# A Teacher-facing Learning Analytics Dashboard for Process-oriented Feedback in Online Learning

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## ABSTRACT

In online learning, teachers need constant feedback about their students' progress and regulation needs. Learning Analytics Dashboards for process-oriented feedback can be a valuable tool for this purpose. However, few such dashboards have been proposed in literature, and most of them lack empirical validation or grounding in learning theories. We present a teacher-facing dashboard for process-oriented feedback in online learning, co-designed and evaluated through an iterative design process involving teachers and visualization experts. We also reflect on our design process by discussing the challenges, pitfalls, and successful strategies for building this type of dashboard.

## CCS CONCEPTS

• **Human-centered computing**; • **Visualization**; • **Applied computing**; • **Education**;

## KEYWORDS

learning analytics dashboards, process-oriented feedback, online learning, visualization

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## 1 INTRODUCTION

In online learning, teachers need constant feedback about their students' progress and regulation needs [26, 31]. Such feedback is usually provided through Learning Analytics Dashboards (LADs) [25, 29]. Sedrakyan et al. [26] propose a conceptual model connecting learning regulation, feedback theory, and LADs design, where they define the concept of *behavioral process-oriented* feedback, focused on the "procedural aspects of learning" [26]. In a later work [27], Sedrakyan et al. recommends visual encodings for each feedback type but argue that more empirical research is needed to test and refine the proposed recommendations — a persistent issue in LADs research, according to Verbert et al. [29]. Besides, recent literature reviews report few works on the design and evaluation of LADs for process-oriented feedback [30, 31], and even those are either not grounded in learning theories or lack empirical validation [25, 29, 30].

Targeting this gap, this paper presents preliminary results of an on-going work to design and evaluate a theory-grounded LAD tailored for teachers in online learning and focused on behavioral process-oriented feedback. We present data and task requirements collected through interviews and co-design workshops, a dashboard design, results of an evaluation with visualization experts, and reflections based on the first two iterations of our design process.

## 2 BACKGROUND

Several authors discuss Learning Analytics approaches for analyzing learning as a process. Wise [31] classifies them as "temporal approaches", while Lockyer et al. [16] propose the term "process analytics" to define analyses concerned with the *steps* taken by students to complete a task or produce a given outcome. Sedrakyan et al. [26] builds the bridge between learning regulation, feedback theory, and LADs design by looking at dashboards as providers of feedback for different stakeholders, including teachers. The same authors argue that LADs can provide four (not mutually exclusive) types of feedback: cognitive, behavioral, outcome-oriented, and process-oriented feedback. In our work, we focus on the intersection of *behavioral* and *process-oriented* feedback, which provides an "improved awareness of learning progress and potential regulation needs during the learning process" [26]. To further guide our design process, we adopt Barbara Rogoff's social participation theory [23, 24], which proposes to analyze learning as processes of *varying participation* (i.e. "participation" as a continuum, ranging from observation to active involvement in sociocultural activities) in three interdependent planes: community/institutional, interpersonal, and personal (please refer to [24:52–62] for details about each plane).

In the current literature, few works propose interactive teacher-facing LADs for process-oriented feedback in online learning [25, 30]. ViSeq [6] and DropoutSeer [7] focus on identifying and visualizing patterns in massive open online courses (MOOCs), the former for analyzing the sequences of content exploration, and the latter for identifying dropout patterns. CourseVis [17] and the work of Li et al. [15] provide some process-oriented visualizations, but they are not the focus of the dashboard. But the fact remains


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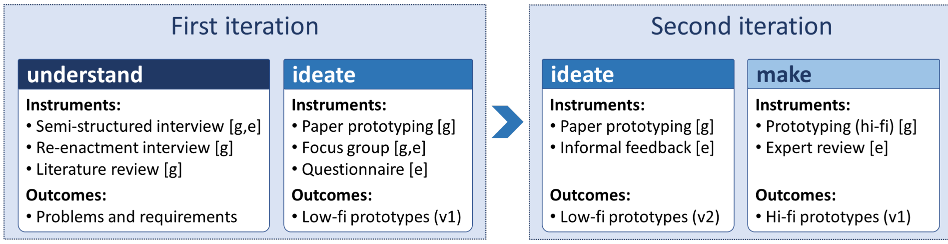


**Figure 1: The two iterations of our design method. The instruments are classified as [g]enerative (generate ideas/artifacts) and [e]valuative (evaluate produced artifacts), as defined by McKenna et al. [18].**

that none of the aforementioned works nor other related research [4, 12, 14] ground their design in learning theories, as recommended in current literature [13, 30, 31]. One exception is the work of Gómez-Aguilar et al. [11], but the authors do not validate the tool with end-users — a problem also present in [4, 12, 14].

