# Data Storytelling Editor: A Teacher-Centred Tool for Customising Learning Analytics Dashboard Narratives


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## ABSTRACT

Dashboards are increasingly used in education to provide teachers and students with insights into learning. Yet, existing dashboards are often criticised for their failure to provide the contextual information or explanations necessary to help students interpret these data. Data Storytelling (DS) is emerging as an alternative way to communicate insights providing guidance and context to facilitate students' interpretations. However, while data stories have proven effective in prompting students' reflections, to date, it has been necessary for researchers to craft the stories rather than enabling teachers to do this by themselves. This can make this approach more feasible and scalable while also respecting teachers' agency. Based on the notion of DS, this paper presents a DS editor for teachers. A study was conducted in two universities to examine whether the editor could enable teachers to create stories adapted to their learning designs. Results showed that teachers appreciated how the tool enabled them to contextualise automated feedback to their teaching needs, generating data stories to support student reflection.



## CCS CONCEPTS

• **Human-centered computing → Visualisation design and evaluation methods**.

## KEYWORDS

LA Dashboards, teacher-centered tool, data storytelling

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## 1 INTRODUCTION

Learning Analytics (LA) dashboards are becoming increasingly commonplace in education as a way to provide teachers and students with insights into learning. These displays visualise metrics for different purposes, such as supporting reflection [45], self-regulation [30, 40], or informing timely interventions [26]. Nevertheless, existing dashboards are often criticised for their limitations in providing the necessary contextual information or explanations to help students interpret their data (e.g., lack of context and complex designs [1]). Research has also shown that both teachers (e.g., [12]) and students (e.g., [5]) find it challenging to understand and take action on the data presented in LA dashboards.

LA dashboards aim to directly support educational stakeholders (e.g., students, teachers, or professional trainees) who may lack the appropriate set of skills necessary to interpret them. Therefore, LA dashboards should promote direct feedback and pedagogical explanations rather than invite data analysis and exploration [17]. One of the strategies to address this challenge is the addition of explanatory features to LA dashboards to guide users' interpretations. Visualisation guidance is a way to design data interfaces to reduce their complexity and make them easier to understand. One way to provide such explanatory features is through *Data Storytelling* (DS). DS techniques and principles provide a way to include narrative and elements to explain and connect the learning design goals with visual elements that aim to guide the user's attention to relevant insights and support deeper reflections effectively [25]. For instance, Echeverria et al. [15, 17] demonstrated the potential of enhancing LA visualisations with DS visual elements (e.g., title, highlights, shaded areas) in helping teachers to explore visualisations by guiding the attention of teachers to key insights. Similarly, Martinez-Maldonado et al. [28] demonstrated the promise of using a layered storytelling approach to communicate insights on team performance. Following a similar layered approach, Fernandez-Nieto et al. [20] crafted data stories to promote students' reflections. The approach presented by Chen et al. [9] used the learning tasks and "teachers' questions" about student progress to design guidance for teachers through narrative slides derived from MOOC data. Similarly, the approach introduced by Pozdniakov et al. [35] explored an alternative design of visual interfaces to explicitly address teachers' questions about student progress. In the last two studies, while feedback from teachers informed the generation of questions, researchers ultimately decided which questions to use to create data stories. Thus, while these prior works have demonstrated that DS can benefit teachers and students when interpreting data from LA dashboards, these approaches also indicate that researchers have manually created the data stories.

Typically, the teachers' pedagogical intentions [21], the learning design [15, 28], and teachers' questions about students progress [9, 35] are used to align the DS elements to enhance LA dashboards. These works were conducted following Human-Centered Design (HCD) approaches to create data stories tailored to the needs of educational stakeholders. However, as the study presented by Verbert et al. [44] pointed out, educational stakeholder needs are not "one-size-fits-all". Wise et al. [46] also emphasised the need for keeping humans in the loop when designing LA systems, arguing that humans should play a role in controlling LA systems and providing the knowledge needed to give students feedback about their learning and help them to identify areas for improvement. Responding to these arguments, we agree that teachers need more control over the insights that are communicated in LA dashboards, so that they can be tailored to their specific teaching needs and provide students with more detailed and relevant feedback about their learning. Based on these prior works, one challenge that remains is to empower teachers to provide the insights that are communicated in learning analytics dashboards, which could potentially improve students' interpretations and increase the chance of adoption of LA dashboards.

To address this gap, this paper introduces the Data Storytelling Editor based as a means for reducing the complexity of LA Dashboards. The Data Storytelling Editor uses *rules* to render data stories that are customised by teachers to communicate key messages to support students' reflections. The editor automatically gives meaning to learning data with the aim to promote learning outcomes as envisioned by teachers. Specifically, this paper's contribution is twofold: i) we implemented a tool to automatically generate data storytelling dashboards in learning analytics and illustrated its use in the context of a high-performing nursing scenario, and ii) we conducted a qualitative study with seven teachers in two universities to explore their perceptions of the Data Storytelling Editor and their envisaged uses in nursing simulations. We found that the teachers valued the tool's ability to tailor visualisations to their specific teaching needs and to generate data stories that could prompt deep reflections on students' learning performance.

# 2 BACKGROUND AND RELATED WORK

## 2.1 Foundations of Data Visualisation and Data Storytelling

Research in information visualisation argues that computer-assisted *guidance* can be provided to support casual users, or users with less experience in data analysis, to interpret data visualisations [8, 39]. Schulz et al. [39] described different ways in which guidance in information visualisation can be materialised, such as by enhancing the charts using visual cues (e.g., colour highlights, shapes, or text annotations), allowing users to select from various visualisation techniques, and guiding users through prescriptive data exploration workflows or via *data storytelling*. Data storytelling is rapidly gaining prominence as an information compression technique for communicating insights to an audience through the combination of data, visuals, and narrative [13, 37]. It has been suggested that articulating a story that emerges from the analysis of data while emphasising relevant data points can be more effective compared to simply plotting data and expecting non-experts in data analysis to interpret such data [25].

Data storytelling uses prominent visual features, such as colour and shape, to capture attention and guide the interpretation of key information, while minimising visual clutter to prevent cognitive overload [2, 3, 31]. Textual narrative also plays a crucial role, often being the first element to draw human attention. It helps to explain the data points and emphasises important sections of visualisations [17, 25, 31, 41]. The choice of visual representation is vital for comprehension and inference making in different educational contexts [2]. Data stories, combining visual and narrative elements, are proposed to foster reflective thinking, capitalising on students' familiarity with storytelling for reflective discussions.

