Beyond the Learning Analytics Dashboard: Alternative Ways to Communicate Student Data Insights Combining Visualisation, Narrative and Storytelling

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ABSTRACT

Learning Analytics (LA) dashboards have become a popular medium for communicating to teachers analytical insights obtained from student data. However, recent research indicates that LA dashboards can be complex to interpret, are often not grounded in educational theory, and frequently provide little or no guidance on how to interpret them. Despite these acknowledged problems, few suggestions have been made as to how we might improve the visual design of LA tools to support richer and alternative ways to communicate student data insights. In this paper, we explore three design alternatives to represent student multimodal data insights by combining data visualisation, narratives and storytelling principles. Based on foundations in data storytelling, three visual-narrative interfaces were designed with teachers: i) visual data slices, ii) a tabular visualisation, and iii) a written report. These were validated as a part of an authentic study where teachers explored activity logs and physiological data from co-located collaborative learning classes in the context of healthcare education. Results suggest that alternatives to LA dashboards can be considered as effective tools to support teachers' reflection, and that LA designers should identify the representation type that best fits teachers' needs.

CCS CONCEPTS

• **Applied computing** → *Collaborative learning*; *Computer-assisted instruction*; *Learning management systems.*

KEYWORDS

multimodal data, qualitative analysis, visual learning analytics

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1 INTRODUCTION

Dashboards have become a common visual medium in Learning Analytics (LA) for communicating insights extracted from student data to a wide range of educational stakeholders [29, 43, 44]. LA dashboards have been defined as *"single displays that aggregate different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualisations"* [37]. These displays have been used to visualise metrics with varying purposes such as: supporting reflection [45]; self-regulation [11]; informed interventions [10]; and augmenting academic advice [20]. However, an ongoing debate about the effectiveness of LA dashboards has emerged in the field. Some authors [10, 33, 46, 48] have questioned the visual design of dashboards, critiquing the complexity of the data and visuals they portray. Both teachers [13, 36], and students [6, 22, 40] have reported challenges in interpreting dashboard visualisations and thus, acting upon the information they display. Other authors have pointed at the lack of studies evaluating LA dashboards' adoption and impact on learning (e.g. [6, 41]), teaching (e.g. [16]), or both (e.g. [37, 44]).

The field of Information Visualisation (InfoVis), has provided a historical explanation for these issues [19]. Dashboards were initially created for business purposes, and their users were typically experts in data analysis (or at least professionals dedicated to the analysis of data). These users were expected to explore the visuals, look for business insights, and support decision-makers in the organisation [31]. Yet, in an educational setting, many of the final users of LA dashboards (commonly students and teachers) are *casual users* who cannot be assumed to be data savvy, nor know how to extract insights from charts [12]. Indeed, often these LA 'consumers' are *not* expert data users. For example, Maltese et al. [24] demonstrated that even STEM undergraduate students often struggle to understand even simple charts shown by teachers in lecture slides. Moreover, even if students can effectively interpret dashboard visuals, they can often face interpretation bias [3]. Similarly, it is a complex challenge for teachers to develop the analytical skills required to interpret them for the purpose of making informed decisions [34].

As experts in data analysis, LA practitioners often fall prey to the appeal of the dashboard, assuming that it is most useful to visually display important information on a single screen so that it can be monitored at a glance. However, the InfoVis community emphasises that the ultimate goal of the dashboard is *communication* of key information rather than just plotting data [18]. This paper will work to explore this sentiment, unpacking how such communication might be facilitated for non expert users.

In this paper, we explore three design alternatives to represent student data by combining data visualisation, narratives and storytelling principles. We conducted a study in the context of authentic co-located collaborative classroom sessions in an undergraduate healthcare unit. Activity logs and physiological data from 25 students were collected from their regular classes. Based on foundations of data storytelling [23], the same data was modelled and visually represented in the form of three visual-narrative interface designs: i) visual data slices, ii) a tabular visualisation, and iii) a written report. We conducted a follow up validation study with teachers to explore i) their perceptions on those in terms of the assessment of student errors and stress-levels during clinical simulations, and b) envisaged uses of such interfaces for supporting teaching and learning.

2 BACKGROUND AND LITERATURE REVIEW

2.1 Foundations of Data Visualisation and Storytelling

Constructs from cognitive psychology and visualisation science, such as visual attention, perception, judgement, and decision making, are critical to designing effective LA end-user interface designs [3]. In this subsection, we summarise some key foundations of data visualisation and storytelling, in relation to these constructs, in the form of four principles that we will use later to describe our own LA interface designs.

The ultimate aim of data visualisation in LA is to ease educational stakeholders' cognitive load and facilitate the interpretation of the visual elements used to encode educational data [3]. One way to support teachers and learners' interpretation process is by *using salient visual features to influence attentional capture (Principle 1)*. Attentional capture is the phenomenon in which attention is involuntarily directed towards a target stimulus based on the characteristics of that stimulus [23, 27]. This means that *pre-attentive attributes*, which are properties of the visualisations that we notice without using conscious effort (such variations in colour, shape, enclosure, intensity, hue, or size), can actually be configured/designed for helping 'end-users' interpret the key information that is relevant to them [5]. In order to emphasise some visual elements, others need to be de-emphasised. It is therefore key to *avoid visual clutter as it can severely degrade attention and impair comprehension (Principle 2)*. Reducing visual clutter, or the excess of information and lack of order enables the 'end-user' to allocate more cognitive capacity for essential processing [3, 30].