## 3 METHOD

We frame our work as a design study [19]. Our method follows the Design Activity Framework for Visualization Design [18], which proposes an iterative process composed of four activities: understand, ideate, make, and deploy. As shown in Figure 1, we conducted two design iterations involving the understand, ideate, and make activities.

In the first iteration, we worked in cooperation with teachers from a public state school in Recife, Brazil, which offers free online vocational courses, mostly to students from underprivileged backgrounds. The instruments and procedures used in this iteration, detailed in a previously published work [8], are summarized below.

**First iteration — *understand.*** To understand the problem domain and the target users and their needs, we reviewed the literature on learning process visualization and interviewed ten teachers (gender: 8F, 2M; years of experience with online learning: mean 2.69, SD 2.48) using two types of ethnographic interviews. First, we conducted a *semi-structured interview* about the practices, challenges, and expectations on the use of process-oriented feedback in their work. Then, we carried out a *re-enactment interview* [21], where teachers were asked to demonstrate, using their own workstation, how they managed to obtain feedback from their students' learning process. Both interviews were conducted by the first author between March 26th and April 8th, 2019 in the school building. We analyzed the audio and video recordings using Ethnographic Content Analysis [2] with deductive open coding and the categories proposed by McKenna et al. [18].

**First iteration — *ideate.*** To generate and evaluate a set of ideas addressing the requirements identified in the previous "understand" phase, we developed six paper prototypes and evaluated them using focus groups. Nine teachers (gender: 5F, 4M; experience with online learning: mean 2.84 years, SD 1.7) participated in two focus groups (5 and 4 participants, respectively) held in one of the school's office rooms on August 22th, 2019 by the first author and another researcher. On each session, we presented and discussed the six prototypes, invited teachers to modify them using creativity toolkits, and asked them to evaluate each prototype by answering the question "This visualization can help me to better follow my students' learning process" using a five-point Likert scale ("1: Completely disagree" to "5: Completely agree"). We transcribed the audio recordings and analyzed them using Thematic Analysis [5] with deductive open coding and the categories proposed by McKenna et al. [18].

In the second iteration, conducted in cooperation with another HCI group during a research visit, we improved the low-fidelity prototypes and built the dashboard, as detailed below.

**Second iteration — *ideate.*** Based on the focus groups' results (first iteration, *ideate*), we discarded some prototypes, improved others, and devised new ones focused on aggregated learning patterns. We used paper prototyping as a generative method and informal feedback from senior researchers in data visualization as an evaluative method. As a result, we produced a new set of low-fidelity prototypes and a layout for the dashboard.

**Second iteration — *make.*** We developed the dashboard as a web-based application (Python and D3.js) and configured it to use a dataset provided by the same school where we conducted the interviews and focus groups (first iteration). This dataset consists of 9 months of anonymized interaction logs (March to November 2019) from a Moodle Learning Management System (LMS) with more than 70,000 students in 12 short-term courses. The courses are divided into four or five units and require four minor assignments plus a final exam. We evaluated the dashboard through an heuristics-based expert review to identify early usability problems [28]. As recommended by Tory and Moller [28], we conducted the reviews individually, starting by explaining the prototype's goal, context of use, target users, and dataset, and then asking each expert to: i) execute a simple warm-up task; ii) execute five pre-defined analytical tasks and simultaneously discuss eventual issues; and iii) fill a questionnaire about the dashboard compliance with Forsell & Johansson's heuristics set [10] using 5-point Likert scales. The five analytical tasks were: 1) search for a specific student and decide whether she deserved an increase in her grade for a given assignment; 2) identify which students in a given course unit did not follow a specific learning path; 3) check how many students in a given course unit submitted the assignment before posting on the forum; and 5) identify the most successful learning paths for a given assignment. Five Ph.D. students from the HCI research group participated as evaluators (1F, 4M; age average 26, 1.5—4 years' experience with data visualization). No participant had previous contact with the prototype, four had previous teaching experience, and two had previous experience or exposure to Learning Analytics. The sessions lasted between 0.5—2hs. We recorded and transcribed