## 2.2 Data storytelling in LA interfaces

There is a growing interest in creating LA user interfaces (e.g., dashboards, visualisations, or reports) to support educational stakeholders in monitoring learning tasks [38]. However, recent literature reviews and empirical studies report that most of these LA dashboards have serious limitations, such as showing visualisations that are difficult to understand by non-data experts [11, 23], lack of effectiveness in communicating insights [5], and failing to align with teachers' pedagogical needs [24, 43].

Educational stakeholders, including teachers and students who may not be data analysis experts, often find it challenging to interpret analytics and visualisations in contemporary LA user interfaces. To address this challenge, recent research has emphasised the use of *data stories*, which are enhanced LA interfaces designed to communicate meaningful and contextualised visualisations more effectively. In particular, Echeverria et al. [17] explored DS elements in visual learning analytic prototypes to direct teachers' attention to specific learner data. They identified key principles of effective data storytelling: (1) focus on purposeful communication, (2) drive audience attention through meaningful visual elements, (3) select appropriate visuals for different purposes, (4) adhere to the basic principles of information visualisation design, such as removing unnecessary elements and using captions, space, shape and colour wisely, and (5) incorporate narrative structures, as in narrative visualisation or visual narratives [41]. The Data Storytelling Editor presented in this paper incorporates these principles and the foundational principles (Section 2.1) of DS (see Figure 1).

Moreover, research indicates that direct feedback and pedagogical explanations in data storytelling benefit educational stakeholders more than mere data exploration. Echeverria et al. [17] developed explanatory visualisations aligned with learning design, found to be easier and quicker for teachers to read than exploratory visualizations. Similarly, Martinez-Maldonado et al. [28] presented data storytelling prototypes using a layered approach, showing positive effects in encouraging deep reflections among teachers and students. Studies by Fernandez-Nieto et al. [20] and Chen et al. [9] further highlight the advantages of data storytelling in aiding students understand their learning process and in helping teachers convey data stories effectively. Pozdniakov et al. [36]'s work on LA dashboards enhanced with data storytelling elements shows that such tools are especially beneficial for teachers with lower visualisation literacy. While previous research has demonstrated the potential of data storytelling interfaces to support student learning, these interfaces have been developed manually for design and research purposes and are not yet readily available to teachers.

Following human-centered design approaches, previous work on data storytelling visual interfaces has been informed by learning design [15, 28], teachers' pedagogical intentions[20, 21], and teachers' questions about students progress [9, 35, 36]. The existing research offers a promising direction for the development of LA user interfaces, as it ensures that the data storytelling visual interfaces are aligned with the learning objectives and teaching methods of the teachers. In fact, the work presented by Verbert et al. [44], summarising experts' concerns about LA-Dashboards, emphasised the trend of using participatory design methods (e.g., co-design) to tailor LA dashboards to the needs of educational stakeholders. However, their study also pointed out that "one-size-does-not-fit-all" stakeholders needs. We agree with Verbert et al.' recommendations for future work in LA dashboards, and believe that there is a need for human-in-the-loop dashboards where humans and dashboards work together to provide more contextualised LA dashboards. In the same way, Wise et al. [46] highlighted a core tension of LA dashboards: the balance between technology and human agency. Wise et al. argued that LA tools should be designed to facilitate educational stakeholders in using their knowledge to promote learners' reflections. Teacher-centered LA should empower teachers to customise the learning experience for each student. Technology can automate many of the tasks involved in creating and maintaining LA dashboards, but teachers must have agency over the data stories presented to their students. This argument builds on the work of Ez-Zaouia [18], who defined a list of recommendations for designing teacher-centered dashboards. Yet, existing LA dashboards offered limited functionalities to enable teachers to fully expertise their agency by being able to define or configure the data stories according to their specific needs.

Our work builds on previous work reported above, mainly on the human-centered studies that inform the potential of data storytelling to support educational stakeholders sensemaking of learning data to inform teaching and learning [21, 35]. We went beyond previous research by introducing an automated approach to enhance LA user interfaces through a *Data Storytelling Editor* for teachers to customise stories according to their specific assessment criteria. The Data Storytelling Editor is a tool that empowers teachers to create data stories tailored to their specific teaching needs and provide students with more detailed and relevant feedback about their learning.

### 2.3 Research Gaps

Considering the gaps identified in this section, our research is motivated by the following two research questions (RQ):

- **RQ1**: *Do teachers find the Data Storytelling Editor useful to make use of LA Dashboards to create data stories to support students' reflections?*
- **RQ2**: *Do teachers perceive the data stories as useful to potentially help students reflect on their learning activity?*

## 3 CONTEXT: LEARNING DESIGN

This study focused on supporting teachers in creating data stories that can be used to promote student reflections after completing embodied teamwork simulations in healthcare education. Healthcare simulation is a pedagogical approach that uses a constructivist learning model to provide students with opportunities to experience teamwork and patient situations without compromising the care of real patients [4]. Simulations often start with a description of learning goals, followed by the simulation itself, concluding with a debrief aimed at provoking students' reflection on performance and errors made. To increase opportunities for the use of our Data Storytelling Editor, we identified different simulation scenarios that are used in nursing education at two different universities in Australia.

### 3.1 Simulation 1 – Prioritisation of beds

This simulation was run in 38 classes by different teachers. A total of 261 students in their third/fourth year volunteered to participate in the study and for their data to be recorded. The goal of the simulation was to provide care to four patients and prioritise the care of each bed as a team. The students in each team played the *roles* of Graduate Nurses (GN) 1 and 2 (i.e., primary nurses) and the Ward Graduate Nurses (WN) 1 and 2 (i.e., secondary nurses). The simulation also involved four manikins that played the role of patients. According to the assessment criteria set by the coordinator of the course, a highly effective team should have performed the following six *actions* on the main bed that was connected to the primary task of the simulation: i) administer oxygen after patient respiratory depression; ii) asess vital signs every five minutes; iii) cease PCA (patient-controlled analgesia) after patient altered conscious state; iv) activate MET (medical emergency team) calls after patient deterioration; v) administer naloxone timely; and vi) students are supposed to take care of the other three beds (i.e., secondary task) in the simulation ward room, meaning that they have to prioritise care. The simulation had three critical phases of interest: i) *Phase 1:* patient assessment (from the beginning of the simulation to the patient's respiratory depression); ii) *Phase 2*: patient altered conscious state (since the patient starts feeling sleepy until ceasing the PCA); and iii) *Phase 3:* patient recovery (after ceasing the PCA to the end of the simulation)

