Enhancing the Professional Vision of Teachers: A Physiological Study of Teaching Analytics Dashboards of Students' Repertory Grid Exercises in Business Education

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Abstract

This paper reports on a study of the design, development and evaluation of two teaching analytics dashboards that visualize students' repertory grid exercise data. The technical objective of the dashboards is to support teachers to investigate and compare personal constructs and element ratings by students for given topics of study at the individual student, group or classroom levels of analysis. The pedagogical objective of the dashboards is to facilitate formative assessment feedback to students and feed-forward refinements to ongoing instructional practices. The teaching analytics dashboards were evaluated with six university teachers in a bio-metric usability study with integrated physiological and performance measures. Eye-tracking data from the two dashboards showed the relative importance of dashboard areas in each case in terms of aggregate gaze allocation. Findings informed the iterative design of the dashboards leading to teachers not being adversely affected by the visual clutter of the less important dashboard areas in their pedagogical decision-making. The results also showed that the dashboards were efficient and effective from a task performance perspective and were rated to be pleasant from a subjective satisfaction perspective. Regarding education technology innovation, teachers reported that such dashboards are lacking in their regular practice and would recommend their use in formal business educational settings.

Keywords

Teaching analytics; dashboards; repertory grid; bio-metric usability study;

1. Introduction

Today's technologies provide great opportunities for generating valuable learning resources. Capitalizing on the development within technology towards data, education can better utilize information, which can improve learning and teaching. Unlike several years ago where data collection was sparse and inadequate to support teachers, nowadays, technology supports them with easy and systematic collection of data [32]. Consequently, new technologies are shifting education from a scarce data environment towards an abundant and fine-grained data environment. This transformation [8] demands that teachers create effective, efficient, enjoyable and sustainable learning practices, which often requires additional time and effort. Different tools have been developed to enhance analysis for various skilled users (e.g. programmers, end-user developers), but still there is room for improvement [36] towards the main goal: engage teachers directly. Therefore, researchers are continuously studying educational data and tools in order to improve learning.

Learning Analytics (LA) is an emerging research discipline that investigates "the collection and analysis of usage data associated with student learning" and aims at improving education through interventions after observing and understanding learning behaviors [7]. Vatrapu et al. [47] introduced a new theoretical approach called teaching analytics, which combines visual analytics, teaching expertise and design-based research in a triadic model to support teacher's diagnostic pedagogical decision-making in classrooms. Enabling teachers perform analysis through visual representations aims at facilitating assessing students' understandings and knowledge [9], [42]. Teachers can identify new learning insights and study concepts and ideas that were almost unfeasible to investigate within the allocated time. Therefore, the goal is to enhance teachers' experience and ability through teaching analytics and visual representations.

In this respect, we endeavor towards designing, developing and evaluating teaching analytics dashboards, and focus our attention on visual representation of the repertory grid data. Repertory grid data can indicate to teachers the knowledge students have on specific topics [46] and visual representations aim to enhance human cognition [9]. Therefore, we utilized the repertory grid and visual techniques to augment teachers' vision. We used design principles from the visualization area ([5], [42]) and developed visual representations (i.e. dash-

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boards) using uVis [35] that visualize personal constructs and element ratings of students at an individual and/or a group level. For this purpose we designed and developed dashboards that are single screen visual displays that utilize concise, clear and intuitive visual objects to present data in order to reveal trends, patterns and outliers [17]. These dashboards were evaluated with six teachers from our faculty.

The findings showed that current teaching practices of knowledge diagnostics of students are primarily based on questions and group/class discussions, where data are not systematically collected and analyzed. The results also showed that teachers need tools to explore different types of questions about declarative and procedural knowledge of their students, ongoing teaching practices and emergent learning outcomes. The eye-tracking data from the dashboards showed the importance of screen areas in each case, indicating the need for high level of perceptibility and simplicity. The emotions computed from the electroencephalogram (EEG) data did not denote any preference on performing tasks in different dashboards. (suggested from the guidelines [51] related to the overwhelming screen). This paper is a first attempt towards teaching analytics dashboards and provides useful insights for existing learning practices in educational environments.

The remaining of this paper is organized as follows. First, we discuss related work on repertory grid, learning analytics and dashboards. Next, we describe the design of the study. Results are presented in the next section, followed by the limitation section. The paper concludes with final remarks and future work.

2. Related Work

2.1. Repertory Grid

Repertory grid (RG) is a technique to elicit the personal constructs of individuals to determine the relationships among concepts of a topic. This technique is based on the personal construct theory developed by George Kelly [25].

A grid consists of: a topic, a set of elements, a set of personally elicited constructs, and a set of ratings of elements of the personal constructs. Vatrapu et al. [46] provide a clear example of a grid, and discuss how to integrate the repertory grid technique in "teaching analytics" as in-class activity or a take-home exercise. The repertory grid technique can be used as a pedagogical method by teachers for knowledge diagnostics of students about a specific topic of study [46].

In this paper, we aim to support the pedagogical method of the repertory grid with computational tools (teaching analytics dashboards) to support teachers professional vision [47].

2.2. Learning Analytics

Learning Analytics aims at improving education through interventions after observing and understanding learning behaviors [7]. That is, "the collection and analysis of usage data associated with student learning" [7]. The importance of learning analytics in enhancing the learning and teaching practices towards better education is depicted in the increasing number of studies (e.g. [21], [45], [49]).

Previous research [1], [26], [28] has discussed the challenge of learning and teaching. Marjanovic [28] presents a modeling language, which can be utilized to articulate new learning designs. Furthermore, supporting teachers with more appropriate guidance can allow them to better perform, adjust, and re-use their teaching procedures [28]. New approaches are being investigated in the established field of learning sciences and emerging field of learning analytics to improve traditional learning and teaching strategies and practices.