**Table 1: Domain data mapped to abstract data types.**

| # | Domain data type | Abstract data type & attributes |
|---|---|---|
| 1 | Assiduity: access to the LMS over time | Table: timestamp/session duration, device, location |
| 2 | A - Access pattern to learning materials (single student) | Table: access order, context (material type, title, etc.) |
| | B - Access pattern to learning materials (group/class) | Tree: material type (nodes); access order (links); support and outcome results (attributes) |
| 3 | Assignments: access, attempts, and handouts over time | Table: timestamp, event type (vis., access, handout), grade |
| 4 | Student questions/help requests (forums, chat, etc.) | Table: timestamp, medium (forum, direct message, etc.), context (assignment, lecture, forum, etc.) |
| 5 | Progress in relation to course schedule/milestones | Table: timestamp, progress measure |
| 6 | Overall student trajectory in the course | Table: timestamp, event type, context |

the speeches and screen interactions and analyzed them using Thematic Analysis [5] with deductive coding (181 quotes were coded), focusing on the issues, strengths, and improvement opportunities.

# 4 RESULTS

In this section, we present the results from the two design iterations shown in Figure 1

## 4.1 Design Requirements

This subsection summarizes the design requirements identified during the first iteration of our method. A detailed description is available in a previously published article [8].

**Problems and opportunities.** Teachers reported that the LMS offers restricted feedback and, as a result, they tend to play a "reactive role" in the course: they cannot know that a student is struggling before s/he explicitly asks for help. They try to cope with this issue by performing a daily "checking routine" on the LMS discussion boards, direct messages, assignments submission status, and some simple reports. During the interviews, teachers repeatedly used the words "investigate" and "synthesize" when stating their expectations from the use of LMS logs for process feedback.

**Data and task abstraction**. As recommended by Munzner [19] and McKenna et al. [18], we mapped the domain data types (or "proxies" [31]) identified during the first iteration to the abstract data types defined in [19], as presented in Table 1. Likewise, we mapped the identified domain tasks to the abstract visualization tasks proposed by Plaisant & Shneiderman [22], as shown in Table 2

## 4.2 Dashboard Design

This subsection describes the dashboard developed in the second iteration of our method. Table 3 shows how we mapped the learning events available in the dataset to the data requirements described in Table 1

As shown in Figure 2, our dashboard is composed of four panels with coordinated views: Overview (A), Pattern Discovery (B), Details (C), and Legend (D). After choosing a course to analyze (A), users can get an overview of performance (A1) and participation (A2), select a subgroup of students and explore their learning patterns (B), and finally select one or more students to analyze their trajectory in detail (C). This layout is connected with the three planes of analysis defined by Rogoff [24]: (A) and (B) represent the cultural/institutional plane, (B) and (C) the interpersonal plane, and (C) the personal plane. We explain below the components of each panel in detail.

**Overview panel.** Although the charts in this panel do not focus on the learning processes, they are important as entry points for the analysis, as suggested by teachers during the focus groups. The participation chart (Figure 2 – A1) shows five participation levels — according to the percentage of days in the course that students accessed the LMS (≥60%, ≥40%, ≥20%, ≥10%, <10%) — and presents the result as a horizontal color coded bar chart (the color scale green—yellow—red is used throughout the dashboard to represent desirable/undesirable outcomes). Similarly, the performance chart (Figure 2 – A2) shows the distribution of grades (normalized as 0-100%) for the selected assignment as a histogram. Both charts allow brushing to select a subgroup of students for further analysis in the other views. A "Lookup" tab is also available (Figure 2 – A3), allowing teachers to search for specific students and visualize their trajectories in the "Details" panel (Figure 2 – C), thus supporting the analytical task #2 (Table 2).

**Pattern discovery panel — "Real time" tab.** The two tabs under "Pattern Discovery" allow teachers to discover or look for specific learning paths in their classes. The "Real time" tab (Figure 2 – B) serves the latter goal: it allows teachers to define a learning sequence and check which students followed it or not (within the chosen course unit period), thus being useful to monitor student progress in real time and supporting the analytical tasks #1, #3, #4, and #5 (Table 2). We represent this data using a Sankey-like diagram (Figure 2 - B) to emphasize how many students followed each path. The bands are color-coded to distinguish "NO"/"YES" paths and identified with the corresponding event icon. Users can interact with the chart by clicking on a band to see the list of students (right table), clicking on a node to collapse a path, hovering over a band/node to get a details tooltip, reordering the events in the sequence through drag and drop, and panning/zooming.

