Data Storytelling in Learning Analytics? A Qualitative Investigation into Educators' Perceptions of Benefits and Risks

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ABSTRACT

Emerging research has begun to explore the incorporation of data storytelling (DS) elements to enhance the design of learning analytics (LA) dashboards. This involves using visual features, such as text annotations and visual highlights, to help educators and learners focus their attention on key insights derived from data and act upon them. Previous studies have often overlooked the perspectives of educators and other stakeholders on the potential value and risks associated with implementing DS in LA to guide attention. We address this gap by presenting a case study examining how educators perceive the: i) potential value of DS features for teaching and learning design; ii) role of the visualisation designer in delivering a contextually appropriate data story; and iii) ethical implications of utilising DS to communicate insights. We asked educators from a first-year undergraduate program to explore and discuss DS and the visualisation designer by reviewing sample data stories using their students' data and crafting their own data stories. Our findings suggest that educators were receptive to DS features, especially meaningful use of annotations and highlighting important data points to easily identify critical information. Every participant acknowledged the potential for DS features to be exploited for harmful or self-serving purposes.

CCS CONCEPTS

• **Human-centered computing → Visualization design and evaluation methods**;

KEYWORDS

learning analytics, data storytelling, information visualisation

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1 INTRODUCTION

A central goal of learning analytics (LA) innovations is to "*close the loop*" by making the outcomes from data analysis available to educators, students and other educational stakeholders, empowering them to make data-informed decisions that can influence teaching and learning processes [24]. In turn, dashboards and various forms of data visualisation have become some of the most common forms of LA user interfaces, highlighting the key role of effective visual representation in leveraging data [3, 35, 39]. Yet, as the volume of learning data expands both in size and complexity, it has become progressively challenging for educators and other education staff – who often lack expertise in data analysis [28] – to extract the essential insights that can guide decision-making and educational strategies [19, 20, 40].

This challenge extends beyond LA, as it highlights the growing need to assist non data-savvy individuals in effectively gaining insights from data visualisations. In response, the notion of *data storytelling* (DS) is gaining prominence [2, 32]. DS has been defined as an approach for effectively communicating insights gleaned from data to an audience by combining both narratives and graphs [13]. Conventional visualisations can be enhanced with DS features by emphasising key messages conveyed in the data. This can be achieved by using colour and shading to highlight trends, adding text to explain outliers or salient data points, and using titles and annotations to emphasise key findings, while de-emphasising less relevant visual elements and data points [2, 23, 36]. DS has been utilised across several domains, such as journalism [29], science education [26], and LA [14], to help people understand and make decisions based on data. Unlike *exploratory* visualisations, which often require a suitable level of data literacy or analytical expertise from the audience for effective interpretation [12], DS aims to offer *explanatory* visualisations that strategically underscore notable features or insights, crafting a cohesive data narrative [4, 46]. DS aligns well with the effective design principles for LA dashboards discussed by Park and Jo [31] which leverage the principles of visual perception, as well as understanding of human cognition, to ensure that information is digestible at a glance.

In LA research, DS is emerging as a promising approach to distill learners' data to various stakeholders in an accessible format [8, 9, 14]. However, questions remain regarding the perspectives of educators and administrative education staff on the applicability of DS in authentic educational contexts. Moreover, the role of the data story designer and the potential for using DS for undesirable manipulative purposes is yet to be explored, despite warnings from researchers such as Correll [10] and McNutt et al. [27] about potential deceitful practices in conventional visualisation.

This paper contributes to the existing literature by exploring how educational stakeholders perceive and interact with DS-enhanced visualisations. More specifically, we present a qualitative study that examines how educators and student engagement staff perceive: i) the potential value of DS features for teaching and learning design; ii) the role of the visualisation designer in delivering a contextualised data story; and iii) the ethical implications of utilising DS to communicate insights. Participants were drawn from an authentic learning program designed to teach foundational programming concepts to first-year undergraduate students. They were asked to review sample data stories using their students' data and to design their own data stories, gaining first-hand experience of the role of the DS designer. The findings from this study can inform LA researchers and designers about visual features and strategies that could be leveraged when creating LA tools for educational stakeholders

2 BACKGROUND

2.1 Foundations of Data Storytelling

2.1.1 Visualisation-Aided Sensemaking & Data Storytelling. The term *sensemaking* describes the subjective process by which humans assign meaning to a stimulus or collective experience [7]. Prior research has shown that sensemaking is strongly connected to the process of decision-making; however, while the outcome of sensemaking is generally an interpretation, the outcome of decision making is generally actionable [7, 42, 44]. Data visualisations can in principle be utilised as a tool to facilitate this processes for non-data experts [11]. Knaflic [23] has described that not all the visualisations serve to the same purpose. The author described two main types of visualisations commonly used to communicate data – *exploratory* and *explanatory*. Examples of these are depicted in Figure 1.

Exploratory visualisations have minimal visual embellishments and are designed for individuals with the necessary context and analytical expertise to be able to extract insights [25, 38]. The reliance of the readers' ability to be able to interpret the data often makes exploratory visualisations inappropriate for non-data experts as these do not always have the necessary skills to make sense of the information and derive actionable insights [14]. In contrast, explanatory visualisations are designed to leverage specific visual attributes, such as colour and/or text, to tell a story that facilitates understanding for readers with varying levels of data literacy [14, 32], aiming at supporting sensemaking and decision-making. The designers of these visualisations often incorporate DS features to compress the data displayed in a visualisation and draw the target audiences' attention towards salient information [14, 46]. Thus, it is the responsibility of the visualisation designer to present the story and the DS features in a format accessible to an audience [34].

