# The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry?


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## ABSTRACT

One of the ultimate goals of several learning analytics (LA) initiatives is to close the loop and support students' and teachers' reflective practices. Although there has been a proliferation of end-user interfaces (often in the form of dashboards), various limitations have already been identified in the literature such as key stakeholders not being involved in their design, little or no account for sense-making needs, and unclear effects on teaching and learning. There has been a recent call for human-centred design practices to create LA interfaces in close collaboration with educational stakeholders to consider the learning design, and their authentic needs and pedagogical intentions. This paper addresses the call by proposing a question-driven LA design approach to ensure that end-user LA interfaces explicitly address teachers' questions. We illustrate the approach in the context of synchronous online activities, orchestrated by pairs of teachers using audio-visual and text-based tools (namely Zoom and Google Docs). This study led to the design and deployment of an open-source monitoring tool to be used in real-time by teachers when students work collaboratively in breakout rooms, and across learning spaces.



## CCS CONCEPTS

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

## KEYWORDS

human-centred design, learning analytics, inquiry-driven practice, dashboard, CSCL, online learning




*LAK22, March 21–25, 2022, Online, USA*



ACM ISBN 978-1-4503-9573-1/22/03…$15.00
https://doi.org/10.1145/3506860.3506885

**ACM Reference Format:**
Stanislav Pozdniakov, Roberto Martinez-Maldonado, Yi-Shan Tsai, Mutlu Cukurova, Tom Bartindale, Peter Chen, Harrison Marshall, Dan Richardson, and Dragan Gasevic. 2022. The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry?. In *LAK22: 12th International Learning Analytics and Knowledge Conference (LAK22), March 21–25, 2022, Online, USA.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3506860.3506885


## 1 INTRODUCTION

The field of Learning Analytics (LA) has emphasised the need for enabling teachers and learners to gain a deeper understanding of their own processes and progress, rendered in ways that were until recently accessible only to educational researchers [22]. This has led to the design of various *"end user" interfaces* (EUIs) that have taken the form of prompts [47], alerts [12], recommendations [48], reflection tools [18], and dashboards [45]. Dashboards have been particularly attractive since they follow the metaphor of car dashboards to provide only the most critical indicators needed to ensure the effective operation of a complex system. Yet, evidence is pointing at the multiple challenges that both educators [26] and learners [24] are facing while trying to interpret LA interfaces to make sense of the complex learning activity. In some cases, learning dashboards have even been detrimental to students' learning [25] and motivation [38]. In fact, recent reviews of dashboards have consistently flagged difficulties learners commonly have in in interpreting and acting on data representations to improve learning [7, 21, 29, 41].

Since the *interpretation* of such dashboards and other visual interface elements is central to their effectiveness [9], there has been a corresponding interest on the human factors of EUIs in LA [36]. Some authors (e.g. [3, 20] have recently proposed ways to include educational stakeholders in the design process to create LA interfaces that are aligned with authentic needs, learning design, and pedagogical intentions that characterise the context in which the LA interfaces are intended to be deployed. However, whilst progress has been made in proposing design methods to engage teachers and learners in design practices (reviewed in the background section), less attention has been paid to visual techniques that can facilitate the interpretation of dashboards for the purpose of supporting sensemaking.

Verbert et al.'s model [44] has been foundational in the LA community to explain the sensemaking process that is expected to occur when people face a LA dashboard. This model suggests that, since data by themselves are not very useful, teachers and learners are expected to formulate questions and assess how useful or relevant data are for addressing those questions. Qiujie et al. [23] and Bakharia et al. [5] also emphasised the need for mapping teachers' questions to educational concepts for data to be rendered, reported back, and be actionable. This emphasis on *"asking questions"* that data should address is critical because it latches on the inquiry cycle that teachers commonly engage in to reflect on their practice [33]. However, there is a shortage of the literature that can guide how the mapping between teachers' questions and educational constructs can be explicitly reflected in the visual design of LA interfaces.

This paper investigates this issue by answering the question to what extent can we design end-user learning analytics visual interfaces that explicitly address teachers' questions. As a result, we propose a question-driven LA design approach to ensure that EUIs *explicitly* address teachers' questions about student progress and their own practice. We illustrate the approach proposed in the context of synchronous online activities mediated by an ecology of communication and collaborative writing tools. We conducted a study divided in two parts: *design and validation*. For the first part, we conducted interviews with 15 university teaching assistants (TAs) to understand how they monitor groups of students in breakout rooms using video-conferencing software. A lightweight inductive process is proposed to extract TAs' questions, identify the evidence that can be used to address them, and create prototype data representations that are explicitly mapped to their questions. The execution of this process resulted in the design of an open-source dashboard for teachers to monitor synchronous online activities across learning spaces (namely Zoom and Google Docs). In the second part, a functional version of the question-driven interface design was deployed and validated in an authentic university context. Both studies received ethical approval. The tool was used by two TAs for three consecutive weeks to orchestrate breakout room sessions. Follow up stimulated recall interviews were conducted with eight participants (four TAs and four students).