**Pattern discovery panel — "Retrospective" tab.** This tab (Figure 3 – A) allows teachers to discover common learning patterns and correlate them to assignment results (analytical tasks #1, #3, and #5 in Table 2). When the user chooses an assignment, the dashboard retrieves the students' learning sequences and applies the following simplification strategies (proposed in [9]) to each of them: i) *temporal windowing*, by removing all events outside the period defined by the assignment open date and the student last submission;

**Table 2: Domain tasks mapped to abstract visualization tasks[1]**

| # | Domain Tasks | Abstract Task(s) |
|---|---|---|
| 1 | *Evaluate the instructional design* (for course planning and learning materials evaluation) | T2 |
| 2 | *Investigate individual learning trajectories in detail* (for assessment purposes, knowing the students, their complaints, and their improvement needs better, and getting more information to answer their questions) | T1 |
| 3 | *Identify patterns* (to give advice on learning strategies, improve learning design, and prevent evasion) | T7, T2 |
| 4 | *Compare the progress of a student/group of students against expected goals/milestones* | T3 |
| 5 | *Find struggling or "idle" students* | T5 |

**Table 3: Mapping of the learning events in the dataset to our data requirements.**

| Glyph | Event | Domain datatypes | Glyph | Event | Domain datatypes |
|---|---|---|---|---|---|
| | Accessed the course | 1, 5, 6 | | Posted on a forum | 2, 4, 5, 6 |
| | Accessed a learning resource | 2, 5, 6 | | Visualized an assignment | 2, 3, 5, 6 |
| | Sent a direct message | 4, 6 | | Attempted to solve an assignment | 3, 5, 6 |
| | Read a message | 6 | | Submitted an assignment | 3, 5, 6 |
| | Accessed a forum | 2, 5, 6 | | Downloaded a learning resource | 2, 5, 6 |
| | Subscribed to receive forum updates | 2, 6 | | | |

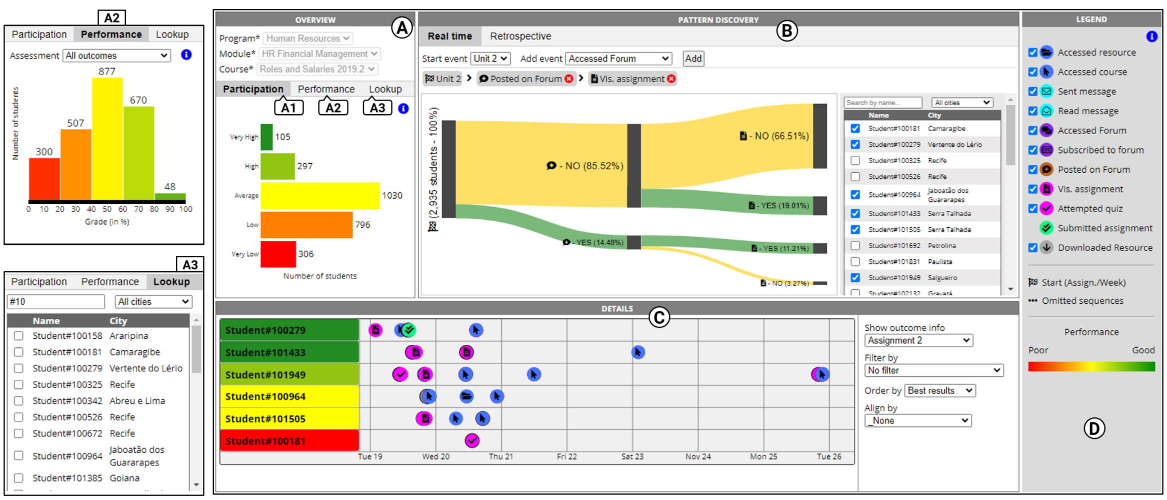


**Figure 2: Dashboard layout with four panels: A) "Overview", for general course information; B) "Pattern Discovery", for real-time and retrospective pattern analysis; C) "Details", for individual students' learning path analysis; and D) legends and event selection.**