### 3.2 Simulation 2 – Allergic Reaction

This simulation was run in five classes taught by three teachers (including the same subject coordinator). A total of 25 students in their third year (21 females and 4 males) volunteered to participate. The purpose of this simulation was to help nurses learn how to react when a patient had an allergic reaction to some medication. The students in each team played the *roles* of team leader, registered nurses (RN1 and RN2), scribe (RN3), and the patient According to the assessment criteria, a highly effective team should have performed the following six *actions*: i) perform an initial set of vital signs, after the teacher reads the initial handover; ii) administer the intravenous fluid -IV antibiotics; iii) perform another set of vital sign checks after the patient complains of chest tightness; iv) stop the IV antibiotic after the patient reacts to chest tightness; v) perform an ECG after the patient complains of chest tightness; and vii) call the doctor after stopping the IV antibiotic. Based on the critical actions described above, the simulation can be divided into three phases: i) *Phase 1:* patient assessment (from the beginning of the simulation to the patient's chest tightness) ii) *Phase 2*: critical patient deterioration (since the patient starts complaining about the allergic reaction until recovery) iii) *Phase 3:* patient recovery (from the patient recovery to the end of the simulation).

# 4 DESIGN: DATA STORYTELLING EDITOR

The Data Storytelling Editor allows teachers to define rules to create data stories aligned with their assessment criteria. This section describes the four-step design process of the Data Storytelling Editor that we used to explore teachers' perceptions of usefulness to create stories after their evaluation (see Figure 1).

## 4.1 Step 1. Assessment Criteria

Teachers carefully and deliberately sequence or otherwise structure the learning activity design in a learning workflow [7]. We designed a user interface to allow teachers to specify their learning goals in a way that the system can understand the learning activity design in the form of learning workflows (Figure 1 -1). In our previous research, rule-based algorithms were proven effective for aligning teachers' pedagogical intentions with learning data [15, 20, 28]. Building on this, we adopted a similar approach, in which the editor enables teachers to create rules to communicate their assessment criteria. Considering the *critical actions* expected from highly effective teams, described in Section 3, the user interface allows the creation of four types of *rules* (R). That way, the assessment criteria created by the teacher provided four types of feedback to teams in Simulations 1 and 2. (R1) Feedback based on the sequence of actions: **sequence rules** (e.g., provide oxygen after the patient's respiratory depression). (R2) Feedback based on the timeliness of actions: **timeliness rules** (e.g., stop the IV device in less than five minutes). (R3) Feedback based on the frequency of actions: **frequency rules** (e.g., validate vital signs every five minutes). (R4) Feedback based on interpersonal proximity: **proximity rules**.

## 4.2 Step 2. Data sources as dashboard inputs

Capturing learning data can provide a wider understanding of physical and online learning activity (Figure 1 -2). Sensor data can be analyzed to generate immediate outcomes, but it often lacks higher-order meaning [46]. Humans can observe physical and social events and give meaning to certain physical actions, but they are not as accurate and precise as sensors [16]. The Data Storytelling Editor is designed to facilitate the coordination of multiple data sources (e.g., wearable sensors and humans-as-sensors) by collecting and storing different modes of physical interactions, including human observations, physiological data, indoor positioning data, audio, and video.

To illustrate our design, we captured critical actions and positioning data from the nursing learning context described in Section 3. *Critical actions* (i-vi) and additional actions (e.g., writing charts) performed by each student were manually logged by an observer (i.e., a researcher), but it could also be a student using a web application. These human inputs were considered a modality of analysis (human-as-sensors) and were captured using a customised web tool [1]. Students' low-level *positioning data* were captured through wearable tags[2] at 2-3Hz. Tags, carried in waist bags or armbands, were worn by students during the simulation. The positioning system triangulates the exact location of each tag with reference to 8 anchors affixed to the walls of the classroom. The raw data captured by the positioning tags consisted of $x$ and $y$ coordinates and the body rotation of each student. Positioning data were down-sampled to 1Hz. The data points were formatted as follows: *{studentId, timestamp, x, y, rotation}*.

## 4.3 Step 3. Modelling

Both data modalities (activity logs and positioning data) were modelled differently by following a process based on Echeverria et al. [14]'s two-step multimodal modelling approach: i) converting from low-level data (captured in Step 2) to a discrete data structure, and ii) interrogating these data based on the learning design or educational theory (assessment criteria captured in Step 1). The next subsections illustrate this two-step modelling for each data modality.

### 4.3.1 *Critical Actions Modelling.*

This modelling is informed by rules R1-3 introduced in Section 4.1 (Step 1). We represented the absence or presence of certain key actions described captured in Step 2 as binary flags (1, 0) (Step 1). Based on these and the assessment criteria for the learning task, teachers defined six rules (one per critical action in Section 3) to automatically *detect errors* in the order or timeliness of the student actions in the simulation task (Step 2). Three types of errors were automatically identified. The sequence errors were flagged if the team performed a critical action using the wrong sequence. For example, if students forgot to perform a vital signs assessment after the patient had complained of serious chest pain (see example of data story presented in Figure 1 -4). Timeliness errors were identified when students reacted slowly and performed certain actions too late according to relevant healthcare guidelines. For example, this would happen if the students took too long before calling the doctor after a patient's crisis in Simulation 1 or if they took too long to stop a medication that was causing an adverse reaction, which should be done in less than five minutes in Simulation 2. An error related to frequency was assessed by calculating the timestamp difference between two key logged actions that are meant to be repeated, e.g., assessing a patient's vital signs at least every 5 minutes (see Figure 3 -B).