2.1.2 Data Storytelling Features. Knaflic [23] and Zdanovic et al. [46] have suggested a set of DS features aimed at reducing the cognitive load of the target audience and strategically draw attention to important parts of the visualisation. Figure 2 visually summarises the main DS features that we considered. These are the following:

- **Prescriptive titles** (Figure 2, top-left) serve to succinctly communicate the main insight of the visualisation [14]. Unlike descriptive titles, that are generally used in exploratory visualisations to describe what is being graphed, prescriptive titles can be used to clarify the main takeaway message or suggest a potential action [23].
- **Highlighting important data points** refers to the judicious usage of visual attributes such as colour, contrast, size, etc. to ensure that the attention of the audience is directed towards salient information [23, 34]. As shown in the top-right of Figure 2, visual elements of the visualisation can be emphasised using colour, while textual elements can be bolded to draw attention [23].
- **Annotations** are textual elements that can be added to the visualisation to explain the data story or any particular data point(s) of interest [23]. Figure 2 (bottom-left) illustrates how annotations can provide context to data points in a line chart [23].
- **Decluttering** (bottom-right) involves the removal of visual elements that are not contributing to the data story [23]. It is believed that removing unnecessary visual elements such as gridlines, colours, or text can make the information easier to digest and aid the audience in identifying the key insights [34].

2.2 The Visualisation Designer & Ethics in Data Visualisation

There is a growing body of literature exploring the role of data analysts and visualisation designers. For example, when reflecting on the competency of the visualisation designer, Xiong et al. [45] and McNutt et al. [27] both concluded that designers need to be aware that the different audiences will process visual information differently and therefore may not derive the same meaning from the same visualisation. The ethical obligations of the visualisation designer have also been examined by Correll [10] and McNutt et al. [27] who suggested that, as authority figures, designers often wield the power to create misleading visualisations based on biased, deceptive, or erroneous analyses without being scrutinised. This led Correll [10] to recommend that all stakeholders should be involved in the data analysis and design process. The concept of "*co-design*" has become increasingly popular in human-centred research, with also a growing number of LA studies incorporating non-data experts into analysis and visualisation design [7, 22, 25]. Yet, it is noteworthy that most of this research has focused on exploratory data visualisations. There has been limited exploration in the LA literature regarding the potential for manipulative applications of DS features, despite this being mentioned in related works as a potential topic for future research [14, 15, 41], which we discuss next.

2.3 Related Work and Research Questions

Research on DS in the LA literature is not new. For instance, Jivet et al. [17] introduced an LA system using graphs and text annotations to help students customise an LA dashboard. Echeverria et al. [14] studied DS in teacher LA dashboards using eye-tracking. They found that DS features effectively guided teachers to key data points, mainly via annotated data and prescriptive titles. Teachers appreciated data stories as being "*explicit*" and took less time to review. Similarly, Pozdniakov et al. [32] examined how DS features

Figure 1: Examples of an *exploratory* visualisation (left) and an *explanatory* visualisation (right) of the same data.

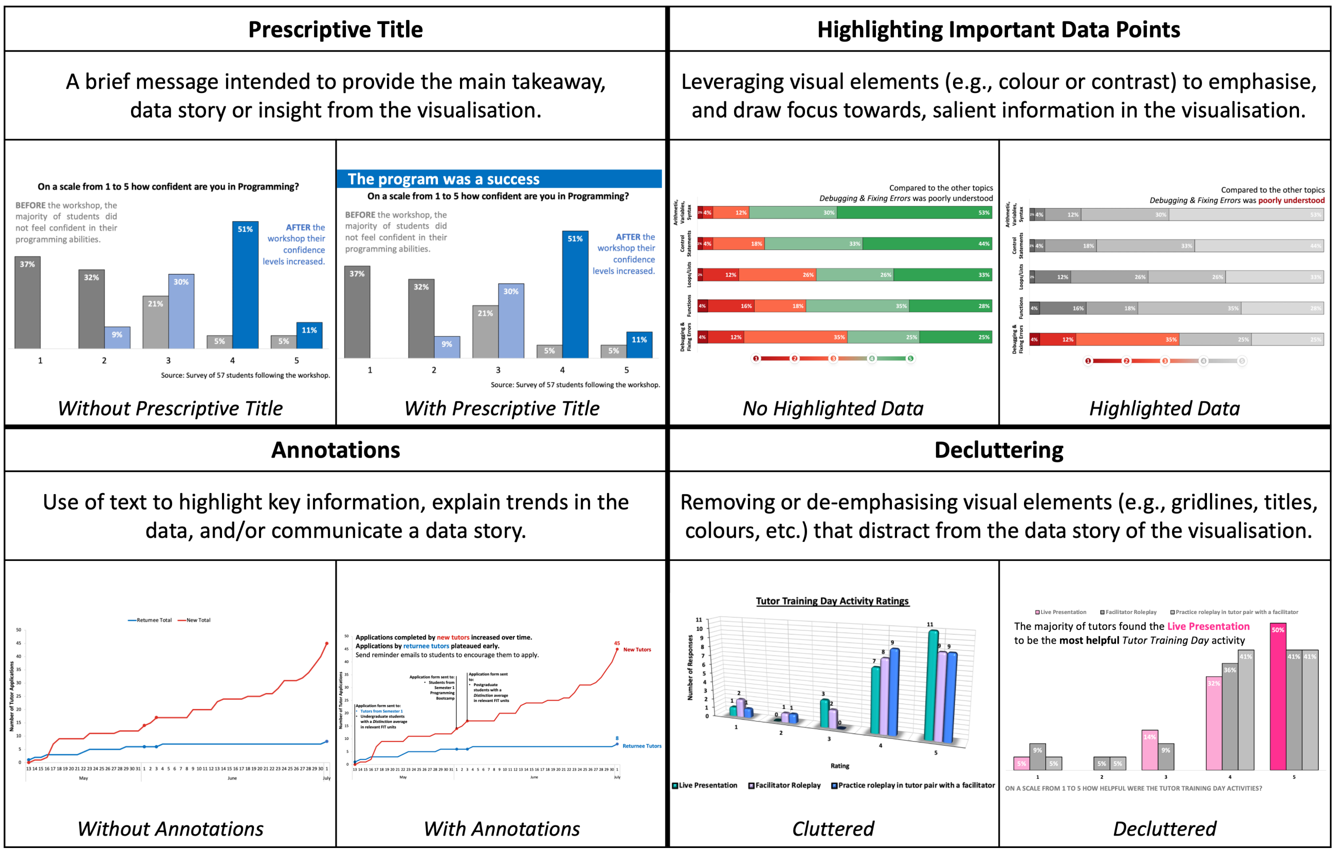

Figure 2: Data storytelling features: i) prescriptive titles, ii) highlighting important data points, iii) annotations and iv) decluttering.

in a teacher’s dashboard can lessen the cognitive load for data interpretation.