ii) *goal-driven record/category extracting*, by removing submissions related to other assignments and the "accessed the course" event (high occurrence but low relevance in this context); and iii) *temporal folding*, by keeping only the first occurrence of each event type in the sequence. We then group identical sequences to build a tree with the most common learning paths. The nodes represent the learning events and, when at the end of a learning path, are colored according to the subgroup's pass rate. A special node called "Others", under the root node, represents the discarded sequences (below the support threshold chosen in the "Simplification level" option). Finally, the link's thickness represents the percentage of students that followed the respective path. Users can interact with the visualization by: clicking on a node to see the list of students that followed path (right table); collapsing branches by ctrl-clicking on nodes; hovering on a node to highlight the corresponding path and get a tooltip with additional information; removing event types

[1]T1: Review in detail a few records; T2: Compile descriptive information about the dataset or a subgroup of records and events; T3: Find and describe deviations from required or expected patterns; T5: Identify a set of records of interest; T7: Study antecedents or sequelae of an event of interest

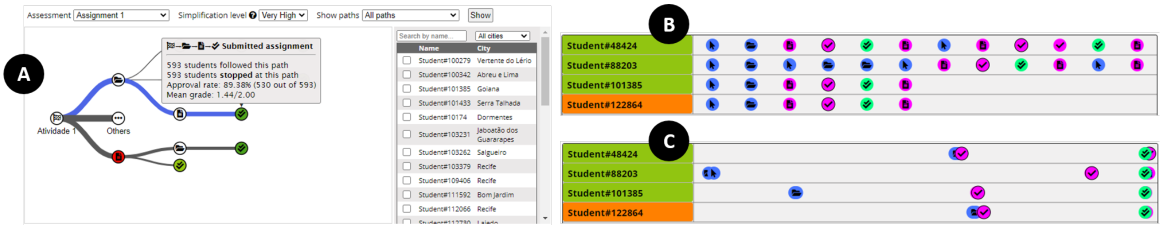


Figure 3: (A) "Retrospective tab" on "Pattern Discovery" panel; (B) and (C) shows two alignment options in the timeline: by event occurrence order (B) and by the "assignment submitted" event (C).

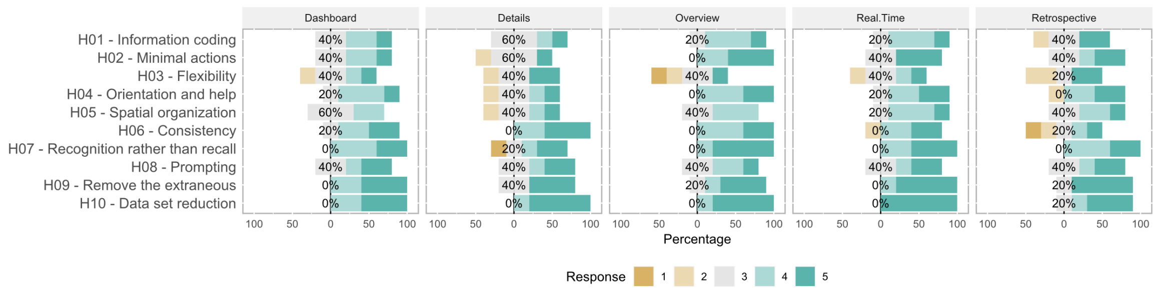


Figure 4: Heuristics questionnaire results by component. The scale ranges from 1 (totally non-compliant) to 5 (completely compliant).

from the analysis by unchecking them on the dashboard right panel (Figure 2 – D); and zooming/panning.

**Details panel.** In this panel, teachers can explore students' individual learning paths on a timeline (Figure 2 – C), thus supporting the analytical tasks #2 and #4 (Table 2). To reduce the number of events plotted in the timeline, we use the strategy of "Coalescing Repeating Point Events into One" [9] by grouping same-type consecutive events into a single one. Events are represented by circles with the corresponding glyph; circles representing grouped events have a black border. Users can interact with the visualization by: hovering over the circles to get a tooltip with event details; removing event types from the timeline by unchecking them in the Legend (Figure 2 – D); and zooming/panning on the x axis. Additional interaction features are provided on the panel's right box: "show outcome info", to color-code student names according to their grades; filter or order students by outcome result; and align events [9] by order (Figure 3 – B) or by the first occurrence of a given event type — for instance, the submission of a given assignment (Figure 3 – C).