2.3. Dashboards

Dashboards are single screen visual displays that utilize concise, clear and intuitive visual objects to present data in order to reveal trends, patterns and outliers [17]. Furthermore, Few discusses that a well-designed dashboard aims at presenting data and revealing trends, patterns and outliers, which in response may guide viewers towards effective decisions. Dashboard is related tightly to information visualization that aims to enhance human cognition [9]. As in a pedagogical environment professionals has to monitor several data (e.g. questions, mood, ratings, progress, etc.), dashboards become an important factor to improve and conduct successful teaching.

To design the teaching analytics dashboards, we adhered to the design principles from information visualization [42], [10], [5]. Duval [14] highlighted the importance of information visualization in education. Although considerable work has been done on interactive visualizations in the information visualization community, there are still large knowledge gaps when it comes to visualizations and dashboards for educational data.

Verbert et al. [49] present the concept of learning analytics dashboards. Their study introduced a conceptual framework to support learners and teachers utilize applications that visualize learning traces. The authors [49] reviewed 15 educational tools and investigated the use of dashboards by focusing on students, teachers and tracked data (i.e. time spent, social interaction, document use, tool appropriation, artifacts produced and exercise results. Their results showed that only Course Signals tool validated the usefulness of dashboards to learning and highlighted the need for further studies to investigate the role of dashboards in learning contexts and educational settings.

In this paper, we utilize the repertory grid data for dashboards and visual analysis. In comparison to previous work on learning analytics dashboards, our work concentrates on teaching analytics dashboards that are meant to enhance teachers' professional vision. The dashboards provide teachers with an overview of the teaching topic and details-on-demand about the personal constructs and element ratings on individual and/or group level.

2.4. Evaluation Methods

A considerable amount of work has been done in identifying evaluation methods, design principles and challenges faced during evaluation sessions. It is a common practice to employ usability tests or controlled experiments for evaluations.

A usability test is cheap and provides useful information of what domain users believe [31]. Usability studies are subject to biases and according to Hertzum and Jacobsen [23], the evaluator effect can have an impact on data validity. Controlled experiment results primarily rely on performance data: task accuracy and completion time. However, controlled experiments do not provide the same insights as usability tests and are also subject to biases. Designing and conducting a controlled experiment can be biased because it involves several steps: including defining the hypothesis and the dependent and independent variables, selecting a random sample, analyzing the data, etc. These steps have to be designed and performed in standardized routines [27]. Despite open issues regarding evaluation biases, it seems to us that evaluations primarily rely on the case and what you want to learn.

Cognition or cognitive lead is concerned with the mental effort spent when a particular task is performed [34]. Mental load, mental effort and performance are three aspects of cognitive load. In their model Paas and van Merienboer [34] refer to mental effort as the aspect that is related to cognitive load, and is recorded while users execute a particular task. Therefore, in visualization cognitive load can be seen as a major factor that defines the success of visualization.

Cognitive Load Theory (CLT) [37], [38], [39] suggests that humans have limited cognitive processing capacity to utilize while they learn and solve a particular task, and their working memory can be affected by the presentation (in our case by the visualization). According to CLT, task failures occur when task demands overload cognitive capacity, provide insufficient distribution of cognitive sources, or both [33]. It is recommended that cognitive load caused by an instructional design (visual representation in this case) should not exceed the working memory [33].

Information visualization enhances human cognition [9], thus it is important to investigate cognitive process involved in the perception and appropriation of the affordances [48] of multiple view dashboards. More specifically we refer to the relevance of cognitive load and CLT to understanding the performance of users with respect to dashboards in teaching analytics.

Eye movements provide important information regarding users' gaze behaviors while they perform visual-cognitive tasks [22]. Therefore, it can be said that well-designed visual representations can enhance human cognition [9].

Fixations are eye movements that occur when the visual gaze is stabilized in an area of interest [22]. High number of fixations imply additional cognitive effort in visual search, and may result to low performance level [52], [43], [24]. According to Tatler et al. [41], scan paths and the number of fixations vary on task type.

Measuring the electrical activity of the human brain is a common practice in cognitive neuro science, and the first study goes back in 1930 when Berger recorded brain activity as an electroencephalogram [4]. Brain activity depicts information processing and is used to measure cognitive task performance. Analyzing EEG data collected during a cognitive task can determine the level of involvement [12]. Brain activity is also used to measure emotional states during different situations [53], [19].

Studies [19], [53] have shown that the frontal lobe activity has been found to be correlated with emotions. Other studies [18], [11] have investigated how emotions affects decision making. These studies showed that emotions are important for decision making and problem solving.

Moreover, trying to minimize the effects on evaluation, we employ physiological devices. We incorporate physiological measures as rigorous and unbiased data collection techniques [29], [13].

Therefore, we used usability tests because we wanted to learn what real users believe and enhance our results with data collected by an eye tracker and an EEG headset. In this way, this evaluation combines subjective, performance and physiological measures.

3. Teaching Analytics Dashboards

3.1. Dashboard Design

Inspired by [47], we developed teaching analytics dashboards. They combine visual representations, teaching expertise and design-based research in to support teacher's diagnostic pedagogical decision-making in classrooms. Therefore, we performed an iterative process and designed and developed a pedagogical visual representation for teachers for knowledge diagnostics of students about a specific topic of study.

We utilized the repertory grid technique and several visual design principles to create teaching analytics dashboard. Figure 1 shows how repertory grid data from a Social Media Analytics course were used to design and develop the teaching analytics dashboard. The dashboard contains: a word cloud, a bubble graph, a track bar for frequency, and two check boxes for selecting triads and students.