## 2 BACKGROUND AND RELATED WORK

### 2.1 Sensemaking of Learning Analytics Dashboards

The *interpretation* of dashboards and other visual interface elements is central to their effectiveness in supporting *sensemaking* of teaching and learning activities. As already mentioned, several authors have followed Verbert et al.'s model [44] when designing their LA interfaces to support the sensemaking process. The model consists of four steps that continue iteratively in what the authors call the "learning analytics process model". The first step is i) *visualising and presenting* data to the user (which is the only step that occurs at the side of the technological development). The second step expects that teachers and learners will ii) *formulate questions and assess* how useful data are for addressing those questions. The final two steps are concerned with the sensemaking process with the purpose of iii) *responding to those questions* (i.e. generation of new insights) in order to iv) *perform educationally meaningful actions* (e.g. for learners to change behaviours and for teachers to perform interventions). However, Echeverria et al. [14] argue that, according to this process, interpretation and sensemaking are expected to spontaneously occur without any support from the technological side. In response, the authors suggested to scaffold this process by enhancing the visualisations of dashboards through the addition of visual elements that emphasise only the relevant data points and trends, and text that explains the data. Similar enhancements have been proposed by other LA researchers through using metaphoric visualisations [30], providing frames of references for learners to compare their performance against [24], or creating threads of visualisations to tell a meaningful story [11].

In contrast, Wise and Yeonji [46] suggested that making sense of dashboards is a process we should fully understand and design for. These authors proposed a sensemaking framework, particularly for teachers, in which the process starts, again, by identifying the educational questions that the analytics can address. This is the foundation for sensemaking, decision making and taking pedagogical actions. This emphasis on *"question formulation"* is present in several other LA works. For example, Sampson [33] and Rodriguez-Triana et al. [32] consider the LA process as a teacher-inquiry loop in which a teacher's questions can drive the customisation of the enabling technologies. Similarly, Bakharia et al. [5] investigated ways to link LA with the learning design and found that teachers would like to map questions to educational concepts and features in LA reports.

In short, previous works have conceptually emphasised the importance of identifying the authentic teachers' questions to be answered [32, 33, 44, 46]. However, it is still unclear how the mapping between teachers' questions and educational constructs can be explicitly reflected in the design of the EUIs in LA. The user interfaces are commonly the only contact points the teacher or learner would have with LA, but not much work has focused on supporting the visual design of such interfaces. This requires a careful consideration of human factors that shape the effective use of LA interfaces.

### 2.2 Human-centred Learning Analytics

The term human-centred learning analytics (HCLA) was recently coined [36] to refer to the subcommunity of LA researchers and practitioners interested in human factors that can influence the effective use of LA innovations, and in the adoption of concepts and methods from design communities, such as participatory design and co-design, to design more effective LA innovations. The essence of these methods is that the meanings, interaction opportunities, functions, and attributes associated with technological systems are co-defined with the people for whom the system is intended. This is in contrast to having designers or researchers imposing design decisions.

The importance of human-centred design (HCD) has been emphasised by Ahn et al.[1] who suggested that, although topics like fidelity of the data and maximising adoption are crucial, it is also critical to design LA interfaces that incorporate local needs and that ensure productive adaptations between educational practices and the technology. Some authors have described certain ways to implement HCD to create LA tools. For example, Echeverria et al. [15] suggested to base the design of LA interfaces on the teacher's existing requirements coupled with educational theories. Alhadad [2] more particularly suggested to consider human-interaction foundations, such as principles of cognitive load, attention, human perception and data literacy, since they have direct implications on the design of effective LA user interfaces. More specifically, Echeverria et al. [14] shared data visualisation principles adopted from Information Visualisation theory – such as relying on fitting, goal-oriented chart types, de-cluttering the interfaces and employing narrative elements – to effectively convey insights from LA dashboards.

Another stream of HCLA research has focused on providing methods to engage learners and teachers in the LA design process. For example, Dollinger and Lodge [13] and Prieto-Alvarez et al. [3] incorporated principles of co-creation and co-design (respectively) to give an active voice to teachers, learners and other educational stakeholders in decisions that would shape a LA innovation. Wise and Jung [46] and Sarmiento et al. [34] also adopted co-design methodologies, such as the use of ideation cards, sketching and prototyping to understand teachers' and learners' authentic needs, respectively, to allow educational stakeholders to define characteristics of the tools that they will end up using. Holstein et al. [20], through a longitudinal design project in which several design tools were used, demonstrated how co-design approaches can lead to unexpected technological innovations and can increase the likelihood of technology acceptance and adoption.

In sum, recently, there has been a growing interest in adopting human-centred design principles in LA by 1) considering foundations of human-computer interaction, and 2) bringing human-centred methodologies to engage educational stakeholders in the LA design process. However, less attention has been paid to design approaches and visual techniques that can facilitate the interpretation of dashboards for the purpose of supporting sensemaking. In this paper, we contribute to the growing body of HCLA literature by proposing a design approach to establishing explicit connections between teachers' authentic questions and the visual design of LA interfaces.

## 3 APPROACH

Inspired by the emphasis on *"question formulation"* as a key step in the LA sensemaking process [32, 33, 44, 46], and the need for HCD practices to address authentic needs of stakeholders in LA [20, 34, 36, 46] we propose a question-driven LA design approach to ensure that the end-user LA interface *explicitly* addresses teachers' questions. We particularly focus on teachers to connect to the inquiry cycle that they commonly engage in to reflect on their practice. The design approach consists of the following five steps.

