem (AVAs) coletam e armazenam ricos conjuntos de dados relativos às interações dos alunos com o ambiente. Contudo, a maioria dos relatórios oferecidos pelos AVAs não oferece aos professores uma representação detalhada e de fácil compreensão dos caminhos percorridos pelos alunos durante seus processos de aprendizagem. Este trabalho propõe um *dashboard* para ajudar professores que atuam na EaD a explorar as trajetórias de aprendizagem dos alunos de forma fácil e intuitiva. A ferramenta foi desenvolvida por meio de um processo de design iterativo e avaliada com dados reais em um estudo de usabilidade envolvendo professores de uma escola pública que oferece cursos técnicos à distância. Os resultados mostram que os professores puderam obter vários tipos de *insights* utilizando a ferramenta e também conceber possíveis intervenções pedagógicas baseadas em dados. Além disso, os resultados do questionário de utilidade percebida EFLA sugerem que a ferramenta pode ser útil para professores que trabalham na EaD.

Palavras-chave: dashboards, educação à distância, visualização de dados, trajetórias de aprendizagem.

1. Introduction

With the widespread use of Virtual Learning Environments (VLEs) to mediate teaching and learning activities, especially in Distance Education, it has become possible to collect and store a large amount of data relating to students' interactions with these platforms, such as number and timestamp of accesses to the environment/learning materials, completion of assignments, student communication with teachers, tutors, and other students, among other information. The challenge of analyzing and extracting knowledge from these datasets led to the emergence of Learning Analytics (LA) (WISE, 2019), an area of research that aims to understand and improve teaching and learning processes through the analysis of data collected in educational contexts.

Among the various actors who can benefit from the analysis of educational data are teachers who work in distance learning courses (LOCKYER; HEATHCOTE e DAWSON, 2013). Given the communication difficulties between teachers and students in this context, teachers are often unable to monitor the class's progress or identify students with learning difficulties in advance, which makes the practice of formative assessment challenging (SEDRAKYAN *et al.*, 2018). In this scenario, tools that present the data collected by VLEs in an easily understandable way can help teachers identify students with learning difficulties early on and also reflect and improve their pedagogical practices and the course instructional design (LOCKYER; HEATHCOTE e DAWSON, 2013; MANGAROSKA e GIANNAKOS, 2019).

In Learning Analytics, this type of tools are usually called Learning Analytics Dashboards (LADs) (SCHWENDIMANN *et al.*, 2017; VERBERT *et al.*, 2020). LADs are interactive interfaces that use Data Visualization techniques (MUNZNER, 2009) to communicate educational data in a easily understandable way through interactive graphical representations such as scatter plots, bar graphs, line charts, among others.

Although many previous works have proposed dashboards to help teachers monitor their students' learning (SCHWENDIMANN *et al.*, 2017; VERBERT *et al.*, 2020), most of these proposals are restricted to analyzing products of learning (e.g.: assignments delivered and formal assessments) or quantifying simple indicators (number of log-ins to the VLE, accesses to the course page, etc.), neglecting aspects related to the actual *process* of learning, such as the order in which the students access the learning resources. In other words, in current works learning is not analyzed as a continuous process over time (MOLENAAR e WISE, 2022; VIEIRA; PARSONS e BYRD, 2018; WISE, 2019).

Considering this gap, this work proposes the use of event sequence visualization (GUO *et al.*, 2022) and Data Storytelling (ECHEVERRIA *et al.*, 2018) techniques to represent and analyze students' learning paths in online courses. The remainder of the text is organized as follows: Section 2 presents the background and related research; Section 3 describes the materials and methods; Section 4 presents the results; and Section 5 discuss the conclusions, limitations and future work opportunities.

2. Background and Related Work

Several authors reinforce the importance of approaches based on Learning Analytics to analyze learning as a process. Wise (2019) classifies them as "temporal approaches", while Lockyer et al. (2013) propose the term "process analytics" to define the type of analysis that focus on the steps taken by students to complete a task or produce a certain result.