Besides highlighting and de-emphasising elements, *the use of text to communicate insights can directly support inference-making (Principle 3)*. Visual narrative refers to the use of visual and textual elements to convey a story [38]. Commonly, viewers' attention is oriented towards *text* [27]. This can be used for explaining the meaning of certain data points (if known) [16] or to emphasise sections in a visualisation that require the attention of the viewer (e.g., using text to also achieve Principle 1 [23]). Finally, *some types of visual representations inherently help or hinder the understanding of data and subsequent inference made (Principle 4)*. This means that choosing the right type of visualisation representation for particular goals and educational contexts is key [3]. In the next section we present examples of LA research in which some authors have started to apply these principles in their LA tool designs.

2.2 Visual LA alternative designs

Some seminal work on alternatives to dashboards and design techniques to communicate learning analytics is emerging. Alhadad [3] provided a theoretical account and suggested the LA community to re-think about the value of visualising data as a means of communication instead of as a way to encode educational data. The author also suggested that advancements in this area requires to build on robust cognitive psychology and information visualisation principles (some which have been presented in the previous section) the community needs to also embrace visualizing data as research methodology.

Addressing this call, Echeverria et al. [15] created the first LA prototypes that incorporated data storytelling elements (DS). Authors used eye-tracking technology, in a small-scale study, to illustrate how salient visual features in a data visualisation can drive the attention of teachers inspecting a line chart representing student data in the context of programming and design. Authors added narrative to the visualisation to provide an overview of students' progress and to explain certain data points or changes in the line chart trend. Similarly, Chen et al. [9] explored the use of *data slices* as an alternative to facilitate teachers' exploration of large volumes of data. Authors divided the data and insights obtained from the data into various "slideshows" that teachers can navigate through. Each of these combined charts and briefs snippets of text explaining major trends based on pre-defined questions (e.g. how many assignments did learners finish?). Also based on data storytelling elements, Wiley et al. [47] took a different approach compared to the two previous works. Authors extracted analytics from student data to generate written report that mostly contained text and the visual elements were kept to the minimum. Finally, Martinez-Maldonado et al. [25] proposed a conceptual approach and an architectural design to translate teachers' pedagogical intentions into 'data stories' that contain emphasised visual elements and narrative that can be edited by teachers to facilitate interpretation once the LA interfaces are presented to students or other teachers. In sum, there is a recent, growing interest in considering alternative forms to communicate educational data by embracing data visualisation and storytelling principles. Some of the emerging works have been proposing some potential alternatives to dashboard designs. In this paper, we build on these works and design and ask teachers to compare three visual-narrative interfaces that incorporate narrative and visuals to various extents in an authentic learning context, which is described in the next section.

3 LEARNING TASK

This paper focuses on five simulation classes, part of the unit *Integrated Nursing Practice*, conducted with students in their third year at the [*Anonymous university*]. Approximately 25 students typically attend a class in the simulation ward, and they are organised in groups of 4–6 students, each working in a simulated training scenario around a patient bed. One group in each of the five classes volunteered to participate in this study and have their activity tracked (groups G1-5), completing informed consent (ethics approval number ETH16-0582). The average duration of the simulation was 1.09 hr (std=14.4 min). A total of 25 students (21 female) participated in the data collection (aged 20-45 years, mean=23.5, std=5.4). Four teachers were involved in teaching the five classes.

In this simulation, students enacted various nursing roles to collaboratively care for a patient experiencing an allergic reaction. Three register nurses (RN1-RN3) and a team leader (RNL), and one student played the role of the patient, giving a voice to the manikin. Commonly, after the simulation there is a debrief session which is a class reflection led by the teacher. According to the learning design, a highly effective groups should carry out the following *critical actions*:

(1) Measure an initial set of vital signs;
(2) Administer the intravenous (IV) antibiotics;
(3) Take a second set of vital signs;
(4) Stop the IV antibiotic after the patient reacts with chest tightness;
(5) Perform an electrocardiography (ECG); and
(6) Call the doctor after stopping the IV antibiotic.

Based on these, the simulation can be divided into 3 phases: *Phase 1:* patient assessment (from the beginning of the simulation to the patient' chest tightness); *Phase 2*: critical patient deterioration (since the patient starts complaining about the allergic reaction until recovery); and *Phase 3:* patient recovery (from the patient recovery to the end of the simulation).

3.1 Data Collection

Key student *actions*, such as vital signs assessment, were detected by the mid-fidelity manikin (Laerdal Nursing Anne). Other actions performed by each student (e.g. stopping intravenous-IV fluid, writing on charts and calling the doctor) were *logged* by an observer (a researcher but it could also be a student, or a higher-fidelity patient manikin not available in all the classrooms of the hosting university) using a web application. Actions are logged in a database with the following structure: i) action description, ii) timestamp, and iii) student-role who performed the action. Students' *physiological data* was captured through (Empatica e4) wristbands. We used recorded electrodermal activity (EDA) at 4Hz. EDA signals are composed of both skin conductance responses (SCR) and skin conductance levels (SCL). The analysis of such components can be used to signal student-measures of stress [32] or cognitive load [42].

Type of Rule	Purpose	Example	Data modelled
Sequence	Gave feedback base on sequence of actions	Provide oxygen **after** the patient respiratory depression	Activity logs
Timeliness	Gave feedback base on timeliness of actions	Stop the IV device in less than **5 minutes**	Activity logs
Frequency	Gave feedback based on frequency of actions	Validate vital signs **every** 5 minutes	Activity logs
Arousal Peak Level	Categorise the arousal experienced by a student as very low, low, mild, high or very high)	Team leader presented **very high arousal peaks** after the patient deterioration	Activity logs and physiological

Table 1: Types of rule-based algorithms used to model multimodal data

4 DESIGN

This section describes the design process of three visual-narrative interfaces that we used to explore teachers' perceptions after their evaluation.

4.1 Modelling

Both data modalities (activity logs and physiological data), were modelled differently but following a three-steps process based on Echeverria et al. [14]'s multimodal modelling approach: i) converting from low-level data to a discrete data structure; ii) interrogating these data based on the learning design or educational theory; and iii) crafting the visual-narrative interface. The next subsections provide details about the first 2 steps for each modality.