Other works have gone beyond the notion of annotating a single visualisation to instead create multiple data slices to scaffold the interpretation process for teachers or students. For example, Chen et al. [9] developed a slideshow that guided educators in navigating various data stories with annotated graphs, suggesting the next chart to consult. Martinez-Maldonado et al. [25] proposed an interactive layered approach to sequentially present different insights to students, previously identified by teachers, using the same visualisation but leveraging various DS features and introducing various modalities of data. Fernandez-Nieto et al. [15] ventured into automating DS crafting based on teachers’ learning designs, encoded through a rule-based configuration script that the LA system could interpret. This study raised concerns about potentially missing critical data points or narratives being obscured by the emphasis on other pre-defined prominent data points, as voiced by both teachers and students interviewed.

While these prior works have explored the integration of DS features into LA systems, they have not deeply considered educators’ perspectives on DS use in authentic educational contexts. Moreover, as noted by Ifenthaler [16] and Kaliisa et al. [21], other educational stakeholders in higher education institutions, such as administrative staff and educational designers, also utilise learner data to shape educational experiences, for instance, by recommending changes that educators should consider. However, a knowledge gap remains about how best to incorporate DS features to present learners' data to diverse educational stakeholders, and understanding which features they deem valuable. Moreover, while literature beyond LA [10, 27] has highlighted the potential for data and visualisations to be manipulated by data scientists and designers, the depth of this problem when applying DS-enhanced visualisations in LA is yet to be explored. Initial concerns have been raised [15], suggesting a need for deeper examination of DS in LA, especially around the ethical considerations of using learner's data to convey a particular narrative and whether those receiving these visualisations are aware of the inherent manipulative capabilities of DS.

This study aims to build upon and go beyond previous LA works by exploring the applicability of DS features, with a particular lens on how different educational stakeholders (namely educators, tutors and student engagement staff) perceive the strengths and risks of DS implementation. This is investigated through the following research questions:

- RQ1: To what extent can educational stakeholders identify key insights from LA visualisations that contain data storytelling features versus conventional visualisations?
- RQ2: How do different educational stakeholders perceive the potential value of data storytelling features in improving the interpretation of student and program data?
- RQ3: How do different educational stakeholders perceive the role that the visualisation designer has in determining data-driven insights from learning analytics data in terms of **a)** their influence on, or ability to *mislead*, their audience, and **b)** the *data storytelling features that are emphasised* when designing data stories?

3 METHOD

3.1 Context

3.1.1 The Learning Scenario. This case study focuses on educational stakeholders from an introductory coding program taught to commencing undergraduate students enrolled in IT programs at Monash University. There are three educational stakeholders within the teaching team of the program: i) *Student engagement staff* members (SE) who oversee LA data and receive analytics about the program once it has completed to make high-level decisions; ii) Lead *Educators* (E), who coordinate this program, liaise with the other educational stakeholders, and are involved in the coordination and execution of the teaching design and collection of student engagement and learning data; and iii) *Tutors* (T) who interact directly with the students to guide them through the learning content. Generally, the student learning and program data is collated by the educators into a standard report that, in the past, has mainly included exploratory visualisations and text to convey important details or findings.

3.1.2 Participants and Visualisation Design. Ten educational stakeholders aged between 21 and 52 (std = 9.4, five females and five males) participated in the study. They were two student engagement staff (SE1-2), four lead educators (E1-4), and four tutors (T1-4). Six visualisation prototypes were generated using authentic student learning and satisfaction data from the program - two pairs where one member was an *explanatory* version and the other an *exploratory* version, and two standalone visualisations. The first pair can be seen in Figure 3 (top), where the *exploratory* bar chart has had the following DS enhancements:

- **Annotations:** Text was added to convey key insights via text annotations. A survey question that students were asked following the program was added as a title, and each was labelled with its respective percentage.
- **Highlighting important data points:** Colour was consistently utilised to create contrast between the pre- and post-program groups, and offer a visual cue to accompanying annotations. As a result, the most important bars in the chart, that demonstrate the main message of the visualisation, are visually distinct from other bars.
- **Decluttering:** Gridlines and superfluous labelling were removed.

The second pair depicted a waffle chart (see Figure 3 – bottom). The other two prototypes included a DS-enhanced line chart (prototype #3) and an exploratory bar chart (prototype #4). All the visualisations used in the study can be accessed via the following link.

3.2 Study Design

To address the above RQs, a 90-minute Zoom interview was conducted with each of the participants using a *"think-aloud"* protocol. The structure of the interview consisted of three tasks that were designed to map to our RQs. In a pre-interview survey, participants were asked to assess their technological self-efficacy (TSE). This was based on the studies by Jovanović et al. [18] and Wang et al. [43] who described self-efficacy as an individual's personal measure of their capabilities. The questions were designed to complement the answers given in the subsequent tasks and formulate the groupings for Task 1 based on their reported self-efficacy in *"deriving insights from data visualisations"*.

Task 1: Participants were exposed to explanatory and exploratory prototypes of the student learning and program data. Initially they were given the opportunity to describe their thoughts on the design aspects of the visualisation and mention any insights they could derive from the graph. The participants were then shown pre-made insights via a Google Form and asked to select which insights they felt were applicable to the graph. This exercise was intended to address RQ1, expose participants to both exploratory and explanatory visualisations, and provoke reflection on DS features leading into the second activity.

For the first two prototypes, participants were exposed to the exploratory and explanatory versions in randomised order (minimising potential random effect) to see if the addition of DS features made a noticeable difference to the sensemaking process and what pre-made insights were selected.