The data were collected from the Social Media Analytics course using the Repertory Grid for Formative Assessment (RGFA) website. The topic for the repertory grid exercise was social media. The eight elements were: facebook, youtube, vimeo, flickr, foursquare, linked in, twitter and digg. The elements were selected to range from popular to potentially not popular websites, personal taste vs. social influences and ranging from functionality involving little or great consideration time. The teacher made the design decision to select five triads to include in the exercise. The order of presentation of the triads was randomized to control for practice effects. Students filled their preferences and knowledge on eight social media sites. These data were exported in an MS Access file.

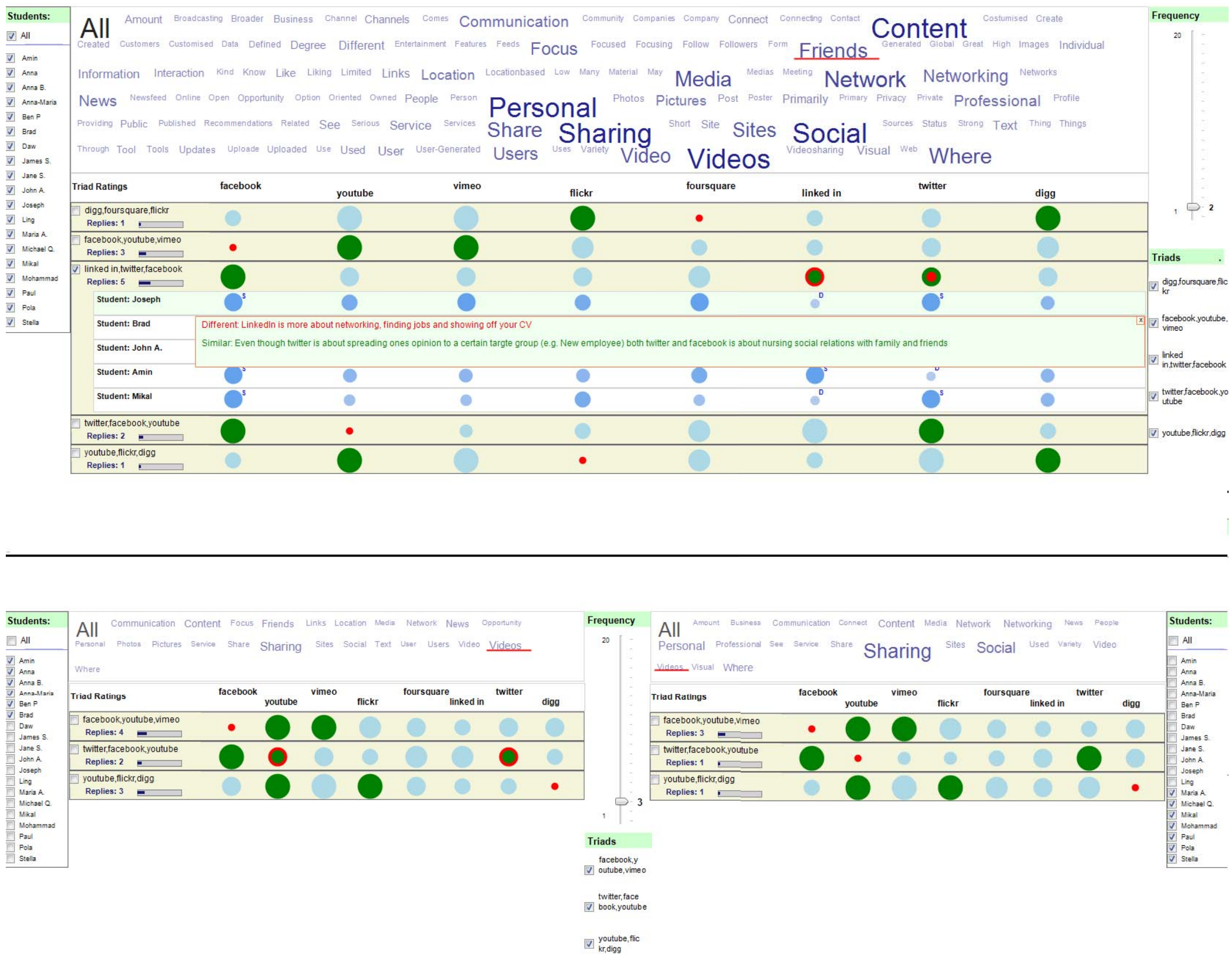

Fig. 1. The repertory grid dashboard for comparative analysis among students. The top shows an overview and details-on-demand of one group. The bottom view facilitates comparative analysis between two groups. Due to space limitations full sized images can be found here [16].

The dashboard uses this MS Access file and generates the representation.

3.2. Dashboard Development

The dashboard was developed using uVis [35] uVis has an integrated development environment, where designers can create visualizations by dragging and dropping controls (e.g. triangle, rectangle, etc.) in the design panel, and specifying spreadsheet-like formulas in the property grid. By means of formulas, controls can be bound to data, refer to other controls, define the appearance, and the behavior of each control.

The formula language and the integrated development environment allowed us to rapidly create several visualization prototypes. Initially we aimed for a scalable user interface that can have more than two dashboards in a screen. However, during development we noticed that space efficiency was an issue and our teaching experience indicated that there was no need for having more than two dashboards in a screen. Therefore, we decided to utilize only two dashboards for comparative tasks. Furthermore, the dashboard is scalable in terms of students and triads used in a study.

The dashboard is an interactive environment that allows teachers narrow down their analysis to specific triads and students. It provides an overview and details-on-demand of the collected data from students. The dashboard goal is to assist teachers conduct easier analysis than in traditional tabular formats, assist them in better assessment, and obtain easier knowledge on students' education on the topic.