Sedrakyan et al. (2018) build a bridge between learning regulation theory, feedback theory and the design of Learning Analytics Dashboards, classifying the latter as feedback providers for different stakeholders, including teachers. The same authors argue that dashboards can provide four (not mutually exclusive) types of feedback: cognitive, behavioral, outcome-oriented and process-oriented feedback. In this work, the proposed dashboard focuses on the intersection between behavioral feedback, relating to the actions taken by the student to complete a task, and process-oriented feedback, which aims to improve the learning process before the end of cycles such as formal assessments. In this way, we aim to offer to teachers an improved representation of students' progress and their regulation needs during the learning process (SEDRAKYAN *et al.*, 2018).

From the point of view of Data Visualization literature, learning processes can be represented visually through event sequence visualization techniques (GUO *et al.*, 2022). These techniques propose visual metaphors and pre-processing strategies suitable for representing databases in which time is one of the dimensions. Learning process data collected by VLEs falls into this category, as they are normally stored as a sequence of student actions during their interaction with the environment. Another technique with the potential to assist in the visualization of this data is Data Storytelling, which provides principles for building visual narratives from data, guiding users in the process of extracting useful knowledge (insights) from the visualizations with which they interact (ECHEVERRIA *et al.*, 2018). Together, these techniques can help teachers identify the obstacles students face along their learning journey and the patterns that lead to academic success.

In current literature, few works propose interactive visualizations aimed at teachers in which learning is actually represented as a process (MOLENAAR e WISE, 2022; SCHWENDIMANN *et al.*, 2017; VIEIRA; PARSONS e BYRD, 2018). The ViSeq (CHEN *et al.*, 2020) and DropoutSeer (CHEN *et al.*, 2016) dashboards focus on identifying and visualizing patterns in massive open online courses (MOOCs), the first to analyze content exploration sequences and the second to identify patterns of evasion. However, besides the complexity of the visualizations proposed in these two works (both involves the use of advanced data visualization encodings such as custom glyphs and chord and arc diagrams) — which can lead higher learning curves to teachers with low or medium data visualization literacy (BÖRNER; BUECKLE e GINDA, 2019) — none of them ground their proposal in learning theories. In previous works (DOURADO *et al.*, 2020; DOURADO *et al.*, 2021), we proposed and evaluated dashboards for process analytics, but the evaluation of these tools with teachers showed the need to develop simpler and more intuitive visualizations for users with little experience with data analysis. These gaps motivated the work presented in this paper.

3. Method

The method used in this study follows the Design Activity Framework for Visualization Design (MCKENNA *et al.*, 2014), a specialized methodological framework proposed by the visualization community to guide the design of data visualizations through four "design activities": understand, ideate, make, and deploy. Figure 1 illustrates the phases of our method, composed of the first three design activities and an evaluation with users, which are described in detail in the following subsections. The "deploy" activity, which consists of deploying and evaluating the developed system in a production environment, is out of the scope of this study and thus left as future work.

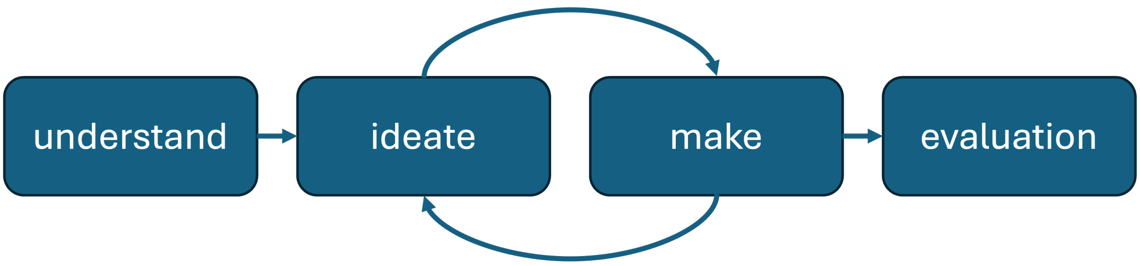


Figure 1. Phases of the method used in this work, based on the Design Activity Framework for Visualization Design (MCKENNA *et al.*, 2014).