**1- Interviews with teachers** This step involves asking teachers about their current practices while monitoring groups of students or individuals. They can be explicitly asked about the kinds of evidence they commonly use to monitor both students' progress and their own teaching practice. Questions should be tailored to the specific educational context. Some example questions will be presented in the next section through our illustrative study.

**2- Lightweight inductive analysis** Based on open answers from teachers, an inductive thematic analysis can be performed to map the most critical challenges they face with the evidence that can be used to address them. Codes emerging through this analysis can be thematically grouped to enable the identification of salient questions that participants commonly have. These themes are then ranked by frequency of appearance.

**3- Questions formulation** Each theme is labelled by formulating the challenges faced by teachers in the form of a question. These questions should be formulated using at least some of the words that participants used to express their actual concerns and the sources of evidence they would require. Semantically similar questions might be grouped together to form overarching questions.

**4- End-user interface prototyping** This is the step that characterises our proposed approach. Based on the teachers' questions identified in the previous steps, the most highly ranked questions (i.e., those that address the concerns of the majority of the participants) are explicitly added to the dashboard or LA user interface. Inspired by the notion of data storytelling [14], each question needs to be associated to a particular data story. A data story is a combination of charts and text narrative that is focused on communicating a particular insight. This way, each component of the interface addresses one (or more) of the core monitoring needs of participants. Each component should be aimed at emphasising certain data points that are only relevant to one question at a time to minimise visual complexity.

**5- End-user interface validation** This step is aimed at addressing a critical aspect of LA dashboard design: the validation of the impact of such design on sensemaking, decision-making, teaching or learning [29, 45]. This can consist of three intertwined parts. First, the relevance of questions for supporting teaching practice should be validated with stakeholders. Second, the mapping between the questions and visual elements in the interface should be scrutinised, ideally, after an authentic deployment. This means that emphasis should be posed on ensuring that the visualisations help addressing the corresponding questions. Third, the full interface should be validated to understand how sensemaking occurs if all the questions and visualisations are simultaneously presented in the interface.

It is desirable that this validation is conducted under authentic conditions [28], since participants might face the situations which are otherwise unforeseen under the planned user scenarios. If this is not possible, at least authentic data can be used to create low-fidelity prototypes to explore how the interface is interpreted by educational stakeholders [20]. It has also been recommended to give an active voice in the design process to the educational stakeholders whose data is being used in LA tools [31]. This means that if the EUI is targeted at teachers but it visualises students' data, then, students should be involved at least in the validation of potential interpretations that other stakeholders can make based on such data. The result of this validation can lead to re-design (i.e., repeating steps 1-5, including potential re-formulation of the questions and/or the visual representations) and re-deployment and validation of the LA interface. The next sections illustrates our approach through an authentic design case with teachers.

# 4 CONTEXT

This section presents i) the educational context of the study that serves to illustrate feasibility our design approach, and ii) details about the system to be used to automatically capture data during synchronous online sessions.

## 4.1 Educational Context and Participants

We illustrate our proposed design approach in the context of the authentic challenges that TAs face while monitoring synchronous online activities conducted as a part of the graduate course *IT research methods*. In this course, students engage in weekly 3-hour online workshops facilitated by two TAs. Students commonly perform a varied range of collaborative activities by forming small groups of 4-6 members, using audio-visual and text-based tools (namely, Zoom and Google Docs). The types of tasks range from those where students are expected to discuss a topic to those where the main output is a written report. When students go to breakout rooms to work on group tasks, TAs cannot commonly observe what is happening in each room unless they join a particular room and spend some time listening to the conversations or checking the documents generated by the group. This is a critical monitoring challenge that has been reported in CSCL and orchestration literature [43]. Moreover, although Zoom has become one of the staple communication tools to conduct learning activities around the world during the COVID-19 pandemic, it does not offer functionalities that teachers can use to "see" what is happening when several groups are working at once [37], and particularly if other tools are being used (e.g. document editing tools).

## 4.2 Apparatus

An open-source classroom analytics system for Zoom, called ZoomSense[1] [6], was used to capture data traces of activity when students work collaboratively using Zoom . This system works by creating headless digital agents that are distributed across the students' breakout rooms; it can be run as a standalone web application and be used with Zoom. Once in a breakout room, the agent automatically captures who is speaking at each moment, sending messages or performing actions on the interface. If configured by the TA, ZoomSense can also automatically create a Google Document associated to each breakout room, providing the link to students to work on their particular document. All actions and major revisions performed on the document are also logged.

# 5 DESIGN STUDY

This section illustrates how the first four steps of the proposed approach operationalised in an authentic learning analytics design project. A total of 15 teaching assistants (TAs) participated in this study. Most of the TAs had more than a year of teaching experience in higher education. Two interviewees were chief course assistants.