The dashboard provides several interaction mechanisms:

- Teachers can interact using the track bars, as shown in Figure 1. In this way they can select students and set the frequency for the word cloud. Using the tack bars will have an effect on the word-cloud and the triads. In this way the teacher can view the most representative word(s) and in which triad these words are mainly used.

- They can also interact with a concept (word) and investigate it in details. In this way, they can seek answers related to questions of how, who and why a particular concept is elicited more than others and the relative distribution of concepts in the classroom as a whole.
- Teacher can also customize the screen by choosing the triads they are interested in. They use the check-boxes to filter down the presented information.

The dashboard inherits principles and techniques from the visualization field. It employs the word-cloud technique and a custom bubble-chart approach.

- The word-cloud provides an overview of all elicited constructs (i.e. opposite and similarity constructs).
- The bubble chart provides details on demand aggregating and showing element ratings for each triad.

Filtering techniques are employed to support targeted noticing and to increase users' satisfaction. Small letters (i.e. S-similar and D-different) are positioned above bubbles that represent triad's elements. The purpose is to enhance teachers' ability in relating and distinguishing opposite from similar personal constructs and corresponding elements.

Additionally, color and size encodings are used to also denote similarity and/or opposite constructs. The green color decrease as the rating number goes from 5 to 1. The same feature is implemented for the bubble size. It decreases as the value decreases. The small letter S (similar) is colored in green, while the D (different) letter is colored in red. This pattern was inherited from the traffic lights example, familiar to most of us. Teacher can also click on a bubble and a box with specific information regarding similar and different constructs is shown. This aims at increasing understandability by providing context data.

Figure 1 (bottom) also shows a dashboard that utilize the same design principles and functionalities as the above dashboard, but it supports better comparison tasks. The scope of this dashboard is to make comparison easier between groups of students in the same class, between pre- and post-teaching knowledge diagnostics and between different classes that answered the same repertory grid exercise.

The dashboard provides an overview of the results aiming at providing better information than a tabular view. In case a teacher needs more details regarding the content used, the teacher can double click on a single triad, expand it, and click on a bubble. As shown in the figure 1, a rectangle will be opened showing the different and similar constructs. In this way the teacher can obtain an overview but also explore and get detail-on demand regarding triads and students.

4. Method

4.1. Design

Given that the repertory grid technique can inform teachers on the knowledge concepts that their students have on specific topics [46], our design-based research hypothesis was that visual analytics in general and dashboards in particular can enhance teachers' professional vision of knowledge diagnostics. We conducted a study to investigate our design on the usefulness and relevance of the teaching analytics dashboards. We conducted an heuristic evaluation of the two dashboards based on the visual analytics design guidelines formulated by Ware [50].

4.2. Participants

The lab study sample was drawn from university colleagues that were not familiar or involved with the research study. Six authentic users (university teachers) participated and completed in the eye-tracking study. All of them had teaching experience of at least two full courses at the university level.

4.3. Apparatus

The pilot and final study were performed in a usability lab. We used an eye-tracking device, an electroencephalogram (EEG) headset, and iMotions Attention tool [3] to integrate and collect data. The EEG data were collected using the Emotiv EPOC research EEG neuroheadset [15]. The SMI iView X Red eye-tracker device was used to collect eye activity data.

4.4. Procedure and Tasks

The study was divided in five parts and lasted one hour on average. First, the participant was asked a few general questions such as "how many courses have you taught, do you know repertory grid technique, etc."

As they may have not used the repertory grid technique, in the second part, we described to the participants how the repertory grid technique works, and asked them to reply to a training grid (similar but identical to the study with the grid that the students filled in class) using the RGFA tool [46]. The purpose was to create or enforce participant's understanding on the repertory grid technique. Moreover, as they were asked to perform several tasks using the dashboard, it was important to explain them and provide a good understanding of the data used. For example they used triads and constructs to fill the grid (data used in the dashboard).

In the third part, the participant was asked perceive a teaching analytics dashboard, and tell us what sense they can make out of this screen. After their reflections and comments, the instructor explained how the dashboard is used to perform analytical tasks.

The fourth part of the study consisted of a list of two different visual task types: find and compare. The participant had to perform the tasks on their own using the teaching analytics dashboards. As an example, the participant used the first dashboard (Figure 1, top) to answer to tasks such as: "which triad/s show/s that students share the same understanding?, "which concepts (words) are most popular in the topic?" and "looking at the word-cloud and the bubble-chart, what sense can you make out of this screen?".

In the fifth part, task where more comparative, and the participant was asked to create two groups and compare what it was shown in the screen (Figure 1, bottom).

We positioned participants in front of a screen at a distance of about 70 cm. All participants were calibrated with the eye tracker (SMI iView X Red), which used a nine-point calibration mode. Data were collected on the rate of 60 Hz. The eye-tracker was connected with the iMotions Attention Tool 4.8. Dashboards were imported in the study created with Attention Tool.

4.5. Dataset

We used data collected during a Social Media Analytics course at our university. Students were asked to use the RGFA website [46] and answer to a grid designed for the course. The responses provided information regarding their knowledge related to the social media websites. Eight popular social networks (i.e. facebook, youtube, vimeo, flickr, foursquare, linked in, twitter and digg) were used as grid elements.

Personal constructs of students were elicited using the triadic sorting method. The teacher of the course designed 8 elements and configured five triads (groups of three elements). For each triad, students described why one of the elements is different from others (opposite construct) and why the other two are similar (similarity construct). Then, the students were asked to rate the rest of elements using a five-point Likert scale, from their own personal constructs of opposite (1) to similar (5). For example, some rated with 5 youtube and vimeo as similar sites. Facebook was rated with 1 as an opposite site to the others.