Task 2: Participants were asked to reflect on the value of the DS features by first evaluating their perceived helpfulness on a scale of -2 (not at all helpful) to +2 (very helpful). A similar rating activity was used by Echeverria et al. [14] to establish what the teacher's preferences were. This has been extended in this study to determine

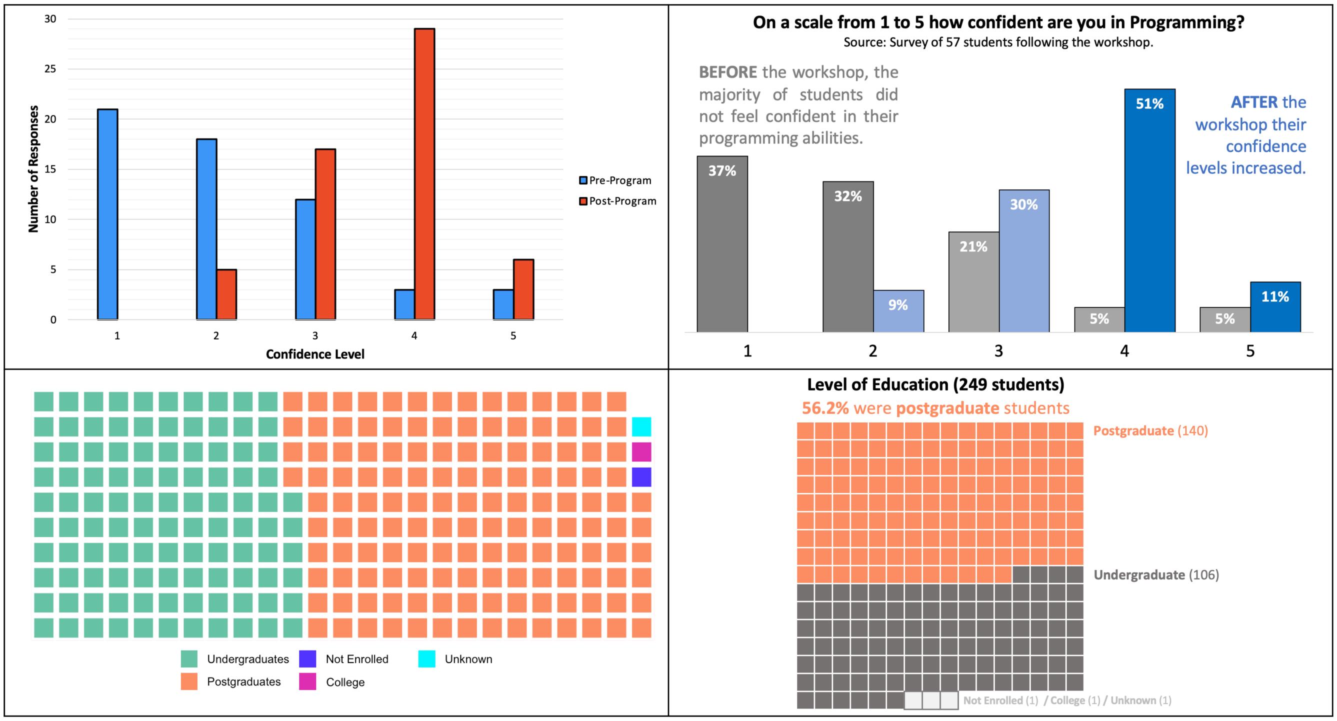

Figure 3: Example prototype pairs #1 bar charts (top) and #2 waffle charts (bottom). Left: exploratory versions. Right: explanatory versions based on [23].

if there is a relationship between the educational stakeholder role and DS feature preference. Participants were asked to reflect on the value and opportunities (if any) for DS features in LA, as well as verbalise any concerns or limitations. This activity concluded by shifting the participant's focus from the visualisation to the visualisation designer in order to address RQ3. Reflecting on the role of the visualisation designer in shaping the data story created an opportunity for many of the participants to provide commentary on the ethical concerns of DS and allowed a seamless transition into the next co-design activity.

Task 3: The final task allowed participants to create their own DS-enhanced prototype visualisation in Google Sheets using a subset of the authentic program data. Co-design has been employed in various LA studies to engage educational stakeholders in the design process and to gather their feedback on LA tools [25]. This prototyping task was intended to prompt participants to reflect on the DS features they encountered throughout the interview, but now through the lens of a designer. The task concluded with participants being prompted once more to contemplate the role of the visualisation designer and to discuss the influence of educational stakeholders who might employ DS-enhanced visualisations, thereby offering insights for RQ3.

3.3 Data Analysis

The interviews were recorded and fully transcribed electronically using the One AI Language Studio. The interview transcriptions were initially inductively analysed by one researcher using the method described by Braun and Clarke [6] to produce a set of themes and codes. These were double-coded with another researcher until a consensus was reached. The resulting codes can be seen in Table 1.

4 RESULTS

4.1 RQ1: Stakeholders' ability to interpret data storytelling enhanced and exploratory visualisations

4.1.1 Self-Efficacy. SE1-2, T1 and T3 agreed with the statement of *"I have the ability to derive insights from data visualisations"*. The remaining participants reported that they strongly agreed with this statement.

4.1.2 Type of Chart. When asked to reflect on the visual features of the prototypes, participants generally commented on the type of graph and the colours. When commenting on the bar charts used in prototypes 1 and 4, T3 explained *"I feel like everyone understands bar graphs. You learn how to interpret them from a young age"*. Others were more critical of bar charts. E4 expressed that *"they are kind of boring … I don't know [if] other people are going to particularly care about looking at a bar chart"*, while SE2 stated *"Bar graphs are not my preferred way of displaying data"*.