3.1. Understand activity

In the "understand" activity, the goal is to understand the problem domain, the datasets it produces, and identify the user needs. To fulfill these goals, we started with a narrative literature review on visualization of temporal event sequences, Learning Analytics, and Data Storytelling. After that, we analyzed the project's dataset, which consists of records of interactions between students of online vocational courses offered by a public school on the Moodle Virtual Learning Environment. Finally, the user requirements for building the tool were defined based on the results of a previous work (DOURADO *et al.*, 2020; DOURADO *et al.*, 2021), where we interviewed 16 teachers from the aforementioned public school.

3.2. *Ideate* and *Make* activities

In the second and third activities, we iteratively developed a set of low- and high-fidelity prototypes in order to test different visualization possibilities for the dataset. Several designs and visual representations were considered, initially conceived as low-fidelity prototypes and then implemented to verify their feasibility. These designs were discussed in regular meetings of the project team, and those considered as most promising were integrated into a dashboard, which will be presented in detail in Section 4. The dashboard was implemented as a web application using HTML, CSS, JavaScript and D3.js[1] a specialized JavaScript library that enables the development of non-standard and highly interactive data visualizations.

Finally, the original data was pre-processed in three steps to build a custom event sequence dataset to be used by the visualizations. First, only events related to student interactions with the environment and/or with other students/teachers were extracted from the database, via SQL scripts, removing events such as system logs and logs from other users (teachers, managers, etc.). Second, the logs were classified into a set of learning events according to categories defined in our previous interviews with teachers from the school mentioned in the previous subsection (DOURADO *et al.*, 2020). Finally, we used the "Temporal folding" simplification strategy for event sequence data (DU *et al.*, 2017) to reduce the volume of data, so that only the first occurrence of each type of learning event was kept.

3.3. Evaluation

We evaluated the dashboard with four teachers (3 female, 1 male; age average 34 years) from the same school that provided the Moodle dataset. We chose teachers from different backgrounds to enhance the sample heterogeneity, namely: Software Engineering, Environmental Engineering, and Business Administration.

The evaluation was conducted remotely and individually via Google Meet, with an average duration of 37 minutes per participant. Before the start of each meeting, we sent a Google Form where participants signed a consent form agreeing to participate in the study and authorizing the recording of their voices and screen. Then, they received a link for a tutorial video describing the dashboard and its main functions. After they finished the video, we reserved a moment for answering questions about the tool's functionalities.

After this introductory phase, we sent to the participant a link to access the dashboard (loaded with real data from a course taught in their school) and a list of analytical tasks that they should perform using the tool, which is reproduced in Table 1. As recommended in the visualization literature (LAM *et al.*, 2012; CARPENDALE, 2008), it is important to start the evaluation with a set of simple "warm-up" tasks so

[1] ⟨http://d3js.org⟩

users can familiarize themselves with the tool. “Task 0” in Table 1 served this function in our evaluation. After completing this warmp-up task and answering eventual questions about the dashboard, we asked the participants to perform tasks 1-3 without offering any help or further guidance.

Table 1. Analytical tasks used in the dashboard evaluation.

Task 0 (warm-up)	
Step	Instructions
0.1	At the top left corner of the screen, select Assignment 2 and proceed with the following tasks.
0.2	In the bubble chart (Grouped View), click on the bubble in the bottom left corner.
0.3	On the right side of the screen, in the “Histogram” chart (Distribution of grades), select the bar of the chart representing students with a grade of 5.
0.4	In “Selected Students,” choose the student “André Lima.”
0.5	Analyze and describe the learning path followed by this student.
Task 1	
Step	Instructions
1.1	Refresh the page.
1.2	Select “Assignment 1”.
1.3	Describe what you can perceive about the students’ behavior in the bubble chart (“Grouped View”).
1.4	In the bubble chart, click on the bubble representing the students who accessed the assignment on Wednesday.
Task 2	
Step	Instructions
2.1	In the “Histogram”, select the bar showing students with the lowest grades.
2.2	Select the student “Julia Lima” and add her to the “Individual Path.” visualization
2.3	Analyze and describe the activities carried out by this student.
Task 3	
Step	Instructions
3.1	Refresh the page.
3.2	Select ”Assignment 4”.
3.3	Identify the group of students who submitted the assignment on the last day of the deadline by selecting the corresponding bubble.
3.4	Considering the average grade for this assignment, select the bar in the “Histogram” representing the maximum grade, then select students “Melissa Cavalcanti” and “Kai Silva” to visualize their learning paths.
3.5	Similarly to the previous step, select the bar in the “Histogram” representing the minimum grade and then select students “Renan Ribeiro” and “Cauã Gomes” to visualize their learning paths.
3.6	Identify, by analyzing the paths of each student, the differences that resulted in the difference between the student with the maximum grade and the one with the minimum grade.