4.1.1 Activity Logs Modelling. We represented the absence or presence of certain key actions described in section 3 actions as binary flags (1, 0) (Step 1). Based on these and the assessment criteria of the learning task, we created rule-based algorithms to automatically detect errors in the order or timeliness of student actions in the simulation task (Step 2). Three types of errors were automatically identified (see first three rows in Table 1). The *sequence* errors are flagged if the group performed a critical action using the wrong sequence. For example, if students forget to perform a *vital signs assessment* after the patient has complained of serious chest pain. *Timeliness* errors are identified when students reacted slow and performed certain actions too late according to healthcare guidelines. For example, this happens if they take too long before calling the doctor after a patient's crisis or if they take too long to stop a medication that is causing an adverse reaction, which should be done in less than 5 minutes in this simulation. An error related to *frequency* is assessed by calculating the timestamp difference between two key logged actions that are meant to be repeated, for example: assessing patient's vital signs at least every 10 minutes.

4.1.2 Physiological data modelling. The recorded EDA at 4Hz, was passed through the EDA Explorer [1] algorithm to detect non baseline-based arousal peaks (sudden changes in skin conductance levels) in each student's EDA signals [39]. The number of arousal peaks per minute are counted and recorded in a matrix for each team member (step 1). Then, a switch algorithm was developed to assess the *arousal peak level* (Table 1, row 4). This categorises nurses' levels of arousal during each of the 3 phases by calculating the ratio of arousal peaks for each nurse compared to the highest ratio of arousal peaks experienced by a single student that we have detected in all of our nursing simulation studies, including previous works (5 peaks/minute) [17]. This maximum ratio is divided into quintiles of equal size which are used to categorise the arousal experienced into very low, low, mild, high, or very high levels. Thus, for instance,

[1] https://github.com/MITMediaLabAffectiveComputing/eda-explorer

teachers can know if the student playing the role *RN1* presented *high arousal peaks* during *phase 2* (step 2).

The next section presents the visual-narrative interfaces (step 3) designed following the steps described above.

4.2 Visual-Narrative Interfaces

Three visual-narrative interfaces were designed to communicate information about the group(s) and class outcomes, namely, i) visual data slices, ii) tabular visualisations and iii) written reports.

4.2.1 Visual-Narrative Interface 1 - visual data slices. The first interface was designed based on the *timeline* metaphor, which is commonly used to represent temporal relations in student actions [35], and the notion of data slices reviewed above [9]. Five data slices were created based on the interactive slideshow metaphor. Activity logs were grouped into four slices, related to the critical actions modelled by the rule-base algorithms described in the previous section. Critical actions, that involved similar activities, were aggregated in the same slice to avoid a big number of them. That way, critical actions related to vital signs validation (at different moments during the simulation) were condensed in the same slice, as well as IV antibiotic actions (ether administer or stop it).

Figure 1 presents an example of data slices that communicate nurses errors. It includes visual enhancements such as *enclosing areas*, shaded areas and boxes, to emphasise where the error was detected or to explain what was the error (A); *changing colour*, to guide attention to certain points or messages such as errors (yellow) or correct actions (blue) (B) (principle 1); and *text annotations* such a *title* that summarises the take-away message of the slice (C), or additional *explanations* for particular data points (D) (principle 3). Gestalt principles [4, 23] of proximity and similarity were used to group similar elements of the messages, for example using the same color for shaded areas, messages and highlighted points or including annotations in close proximity to points of interest (principle 2).

One additional slice was included to communicate student's arousal levels. Figure 2 was build to communicate the different levels of arousal peaks that nurses experience during the simulation. This visual-narrative interface includes *changes in colour* (A), indicating levels from very low to very high levels of arousal peaks (principle 1). The use of *text* in this interface helps to emphasise the intended message to be communicated (principle 3). For example, it explicitly flags those roles that were highly aroused in the title (B), and at the level of the phase of the simulation (C).

4.2.2 Visual-Narrative Interface 2 - tabular visualisation. The purpose of this interface is to visually report the outcomes of all groups that participated in one simulation (normally 5). The story of the whole class is communicated using a tabular structure based on a tabular heatmap approach [23]. That way, the table mixes the detail of groups and critical actions while also making use of visual cues to guide teacher's attention. The first *column* of the table in Figure 3, introduces the learning intentions to provoke class discussion in terms of the simulation performance or arousal experienced by the students. The other 5 columns aggregate specific outcomes for group 1 to 5. *Rows* in the table, represents each of the critical actions (6 as per the learning task) and one additional row to present the groups' arousal peak levels. Unfortunately, the physiological data of group 1 was not captured because of some issues with the sensing technology.

In this case, *textual explanations* (A), were included to explicitly explain the rules used to generate groups' outcomes. For example, the rule used to generate values in row 4 was presented as follows: *"(Stop IV antibiotic after erythematous torso rash)* ***AND*** *(Stop IV antibiotic in less than 5 min)"*. Additional explanations were included in certain cells when actions were partially correct. For instance, group 3 performed an action but their time response was not appropriate: *"The group called the doctor* ***6 minutes late****"* (B). *Changes in colour*, were used to either emphasise errors (yellow) or assertive responses (blue) regarding critical actions (C). In this case, the levels of arousal were counted and shown explicitly through the interface (D).