Participants were generally critical of the waffle charts used for prototype 2 (see Figure 3 – bottom or further details through this link). The student engagement staff members (SE1-2) respectively expressed that *"a bar graph or a pie chart … would have been easy to decipher"* and *"I don't like the boxes"*. Interestingly, the waffle chart

Table 1: Thematic analysis themes and codes by RQ

Relevant RQ	Theme	Emerging Codes
RQ1	Role of visual elements	Use of colour Type of chart
RQ2	Value of data storytelling	Summarising key insights Leveraging data storytelling to focus the attention of viewers
RQ2	Risks and limitations of data storytelling enhanced visualisations	Flawed implementation of data storytelling features Manipulative potential of data storytelling Operational/practical challenges of data storytelling
RQ3	Human elements of data storytelling	Literacy of the consumer/audience Expertise of the visualisation designer Agency of the educators Role of context in data visualisation

sparked discussion about pie charts with many participants showing contrasting viewpoints. The participants who reported *"agree"* for the aforementioned TSE question (SE1, SE2, T1, T3) praised pie charts with one of them (SE2) stating, *"I love pies in all shapes and forms"*. Conversely, T2 highlighted that *"pie graphs shouldn't be used [as] humans aren't good at comparing areas and even worse at comparing volumes"*. E2 raised an interesting perspective with their comment that *"the type of visualisation that appeals to me might not appeal to another person, which is why we have the tenets of design that you're supposed to follow. . . . Line charts [and] bar charts . . . are tried and tested. But we are breaching into . . . different types of data, and we need to evolve our data visualisation style to go with it"*.

4.1.3 Use of Colour. Some participants flagged that the use of colour in the visualisations can influence their feelings about the data being shown. Some participants (E1, E2, E4, T1) described the colour red as *"alarmist"* and indicated that it should be used to portray something as *"bad"* or *"a cause for concern"*. The same participants associated green with positivity calling it *"calming and relaxing"*. While musing about the feelings that colours can evoke in visualisations E2 surmised that *"people don't remember numbers they remember feelings"*. Non-judicious choice of colour was largely criticised by the participants who felt that it was *"juvenile"* (SE1, E4), *"distracting"* (T4), and *"garish"* (T2).

4.1.4 Insights from Explanatory & Exploratory Visualisations. Without the aid of certain features like a title, description, or annotation some participants struggled to draw meaningful insights from the visualisations. This was particularly noticeable for prototype 2 where some participants became uncomfortable with having to count the squares of the waffle chart, or refused to engage meaningfully with the pre-made insights as there was no description about what one box symbolised. Some participants noted that insights were hard to derive without additional context or description about what the visualisation was aiming to portray. When examining an exploratory visualisation, T2 and T4 highlighted the importance of knowing the question that the visualisations were aiming to answer stating *"depending on your questions this graph might tell you something or it might tell you nothing"* (T2) and *"I don't get what you are trying to answer at first view. I think [a] question can be answered but it's not straightforward on this graph"*. This was supported by SE1 who said, *"I don't know what the purpose of this survey was. I need a bit more information as to what the responses were for"*.

4.2 RQ2: Perceptions of Data Storytelling Features

4.2.1 Potential Value of Data Storytelling. Figure 4 presents an overview of how the participants rated DS features. It shows that participants mostly found these DS features to be helpful, with Highlighting Important Data Points and Annotations rated particularly favourably among the educational stakeholders. When asked to comment on the value of DS-enhanced visualisations, many participants noted that it took less time to analyse an explanatory visualisation than an exploratory one. The student engagement staff both praised that DS *"brings the ideas straight to the reader without them having to spend too much time on the nitty gritty or working your way through the graph"* (SE1) and that *"it's easy to quickly make assumptions on the information [without requiring] much thinking for the end user"* (SE2).

Some of the lead educators believed that DS was a valuable tool to communicate actionable insights. E1 enjoyed how DS-enhanced visualisations *"tell me what action that I should take based on the data [and] the story that I'm being told from this data"*. The actions were not just limited to explicit messages in the graph. Highlighting the potential to gain feedback from DS-enhanced visualisations, E3 felt they were *"able to actually glean important insights from this and [look] for ways to perform better"*.

DS features were also seen to make data more accessible to non-data experts. T2 suggested that *"it helps turn data vis and numbers and stats into something for the layman"*, whereas E4 focused on the appeal of DS to potentially apathetic consumers stating that *"not everyone cares to actually explore exploratory data . . . not everyone is going to discover the story on their own - whether or not they can or they don't care"*.

4.2.2 Prescriptive titles. Participants generally responded positively to Prescriptive Titles. SE1 explained that *"we need a good title to set the tone so we can have a proper understanding of what the data entails and also to help work out what the objectives are"*. Lead educators and tutors agreed with this sentiment citing that Prescriptive Titles enabled them to *"know the motivation behind the answers [and] what the visualisation is representing"* (E1) and relay *"the main takeaway in a short snapshot"* (T3).

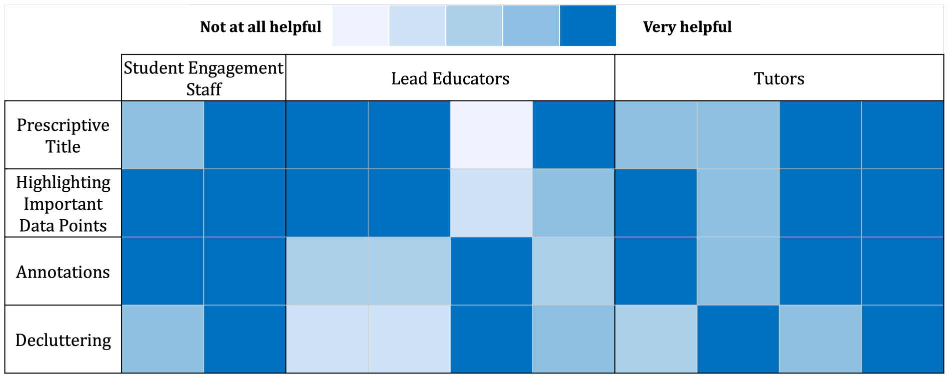

Figure 4: Educational stakeholders' rating of different DS features

4.2.3 Highlighting Data Points. On the value of Highlighting Important Data Points, an administrative staff member (SE1) stated that *"specific data that is highlighted to help extend a point or to help highlight an area that is worth focusing on - I think that's great"*. They went on to say that *"people don't read a full article [they] just get to the crux of it. This is a great tool to help draw attention"*. This was supported by one of the tutors (T3) who criticised the exploratory graphs as having *"so much noise, it is hard to figure out what's important about the graph, whereas if you highlight something, then you know immediately what's supposed to be important"*. However, some were concerned that Highlighting Important Data Points could prevent readers from deriving their own conclusions or insights from the data. T2 felt that *"if you're specifically telling someone what you want them to see you may selectively erase their ability to see other data points unless they're very attentive"*. Two of the lead educators came to a similar conclusion stating that *"if you want to present people with data and allow them to make their own conclusions on the matter then this is probably not helpful"* (E2) as it *"could potentially detach from a more holistic analysis"* (E3).