## 5.1 Question Elicitation (step 1)

Each TA was interviewed via an online communication system in accordance to the current government guidelines for physical distancing. A typical interview lasted around one hour. Some interview questions aimed at capturing the general monitoring challenges that TAs face. We asked, for example: *"how do you usually monitor students during synchronous online activities?"*, *"what do you do first when joining a group breakout room?"*, and *"what unforeseen events have you faced while monitoring groups in breakout rooms?"*. Other questions aimed at identifying the evidence TAs currently use to monitor progress, for example: *"what information do you currently use in order to understand students' progress or collaboration?"* and *"what information would you like to have to improve the attention you provide to groups?"* The full questionnaire with a total of 40 questions is available online (https://bit.ly/design-guide-qdla). Then, based on the data capture capabilities of the ZoomSense system, some examples of the evidence that can be captured were communicated to the participants. This included the *amount of time each student is speaking*, *when each student starts and stops speaking*, the *order in which they speak* and *the progress of their writing*. TAs were asked about the potential usefulness, envisaged usage and potential visual representations for this evidence.

## 5.2 Question Extraction (steps 2 and 3)

Two researchers coded the interviews' transcripts. Table 1 summarises the resulting questions elicited from the 15 interviews with participants. Each emerging code (see codes in column 3) were grouped together and linked to a main question (column 1) formulated based on the words used by the TAs. For example, the first row presents the question "Q1. Are students inactive in Zoom?" (column 1) which corresponds to TAs wanting to know if there are disengaged students in a breakout room (column 2) and was mentioned a total of 16 times (column 4) by 12 TAs (column 5).

## 5.3 End-User Interface Prototyping (step 4)

Based on the questions elicited from the TAs, a dashboard prototype was designed to explicitly address some of these questions. Figure 1 presents the prototype that consists of five main components, each addressing one of the questions which participants highlighted (Table 1; Note: Questions 6 and 7 were not considered in this design given the current data capture limitations of the ZoomSense system). Due to the fact that we aimed to implement a LA interface for monitoring breakout rooms *in real time*, we decided that the whole interface should fit in one browser tab to enable TAs to assess the status of the session at a glance while being connected to the other tools as needed (i.e., Zoom and Google Docs). To enable rapid comparison of groups in breakout rooms, student data are aggregated at a breakout room level.

All the components in the LA interface are dynamic and are updated in real-time. Following data storytelling principles [14], the charts in the interface are de-cluttered, showing only the data that can enable rapid comparisons between groups. Only three contrasting colours are consistently used to emphasise elements and also to create a user interface that is colour-blind friendly. Gray and navy blue are used for the majority of the visual elements. Orange colour is used to emphasise cases that may need closer attention. This interface is implemented as an open source tool and the code is available and added to the open source [2]ZoomSense. The ZoomSense is currently being used in authentic learning scenarios

[1]https://zoomsense.io

[2]https://gitlab.com/Stalkcomrade/zoomsense-web-client/-/tree/icalt-stable

| Question | Description | Code | *i* | *n* |
|---|---|---|---|---|
| Q1. Are there students inactive in Zoom? | This question addresses TAs' needs to know if all students within a group are contributing equally and to identify: dominant students, "scribes" and "ghosts" (students completely inactive in Zoom). | Equality of participation | 16 | 12 |
| Q2. How are groups progressing in Gdocs? | This question addresses the TAs' interest in knowing if students are progressing in their writing. | Writing progress | 12 | 10 |
| Q3. Are there groups that are not discussing much? | This question reflects the need to know the relative extent of discussions within a breakout room in comparison to other rooms. | Level of discussion | 10 | 10 |
| Q4. How are students interacting in Zoom? | TAs wanted to gain understanding of how a discussion was happening in each room: if one or two students are dominating, and if everyone or some are completely silent and disengaged. | Interactions | 10 | 10 |
| Q5. In which room have I spent the least time? | This question addresses TAs' concerns about allocating unequal amount of time to groups or unintentionally neglecting students. | TAs' time distribution | 3 | 3 |
| Q6. What do I know about students' previous learning?* | This question reflects TAs' needs to use historic evidence from previous online classes and rely on information from other data sources. | History | 8 | 8 |
| Q7. Who is asking for help and what kind of help is needed?* | This question reflects TAs' interest in knowing which groups are asking for help and any information about their problem they are facing so they can prioritise the attention. | Help seeking | 6 | 6 |

**Table 1: Questions formulated based on the coding from 15 interviews with teaching assistants (TAs). *i* = number of instances that support the code. *n* = number of TAs that mentioned the question. * – questions that were not mapped to any component in the dashboard due to data capture limitations.**