As a last step in our evaluation, we asked participants to answer the Evaluation Framework for Learning Analytics (EFLA) questionnaire (SCHEFFEL *et al.*, 2017), an instrument for assessing the perceived usefulness of Learning Analytics tools. The questionnaire is divided in four areas: data, awareness and reflection, and impact, and can be used with both students and teachers.

We analyzed the interview recordings quantitatively regarding task completion rates, errors committed, and help requests during the tasks (task 0 was not included in this analysis). We also transcribed (abridged) participants answers to the analytical tasks and analyzed them through Thematic Analysis (CLARKE e BRAUN, 2017) and deductive coding in search of insights and intervention opportunities triggered by the dashboard.

4. Results

In this section, we present the proposed dashboard, its main functionalities, and the results from its evaluation with real users.

4.1. Dashboard

Figure 2 presents the dashboard proposed in this work, which uses three graphical representations: a bubble chart (Figure 2 - B), a histogram (Figure 2 - C), and a Line chart (Figure 2 - D). These elements are arranged to guide the user through an analysis that starts with an overview (groups of students) and ends with an individual analysis of a student's learning path, following the "overview first, details on demand" guideline recommended by Shneiderman (1996). At the top of the dashboard (Figure 2 - A), the icons representing the learning events performed by students in the VLE are displayed in the "expected order", as mentioned by teachers that participated in the interviews conducted in our previous works (DOURADO *et al.*, 2020). The same set of icons is used throughout the dashboard. Also, please note that the students names are fictitious; they were assigned to the anonymized user IDs in the database using the mock data generator Mockaroo[2]to make the usability test closer to a real world scenario.

At the top of the dashboard, users can choose which assignment they want to analyze. Based on the chosen assignment, the dashboard updates the bubble chart (Figure 2 - B), which shows the number of students (represented by the size of the bubble) who performed each learning event for the first time (Y-axis) on each day of the week (X-axis). The bubbles are colored on a three-level color scale, according to the average grades obtained by the students in that group: green represents averages greater than or equal to 7, yellow represents averages greater than 4 and lower than 6, and red represents averages lower than 4. Thus, it is possible to analyze the relationship between how early students perform an action and the impact of that action on their performance.

By clicking on one of the bubbles in the bubble chart, the dashboard displays a histogram (Figure 2 - C) detailing the distribution of the students' grades contained in that bubble. The histogram allows for a more detailed analysis of the grades of each group (which may show considerable variation) using the same color scale as the bubble chart (red to green).

Finally, to analyze individual students, users can click on one of the bars in the histogram, which will update the list in the right table with all students who obtained that grade. By selecting a student from this list, the system displays a stylized line chart (Figure 2 - D) that describes the student's learning path during the assignment period, following the Data Storytelling principle of guiding the user through data analysis. The icons are connected by a horizontal line which slopes up and down according to the adherence of the student learning strategy to the expected path. When there is more than one event on the same day, they are stacked vertically. This arrangement aims to