4.2.4 Annotations. Annotations were seen as a useful tool to add context to the data. Some participants (SE2, E4, T3) expressed that *"without the annotations the graph would have meant absolutely nothing to me"*. Some of the tutors noted that annotations could *"tell [them] things that [they] may not initially notice about the graph"* (T3) and *"give [them] some extra information that [they] should focus on"* (E4). Despite Annotations performing well in the rating task, some tutors were critical of particular ways that annotations can be implemented in a visualisation. Commenting on the presence of actionable insights, T2 said *"I'm not sure recommendations for how to act on the data are appropriate for the graph"* while T1 explained that using annotations *"to communicate the data story is more important"*.

4.2.5 Decluttering. Figure 4 indicates that Decluttering was ranked lower than the other DS features. Some participants acknowledged that decluttering the graph was useful to *"help make clear assumptions"* (SE2) but believed *"that there are other [features] that are more important"* (T1). SE1 felt that while decluttering could be leveraged to reduce *"background noise"* that *"presentation wise, you can sometimes clutter it up and make it look nice … it [depends on] each individual and how they want to digest their information"*. E3 warned that premature use of decluttering at *"an analysis stage [could make it] difficult to derive insights"*.

4.2.6 Risks & Limitations of DS-Enhanced Visualisations. In addition to the aforementioned criticisms of specific DS features, some participants were concerned that DS-enhanced visualisations *"are not objective in the sense that they don't present the entire data as it is and allow the audience to glean insights for themselves. They have a purpose; they have an argument that they want to put forward"* (E3). E3 went on to say that *"it's easy to potentially tell the wrong story or tell a story that is deviating from something else that could have been a bigger and truer story"*. As a non-data expert, T1 expressed worry that DS-enhanced visualisations are *"forcing a perception of what's happening … because [a] normal person like me who might not know anything about data … could take the wrong takeaway from that and then you're influencing people's opinion"*. SE1 and T4 also acknowledged the operational challenges of DS expressing that implementation of these features takes *"an extra two steps when completing a presentation or a survey"* and that businesses would *"need to invest more time [and] more budget"*.

4.3 RQ3: Perceptions of Visualisation Designer

4.3.1 Preferences When Designing Data Stories. All of the participants used a variation on a bar chart to visualise student ratings about specific activities or support mechanisms from the authentic learning scenario. Some participants (SE1, E2, T2, T4) created more elaborate visualisations that incorporated most - if not all - of the main DS features discussed in Activity 2. In contrast, other participants preferred to be sparing with their implementation of DS features believing that highlighting particular bars or adding text to the chart was sufficient to convey the data story they wanted to tell. While the instructions were to construct a DS-enhanced visualisation, many of the participants (7 out of the 10) preferred the use of a *descriptive* title over a *prescriptive* title. Notably all of the participants incorporated a textual element into their visualisation in some way – be it in the form of a title, annotation, or a label on the bars.

4.3.2 Ethical Obligations of the Visualisation Designer. The main concern that participants had about the role of the visualisation designer was the potential to portray a story that is manipulative or self-serving. E1 believed that DS features could be leveraged

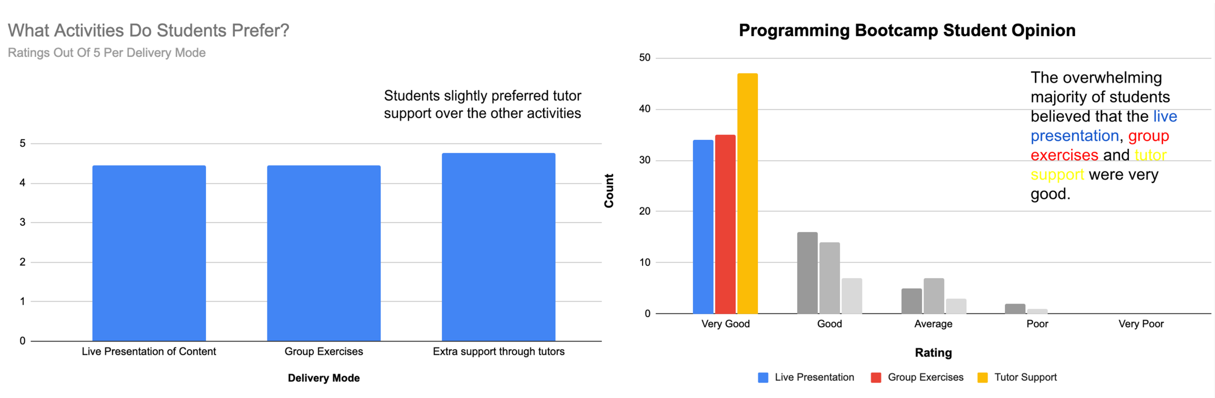

Figure 5: Example data stories designed by E1 (left) and E2 (right)

"maliciously [to] hide certain data or insights from people if they are less flattering". This opinion was shared by E2 who quoted Mark Twain, *"'There's lies, damned lies, and statistics' and this is exactly what we're doing here"*. Some participants acknowledged the manipulative potential of DS after partaking in the co-design activity. E3 expressed that creating DS-enhanced visualisations *"makes me feel more powerful in a sense that I get to drive the discussion, the narrative, and I get to spell it out for my readers or my audience. I am more than just an analyst, I'm an influencer which is scary but [also] empowering"*. E4 realised that they *"have a lot of sway [on] the story that's being told, and the way it's being told"*. In the context of an educational program, E3 suggested that if designers have *"certain personal goals [for] the program ... it's important that they put that bias aside and work with a team of different stakeholders in terms of picking which stories to present"*.