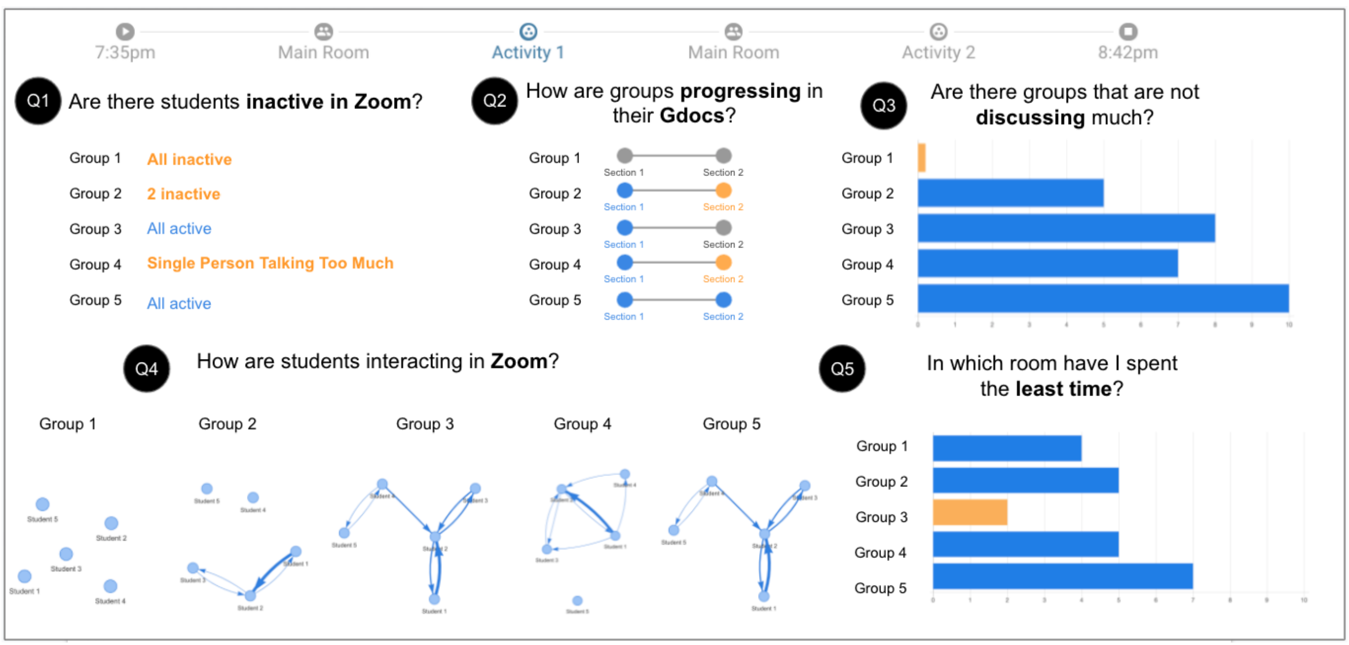


**Figure 1: Question-driven interface design to be used in real-time by TAs when students work in breakout rooms.**

in different institutions. Each visual component is explicitly labelled with one of the five questions that were included into the design (Q1-Q5 in Table 1, column 1). Below, we provide a short description of each visual component that is mapped to a question.

**Q1. Are there students inactive in Zoom?** The visual component addressing this question was designed as a narrative-based visualisation that explicitly communicates to TAs about students' activities in breakout rooms. For example, Figure 1 shows some groups of students are being active (Q1, groups 3 and 5) or inactive (Q1, group 1), or that some students are being inactive or dominant in their groups (Q1, groups 2 and 4). As described earlier, the orange colour is assigned as part of the storytelling principles to attract TAs' attention. Here, this colour indicates groups that show inactivity or unbalanced engagement among students.

**Q2. How are groups progressing in Gdocs?** A simple horizontal state bar is provided for each group signalling the progress in the written activity by assessing the progress of their Google

Docs (e.g. see Figure 1, Q2). Written tasks might have several *sections* to be written. These are specially dedicated places in a Google Document where students are expected to write. For each section of the document (visualised as nodes connected through a horizontal line) the progress is indicated as follows: not yet started (coloured in grey); students still working in the current section (coloured in orange); and section completed (coloured in blue). A custom heuristic is used to consider that the section is completed. If students have not been working on the sections for a certain amount of time and are working on the next section, the previous section is considered to be completed. This way TAs might get an indication about which sections groups are working on and what is the state of their progress. For instance, Figure 1 (Q2) shows that group 1 has not yet started to work on any of the two sections expected to be developed in their Google Doc (both nodes in gray); groups 2 and 4 completed only first section and are working on the second; and group 5 has completed sections 1 and 2.

**Q3. Are there groups that are not discussing much?** The main goal of this component is to provide a way for rapid comparison between groups in terms of the amount of time students are speaking in their breakout rooms. This way, instead of depicting granular information about each student, we treat a group of students as a data unit. A horizontal bar chart (see Figure 1, Q3) allows TAs to compare the extent to which verbal participation differs across breakout rooms. This technique also provides a visual horizontal alignment with the visual components in Q1 and Q2. Following data storytelling principles [14], for the least performing group of students (Group 1), the corresponding bar is highlighted and coloured in orange to attract attention. The orange colouring is automatically updated if the communication levels are lower than a half of the average of communication across groups.

**Q4. How are students interacting in Zoom?** The design of this component provides more details about interactions among students during discussion in breakout rooms. The type of chart is a directed sociogram (see Figure 1, Q4), where each node corresponds to a student. Two nodes are connected if one student has spoken after another student, thus signalling the presence of 'communication'. The network is dynamically weighted, meaning, a connection gets thicker if two or more speakers have consecutively spoken after each other. The thickness of the connections need to be normalised to enable comparison across breakout rooms. Since some TAs indicated that they consider individual students as a proxy to understand whether a group should be monitored more closely, this chart can provide a way to identify students who are not involved in the discussions. For example, some students in groups 1, 2, and 4 are completely disengaged from the Zoom breakout discussions (see nodes without edges connecting them to other nodes).