[2]⟨https://mockaroo.com⟩

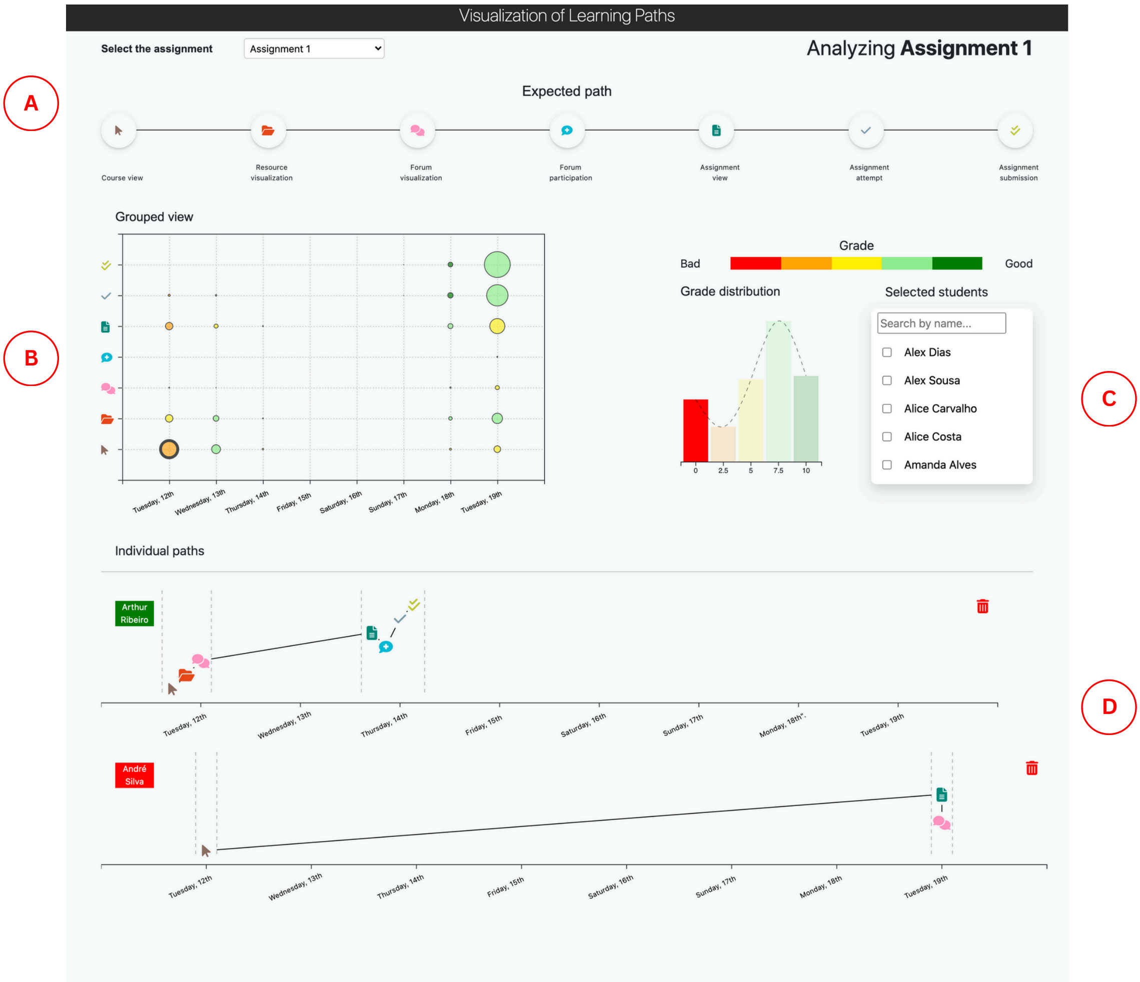


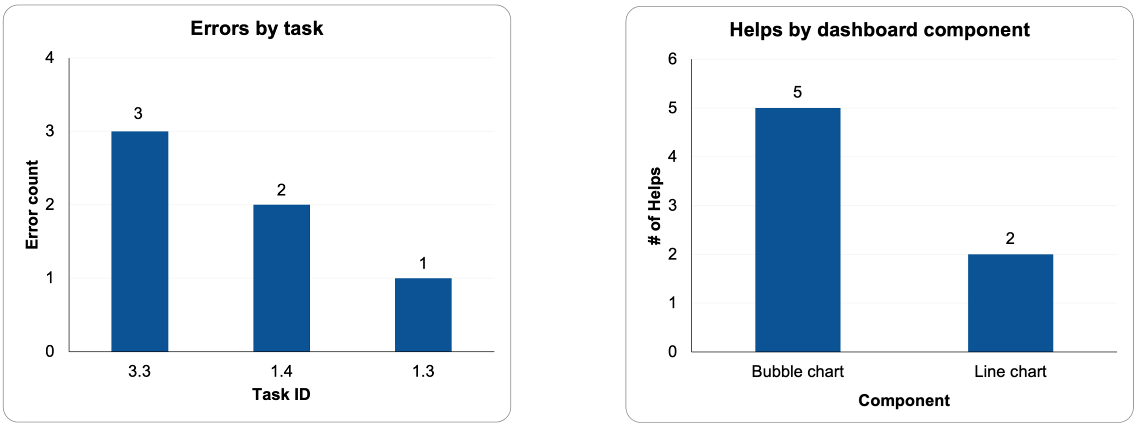
Figure 2. The proposed dashboard. The tool offers three visual representations: a bubble chart showing the overall class learning patterns (B), a histogram to show group details (C), and a line chart (D) individual path analysis. The names are fictitious and were created using the mock data generator Mockaroo to make the usability test closer to a real world scenario.

show how closely the student's path resembles the "ideal path" expected by the teachers (Figure 2 - A).

4.2. Evaluation

As stated in Section 3, we evaluated the dashboard through a user study where participants executed a set of analytical tasks and filled a perceived usefulness questionnaire (EFLA). In this section we present the results of this evaluation with respect to task completion, errors, help requests, insights and actions triggered by the dashboard, and scores in the EFLA questionnaire.

Task completion, errors, and help requests. All participants were able to finish the analytical tasks proposed in the study, with the exception of task 3.3 (c.f. Table 1), related to the Bubble chart, which one participant was not able to finish correctly. In fact, the Bubble chart was the component that participants had more difficulties working with. As can be seen in Figure 3 (a), all registered errors occurred in tasks associated with this component, which fell in one these three situations: i) difficulty in identifying which day corresponded to the assignment deadline (3 occurrences); ii) difficulty in identifying which bubble corresponded to each learning event (2 occurrences); and iii) confusion regarding the meaning of each event icon (1 occurrence). The results were similar for the total number