Furthermore, students used several keywords to describe similarity and construct. These keywords were manually filtered and used in our analysis to create the word-cloud in the dashboard. In order to produce a realistic word-cloud several random words (e.g. the, is, a, etc.) were removed by our text-analysis program. In addition, to preserve acceptable levels of realism as well as anonymity, student data from the classroom were de-identified and random unrelated names were used in the lab study.

4.6. Data Collection

The study was performed in a usability lab. All participants were informed to follow the think-aloud protocol [6]. The aforementioned devices were connected with iMotions Attention Tool 4.8 [3]. This tool supports synchronized data collection of EEG and Eye-Tracking activity. Furthermore, it facilitates data gathering and data analysis. Performance measures, subjective ratings, EEG and eye-tracking data were analyzed. The instructor observed, kept notes and screen-voice recorded each study.

5. Results and Discussion

Six participants were recruited: one associate professor, three assistant professors and two PhD students. We report on participants' satisfaction, performance, eye-tracking data and usability issues.

5.1. Preference and Performance Data

Table 1 summarizes their teaching experience utilizing different technologies in order to facilitate teaching. Students' assessment is primarily based on questions and group/class discussions, where data are not systematically collected and analyzed. Thus, teaching data is analyzed in an ad hoc manner and using non-standard ways rather than systematic and standardized approaches.

All participants were able to answer correctly to questions that related to identifying the concepts that are the most popular in a topic, compare students ratings, etc. Table 2 and 3 provides an overview of the questions used in each dashboard.

In the first dashboard, the word-cloud made teachers reflect more as evidenced by their think aloud comments. Further, three participants pointed out the popularity of these social networks and looked into the details. Looking at the opposite and similarity construct, participants were able to identify why a student rated differently a triad than the other.

In the second dashboard, participants were asked to perform comparative analysis between two groups of students. Table 2 and 3 shows the questions, instructions and answers. As an example, one of the participants said "the two groups have used the concept of sharing (facebook, youtube, vimeo are understood the same, while the other shows some differences). If I go into details, I assume I will find out more."

Rather than investigating tabular data, participants appreciated the visual approach for collecting and analyzing data. We observed that reading and comparing concepts in the word-cloud between groups was easier than understanding the triads. These observations provide preliminary evidence for our design hypothesis that teaching analytics dashboards can help teachers better analyze the data and reason pedagogically.

5.2. Physiological Measures: Eye-Tracking Data

The study was performed with six participants, but we decided to reject participant 5 because the quality of data gathered from the device was lower than 85%. Therefore, we report eye-tracking data from the other five participants.

We defined areas of interest (AOI) and investigated the time spent and number of fixations. Figure 2 shows the averaged participants' results for each AOI. More specifically, participants' fixation number and time spent is higher in the bubble-chart and word-cloud, as we expected. However, the other areas of the dashboard that occupy valuable screen real estate do not get the same attention as evidenced from aggregate gaze behavior distribution. This resulted in the design implication that these areas could be hidden.

TABLE 1. Participants' experience with teaching, assessment, data collection and repertory grid technique.

Participant	No. of Courses	No. of Students	Technology to facilitate teaching	Student's Assessment	Data collection during a class	Knowledge on the RG
1	50	40	BPM, E-learning, Beer Game	Summative examination, Questions in class	No data collected	To some extent
2	3	30	PowerPoint	Discussions, Asking questions	No data collected	To some extent
3	2	25	PowerPoint, Laptops for research	Group discussions, Asking questions	Natural feedback	No
4	3	60	Laptops / Smartphones to interact, clickers and projector	Group discussion, reading individual comments	Coded questions. Individual comments	No
5	4	35	SAP, process models, PowerPoint, blackboard, simulation games, YouTube	Quiz, Questions, Participation, Group exercises	Nothing formal, Read something about it but would use MS Excel to categorize if so	No
6	12	10	PowerPoint, Java and Python examples	Exercises at the end	No	No

TABLE 2. Questions (Q), instructions (I), participants and their answers using the dashboard in the fourth part.

Question / Instruction	Description	Answers
I1	Create two groups of students (using the filters to the left and right of the screen) of 5 students: Group 1 All the students, excluding Polo Group 2 Only Polo	6
Q1	Which concepts (words) show that Pola shares the same understanding with the others?	6
Q2	Which triad or triads show that Pola share the same understanding with the others?	6
Q3	Which triad or triads show that Pola does not share the same understanding with the others?	6
I2	Create two groups of students (using the filters to the left and right of the screen) of 7 students: Group 1 Top 7 Group 2 Last 7	6
Q5	Select "All" in each word-cloud and set frequency to 2. Looking at the word-cloud and the bubble chart, what sense (same as above) can you make for each group?	6
Q6	Select "Sharing" in each word-cloud. Looking at the bubble chart, what sense (same as above) can you make for each group?	6

TABLE 3. Questions (Q), instructions (I), participants and their answers using the dashboard in the fifth part .

Question / Instruction	Description	Answers
I1	Look at the default view of the dashboard: all students 6 selected and all triads selected and frequency = 2.	6
Q1	Which concepts (words) are most popular in the topic?	6
Q2	Which triad or triads show that students share the same understanding?	6
Q3	Which triad or triads show that students do not share the same understanding?	6
I2	Look at the default view of the dashboard: all students selected and all triads selected and frequency = 2.	6
Q5	Which student or students show similar and different understanding in triad's ratings?	6
Q6	Can you find out why Stella's rating differs from Brad's rating?	6

The same observation was made when teachers performed compression task. The eye-tracking findings reveal which dashboard areas are mostly used in visual analysis and provide design directions for future iterations, indicating the importance for perceptibility and simplicity.