**Q5. In which group have I spent the least time?** This visual component aims to address the TAs' concerns about not being aware of how they have been dividing their time while entering into specific breakout rooms to check the progress of a particular group or to engage in a dialogic feedback. This is presented as a horizontal bar chart, which depicts the amount of time the TAs have spent with each group of students. For instance, the TAs in the example shown in Figure 1 (Q5) spent the least amount of time with group 3, for which the corresponding bar is coloured in orange to draw attention (following a similar design as the bar chart in Q3).

# 6 VALIDATION STUDY

In this section, we illustrate the validation step of the the question-driven design approach (step 5) in the context of an authentic deployment of the designed dashboard interface.

## 6.1 Educational Context and Participants

A fully functional version of the question-driven interface was deployed in an authentic university context as part of a unit of study in Information Technologies Research Methods at Monash University. The tool was used by two TAs in this unit for three consecutive weeks to orchestrate breakout room sessions via Zoom and Google Docs. The validation study was conducted one week after this. Eight participants (four TAs and four students) were involved in the validation study. Among them, two TAs (TA1-2) were part of the teaching team delivering the latest instance of the unit delivery while the other two (TA3-4) participated in the earlier design study (presented in Section 5.2). The rationale for inviting both cohorts is to give an active voice to participants who were engaged in the design of the LA interface as well as to gain a deeper understanding of the new stakeholders' first-hand experience using the LA innovation [31]. The four students (S1-4) were enrolled in the unit, and therefore their data were shown to TAs through the LA interface. The rationale for including students is that their perspectives are usually omitted during the evaluation of LA tools [4], yet researchers have argued that students can contribute valuable insights for the design of learning analytics based on their unique experience as learners [13]. Since TAs could not be omnipresent at all the breakout rooms in Zoom, we asked students' opinions on whether the visualisations sufficiently reflect their individual and group progress.

## 6.2 Validation Protocol

The protocol described in this section should be seen as only an instance of various ways that can be followed to validate a question-driven LA interface with educational stakeholders. The validation consisted of a semi-structured interview with each participant. Before showing any visual interface, participants were encouraged to get familiarised with the learning tasks that students had to complete. A short video of what happened in the breakout room, which the participant was a part of, was shown to each participant. This served as a stimulated recall for participants to consider the learning context while exploring the LA EUI [8]. The rest of the protocol consisted of the following three parts:

*i) Question validation.* In the first part, participants (only TAs) were asked whether each question that appeared on the visual interface was relevant for their practice.

*ii) Validation of the mapping between questions and visual elements.* In the second part, the questions coupled with the visualisations were showed to participants (both to TAs and to students). The purpose of this was to ensure that correct evidence (data) was provided and that the visualisation designs supported the questions.

*iii) Validation of the full interface.* In the third part, the full interface was shown to the participants. The aim was to investigate how close-to-authentic question-driven sense-making would happen if all questions and visualisations were simultaneously presented in the interface.

Evaluation interviews with both TAs and students followed nearly the same procedure with minor differences. Both students and TAs were asked questions from “Validation of visualisations” (item ii) above) and “Validation of full-interface” (item iii) above). The students were asked questions regarding their learning experience and TAs were asked questions regarding their teaching tasks. The full guide is available online (https://bit.ly/lak22_prot_qdla). The interviews conducted with the participants were both audio and video recorded and transcribed for subsequent analysis.

## 6.3 Analysis

Statements of interest were jointly identified by three researchers from the interview transcripts. The interviews with TAs and students were initially thematically coded by one researcher. Resulting codes were grouped according to the three part of the protocol: i) question validation, ii) mapping between questions and visual elements, and iii) validation of the full interface. These were discussed with two other researchers and revised until full agreement was reached. The same coding scheme was applied to all TAs and students. In addition, we counted the number of instances in which participants explicitly used the wording of the questions presented on the LA interface to externalise their sense-making process.

## 6.4 Results

The following subsections are organised according to each of the three different parts of our validation protocol.

*6.4.1 Question validation.* All TAs agreed that the questions were generally relevant to monitoring student discussions in real-time. Yet, some TAs questioned the relevance of questions Q2 and Q5 for certain tasks and situations. These were intended to present information about participation in Google Docs and how the TAs divided their attention across the student breakout groups, respectively. For example, regarding Q2, some participants explained that they did not always have access to student Google Documents and, if this was the case, information about their progress in Google Docs would not be so relevant for the purposes of monitoring. Regarding Q5, a couple of TAs mentioned that they may not have always followed the visualisation that warned them about potentially neglected groups of students, because in some circumstances, the TAs needed to divide their attention unevenly. For example, TA2 explained this as follows: *"I do sometimes feel bad about spending less time in some rooms but, at the same time, I don't think it's an indicator of the quality of feedback I'm giving. Some rooms don't really need you to be there that much. So I ask myself, is this a very relevant question all the time? It really depends on the needs of the rooms"*. The same TA suggested that an alternative question (and related data to show) would be: "Have I spent enough time with rooms *that need help?*".