4.2.3 Visual-Narrative Interface 3 - written report. This written reports summarise the key insights concerning critical actions and arousal peaks. The story which summarises the main insights from the class is presented using a textual *narrative* representation. That way, the straightforward key messages supports teachers' inference-making of what happened during the simulation (principle 3). The report was organised similarly to the tabular visualisation presented above, with columns and rows referring to groups of students and educational constructs, respectively. Pre-attentive attributes (see section 2) were also used in the form of text formatting with the aim of directing the audience attention [23] (principle 1). Figure 4 presents an example of a resulting written report as a result of our modelling. *Bold* format (A), was used to present text that described critical actions. *Underscored text* (B) emphasises common errors that groups made during the simulation. In regards to arousal peaks, roles and group members were grouped using text in bold (C). Finally, the summary gives and emphasis to the roles that were most highly aroused during the simulation. Because of that, color in text was used (D) to present students, who experienced the most arousal peaks.

5 STUDY AND ANALYSIS

5.1 Participants and Protocol

A qualitative validation study, using a retrospective reflection technique [21], was conducted to investigate the Nursing educators' responses to the 3 visual-narrative interfaces. Four teachers (T1-T4) were interviewed (3 females, 1 males, years of experience as register nurses from 40 to 9, avg=21, std=14.6). Each of them belong to the teaching team delivering the unit, to preserve the authenticity and value of the study.

This validation study sought to address two research questions:

- RQ1: What are teachers' perceptions of representations of student data using i) visual data slices, ii) tabular, and iii) written report formats?
- RQ2: What are teachers' potential envisaged uses of the visual-narrative interfaces to support teaching and learning?

To address these questions, a think aloud protocol was defined. The interviews were conducted in the form of 45-minutes, individual interviews (3 in person and 1 via Zoom). The interview was structured in two parts as follows.

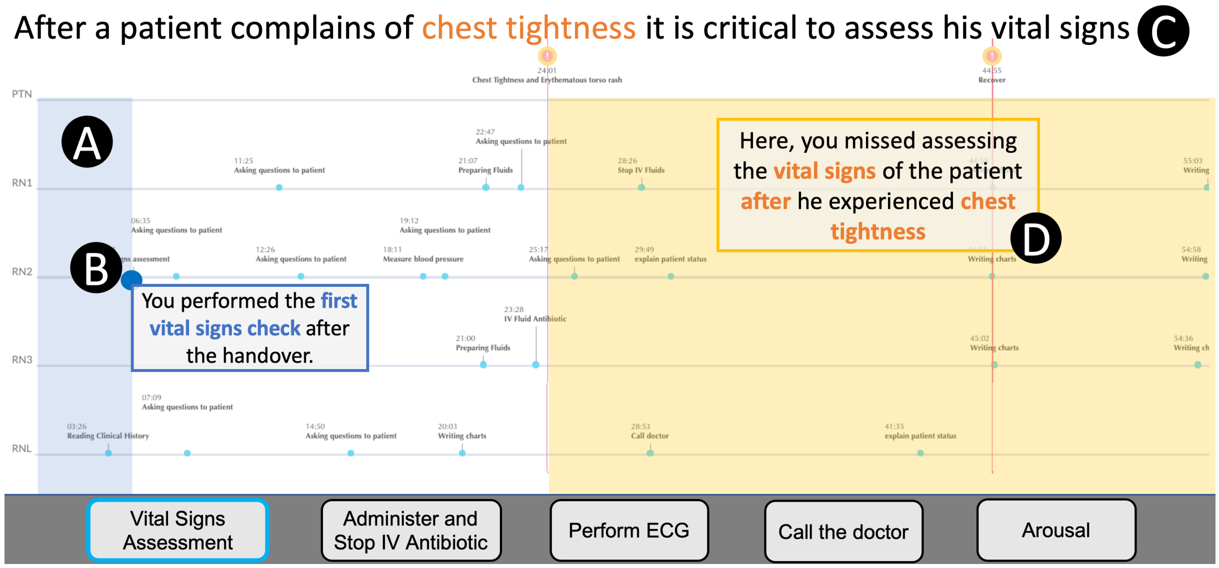

Figure 1: Data slice example, communicating that the group of students skipped some actions, including: A) shaded areas to group relevant data points according to the learning task; B) annotated data points; C) a summary of the main story of the data slice; and D) text narrative explaining the main issue in student's performance.