This behavior was also noticed during the studies from our observations where the bubble chart and the word cloud were mainly used. These areas took mainly their attention. This can be explained because the answers of the tasks were in these areas. Therefore, it is crucial to highlight these areas more and provide less space or the possibility of minimizing them. This will enhance teacher analysis and provide a more pleasant experience.

5.3. Physiological Measures: EEG Measures

The study was performed with six participants, but we decided to reject participant 5 because the quality of data gathered from the device was lower than 85%. We report on EEG data from five participants.

Using EEG data, we investigated emotions, which are automatically generated by EEG headset. More precisely, the EPOC framework generates data that relates to levels of frustration, engagement, meditation and excitement. The fact that these measures are generated automatically does pose questions regarding data provenance, construct validity and reliability. That said, the purpose of the paper is not to verify and validate the EPOC output but to illustrate the potentials of this approach in teaching analytics.

We selected the average values of emotions produced during task execution of two parts: dashboard 1 and 2. Figure 3 shows that, in general, participants had almost the same level of engagement and frustration in each dashboard. We would expect that the second dashboard would cause more frustration due to its overwhelming screen. From the visualization field, guidelines suggest the use of minimum views in a visual representation [51] to avoid cognition impact. However, the results did not yield this.

Our results showed that teachers perform almost equally in both dashboards. Also, it seems that four participants were more exited using the second than the first dashboard. On the other hand, the level of meditation increased when they used the second dashboard. This can be explained because participants had to compare groups. However, this observation needs more research in order to determine which how a task influences human meditation.

5.4. Usability Issues

Several usability issues were identified from the participants' think aloud comments, the study facilitator's notes and the data analysis of study sessions. For instance, the dashboards provided participants with an overview, which pointed out differences but did not inform them on similarity and/or opposite constructs.

Another usability issue relates to reducing the number of clicks. We noticed that participants found interesting to observe similar or different construct, but cumbersome to click over the bubble to view details. This relates to the known question faced in visualization areas on how to integrate and present an overview with details.

Performances, space issues, more visualization and interaction types, are also some of the findings and recommendations that are being investigated and will be addressed in the next version of the teaching analytics dashboards.

The space-efficient issue was also pointed out by the eye tracking data. This result complies with our observation and yields for a more space efficient solution. While the EEG data did not yield any important result, they showed that the teachers were almost similarly affected by the dashboard. This was also observed from the instructor during the study.

5.5. Reflections

Understanding and enhancing teachers' professional vision [2] is an essential but understudied research topic within learning analytics. Our research program on teaching analytics [47] seeks to address this research gap by involving teachers in the design, development and evaluation of visual analytics tools and services that enhance their dynamic diagnostic pedagogical decision-making. We believe that this paper can serve as an illustrative case study of the need for and value of integrating physiological measures into the traditional evaluation of performance and preference measures for better understanding teachers' professional vision with respect to their classrooms, students, learning resources and, teaching and learning data.

6. Limitations

This study provides data and results for enhancing the professional vision of teachers using teaching analytic dashboards. However, it has several limitations that are worth mentioning.

We utilized simple visual search tasks, which we believe are common tasks in daily practice. While we expect our findings to generalize to other tasks, more tasks and visual types need to be tested in future investigations.

As participants were not used to dashboards, we observed that guidance and basic training on visual aspects and types are required. A methodical explanation on how a dashboard and its views work was noticed in the studies. We think that an explanation can be part of the training, which will enhance their performance and subjectivity. Furthermore, our observations regarding their use act in accordance with the design guidelines described in [44].

Recruiting real domain users it is challenging due to their tight schedule. Moreover, there is no suitable number for conducting usability studies as researchers debate regarding the number and their opinions differ [30], [20], [40] Also, we are aware that the number is limited, but usability tests with 5 participants [30] can provide good indications. In our case

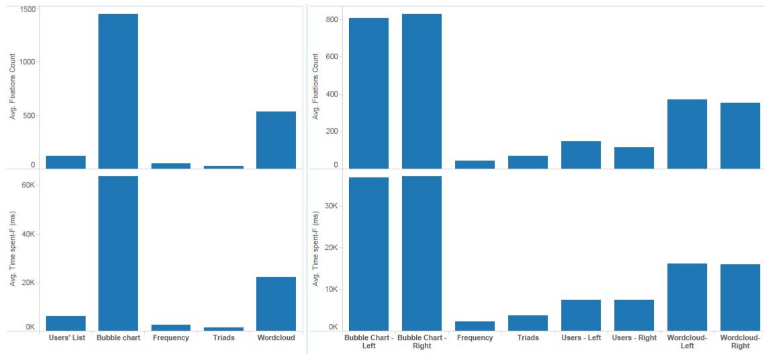

Fig. 2. Average fixation count and time spent for each AOI.

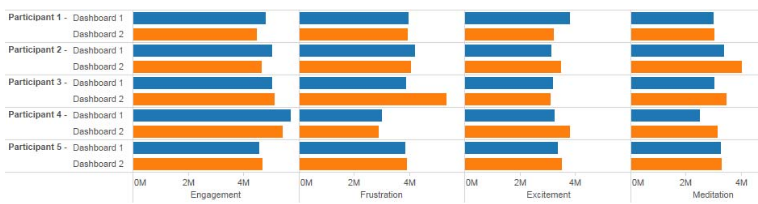

Fig. 3. Average values for engagement and frustration.

we evaluated a new concept for the teachers: how teaching is performed and how the dashboards are perceived by real teachers. This information provided useful insights towards a better understanding of their needs and allowed us to collect data for the next versions of teaching analytics dashboard.