### 4.3.2 *Positioning Data Modelling.*

This modelling is informed by Rule four (R4) introduced in Section 4.1 (Step 1). Grounded on "copresence in interactional spaces" literature, we model the low-level positioning data. There were four types of distances, in meters $m$, which defined the interactional spaces [10]: i) intimate (0-0.46m), where the presence of the other person was unmistakable and could

[1]https://github.com/Teamwork-Analytics
[2]www.pozyx.io

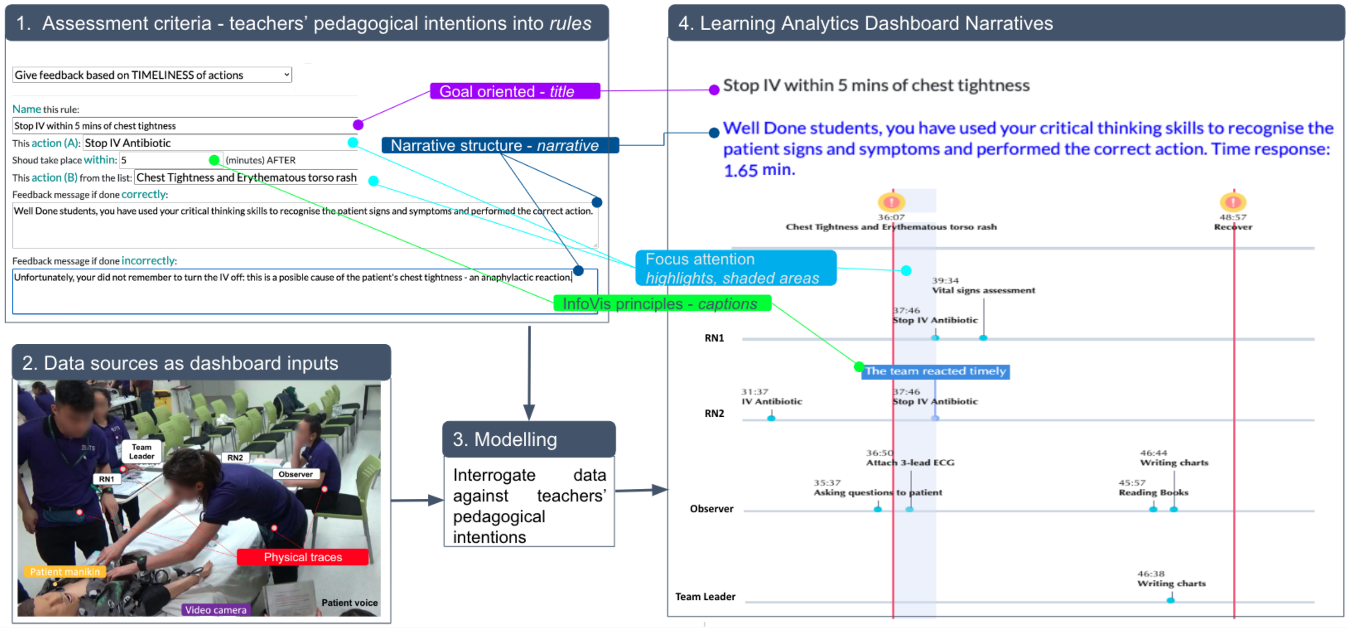


**Figure 1: Data Storytelling Editor four-step design process: 1) assessment criteria; 2) data sources as dashboard inputs, illustrative data capture scenario; 3) modelling; and 4) illustrative data story indicating the timely reaction of the team to a patient's adverse reaction**

be overwhelming; ii) personal (0.46-1.2m), where the majority of intensive and delicate interpersonal transactions occurred; iii) social (1.2-3.7m), where verbal transactions could occur, but it would generally be considered as a distance from which strangers commonly interact; and iv) public (3.7+), where the other person's presence was not well-defined and it could be either acknowledged or ignored. Based on proxemics [27] and empirical work in healthcare [33], the co-presence of two nurses within their intimate or personal spaces can be indicative of some verbal interaction or awareness of each others' actions. Similarly, if a nurse were close to the patient, it could indicate nurse-patient interaction or caregiving.

Co-presence in interactional spaces was thus modelled by measuring the distance between the $x$, $y$ coordinates among each team member and the patient (either the manikin or the nursing student playing the role of the patient) per second (Step 1). Based on these and the teachers' assessment criteria, we identified instances of close proximity (intimate or personal distances) using the parameter $d = 1.2m$ which was an appropriate distance to enable direct interaction between nurses and patients (Step 2). The Data Storytelling Editor lets teachers define the time points or intervals when they are interested in tracking interpersonal proximity. These windows are typically defined by the learning design *phases* described in Section 3. The visualisations generated from the positioning data modelling were termed *positioning graphs*. This designation was used consistently throughout the evaluation and the results section.

## 4.4 Step 4. Data storytelling generator

The editor was designed for teachers as a way to customise an LA dashboard with data storytelling elements. The pedagogical intentions provided by teachers (step 1) were used to generate the *data stories* as illustrated in Figure 3. The outcomes of the modelling (Section 4.3) were enhanced and rendered using data storytelling principles (Section 2.2). Figure 2 illustrates the LA Dashboard enhancements generated using the Data Storytelling generator. Part B of Figure 2 shows an automated data story rendered based on one of the teacher's pedagogical intentions. The story invited students to reflect on their interpersonal interactions with the patient (PTN) during the patient's allergic reaction. For this team, Registered Nurses, *RN1*, *RN2*, and *RN3*, were in close proximity to the patient during the patient's adverse reaction, as expected by the teacher. Also, part B in Figure 3 shows an automated data story rendered based on one of the teachers' pedagogical intentions. The story emphasises that for this team, the assessment of the vital signs was not systematic (e.g., every 5 minutes). Data stories communicate individual and team outcomes using visualisations and text. For example, a story can highlight key data points of interest for the physical activity (e.g., critical event/action) and add descriptions to inform individuals/teams about errors (see Figure 1 -4) or team interpersonal interactions (see Figure 2) that need to be reinforced.

Teachers could use information from their pedagogical intentions to include data storytelling elements. The use of the data storytelling principles explained in Section 2.1 is illustrated in Figure 1). For example, they can: a) add feedback messages to explain the team/individual outcomes using narratives (Figure 4-A); b) add meta-information such as time, roles, or a title to provide additional context to the story (Figure 4 -B); c) use the reference actions as a time frame window to filter the matrices and provide insights about specific moments of the simulation (Figure 4 -C); or d) use the multimodal modelling outcomes to provide textual explanations of the data visualisation (Figure 4 -D).