4.3.3 Expertise of the Visualisation Designer. When reflecting on the role of the visualisation designer, participants acknowledged that designers may not possess the necessary skills to communicate a data story that is contextually and/or factually correct. A primary expectation was that a visualisation designer should understand both the data set they are trying to make a story out of, and their target audience. Three of the tutors highlighted that the *"designer might not emphasise the right features of the data"* (T3) and if they do not have the sufficient skill-set to *"know how to tell a story about it, it might lose its impact"* (T2). T4 recognised that *"there is a risk of the storyteller missing [insights] ... if they are focusing on a specific story"*. Both SE expressed the importance of understanding the audience. SE1 stated that when delivering insights to *"external parties, information is key because any kind of misunderstanding, or something that's misconstrued, can snowball out in the wrong way"*. Similarly, SE2 voiced that *"knowing my end users and who will be using [the data is] important, because you can't make [the visualisation] too complicated"*.

4.3.4 Manipulative Potential of DS. When discussing the value of DS in the second activity, E4 expressed that they *"want to give people the opportunity to explore the data themselves without really being too heavy-handed in what you want them to see"*. Likewise, E2 warned that *"there is a danger with people that pick the elements that go into data visualisations [that they] introduce their own biases"*. However, during the co-design activity, E2 aimed to tell a specific data story that highlighted the positive parts of the program stating, *"if my intention right now is to convince somebody that I'm doing a really good job as [a lead educator], this is all I need"*. They followed this up by saying *"I can't directly lie, but I can tell a small lie"*. Following the co-design activity, E4 was asked how they felt while creating the DS-enhanced visualisation. They answered *"I feel powerful. In the sense that looking at these data, the immediate thing I went to was, 'What do I want to say?' when the question is, 'Does that align with what the stakeholders want?'"*. This demonstrates that while individuals may have certain beliefs about how DS techniques should be leveraged to not manipulate the audience or introduce bias into the visualisation, both participants approached the co-design with their own interests in mind.

5 DISCUSSION

5.1 Implications for Research and Practice

5.1.1 RQ1: Identifying insights from data stories versus conventional visualisations. The qualitative results from participants' reflections on explanatory and exploratory visualisations revealed some interesting insights into common DS features they used in their sensemaking processes. Zdanovic et al. [46] proposed that there is a relationship between the type of chart, DS, and how a reader makes sense of the visualisation. In our study, numerous participants suggested that **the chart type influenced their ability to understand the information and extract insights**. Although experts in DS often critique the use of pie charts to convey insights [23, 34], some participants (especially the administrative staff – SE) expressed a preference for pie charts over less familiar visualisations, like the waffle chart. Interestingly, E2 even proposed that individuals without data expertise might hesitate to interpret unfamiliar visualisations. This observation aligns with the TSE results, where participants who self-reported a high proficiency in extracting insights from data visualisations also exhibited a preference for pie charts for information dissemination.

Moreover, when designing data visualisations, Knaflic [23] recommends choosing colours deliberately to highlight crucial information while also invoking the desired emotional reaction, considering the cultural connotations of colours. In the same vein, Ryan [34] argued that humans tend to first observe artistic elements, such as colour, before delving into intricate details like visualisation type or the underlying message. This was reflected in our research. When asked to comment on visual components, participants frequently remarked on the colours used in visualisations. **Participants often associated the colour with an emotion rather than to highlight data points.** This was particularly evident when participants critiqued the indiscriminate colour use in prototype 4, feeling that the visualisation was too visually busy to interpret effectively. This suggests that LA designers should carefully reduce the colour variation in visualisations and also consider the emotional and cultural meanings of colour in the contexts where their tools will be deployed.

In sum, regarding RQ1, results from Task 1 revealed that stakeholders' ability to interpret DS-enhanced visualisations can be heavily impacted by key data visualisation elements, such as colour and the type of chart. Additional considerations should thus be made by LA designers regarding how much context is given about the data or purpose of the visualisation or data story, as many participants felt (particularly with the exploratory – non DS – visualisations) that they lacked the necessary context to derive valuable insights.

5.1.2 RQ2: Perception of data storytelling features. In response to RQ2, **participants believed that the addition of DS enabled them to understand the key ideas and insights** in a way that they could focus on actioning the insights or improving the learning program. This finding resonates with prior research, which suggests that data stories aligned with learning objectives, coupled with the effective deployment of LA tools, can facilitate educators' reflective processes [15, 37]. The results of the rating task were also consistent with the findings of the ranking task by Echeverria et al. [14]: in both cases **educational stakeholders tended to perceive textual elements, such as annotations and prescriptive titles, as a helpful means to contextualise the data** or distil complex insights into a concise and accessible *"snapshot"*. Beyond LA research, this finding resonates with the results of Borkin et al. [5], who discovered that if individuals find the title of a visualisation lacking, they often turn to textual elements and annotations to aid in sensemaking. Notably, in our study, even though participants rated prescriptive titles (those that convey insights) positively, they showed a stronger preference for descriptive titles (those that simply describe the data shown in a visualisation) during the co-design task. This might suggest that educational stakeholders need further exposure or training to effectively utilise prescriptive titles in the context of DS.