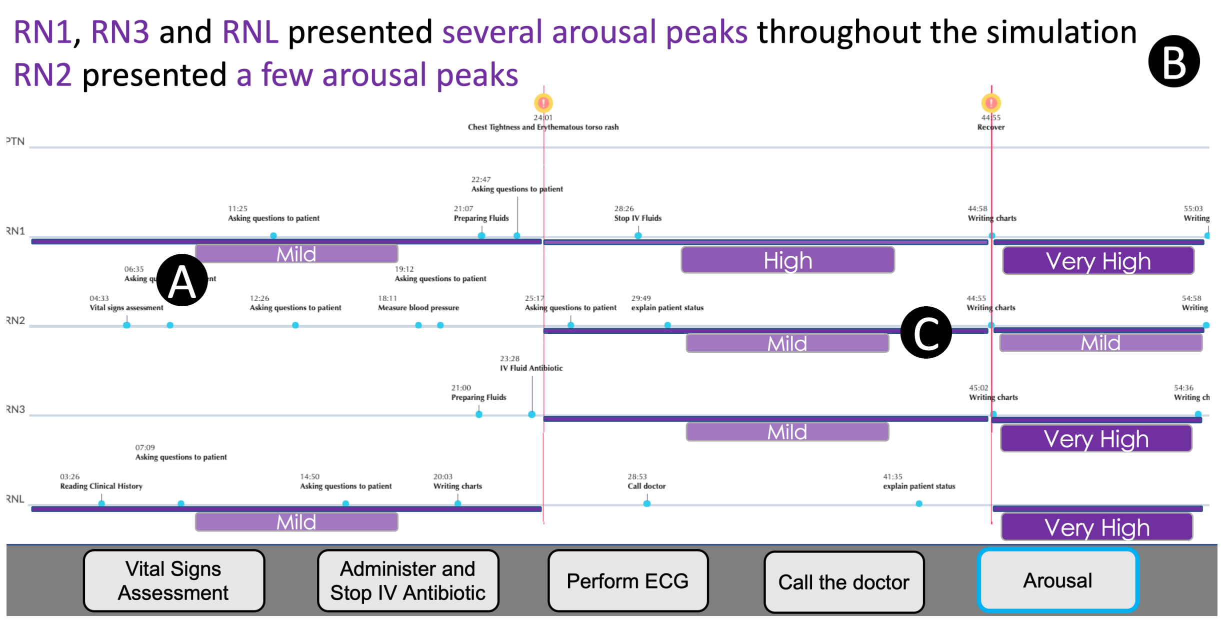

Figure 2: Data slice example, communicating nurses arousal peak levels using text labels, including: A) intensity of colour to visualise a range of values from very low (*lighter*) to very high (brighter); B) text indicating the levels experienced by nurses; and C) explanatory labels indicating the arousal levels per phase.

i) Exploration of teachers' reactions to the three different visual-narrative interfaces: teachers were asked to navigate through each interface while thinking aloud. Teachers were asked to compared two different groups using the data slices and compared 5 groups while inspecting the other two visual-narrative interfaces. For the case of interface 1, teacher's navigated first through the timeline (without data stories) to then explore each of the 5 slices.

ii) Open questions about the alternative uses of the visual-narrative interfaces. Triggering questions were used to investigate how teachers envisaged the use of each prototype to support their teaching practice. The two questions asked were: 1) what would you do with

	Group 1	Group 2	Group 3	Group 4	Group 5
Initial Vital Signs Assessment A (Asses **after** handover)	✓	✓	✓	✓	✓
IV Antibiotics Administration (Administer IV antibiotic **after** handover)	✓	✓	✓	✓	✓
Second Vital Signs Assessment (Asses **after** chest tightness)	- Miss assessing vital signs **after chest tightness**	✓	✓	- Miss assessing vital signs **after chest tightness**	- Miss assessing vital signs **after chest tightness** C
Stopping IV Antibiotics (Stop IV antibiotic **after** erythematous torso rash) AND (Stop IV antibiotic **in less than** 5 min)	✓	✓	✓	✓	✓
Perform ECG (Perform ECG **after** chest tightness)	✗	✓	✓	✗	✓
Call the doctor (Call the doctor **after** stopping IV) AND (Call the doctor **in less than** 5 min)	✓	✗	- The group called the doctor **6 minutes late** B	✓	✓
Arousal D (stress or cognitive load, count of arousal peaks)	**NA**	**RN1: 7** **RN2: 25** **RN3: 38** **TL: 120**	**RN1: 182** **RN2: 22** **RN3: 156** **TL: 110**	**RN1: 92** **RN2: 32** **RN3: 69** **TL: 50**	**RN1: 351** **RN2: 92** **RN3: 42** **TL: 505**

Figure 3: Example tabular visualisation (heatmap metaphor) including: A) rules' textual explanation; B) textual complementary explanations; C) changes in colour to present errors in blue and assertive responses in blue; and D) levels of arousal peaks using a sequential scheme of colour.

	Insights summary
Initial Vital Signs Assessment (Asses **after** handover)	- All 5 groups assess **Vital Signs** after **Handover** A
IV Antibiotics Administration (Administer IV antibiotic **after** handover)	- All 5 groups **administered IV Antibiotics** after **handover**
Second Vital Signs Assessment (Asses **after** chest tightness)	- Groups 1, 4 and 5 failed in assessing **Vital Signs** after **chest tightness** B
Stopping IV Antibiotics (Stop IV antibiotic **after** erythematous torso rash) AND (Stop IV antibiotic **in less than** 5 min)	- All 5 groups **stopped** the **IV Antibiotics** after **allergic reaction**
Perform ECG (Perform ECG **after** chest tightness)	- Groups 1 and 4 did not perform the **ECG** after **chest tightness**
Call the doctor (Call the doctor **after** stopping IV) AND (Call the doctor **in less than** 5 min)	- Groups 2 and 3 failed in calling the doctor in **less than 5 minutes** after **stopping** the **IV antibiotic**
Arousal C	- **TL** in **Group 2** was the role with **more peaks** - **RN3** in **Group 3** was the role with **more peaks** - **RN1** in **Group 3** was the role with **more peaks** - **TL** and **RN1** in **Group 5** were the roles with **more peaks** D

Figure 4: Example Written Report including: A) bold, to emphasise the critical actions; B) underscored, to indicate common errors; C) bold, for arousal to set roles and group number; and D) bold and colour sequential scheme to indicate nurses' arousal peaks

each of these three representations?, and 2) when and for what purpose each representation would help in your teaching or students' learning?

5.2 Analysis

The interviews were video-recorded, fully transcribed, and coded using NVivo. We examined participants' statements and their actions exploring the visual-narrative interfaces. Following Mcdonald et al. [28], and given the direct alignment between the study protocol and the analysis themes, statements of interest were jointly coded [8] by two researchers according to the pre-set themes of the study protocol: (a) educators perceptions on different visual-narrative interfaces while exploring them; and (b) open questions regarding the potential uses of each visual-narrative interfaces. Resulting coded statements were examined by the authors who had several discussions to select instances that illustrate the opportunities and concerns raised by the teachers.

6 RESULTS

This section reports the findings of the individual interviews. Results are presented according to the research questions.

6.1 RQ1. Teacher's perceptions to visual-narrative interfaces

After exploring the visual-narrative interfaces these were the more relevant comments from educators, which illustrate their perceptions and reactions for each interface.