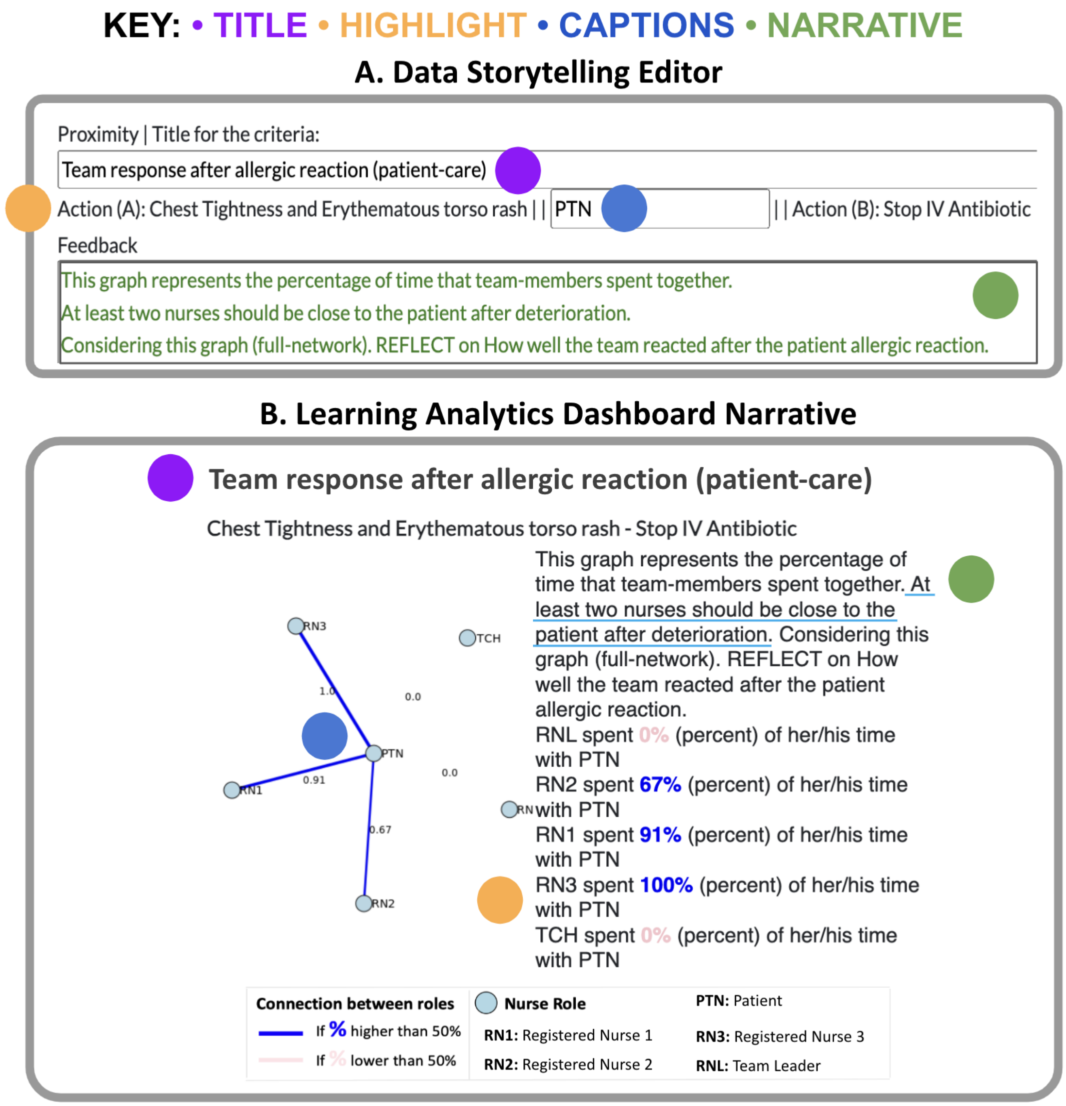


**Figure 2: Data Storytelling Editor to define assessment criteria. A – User interface for teachers to define the assessment criteria in the form of rules. B – Data story driven by the rules predefined by teachers.**

# 5 STUDY

## 5.1 Participants and Protocol

This study aims to investigate the teachers' responses to the Data Storytelling Editor. A qualitative validation study was conducted using a retrospective reflection technique [22]. We invited nursing teachers to evaluate how they translate their pedagogical intentions into instructions (**rules**) that the Data Storytelling Editor could use in the analysis and the data story creation. A total of seven teachers (T1-T7) volunteered to participate in the study (male=1, female=6, aged 44.7 years on average mean=40, std=7.71). Four teachers designed and taught Simulation 1 (Section 3.1) and three of them participated in Simulation 2 (Section 3.2). Teachers of Simulation 2 were familiar with the concept of rules (Section 4.1), as they participated in a previous long-term study to identify such rules [15, 21]. On the other hand, the teachers of Simulation 1 were completely new to the notion of rules to define data stories.

To address the research questions (see Section 2.3), a think-aloud protocol was defined. Seven 60-minute interviews were recorded using an online video conferencing platform (i.e., Zoom) and were fully transcribed. Following a semi-structured format, the interviews were structured as follows:

**RQ1 – RQ2**. (1) A researcher leading the interview explained the purpose of the session. Teachers were presented with the list of the *six actions* expected from highly effective teams for each simulation. (2) Teachers were asked to create the assessment criteria in the form of *rules*, using the editor (see Figure 1). (3) Teachers were asked to access and explore each *data story*, which was rendered based on the rules they defined (see Figure 2, visual story). Finally, (4) teachers were asked to respond to the following questions for each