Participants also acknowledged the potential for DS features to guide the attention of an audience. Knaflic [23] and Alhadad [1] noted that as attention can be limited, visualisations need to minimise visual clutter and leverage pre-attentive attributes such as colour and contrast to highlight salient information. However, while Alhadad [1] proposed that clutter posed a significant barrier to processing the information, participants in our study viewed decluttering as a less essential DS feature with some arguing that a presentation can be cluttered and remain informative. In contradiction of both the rating task from Task 2 and the advice from Knaflic [23] and Alhadad [1], there were divisive opinions on the applicability of highlighting important data points. Many of the participants praised the idea of communicating salient information at a glance and as a result selectively used colour to draw attention to data in their own designed data story. However, some expressed concern that the practice of highlighting particular sections of data could suppress the reader's ability to draw their own conclusions from the data or be used to selectively obscure less flattering data points. Taken together, these contradictions between participants' beliefs and foundational data visualisation principles underscore that **the educational stakeholders' lack of visualisation design skills [28] can pose challenges for LA designers when incorporating their perspectives into the design of data stories**.

In sum, participants generally believed that the main DS features discussed in this study could aid educational stakeholders in being able to make sense of, and action, insights from student data. There was minimal evidence that the role of the educational stakeholder (i.e., educator, tutor or administrative staff) influenced their perception of different DS features. However, this is likely because of the small sample size and can be a potential avenue of future work.

5.1.3 RQ3: Perception of visualisation designer. In a seminal article, Segel and Heer [36] expressed that the creation of meaningful data stories is directly influenced by the skills of the storyteller. Daradkeh [11] supported this by indicating that storytelling competency is a sum of the quality of the data, the story, and the domain knowledge of the designer. In our study, participants focused on two areas that the visualisation designer must understand: the audience and the data itself. They believed that **the DS designer needs to have the necessary expertise and data literacy to be able to uncover key insights, emphasise salient information and tell an impactful story**. Yet, it was also noted that a lack of awareness of the audience's requirements could also damage the impact of the story and confuse the audience.

Another lens that participants considered when reflecting on the visualisation designer was the potential for them to act in deceitful ways. Manipulation of data and visualisations is not a novel concept; however, while researchers like Pandey et al. [30], Correll [10], and McNutt et al. [27] identified this potential in exploratory visualisations here participants focused almost exclusively on how DS could be leveraged dishonestly. Aside from the aforementioned belief that **highlighting specific data could obscure other important insights**, following the co-design activity many participants realised the power wielded by visualisation designers. Comments like *"I am more than just an analyst, I'm an influencer"* illustrated that the persuasive potential of storytelling extends beyond simply using visual features to clarify an insight. Interestingly, while many participants warned of the risk of designers using DS to cherry pick data or present a narrow viewpoint, only a few recognised their own biases in the co-design task. Many chose to craft their own data story rather than showcase a potentially critical perspective on the learning program. This hints at DS's potential misuse as a persuasive rather than supportive tool.

Prieto-Alvarez et al. [33] suggested that involving educational stakeholders in co-designing LA visualisations can provide insights into how LA can be successfully implemented in an educational setting. In our study, while the co-design activity was mostly intended to provoke reflection about the visualisation designer, it is noteworthy that **all the participants were able to use DS features to present a DS-enhanced visualisation rather than being content with a simple exploratory visualisation**. Participants showed a preference towards adding text to communicate their story, which is consistent with the results from the rating task of this study and the participants' inclination towards textual elements in Borkin et al. [5] and Echeverria et al. [14]. Some participants were able to create detailed DS-enhanced visualisations using visual attributes, such as colour, to highlight specific features of the data that they felt were important. Notably, only one of the participants (T2) chose to declutter their visualisation by removing the gridlines. This and the results from the rating task may suggest that *educational stakeholders may not prioritise decluttering as a valuable DS feature.*

Based on the educator's perspectives on DS and ethical concerns that emerged over the course of interpreting and designing their own data stories, as well as the design suggestions from Knaflic [23], we recommend the following:

- LA visualisations can incorporate meaningful textual elements to guide educational stakeholders through the data story and clarify any complex data points.
- LA designers, researchers, and analysts should work with other stakeholders to analyse and present data so that the stories are contextually appropriate and, to a great extent, factually correct.
- DS features that relate to attention (e.g., highlighting and decluttering) can be used strategically to draw attention to salient information without intentionally or unintentionally obscuring other information.
- LA designers might consider leveraging DS features to enhance the communicative effectiveness of LA dashboards and similar tools. However, they should be acutely aware of the power dynamics that can be subtly imposed by the data story's designer.

5.2 Limitations

An important limitation of our study is its reliance on the case study methodology. Given the relatively small sample size of ten participants, the study's results cannot be broadly generalized. However, as the results have been sourced from educational stakeholders who were actually involved in the same authentic learning program, their qualitative insights remain valuable for the LA and data visualisation domain. This also facilitated the adoption of DS in this program, making the transition to practice smoother. Nonetheless, future LA and data visualisation studies could benefit from including the variety of educational stakeholders cited by Ifenthaler [16] and Kaliisa et al. [21], ensuring a comprehensive understanding of how individuals engage with LA in higher education. It is also noteworthy that the educators and tutors all had a Computer Science background and thus prior knowledge of data visualisation principles. However, they lacked experience in DS, particularly the ethical issues associated with its use. Another limitation is associated with using Google Sheets as the main visualisation tool in the co-design activity. The default chart option in Google Sheets is the bar chart and this visualisation type was generally the chart of choice for the participants. It is unclear whether participants were more inclined towards using bar charts because they were the default option or if the categorical nature of the Task 3 dataset lent itself towards use of bar charts over alternatives. Future research may seek to utilise DS co-design activities with categorical or continuous data to explore the potentially different types of visualisations that educational stakeholders create. Finally, as this study focused mainly on static exploratory and DS-enhanced visualisations, future studies might benefit from exploring data interactivity.

6 CONCLUSION

In this paper, we employed a case study approach to gather insights on the implementation of DS features for communicating LA to educational stakeholders within an authentic learning program. Results show that educational stakeholders are open to the meaningful integration of DS in LA visualisations. They expressed a positive response to DS features that facilitated clear communication of key insights, such as annotations and highlighting critical data points. While DS-enhanced visualizations have the potential to aid in sensemaking and decision-making among educational stakeholders, participants expressed concerns over the potential misuse of DS by visualisation designers, fearing it could be used in a manipulative or self-serving manner.

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