Teachers from elementary and high school may produce different results, have other requirements and so forth. Therefore, we believe that this is a first step towards investigating teaching analytics. Employing larger number of teachers from different institution (e.g. elementary school) is another milestone towards effective learning analytics.

Another scenario for formative assessment would involve real-time feedback from the students. This means that the students reply to a grid and the teacher investigates how the dashboard changes during time. Therefore, conducting perspective analysis may discover other issues that retrospective analysis does not. This issue will be addressed in the future.

7. Conclusion and Future Work

This paper describes teaching analytics dashboards for repertory grid data to enable teachers to conduct systematic visual analysis of classroom learning data for formative assessment purposes. The teaching dashboards of repertory grid data can assist teachers in identifying student competencies, strengths, and weaknesses, planning future learning, and can support teachers in obtaining an overview of the whole classroom as well drill-down into details about individual and/or groups of students.

The teaching analytics dashboards were evaluated with six teachers. The results showed that the teaching analytics dashboards were efficient and effective from a task performance perspective and pleasant from a subjective satisfaction perspective. Regarding innovation, teachers said that similar tools are lacking in their regular pedagogical practice and would recommend their use in formal educational settings. Eye-tracking data from the two dashboards showed that teachers will not be adversely affected by less important areas in their pedagogical decision-making. The emotions computed from the EEG data showed similar levels of engagement and frustration for both dashboards.

We presented evaluation results towards teaching analytics dashboards and provided useful insights for existing learning practices in educational environments. However, research should concentrate and investigate further approaches for educational settings. More specifically future work includes: conducting longitudinal studies of dashboard use in real classrooms, investigating teaching analytics dashboards for students engaged in peer-tutoring, and enriching the variety of supported visualizations and interaction techniques.

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References

[1] Agostinho, S.: Learning design representations to document, model, and share teaching practice. Handbook of Learning Design and Learning Objects: Issues, Applications, and Technologies 1, 1–19 (2009)