In contrast, some students used their own first-hand experience in the observed classes to suggest slight changes to the questions being addressed by the interface. For example, S2 explained that an actual problem they faced was not that certain students were less active than others but that they were working individually instead of as a group, because their task instructions included a strong individual component on that specific day: *"It was an individual activity, not a group one, ... we tried to go on an individual hunt for the answers. Discussions were bare minimum."*. Therefore, this student suggested that Q1 could be rephrased as "Are students working individually?" instead of "Are there students inactive in Zoom?" for their TA to notice the situation and intervene if necessary.

*6.4.2 Mapping between questions and visual elements.* In total, 105 instances of participants' reflections on the visual elements were coded. Among those, TAs explicitly used the same words in the questions that appear on top of each visualisation in 62 instances in their process of interpretation as presented in Table 2. For example, when reflecting about the data shown in Q2 visualisation ("How are groups progressing in their Gdocs?"), there were 15 out of 24 instances in which TAs used the question to start their reflection. For instance, TA1 reflected on Q2 as follows: *"Group 2 is behind in terms of* progressing *with the Google Docs."* and TA2 answered Q4 ("How are students interacting in Zoom?") in the following way: *"Group 1 had only three students and there were no* interaction *between any of them."*.

All the participants were able to interpret the visualisations and paid attention to emphasised visual elements in light of the question appearing at the top of each visualisation. Only TA2 mentioned potential mismatches between some questions and their respective visualisation. For example, TA2 explained that the question formulation "How are students interacting in Zoom?" (Q4) can be open to various interpretations that go beyond the actual data being represented through its visualisation (see Q4 in Figure 1): *"The way the question is asked can mean [multiple things]: are they communicating via text? or do they have their cameras on? Do they have their mics open?"*. Another concern was raised by the same TA regarding Q3 ("Are there groups that are not discussing much?"). In this case, TA2 flagged that it would be good to gain a deeper understanding of the rules used to automatically highlight certain elements that contribute to addressing the question. For example, in this case a different colour is applied to flag groups with low levels of discussion (see Figure 1, Q3). This was explained as follows: *"Group 3 is not discussing enough. You've also got a minimum requirement of what you mean by discussing enough? I don't know at what point it becomes blue."*.

For the case of students, S4 flagged that, because some of the learning tasks were ambiguously formulated, they believed that the visual elements signalling groups progression (i.e., Q2 and Q3) could be misleading for their TAs. Similar to TA2, when being presented with the case of Q2 (progress in the Google Doc), S4 also expressed interest in learning more about the rules applied to determine progress status: *"I don't really understand what's the definition of 'complete'. When does this thing turns blue? Because the activities are very vague, [this visualisation] doesn't really represent whether the groups are discussing or not or whether they're finishing the document in a proper way, like, what do you exactly want to see in the document?"*.

Student S4 was also concerned about the relevance of the data that supports Q4 (sociogram depicting students' interactions) in relation to time and group formation strategy. They explained that

| | Q1 | Q2 | Q3 | Q4 | Q5 | *n* total |
|---|---|---|---|---|---|---|
| *n* of reflections using the same words as in the question | 4 | 15 | 12 | 15 | 16 | 62 |
| *n* of reflections using no words from from the question | 6 | 9 | 4 | 24 | 0 | 43 |
| *n* total | 10 | 24 | 16 | 39 | 16 | 105 |

**Table 2: Instances of TAs reflections on the visual elements. TAs used the same words in the questions that appear on top of each visualisation in more than half of all interpretation instances. *n* - a number of instances.**

when a new group was formed, and no one in the group was acquainted with each other, the students would naturally need more time to figure out how to proceed with the task and therefore showing the data at the beginning of the session could be misleading for the TA: *"So we're just confused on what we should do, because we got paired up in new groups. I think that's why we're asking like, okay, what are we going to do and how are we going to do it?"*.

In sum, some concerns raised by the participants might be prevented in future iterations of the tool design by providing additional explanatory legends available on-demand to clarify the match between questions and visual elements. Nevertheless, these mismatches did not impede TAs's understanding of the presented data when the full interface was shown to them.

*6.4.3 Validation of the full interface.* Most participants were able to articulate a narrative about groups' progress by comparing groups based on a single visual component, as illustrated by TA2: *"Group 3 has more discussion time than Group 1"*. Then, their attention would move to other questions and visualisations, often not in a linear manner. The participants would then check other questions/visualisations to ensure that the result of the previous interpretation from a single visual component was still valid after assessing the new information, as demonstrated by TA3: *"Group 2 have completed all three sections and Group 1 have completed two sections [Q2]. Okay. [Q3] shows that the discussion going on in Group 2 is better than in Group 1. Up to now, Group 2 is going in the right direction."*.