## 4.3 Dashboard Evaluation

This subsection presents the findings from the Expert Review conducted in the second iteration of our method ("make" activity). Figure 4 shows the heuristics questionnaire's results. Scores were mostly favorable (between 3 and 5), especially for heuristics "H07 – Recognition rather than recall" (except for the Details panel), "H9 – Remove the extraneous", and "H10 – Data set reduction". All experts praised the glyph consistency throughout the dashboard; E3[2] said that "the use of the same icons all the time makes everything very consistent", which is confirmed by the good scores for dashboard consistency (H06). Heuristics "H03 - Flexibility" and "H05 – Spatial organization" received the least favorable results. Regarding H03, some participants justified their scores by saying that although some components were not flexible, they *should not be*, given that teachers are usually novice users of analytics tools. Regarding H05, the main demand from experts was to make panels collapsible, so the visualizations could occupy more space on the screen.

In the thematic analysis, we identified three types of issues (excessive effort, confusing/misleading features, and lack of affordance), two types of improvement suggestions ("change" and "add" features), and strengths. For the ***dashboard*** as a whole, the confusing/misleading issues and new features suggestions were mostly related to the views coordination: experts were confused by the existence of three tables listing student names (Figure 2 – A3/B, Figure 3 – A), which also makes it difficult to identify where the students shown in the timeline came from. The "***Overview***" panel received generally good scores on the heuristics questionnaire; the issues identified in this panel were mostly related to the "Lookup" tab, which experts agreed that it should be relocated to another area in the dashboard.

The "**Real time**" tab on the "Pattern Discovery" panel had few issues. E3 considered that it could "give insights without a lot of effort" and E5 that "it is a really good way, I think, to show teachers who did what". On the other hand, the "**Retrospective**" tab was the one with most "confusing/misleading" issues, mainly due to the presence of colored nodes in the middle of some paths (representing students that did not hand out the assignment). Some experts also reported difficulties in identifying which were the "best learning

[2]We use the codes E*n* for experts and TE*n* for teachers. The detailed participant list is available as supplementary materials.

paths” on the tree. These issues are reflected in the low scores on heuristics “H01 – Information coding” and “H06 – Consistency” for this component (Figure 4). Despite the issues, participants agreed on the usefulness of the visualization: E3 said that it “could help identifying the best learning strategies, to try to improve the performance” and “It may not be seem simple at first, but once you know how it works I think the teacher can get a lot of insights”; E2 considered that it would “give the teachers a lot of insights [. . .]. It is very interesting in showing how I plan the course and how it is affecting the students, and which students.” The possibility of visualizing the list of students for a given path was also praised both on “Retrospective” and “Real time”.

Finally, in the “**Details**” tab the main issue was the use of “learning event” as the unit of analysis, which caused overplotting when displaying highly active students. Experts agreed that this compromised the view’s actionability and made it confusing in some situations. As a result, this was the view with more “excessive effort” issues (mostly related to panning and zooming) and suggestions of new features, which is reflected in the comparatively low scores in the heuristics questionnaire (Figure 4).

## 5 DISCUSSION

Our **data requirements** (Table 1) corroborate some of the proxies proposed by Sedrakyan et al. [27] for behavioral process-oriented feedback (“optimal learning trajectory” and “intermediary course outcomes”) and extend their proposed “temporal” data type into finer grained categories. Our **tasks** taxonomy (Table 2) extends the one proposed by Sedrakyan et al. [27] by breaking the generic task “[show] trend over time with the focus on intermediate outcomes and overall process” into five tasks, some of which also appear in related works (task #2 in [6, 7], task #3 in [6]). Finally, our preliminary results on **visual encodings** suggest that the *node graph* metaphor — proposed by Sedrakyan et al. [27] and used in our “Retrospective” view (Figure 3 – A) — is promising but needs extra care to prevent unnecessary complexity. We also tested two metaphors not mentioned in [27]: *Sankey diagram* (Figure 2 – B) and *timeline* (Figure 2 – C). The latter was well received by teachers during the co-design workshops and have been used in previous works [6, 7, 17, 20], but none of these provide contextual information or correlate paths to outcome results. The Sankey diagram was positively evaluated by visualization experts and, to the best of our knowledge, only used in one other work [1] to represent learning processes, but as a static, standalone visualization.

Based on our design process, we reflect below on the main challenges, pitfalls, and successful strategies for building teacher-facing LADs focused on behavioral process-oriented feedback.