[2] Goodwin, C. Professional vision. American Anthropologist, 96, 3 1994), 606-633.
[3] Attention tool. `http://www.imotionsglobal.com/`, accessed August, 2014
[4] Berger, H.: Über das elektrenkephalogramm des menschen. Archiv für Psychiatrie und Nervenkrankheiten 87, 527–570 (1929), `http://dx.doi.org/10.1007/BF01797193`
[5] Bertin, J.: Graphics and graphic information processing. de Gruyter (1981)
[6] Boren, T., Ramey, J., Thinking aloud: Reconciling theory and practice. Professional Communication, IEEE Transactions on, 2000, 43.3: 261-278.
[7] Brown, M.: Learning analytics: The coming third wave. EDUCAUSE Learning Initiative Brief (2011)
[8] E. D. Cassidy, A. Colmenares, G. Jones, T. Manolovitz, L. Shen, S. Vieira, Higher education and emerging technologies: Shifting trends in student usage, The Journal of Academic Librarianship, Elsevier, 2014.
[9] Card, S.K., Mackinlay, J.D., Shneiderman, B. (eds.): Readings in information visualization: using vision to think. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA (1999)
[10] Cleveland, W.S., McGill, R.: Graphical perception: Theory, experimentation, and application to the development of graphical methods. Journal of the American Statistical Association 79(387), 531–554 (1984)
[11] Damasio, A.: Descartes' error: Emotion, reason, and the human brain. Penguin Books (2005)
[12] Davidson, R.J., Jackson, D.C., Larson, C.L.: Human electroencephalography. Handbook of psychophysiology 2, 27–52 (2000)
[13] Dimoka, A., et al. On the use of neurophysiological tools in IS research: developing a research agenda for NeuroIS. (2010).
[14] Duval, E.: Attention please!: learning analytics for visualization and recommendation. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge. pp. 9–17. ACM (2011)
[15] Emotiv. `http://www.emotiv.com`, accessed March, 2013
[16] Print screens from the Teaching Analytics Dashboard using social data. `https://goo.gl/SIOKKH`, accessed September, 2015
[17] Few, S.: Information Dashboard Design: The Effective Visual Communication of Data. O'Reilly Media, Inc. (2006)
[18] Forgas, J.P.: Mood and judgment: the affect infusion model (aim). Psychological bulletin 117(1), 39 (1995)
[19] Frantzidis, C., Bratsas, C., Klados, M., Konstantinidis, E., Lithari, C., Vivas, A., Papadelis, C., Kaldoudi, E., Pappas, C., Bamidis, P.: On the classification of emotional biosignals evoked while viewing affective pictures: An integrated data-mining-based approach for healthcare applications. Information Technology in Biomedicine, IEEE Transactions on 14(2), 309–318 (2010)
[20] Hwang, W., Gavriel S., Number of people required for usability evaluation: the 102 rule. Communications of the ACM 53.5 (2010): 130-133.
[21] Haythornthwaite, C., Gruzd, A.: Exploring patterns and configurations in networked learning texts. In: System Science (HICSS), 2012 45th Hawaii International Conference on. pp. 3358–3367 (Jan 2012)
[22] Henderson, J.M., Hollingworth, A.: Eye movements during scene viewing: An overview. Eye guidance in reading and scene perception 11, 269–293 (1998)
[23] Hertzum, M., Jacobsen, N. E., The evaluator effect: A chilling fact about usability evaluation methods, Int. J. Hum. Comput. Interaction 13 (4) (2001) 421–443.
[24] Hyökki, S.: Eye tracking in user research. Interdisciplinary Studies Journal 1(4), 65 (2012)
Hertzum, M., and Jacobsen, N. E. The evaluator effect: A chilling fact about usability evaluation methods. *Int. J. Hum. Comput. Interaction 13*, 4 (2001), 421–443.
[25] Kelly, G.A.: A theory of personality. The psychology of personal constructs. NY: Norton (1963)
[26] Koper, R., Tattersall, C.: Learning Design: A Handbook on Modelling and Delivering Networked Education and Training. Springer (2005)
[27] Lazar, J. Feng, H. Hochheiser, Research methods in human-computer interaction, John Wiley & Sons, 2010.
[28] Marjanovic, O.: Sharing and reuse of innovative teaching practices in emerging business analytics discipline. In: System Sciences (HICSS), 2013 46th Hawaii International Conference on. pp. 50–59 (Jan 2013)
[29] Mehler, B, Reimer, B., Coughlin, J. F. Sensitivity of physiological measures for detecting systematic variations in cognitive demand from a working memory task an on-road study across three age groups. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 54(3):396–412, 2012.
[30] Nielsen, J., Landauer, T.K.: A mathematical model of the finding of usability problems. In: Proceedings of the INTERACT '93 and CHI '93 conference on Human factors in computing systems. pp. 206–213. CHI '93, ACM (1993)
[31] Nielsen, J. *Usability Engineering*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA, 1993.
[32] Expanding evidence approaches for learning in a digital world. Office of Educ. Technology, U.S. Dept. Education, http://www.ed.gov. (2013)
[33] Paas, F., Tuovinen, J.E., Tabbers, H., Van Gerven, P.W.: Cognitive load measurement as a means to advance cognitive load theory. Educational psychologist 38(1), 63–71 (2003)
[34] Paas, F.G., Van Merriënboer, J.J.: Instructional control of cognitive load in the training of complex cognitive tasks. Educational Psychology Review 6(4), 351–371 (1994)
[35] Pantazos, K., Kuhail, M., Lauesen, S., Xu, S.: uVis Studio: An integrated Development Environment for Visualization, pp. 15–30. Proceedings of S P I E - International Society for Optical Engineering, SPIE - International Society for Optical Engineering (2013)
[36] Pantazos, K., Lauesen, S., Vatrapu R., End-User Development of Information Visualization, End-User Development, Springer Berlin Heidelberg, 2013, 104-119.
[37] Sweller, J.: Cognitive load during problem solving: Effects on learning. Cognitive science 12(2), 257–285 (1988)
[38] Sweller, J.: Cognitive load theory, learning difficulty, and instructional design. Learning and Instruction 4(4), 295–312 (1994)
[39] Sweller, J., Van Merrienboer, J.J., Paas, F.G.: Cognitive architecture and instructional design. Educational psychology review 10(3), 251–296 (1998)
[40] Schmettow, Martin., Sample size in usability studies. Communications of the ACM 55.4 (2012): 64-70.
[41] Tatler, B.W., Wade, N.J., Kwan, H., Findlay, J.M., Velichkovsky, B.M.: Yarbus, eye movements, and vision. iPerception 1(1), 7–27 (2010)
[42] Tufte, E.R., Graves-Morris, P.: The visual display of quantitative information, vol. 2. Graphics press Cheshire, CT (1983)
[43] Van Orden, K.F., Nugent, W., La Fleur, B., Moncho, S.: Assessment of variable coded symbology using visual search performance and eye fixation measures. Tech. rep., DTIC Document (1998)
[44] M. Elias and A. Bezerianos. Exploration views: Understanding dashboard creation and customization for visualization novices. In *Human-Computer Interaction–INTERACT 2011*, pages 274–291. Springer, 2011.
[45] Vatrapu, R., Reimann, P., Bull, S., Johnson, M.: An eye-tracking study of notational, informational, and emotional aspects of learning analytics representations. In: Proceedings of the Third International Conference on Learning Analytics and Knowledge. pp. 125–134. ACM (2013)
[46] Vatrapu, R., Reimann, P., Hussain, A., und Beratung, M.P.F.: Towards teaching analytics: Repertory grids for formative assessment. In: Proc. International Conference of the Learning Sciences (ICLS) 2012 (2012)
[47] Vatrapu, R., Teplovs, C., Fujita, N., Bull, S.: Towards visual analytics for teachers' dynamic diagnostic pedagogical decision-making. In: Proceedings of the 1st International Conference on Learning Analytics and Knowledge. pp. 93–98. LAK '11, ACM, New York, NY, USA (2011), `http://doi.acm.org/10.1145/2090116.2090129`
[48] Vatrapu, R.K.: Explaining culture: An outline of a theory of socio-technical interactions. In: Proceedings of the 3rd International Conference on Intercultural Collaboration. pp. 111–120. ICIC '10, ACM, New York, NY, USA (2010), `http://doi.acm.org/10.1145/1841853.1841871`
[49] Verbert, K., Duval, E., Klerkx, J., Govaerts, S., Santos Odriozola, J.L.: Learning analytics dashboard applications. American Behavioral Scientist 57(10), 1500–1509 (Feb 2013)
[50] Ware, C., Information visualization: perception for design. Elsevier, 2012.
[51] Wang Baldonado, M.Q., Woodruff, A., Kuchinsky, A.: Guidelines for using multiple views in information visualization. In: Proceedings of the working conference on Advanced visual interfaces. pp. 110–119. ACM (2000)
[52] Zelinsky, G.J., Rao, R.P., Hayhoe, M.M., Ballard, D.H.: Eye movements reveal the spatiotemporal dynamics of visual search. Psychological Science pp. 448–453 (1997)
[53] Zhang, Q., Lee, M.: Analysis of positive and negative emotions in natural scene using brain activity and gist. Neurocomputing 72(4), 1302–1306 (2009)