6.1.1 Visual data slices. When exploring interface 1 (with no enhancements, only the timeline), teachers tend to miss useful information regarding the critical incidents. For example, groups are expected to assess vital signs at the beginning and after the patient deterioration, all educators were able to identify (pointing) in the visual representation the critical incident *Vital signs assessment*, but, none of them was able to identify that the second assessment was missed. Their interpretations changed after looking at the first *data slice*, as they realised that the groups they were assessing actually had skipped the second set of vital signs validations (e.g., see Fig. 1). Using the data slice, teachers' interpretations were more complete and were more aligned to their pedagogical intentions. For example, T4 explained that *"group 1 took the initial vital signs earlier than group 4"* and then she realised that *"nurses haven't actually performed the second set of vital signs"*, which she *"did not pick up earlier"* exploring the timeline with no enhancements. Likewise, for group T3, indicated that *"nurses did the first check and then after the patient deteriorated or it changed in condition, they should do another vital sign check, which is what we teach them and what we would expect them to do"*. This illustrates the potential for this visual-narrative interface to **communicate one specific message at a time**. This way, teachers can assess how well the team did in specific aspects of learners' task.

With regard to the arousal data slice (see Fig. 2), teachers interpreted the labels that indicated 'high' and 'very high' levels of arousal with those moments when nurses were performing various tasks. For example, T1 explained that *"the RN1 was actually doing a lot of stuff [actions] and so was the team leader, which makes sense, why they have high arousal levels"*. T2 followed a similar interpretation strategy, *"trying to link the high and very high arousal levels with what nurses were actually doing"*. Based on this he indicated that *"RN3 for example was doing an ECG. They've done that really quickly so they've had a fabulous response and RN3' arousal fluctuate to nothing over the beginning of the sim to a very high arousal in the middle and the end of the sim"*. T3, also indicated that high arousal levels can be indicators of nurses feeling more *"involved"*, *"challenged"*, or *"engaged"*, which was also related to the number of actions that students were performing. In contrast, the mild and low arousal values were associated with how *"confident"* (T1, T2), *"calm"* (T4), or *"disengaged"* (T2, T3) a nurse can be. T4 explained that using this data slice teachers can *"talk about how to prevent stress so nurses do not make mistakes in a real situation where stress can affect group responses"*. In sum, in order to **contextualise** the individual levels of stress, teachers used both the description of actions and the arousal peak labels to justify their interpretations.

More specifically, teachers reacted positively to the *highlighted* elements and the *narrative* included on each of the data slices. For instance, T1 explained that the messages looks *"great, they are really clear, straightaway, the message stated that nurses did miss the vital signs, I did see that correctly"*. T2 indicated that he *"liked the tailored messaging in terms of the time sequence"* and suggested that *"the time responses would be quite interesting to also be included as a part of the message"*. Likewise, T4 identified the value of messages and also recommended that they can be complemented adding extra information that can be useful feedback for students. For instance, T4 thought that performing an ECG group G3 *"could have been performed faster because if a nurse has gone in and stopped the antibiotic fluids they can straight away talk to another nurse to get the ECG"*.

T3, explained that textual messages were *"very clear, nurses administered the antibiotic and then after the chest tightness and the rash they stopped the fluid, so I think that's a good way of showing that that's what they're meant to do and they did it fairly quickly, within less than five minutes. So, that's really good"*. Additional elements, such colour were commented by teachers, for example, T1 explained that she *"liked how the visual elements are matching up, and the colours used [for the text also] match up, so it's really easy to see"*. The *shaded areas* were correctly associated with the group time responses, for example while comparing groups, T1 indicated that *"G1 called the doctor quickly, more quickly than G4"*. The same comparison happened while all teachers explored quick reactions of groups to stop the IV antibiotic. The similarity gestalt principle was evidenced here when teachers **read/group elements with the same colour as part of the same message**. For example, the yellow shaded area and the highlighted words in yellow colour were associated as part of the same message (a group error).

Generally, teachers interpreted key messages using each of the data slices. The elements to capture teacher's attention worked as expected, as per their explanations, they interpreted correctly when groups made errors or asserts. We validated teachers' quotes rightness according to the group outcomes and videos. Additionally, the visual enhancements were mostly well perceived and helped teachers to identify the indented goal for each data slice. Messages, were perceived as useful, however, some suggestions regarding the specificity (e.g. include the time response) are evidenced by teachers.

6.1.2 Tabular visualisations. The main reaction of all educators about this interface was that it was particularly useful to compare different **group outcomes from the whole class at a glance**. For instance, T3 compared and reflected that *"two of the groups [G1 and G4] did not perform an ECG, which is quite a big error"* and then she realised that *"two of the other groups [G2 and G3] did not escalate things by calling to the doctor"*. Besides group comparison, educators mentioned that individual interventions could also be planned based on this interface. For instance, T4 explained that *"she might be doing interventions per group to talk about specific points highlighted in the table"*. However, she also mentioned that when many groups missed something *"it is important that the teacher reinforces that for all the class and not individually [to a particular group]"* (T4).

The visual elements used in this interface, such as colour and icons, captured teachers' attention. For example, T1 indicated that *"with the table and the colours you can see visually, straightaway the class summary"*. For the case of T4, her attention was focused on the missing actions (errors) and indicated that *"because every group had yellow parts that is something that need to be debriefed"*. Additionally, T4 mentioned that *"ticks and crosses"* can be used as a *"checklist"* to rapidly assess *"what have students done or not done"*. Two teachers (T2 and T4), were interested to see the time response to complement the report, which can be a way to assess if the rules used should be changed or calibrated.