of help requests participants made during the tasks execution. As shown in Figure 3 (b), participants needed more help with the Bubble chart, which is in line with the error rate with the same component. Although user errors in interfaces, especially by novice users, are normal and even expected to some extent (SHNEIDERMAN e PLAISANT, 2010), the errors and help requests involving the Bubble chart indicate that this component may need some refinement to guarantee a smoother user experience.



(a) Errors by task (b) Help requests by task

Figure 3. Participants errors (a) and help requests (b) while using the dashboard, by task

Insights. We also categorized the insights by type and the associated dashboard components that triggered them, as shown in Table 2. Insights related to students actions' timing and order (type 1), unexpected learning strategies (type 2), discovery of learner profiles (type 3), and auditing students' behavior (type 8) happened only through the interaction with the Line chart component, which is expected since it allows teachers to analyze students' learning paths individually and in detail. Insights related to the class study habits as whole (type 6) occurred only through the Bubble chart, which may indicate that this visualization succeeded in helping teachers to get an overview of the class behavior. Finally, insights related to good/bad learning strategies (types 2 and 3) and reflections about the course instructional design (type 7) occurred while using both the Line chart and Bubble chart components, with the difference that, as expected, the Line chart triggered more student-level insights and the Bubble chart more class-level insights.

Table 2. Types of insights identified, associated dashboard components, and example quotes from teachers.