**Unit of analysis and data cleaning/aggregation**. The visualization experts criticized the use of “learning event” as the only unit of analysis in “Details” (Figure 2 – C). Although we used strategies to reduce the number of events and categories (cf. Subsection 4.2), further data reduction is needed. One alternative is dividing events into two groups: the first one with “milestone” events (strategy S6 on [9]), which could remain in the “event” granularity, and the second with the remaining events, which could be grouped in “sessions” of customizable size (e.g. hourly, turn, day); users could then analyze these sessions in detail on demand through a drill down feature. We believe that this strategy could solve the overplotting issue without losing information that can “carry meaningful signals of study habits” [3] — something likely to happen when a single high-level unit of analysis is adopted, as in [7].

**Defining the period of analysis.** Fixing a time window to analyze any learning process is a challenging task, not only in Learning Analytics, but also in the Learning Sciences [23:27–31]. From a sociocultural perspective of learning, it is unfeasible to look for exact time markers. Instead, we propose the use of approximate markers based on the course structure, the teachers’/school’s pedagogical practices, and the learning theory guiding the dashboard design. In our dashboard, we adopted the following markers: i) *course period*, in the “Participation” and “Performance” visualizations (Figure 2 - A); ii) *course unit period*, in “Performance” and “Real time” (Figure 2 – A/B, respectively); and iii) *assignment post/deadline dates*, in “Retrospective” (Figure 3 – A). The “Details” panel (Figure 2 – C) has no fixed time markers.

**Time representation**. Although not implemented in our dashboard, we discussed with teachers the possibility of estimating how much time students spent on each learning activity. They agreed that, for most activities, it was not necessary: only the events order within the sequence would be enough. Besides, teachers were skeptical about a dashboard’s ability to infer this information; they argued that students might open the LMS and “play a game on another tab [in the browser]” (TE5) or “leave for a coffee” (TE11) and the system would thus give misleading feedback. Therefore, dashboards that offer such estimations should clearly communicate the possible uncertainties and limitations involved.

**Defining and representing “good” and “bad” learning paths.** There is not a single answer to what constitutes a good or bad learning path. In our “Retrospective” visualization (Figure 3 – A), we provide three metrics for each subgroup (tree branch): the mean grade for the assignment, the pass rate, and the support level (number of students that followed the path). During the evaluation, one expert could not decide which metric to use: “The darkest green probably... but successful can also mean most people followed the path” (E4). However, choosing a single indicator would enforce a definition of “good learning path” that may be inappropriate for a given course/activity or the teacher’s pedagogical conceptions. Another challenge is how to visually communicate this information. E5, for instance, associated the longer paths on the tree — even when the outcome result was good — with users that had more difficulties in the assignment; alternatively, one could conclude that those students extensively explored the learning resources and, thus, got better grades. We believe that all these conflicting conclusions are equally valid: each course, assignment, or even teacher may require or expect different learning strategies; the dashboard should not hinder these possibilities.

**Representing “incomplete” learning paths.** Most of the “confusing/misleading” issues identified in the “Retrospective” visualization (Figure 3 – A) were related to the representation of paths that did not end on an “Assignment submitted” event. Our dashboard represents these paths using intermediary colored nodes to signal the common “stopping points” of students that fall short of finishing the selected assignment. However, several experts did not understand this representation. Among the suggestions to improve the visualization were the use of special “end nodes” to signal the end of a path or removing these incomplete paths altogether from the analysis.

## 6 CONCLUSION

In this work, we present preliminary results and reflections from the iterative design and evaluation of a teacher-facing LAD for behavioral process-oriented feedback in online courses. Our results extend earlier data and task taxonomies and provide initial evidence on the usability of our dashboard design. Based on our design process, we reflected on the challenges, pitfalls, and successful strategies of building teacher-facing LADs for behavioral process-oriented feedback. These reflections can be a first step towards the development of design guidelines for building such type of dashboards — a research gap identified by Verbert et al. [29] — and are the main scholarly and practical implications of this paper. Our work's main limitations are: i) the high-fidelity prototype was not tested with end-users and ii) the inherent limitations of using clickstream data for analyzing learning processes — as discussed in [3]. As future work, we plan to address the issues identified in the expert review and validate the new design with teachers to assess its usability, usefulness, and how it can impact their practice. Understanding students' privacy concerns with process analytics is another important step.

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