Yet, all the educators needed additional explanations regarding the meaning of the numbers presented in the last row of the tabular representation (arousal peaks count), because at first they did not understand their meaning. After a short explanation (from the researcher guiding the interview), all educators tried to make sense of the values. At this point, educators indicated that having that information could be of interest and can help them to **trigger interactions with students who are under stress**. For example, T1' interpretations suggested that *"in G5, RN1 and the team leader were very stressed. Well, at least these are the highest numbers in the table, probably followed closely by G3"*. Likewise, T3 mentioned that based on the information presented *"G5 needs a lot of support if the team leader is striking 500 times in one simulation hour"*. T3 used the data to reflect about her practice in regard to the higher number of peaks that students had, she said that having these data *"would make [her] interested if maybe [she] was making the students stressed as their teacher"*. Additionally, some suggestions were mentioned by teachers such *"the use of labels or something more meaningful that communicates levels of stress would be ideal"* (T2), he even suggested the use of *"emojis"*.

In sum, teachers perceived the value in the use of this interface for the particular purpose of comparing groups at a glance. In addition, they proposed additional modifications and improvements to the way that certain data, such as arousal levels, were rendered.

6.1.3 Written summary report. All teachers appreciated the value of text in this interface to create a summary of the simulation outcomes. For instance, T1 stated that *"with the table you can straightaway see exactly what's going on in a nice table, using text like a report or a summary"*. Also, T2 mentioned that *"interface 3 is a really nice written assessment and I see the value of having text in the report"*. He also stated that he would like this interface *"as the classroom dashboard"* summarising the key insights. Two of the teachers (T3 and T4), indicated that visual-narrative interfaces 2 and 3 were really similar. For instance, T4 explained that *"the last two interfaces were pretty much the same but because she didn't see the difference between them two"*. Teachers who saw no differences between visual-narrative interfaces also mentioned their preferences for interface 2, because they *"like visuals a lot better"* (T3) and because interface 3 *"has a lot more reading"* (T3) and because *"is more textual"* (T4), interface 2 was preferred because as it brings at a glance a visual picture of all group outcomes.

6.2 RQ2. Envisaged uses of visual-narrative interfaces

6.2.1 Use of visual-narrative interfaces in the classroom. Generally, teachers expressed willingness to use all the visual-narrative interfaces to support their classes. For example, T2 mentioned that *"having this visual reminders [referring to all the visual-narrative interfaces] as a **debriefing** is really important. So, from the teacher there might be comments about the general group outcomes, but to focus on the missing aspects. This, in order to have the assessed evidence to focus on for a trigger point for debriefing, is fabulous"*. All teacher agreed that interface 1 can be useful to provide more specific **feedback**, T2 explained that she would be able to provide *"much more depth and much more ability to have trigger material for the debriefing"*. T3 thinks that all of them can be used in different moments during the class *"as soon as the class finishes would be very useful for teachers to use prototype 2 and 3 (tabular visualisation and written report, respectively), to show teachers where nurses did miss out on the essential tasks. Then prototype 1 (data slices) would be very beneficial to use in the debrief but probably before you ask students to reflect back on whether they did what they think they did. After that, hit all of the essential criteria with prototype 1, and then bringing up prototype 2 and 3 on the screen to show students if they actually did satisfy these criteria"*.

For visual-narrative interfaces 2 and 3, teachers can see more opportunities to use them to support educators or other academic staff to validate whole class outcomes and **inform** the learning design. T3, indicated that interface 3 *"would probably be good for the subject coordinator or for their actual report"*. Interface 3 *"is really useful from a research and from a teacher evaluation perspective but not for the students"*. This suggests that teachers may find visual-narrative interfaces 2 and 3 useful to **compare performance** of different groups. Interface 1 is not adequate for that purpose in class, as explained by T4, as follows: *"it's really hard to see as a whole, as teachers we have got five groups happening at the same time and exploring slices of all of them would be difficult"*.

Regarding the data slice about levels of arousal peaks, teachers indicated that it can be used in the class by the teacher and individually. For teachers it would be useful *"to continue to reinforce how to manage stress"* (T2) or to identify *"moments where nurses are feeling more stress"* (T3). However, there is some concern regarding how to communicate such data, T1 indicated that *"it all depends on how the teacher explains [arousal and errors], so you've got to showcase your [students] their strengths and if they do have some weaknesses, you need to present it in a way that it isn't condescending. You've got to present it in a way that [students] can learn from it and not be too critical about it"*.

6.2.2 Uses for assessment or as an additional assignment. All teachers agreed that the visual-narrative interfaces can be used as an additional assignment for students to **reflect** on what they did during the simulations. T2, came up with an idea to use the visual-narrative interfaces in which *"students could indicate the role they play (e.g. RN1) so then they [team and individual students] can reflect about the actions that the team performed and the individual role in the scenario. So, then that could form part of an* ***assessment****, the tricky thing is bringing it up to scale"*. Likewise, T3, mentioned that the visual-narrative interfaces can be used for assessment and reflected about her particular case *"I see some of the students might be on the phone not really engaging with the class. So this is a good set of visuals that can be used to improve the way students engage with the class and learn from their outcomes"*.

Also T2, explained that the visual-narrative interfaces can be used for **group assessment** because *"visual-narrative interfaces are linear and show also independent, individual, data. So, this gives a really good indication of what people are doing"*, but T2’ main concern is that visual-narrative interfaces *"don’t give you the indication of the interaction with each other"*, referring to interaction as *both verbal and non-verbal communication.*

7 DISCUSSION

7.1 Summary of Results

Revisiting the research questions (Section 5.1 5.1) we can summarise the outcomes from the teacher interviews as follows (see Figure 5). Regarding RQ1, teachers used the visual-narrative interfaces to gain different levels of understanding of the class, group and individual performance. For example, the visual-narrative interface 1 (the data slices), communicated key information about one specific group’s outcomes at a time. The combination of narrative and visuals in the same interface enabled the interpretation of the meaning of several data points. Yet, this interface is rich and requires moving from one slice to the other.