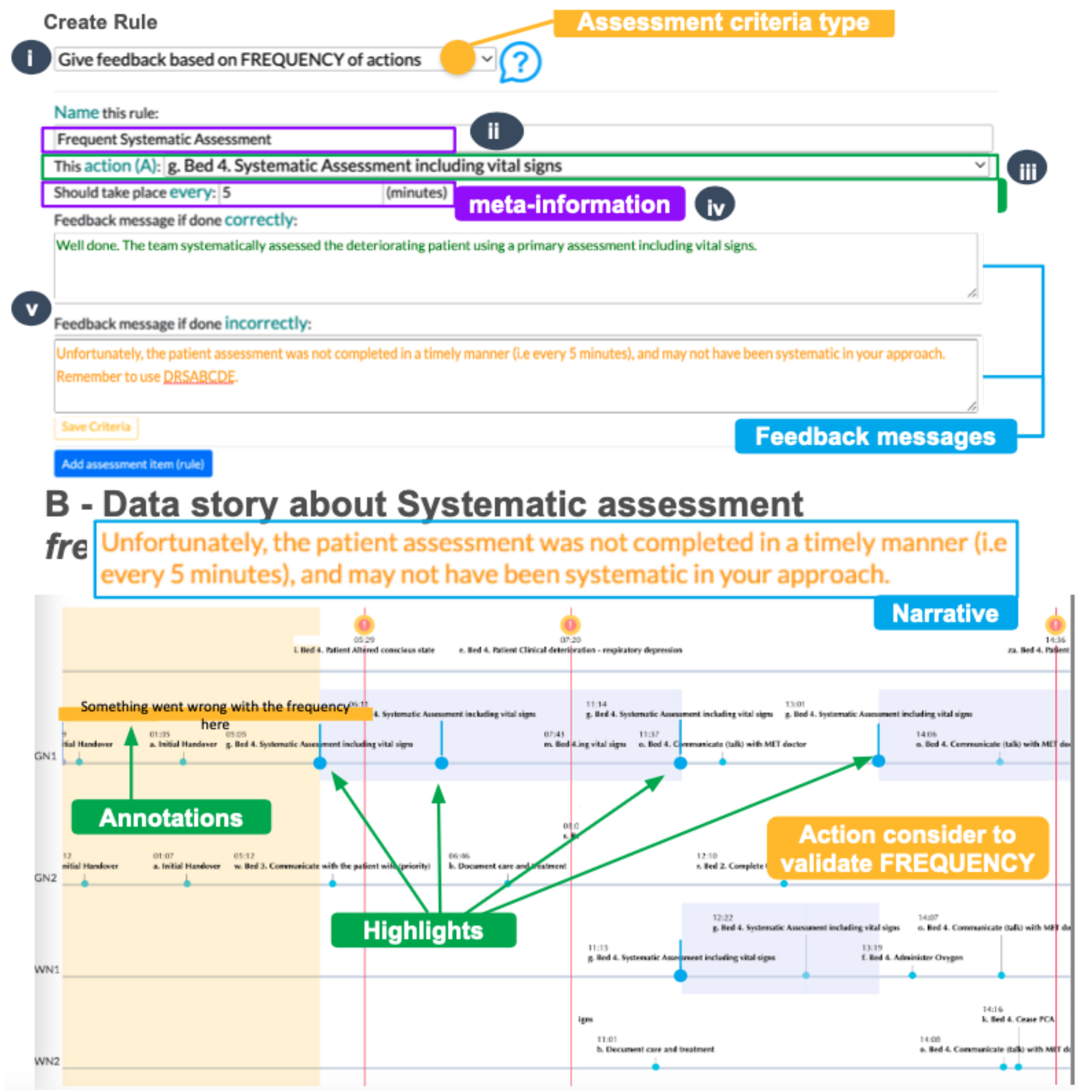


**Figure 3: Data Storytelling Editor to define assessment criteria. A – User interface for teachers to define the assessment criteria in the form of rules, and B – Data story driven by the rules predefined by teachers**

rule they defined: i) *Is the rule you created working as you expected?* and ii) *to what extent could this (story) help students to reflect on their team activity?*

## 5.2 Analysis

**RQ 1 – RQ2.** The transcripts of the seven sessions were coded using NVivo. Using the video recordings and transcripts, two researchers examined participants' statements and their actions performed while exploring the prototypes. Given the direct alignment between the study protocol and the research questions, there was no need for agreement on the defined themes ([32], p. 13). Then, statements of interest were jointly coded [6] by two researchers according to the preset themes of the study protocol (described above).

## 5.3 Results

*5.3.1 Teachers' perceptions of the Data Storytelling Editor to create data stories – RQ 1.* Teachers found the editor useful for *tailoring* their feedback to student's individual needs, using specific assessment criteria. For instance, T2 indicated that the editor was a way to *"provide a systematic feedback that allows the tailoring to occur"*. Although aspects of each story could be tailored (e.g., evaluate if an action was validated in less than $X$ minutes), the teachers also emphasised the need to agree (e.g., with other teachers) on the type of feedback they aimed to provide students with. In that way, the editor offered a *"template"* which *"allows for a good population of the sorts of teaching messages or learning messages that we want to get across"* (T2). This point was echoed by all the teachers but one in our study.