#	Component(s)	Insight type	Example quote
1	Line chart	Action timing and order	"Renan tried to solve the exercise in the last day. He submitted the assignment and only then accessed the course resources" (P02)

#	Component(s)	Insight type	Example quote
2	Line chart, Bubble chart	Good learning strategies	"Melissa did a good job in accessing the course resources before trying to do the assignment" (P3, Line chart) "I see that those who handed out the assignment in the 19th obtained good scores" (P1, Bubble chart)
3	Line chart, Bubble chart	Bad learning strategies	"For what I could see, both students that got a bad grade did not accessed the discussion board. It is important to access the discussion board before you do the assignment" (P04, Line chart) "Students are not accessing the learning resources nor participating in the discussion boards... they are just logging in in the VLE, starting the assignment and handing it out. And this only in the last day of the deadline." (P01, Bubble chart)
4	Line chart	Unexpected learning strategies	"She did something out of order: she accessed the discussion board after submitting the assignment. Usually students access the discussion board before handing out the assignment." (P04)
5	Line chart	Learner profiles	"I can see that Kai is an exceptional student, probably with some previous knowledge on the subject. You can see that he did not needed to access the learning materials. Melissa, on the other hand, is a student that does everything in the last minute." (P01) "It's interesting because we can identify the learners profiles [...] we can see in detail his learning path." (P02)
6	Bubble chart	Study habits	"I can see that in the 19th a lot o students accessed the course, started to do the assignment and hand it out. Few access the learning resources or participate in the discussion boards; they go directly to the assignment and that's it, do not interact." (P01)
7	Line chart, Bubble chart	Instructional design	"It is a way we, teachers, can see how we are doing. If few students are accessing the discussion boards, these boards are not being an attractive place or students are seeing them as useful to help in the assignments" (P02, Bubble chart) "If the student gets a bad grade even though he/she follows all the expected learning path, maybe he/she has a different learning style? And how can the teacher address this?" (P01, Line chart)

#	Component(s)	Insight type	Example quote
8	Line chart	Auditing	“It shows that he did not accessed the learning materials but got a very good grade in the assignment. My guess is that he cheated, submitted the assignment using the answers of another student” (P01, Line chart)

Data-informed actions. Teachers also verbalized a set of actions that they could take based on the insights they extracted from the dashboard. The most cited ones were: recommend a specific learning strategy to a student, or a change in their current strategy when considered ineffective/risky; improve the course instructional design or the learning materials; identify students at risk based on their current learning strategies; identify groups of students with ineffective learning strategies; and use the data shown in the dashboard to help making decisions about student final approval in the course.

Perceived usefulness (EFLA questionnaire). The results obtained from the EFLA questionnaire, although not statistically significant due to the small sample size, indicate a highly positive perceived usefulness of the dashboard, achieving an overall score of 89.58/100. Regarding the individual EFLA dimensions, participants rated the *Data* dimension with a score of 93.6/100, indicating that participants considered the data provided by the tool as relevant, understandable, and beneficial for their educational practices. Similarly, the *Awareness and Reflection* dimension received a score of (89.58/100), suggesting that the tool effectively fostered users’ reflection and awareness of students’ progress and their own pedagogical strategies. However, the *Impact* dimension received a slightly lower score (81.94/100), which may imply that, although the tool was perceived as useful for providing information and encouraging reflection, there may be areas for improvement to ensure that it can successfully impact teachers’ daily work.

5. Conclusions

This work presented a dashboard to help teachers visualize students’ learning paths in online courses. The dashboard is grounded in the concept of behavioral process-oriented feedback and uses event sequence visualization and data storytelling techniques to visually represent learning paths. We evaluated the tool using a set of analytical tasks and the EFLA questionnaire. Four teachers from a public school which offers online secondary courses participated in this evaluation. The results show that teachers could obtain several types of insights from the dashboard and also devise possible data-informed pedagogical interventions. The results also suggest that the line chart visualization was easier to understand and use than the bubble chart. As future work, we intend to improve the dashboard based on the feedback obtained in this initial evaluation, incorporate more Data Storytelling techniques, allow users to customize the “ideal learning path” in order to allow personalized analysis, and conduct a larger user study.

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