The visual-narrative interface 2 visually integrates outcomes from various groups in a whole class at a glance. It uses a tabular format which is an acceptable data visualisation technique [23] without being a chart. It combines icons and text. Although a great extent of detail is lost compared to the data slices, it provides a quick overview of the state of the class that could be used in the debrief by the teacher to lead reflection at a class level.

The visual-narrative interface 3 summarised key insights regarding the class outcomes using text only. Although teachers see value in generating this class of report to document the outcomes of a class, its usage may be more limited to documenting and generating resources for teachers’ own reflection rather than being used to orchestrate reflection sessions with students during the debrief.

In terms of RQ2, teachers complemented their own reflections by suggesting specific opportunities to use the different visual representations. The data slices were seen as useful to provide detailed feedback to a specific group, or to be given to students as input to complete a reflective (possibly assessed) task on their own. The tabular visualisation and the written report could be used to compare group performance, with the former having the potential to be used as the main reflective aiding interface during a debrief with students post-simulation.

7.2 Implications for Research

Reflecting on these findings, several points merit discussion. Alternative renderings provide complementary perspectives on learning and teaching. A given data visualisation technique makes different patterns explicit or obscure [3, 23]. Different representations intrinsically have affordances that are perceived (or not) by various educational stakeholders differently [7]. Despite the efforts that most LA designers may make to generate neutral and objective representations of student data, all information design tend to favour particular perspectives. Although this paper explored three different ways to communicate student data insights, we believe that much more work in this area is needed to identify the impact of the choice of data visualisation technique and the use of visual-narratives on teaching and learning practices.

7.3 Implications for Practice

The envisaged uses that teachers perceived in the visual-narrative interfaces open opportunities to inform teaching and learning in different ways. For example, written reports can serve to document performance of a unit [47] or to revise the learning design (e.g. reinforce the importance of doing specific procedures that the majority of groups missed). For students, the interfaces can serve as a tool for reflection based on evidence collected through multimodal data [25]. Communicating key insights using narrative can also be seen as a way to minimise the need for data literacy or data analysis training of casual users (e.g. teachers, students). Nevertheless, we as researchers or designers, are already making interpretation for teachers. This implies certain risks of bias. To mitigate such risks, interactive design and evaluation processes with ’end-users’ are needed in order to perceive their real needs [1, 26].

7.4 Visualisation of Multimodal, Sensor Data

We did find that using complex data (e.g. physiological data) introduced additional complexities in communicating learner data. This work should be seen as first steps towards the further research needed to create interfaces that support the interpretation of analytics outputs [15, 47]. *Salient aspects* of the visual-narrative interfaces and *messages* included in the visual representations, were perceived positively and we evidenced how a feature such as *colour* was used by teachers to visually group elements and interpret them as part of the same message (e.g. orange in text, points and shaded areas was used to communicate a group error). However, teachers particularly mentioned that certain parts of the message needed to be complemented, particularly the time responses. In this regard, the tool can be implemented so that tailored messages can be generated [2] and modified by teachers, according to their own pedagogical intentions. Likewise, we acknowledge that additional categories of rules to interrogate the data could emerge according to the context, but the ones presented here are generally applicable for this and other contexts.

7.5 Limitations

The evidence reported in this paper should be considered in the context of the limitations of the study. While the clinical simulations were authentic and reflect how healthcare students and professionals nurses are commonly trained, the data collected to generate

Visual-narrative interface	Communication medium	Visual enhancements' perceptions
Visual data slices	**Visuals** enhanced with **narrative**	**Opportunities:** *Tailored messages* describing the meaning of data points. Colour helped teachers to *group data points meaningfully*. **Challenges**: Effective to navigate details but not for teachers to gain a *wide view of the classroom activity*.
Tabular visualisations	A table combining **narrative** and **iconic** visuals	**Opportunities:** Icons, colours and text support *quickly identification of points* that need attention. **Challenges**: Effective to navigate through the class activity but details of *individual team activity get lost*.
Written report	**Narrative** only	**Opportunities:** *Text highlighting and de-emphasising elements* of the class outcomes. Can inform the learning activity design. **Challenges**: Textual information will *require additional time to make sense* of the content.

Figure 5: Summary of Results

the visual-narrative interfaces were from 25 students (5 groups) performing a particular simulation. Four teachers were willing to participate in the exploration of the interfaces. It is possible that other teachers could have reacted differently, and that the design approach documented here may not transfer to other kinds of simulation exercises which require the tracking of student activity that is too complex to automate.

Moreover, although the interfaces are fully automated already, to realise the goal of generating them in a timely manner, to provide intelligible feedback on real collocated teamwork settings, a number of challenges (e.g. data integration and synchronisation) remain.

8 CONCLUSIONS

Inspired by the way teachers provide feedback to students, and how humans communicate, the interfaces described in this paper sought to communicate learner insights with different granularity. As mentioned in the literature review, the LA field can draw inspiration from how other sciences and design disciplines have learnt to communicate complex information in engaging ways. Salience of visuals, avoiding visual clutter, using narrative, and choosing the right type of visual representations can all be used to augment teacher-led reflection. This paper presented the design rationale, and expert critiques, of three visual-narrative interfaces, in the context of authentic nursing simulation classrooms. It was evident that the affordances of each design assisted different teaching tasks.

The exciting potential of *data-driven* stories is, of course, that once LA researchers/designers understand those affordances, they do not necessarily need to choose which one to offer, but can offer them all as automatically generated, linked visualizations, placing the agency in the hands of teachers and students to switch between them as suits the context. Given the well documented limitations of current dashboards, we anticipate that approaches such as data storytelling will grow in importance to help students make the most of the new forms of feedback that are becoming possible.

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