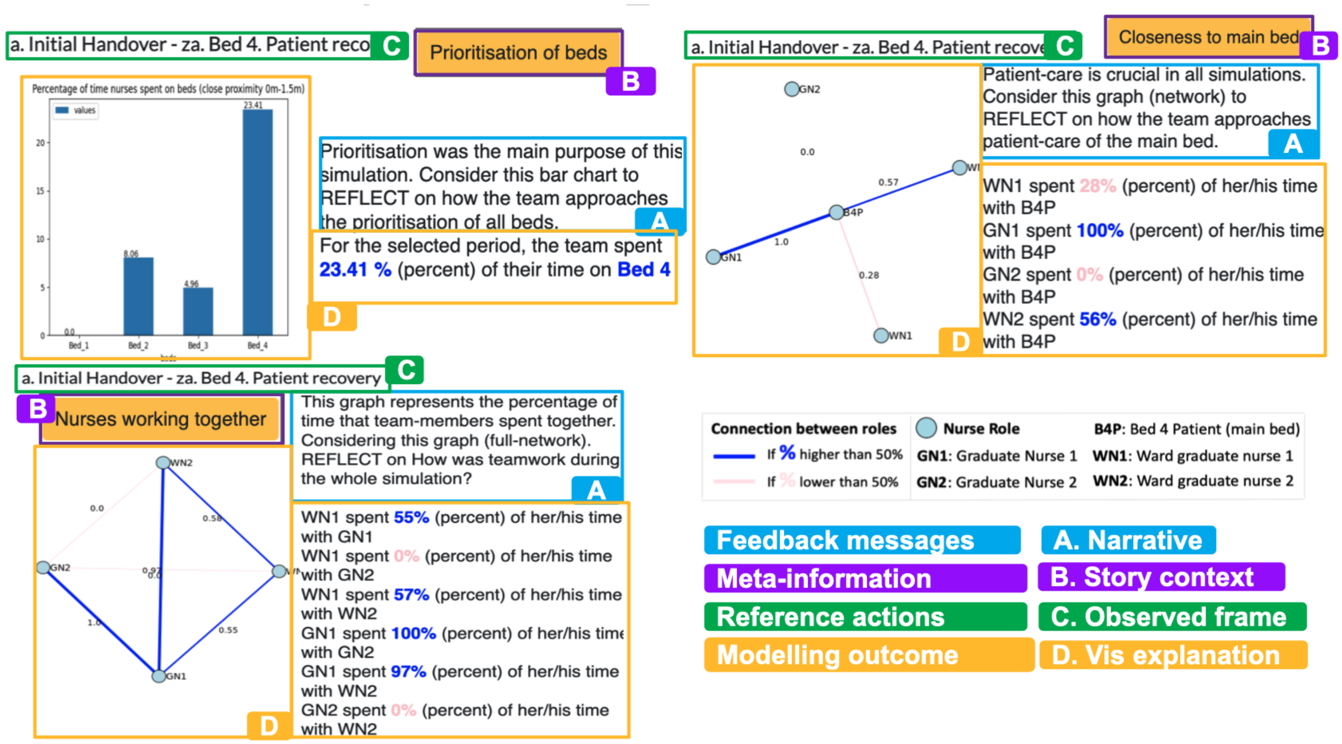


**Figure 4: Students' data stories focused on positioning data. This figure shows three stories: the proportion of time that nurses spent on the four beds (top left), the proportion of time that nurses spent in close proximity to the patient on the main bed (top right), and the proportion of time that nurses spent working together (bottom left).**

As the teachers were able to configure the rules and see their visual results immediately afterwards, it helped them reflect on the opportunities of providing **contextualised** and **relevant** feedback. For example, T4 stated that the editor could *"give them confidence in the feedback they give"* in a way *"it is not our impression of what's happening, but it's actually what's happening"*. T5 saw the opportunities of using the editor to **"design feedback"**. In the same way, T6 indicated that the editor *"would be helpful to reinforce key learning points"* when designing feedback. According to the teachers, the editor should provide messages that support students to reflect *"about the importance of doing something, and if they didn't do something that needs to be very clear in the editor"* (T5). Similarly, T2 indicated that the editor was useful for *"considering what are the key messages that you want to be able to provide to the students, and it also provides obviously standardisation"*.

In addition, the Data Storytelling Editor could visually support teachers to validate whether the feedback they created was adequate. Although teachers were asked to provide general messages and not elaborate much on feedback messages, all were aware of the importance of providing meaningful and formative feedback messages. The editor helped them self-evaluate their **feedback quality** in terms of the messages they were configuring. Using an iterative process, the teachers were able to refine (modify) the rules (assessment criteria) they created. All the teachers focused mainly on providing more constructive and insightful feedback messages to students. After looking at the visual results, T6 indicated that *"now that I've seen it, my feedback would have to change"*. Likewise, T1 indicated that the editor helped her *"make sure that I used concise language, simple, kept, it's concise and simple. So, students would be able to just read and understand the feedback straightaway"*. This was also supported by T5, who indicated that *the writing of the feedback, being concise, would be the challenging part of the editor*. The feedback messages should also be useful for students to prompt reflections *"so there's never, unfortunately, a well-done message, is it better to indicate the time they spent with the patient, for example, to then start discussions and reflections"* (T7).

In terms of **challenges** using the Data Storytelling Editor to create feedback, the teachers agreed that some of the challenging aspects of using the editor to create stories were the identification of the critical actions that needed to be observed. In fact, T7 made a case about actions that could not be prescribed and wondered how the editor could be useful *"if there were things that happened that are not within what we would think and they're things that actually they need to be really addressed within that simulation"*. Although a valid case, the Data Storytelling Editor we proposed assumed that most of the actions could be extracted from the learning design. Regarding critical actions that did not derive directly from the learning design, we saw an opportunity to incorporate other modalities to increase the chances for teachers to customise their data stories. However, the teacher agreed that using the editor could facilitate standardisation of feedback because the editor also provides features (e.g., customised messages - narratives) to personalise details according to the teachers' needs. At first, four teachers considered the Data Storytelling Editor complex to *"understand what the results were showing"* (T7), especially the teachers who were completely new to using the editor (those who taught in Simulation 1 – Section3.1). Yet, after creating two or more rules, they got familiarised with the editor. Three out of the seven teachers recognised the need for training to *"validate how timeliness, frequency, and spatial rules are useful to generate specific feedback"* (T2).

*5.3.2 Teachers' perceptions of the stories to support reflection – RQ 2.* All the teachers agreed that the stories could be used for reflection. For instance, T6 indicated that the editor *"will help students to* ***recognise and reinforce*** *the key learning objectives"*. For this, the teachers agreed that using the editor to guide their debriefing sessions was a good alternative, as it could help them to *"have deeper discussions in the debrief"* (T1) and *"focus on a particular criterion"* (T2) using *"objective data"* (T3). According to T4, the editor could also help them focus on *"getting some feedback on what could have been improved"* based on what the story was showing. As stated by T6 *"there's nothing here that we wouldn't talk about in the debrief, but having that visual will assist students with just reinforcing that conversation"*.

The Data Storytelling Editor could be useful to help students to **recall** what they did and **reduce misconceptions** of their performance (e.g., *"students could believe that they were close to the patient? when they were not"* - T3). As T6 mentioned, *"students sometimes know the protocols, but they might forget what is important because they are under many things"*. T3 supported this view indicating that *"it is impossible for students to remember the simulation with 100% of accuracy, especially if they are under stressful circumstances"*.

The teachers saw the value in the **timeline visual cues** (see Figure 3) generated as part of the data stories to *"reinforce the discussion around key points"* (T6). Then, using different stories *"probably is going to shed some more light on maybe things that students didn't realise they were doing, or things that they forgot to do"* (T1). In the same way, T5 emphasised that *"the colour coding, makes clear what students have done"*.

For the teachers, the **positioning graphs** (Figure 4) could potentially be used to reflect about **patient-care**. For instance, T6 explained that the feedback message to prompt reflection could be something like *"due to the clinical deterioration, seen in bed one (main bed in simulation 2), this patient was the priority. Therefore, it appears that the team did not prioritise this patient"*. Likewise, T2 indicated that the graph provided good indicators in regard to the *"important interaction between nurses and the patient"*.

In sum, teachers' perceptions of the Data Storytelling Editor were positive, and the teachers could see it as a resource that could improve their discussions.

# 6 DISCUSSION AND CONCLUSION

In this section, we summarise the key lessons learnt, discuss the results with respect to the related literature, and note the limitations of the research presented in the paper.

## 6.1 Summary of results

Revisiting the research questions we can summarise the outcomes from the teacher interviews as follows:

**RQ1***: Do teachers find the Data Storytelling Editor useful to make use of LA Dashboards to create data stories to support students' reflections?* All teachers were able to define their assessment criteria using the Data Storytelling Editor. While some teachers found the rules difficult to define at first, after a few iterations, they familiarised themselves with the tool and were able to define different types of rules. The Editor's real-time feedback feature, which shows the resulting data story as the teacher defines the rule, was instrumental in helping teachers customise their feedback to their students' needs. The Data Storytelling Editor has proven to give agency to teachers to create their own visualisations to support their practice. Nursing teachers were able to configure, check, revise, and modify data stories using the Data Storytelling Editor. However, additional human-centered approaches could be used to elicit and incorporate the needs of more teachers, and to identify and support critical actions beyond those extracted from the learning design.

**RQ2***: Do teachers perceive the data stories as useful to potentially help students reflect on their learning activity?* Our study addressed a practical concern regarding the design of quality feedback by demonstrating that teachers can use the Data Storytelling Editor to create customised data stories perceived as useful by students. This finding is significant because it suggests that teachers can be empowered to take ownership of the data storytelling process and create feedback tailored to their students' specific needs.

## 6.2 Implications for Research

Previous research (presented in Section 2) demonstrated that the data stories were used positively to support the reflections of the students on their learning activities. Our Data Storytelling Editor can be used as a role model and a staring point that gives directions to scale up data storytelling in LA dashboards. Scaling the provision of timely and meaningful feedback has been explored in previous research. For instance, Pardo et al. [34]' work personalised comments to groups of students depending on their engagement in online learning activities. Our study with nursing simulations goes beyond previous research by demonstrating how to use massive amounts of multimodal data to augment teachers with LA capabilities to provide evidence-based feedback enhanced with data storytelling elements.

Our Data Storytelling Editor supported rules (Section 4.1) to validate sequence (R1), timeliness (R2), frequency (R3), and students' interpersonal proximity (R4). Rules 1–3 were found useful by the teachers to communicate data stories about students' errors or correct performance of critical actions performed during the simulation. By including the interpersonal proximity rule (R4), the teachers were able to create data stories to provide feedback about student's spatial behaviours. For positioning data, other rules can be created to explore high-order teamwork constructs such as: i) facing-formations, referring to the ways people cluster so that they can have direct and equal access to one another (e.g., being around the patient or the team leader, or being side-by-side during a particular procedure) and ii) spaces of interest, presence of students in certain spaces that have a meaning for the learning activity [19].

The nursing simulations were authentic and reflected how healthcare students and professional nurses are commonly trained, the data collected to generate the data stories were from 261 students in simulation 1 and 25 students in simulation. Yet, the Data Storytelling Editor designed has not only been used for data collection but also to support teamwork research. For example, the collected data may offer new opportunities to explore different modalities of embodied team activity, as presented in recent work by Zhao et al. [47, 48] who combined audio and positioning data. In their research, the authors used audio and positioning data to explore constructs such as communication efficiency and teamwork effectiveness.

## 6.3 Implications for Practice

This paper is a significant step towards empowering teachers to design data storytelling tools that are tailored to their specific teaching needs and practices. Until now, only technical researchers could code and modify feedback rules. The exciting potential of *teacher-driven* data stories is that they allow teachers to switch between different representations of student data, as automatically generated linked visualisations, based on the specific context of the learning activity and the needs of their students. This places the agency firmly in the hands of teachers and students. Investigating alternative representations to provide feedback is also part of the current research agenda of LA researchers [18].

Although this paper did not consider students' interactions with the visualisations created by educators using the Editor. We envisage that our Editor and other similar tools can enhance learning experiences by providing more meaningful and contextually relevant feedback to students. Current research explores the use of data to generate evidence-based feedback tools for professional development. For example, Martinez-Maldonado et al. [29] uses indoor positioning data to visually characterise classroom teaching, aiming to help teachers inform their teaching decisions.

Although the system design was inspired by previous work that was conducted following a human-centred design approach, it is important to recognise that while a user interface may reach a degree of usability, it takes time for teachers to build trust and confidence to be ready to use new tools with students in their classroom practice [42]. Future work should explore how the stories generated using the editor promote and support effective reflections of students in nursing simulations and other learning scenarios. We should also study how teachers build confidence and trust in the data storytelling editor as an effective means to advance their teaching practice. We should also note that it is to ensure that teachers' agency is respected and that they are not rushed into using an LA tool such as our Data Storytelling Editor [46]. Instead, we should enable them to gradually learn how to use the tool to productively augment their practice.

## 6.4 Future Work and Limitations

The evidence reported in this paper should be considered in the context of the limitations of the study. A limitation of this study is the small sample size (seven teachers), as this limits the generalisability of the findings. 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 that require tracking student activity that is too complex to automate. Future research could be conducted with a larger sample size to identify other potential findings and to explore their applicability to a wider range of settings. LA dashboard can be used for teachers to provide timely feedback to students to discuss after their learning activities. Future work should focus on exploring the use of the data stories created by teachers to support reflections in authentic settings (e.g., the debriefing session after the simulations). Likewise, future work should also validate how the editor can be useful in defining quality feedback to provoke effective reflections.

Integrating our Data Storytelling Editor into teaching practices presents challenges. Originally tailored for Nursing Simulations, adapting it for different contexts demands careful thought. Its incorporation into Learning Design activities requires collaboration with educators to align assessment criteria and intended activities, like aiding reflective thinking. Despite these challenges, the Editor is adaptable to various settings, both physical and online. This adaptation, though initially demanding, provides educators with innovative tools to enrich their teaching methods.

## 6.5 Concluding Remarks

This paper has presented the Data Storytelling Editor, a tool that empowers teachers to customise their LA dashboards providing the narratives in the form of data stories that they want students to have to improve their learning. The findings of this study suggest that the Data Storytelling Editor is a promising tool for improving the quality of LA dashboards by incorporating narratives that supports students' interpret their learning progress. The Data Storytelling Editor is just one example of the power of teacher-centered tools. When teachers are given the tools and resources they need to be successful, they can create a more personalised and engaging learning experience for their students.

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