The TAs also stressed the importance of data storytelling elements (i.e., highlighted elements) and used them as means to interpret students' data relative to the corresponding question. TAs approached interpretation in two ways, which are *plain decoding of visualisations*, i.e., denoting what each visual element stands for in relation to aspects of students' learning task mentioned in a question) and a *narrated description*, i.e, description of groups' progress, in which participants combine insights, gained from answering multiple questions via the interface. For example, the following quote offers a narrated description that illustrates how TA3 used the visual elements and the questions embedded in the dashboard to make sense of the Zoom session: *"I think Group 3 is in the worst condition.* ***[Q4]*** *is confirming this because* ***only two persons are interacting properly****, so others are not. Also,* ***[Q5]*** *shows that the TAs did not spend time in group 3. That means, there is a problem from the perspective of the TA because certain students get lost and TAs don't pay attention to them.* ***Group 4 got less time too****, but they are doing a good job in comparison to timing, because they are discussing a lot* ***[Q3]****. They were given less time in comparison to Group 2, but still, they are progressing in a better way. Although, if we just think about progressing in Google Docs* ***[Q2]****, we can see Group 2 have progressed a lot. But if we think about timing and everything, it seems Group 4 is doing better."*

While all students and TAs approached data interpretation via the question-driven interface in seemingly similar ways, a few considerable differences occurred. Notably, the students and TAs had contrasting perspectives towards the way the visualisation for Q4 should be displayed. For example, TA2 was strongly against including TAs in the sociograms, i.e., being mapped to a node and being present along with students (Q4 in Figure 1 in Section 5.3). Surprisingly, TA2 was concerned about the feeling of *"being monitored"* despite the fact that they will be the main users. In contrast, two students raised concerns in regards to having students' names in Q4 (Figure 1 in Section 5.3). They explained that this could expose sensitive information and the insights formulated based on inaccurate visual analytics might be prone to bias.

Finally, TA4 noted that their visits to breakout rooms might cause an increase in communication level in a group. This stems from the implicit connection between Q5 and Q3. As explained by TA4: *"...when you enter the breakout room and spend 12 minutes with the group, students are going to be active there as well for 12 minutes. So if this is the first group I'm entering, then that one will be the first one in terms of discussion [time]."*. A TA visiting a group (Q5) usually results in a burst of communication time (Q3). TA4 then noted that it is unclear whether the identified activity is a result of their intervention to a breakout room or represents a genuine level of group communication.

# 7 DISCUSSION, LIMITATIONS AND FUTURE DIRECTIONS

## 7.1 Implications for Design in LA

Gasevic et al. [16] suggested that learning analytics is composed of three mutually connected dimensions — theory, design, and data science. Yet, whilst the community has advanced in connecting data analytics with educational theory, more work is yet to be done to create robust design practices to create effective LA tools [36]. This paper contributes to expanding the design dimension of LA by presenting a specific design approach to connecting authentic questions that educational stakeholders may have, and the design of a learning analytics interface. This explicit connection between authentic questions and visual elements of the interface can enable the development of LA user interfaces that are directly aimed at addressing the needs of teachers and learners. Our approach is theoretically grounded by considering existing works on sensemaking in LA and design innovations in human centred-design. The current literature on sensemaking in LA [9, 44, 46] indicates that interpretation of visual elements and sensemaking of the meaning of such visual according to an specific educational context are crucial processes which should occur when teachers face analytics. Teacher inquiry literature have also suggested that it is important to consider genuine questions teachers may have [32, 33] to create meaningful LA interfaces. However, there have been limited work demonstrating how those questions can be explicitly embedded in the design of LA interfaces. Our approach aims to address this gap and might be applied as a part of the broader design methodologies, for instance, participatory design.

We see a strong connection of our design approach with the incorporation of frames of references [24] and using data storytelling techniques [11, 14] to help educational stakeholders make sense of their data. In our study, TAs used the questions to start their reflection on students' data in more than a half of all coded instances. Among those reflection instances, we observed two types of sense-making: a plain description of what each visual element stands for, and a description entailing insights, gained from answering multiple questions drawing on the associated data stories. The second type of sense-making and the prevalence of question-driven reflections provide evidence for the effectiveness of question-driven dashboards in supporting teachers' sensemaking. This finding is in line with the previous research on teachers reflections [42], which indicates that their quality is characterised by the elaborated and analytical description of students' activity. The design approach we proposed incorporates principles of data storytelling to aid the interpretations of visual elements, explicitly connected to questions to be addressed, so the sensemaking process can be scaffolded by the design of the interface. However, future work is needed to identify principles to improve the elements of the user interface that can aid in the interpretation of data representations and, thus, teachers' sensemaking process of learners' activity.

We also see a strong connection between what our teachers and students mentioned in our illustrative study and the importance of fairness, accountability and transparency (FAT) in the design of learning analytics [19]. In our study, teachers concerns' regarding the lack of transparency of the LA visual interface were highlighted. Particularly, teachers wondered how phrases in the questions might be connected with the algorithm based on which a data storytelling element changes in the corresponding 'end-user' visualisation. This reflects a more widespread concern in the LA field about how to provide teachers and students with some insight into the design decisions of the analytics intended to represent them [1, 39]. This strengthens the need for engaging stakeholders in the design process to ensure transparency of principles upon which learning analytics can operate [10]. Moreover, this supports the growing interest of explainable interfaces that can contribute to bridge the gap between advanced artificial intelligence and analytics techniques and educational end-user [35].

### 7.2 Implications for Teaching and Learning

The sensitivity of students' data exposed to teachers whilst using learning analytics is yet another important concern raised by students during our validation. Yet, in the LA literature, students have reported varying opinions regarding being observed and being identified by their teachers using LA tools [39, 49], contingent on the learning analytics to be used for formative rather than for summative assessment [49]. While some privacy concerns of educational stakeholders (e.g. students) may seem to limit the ability of learning analytics to capture sensitive data (e.g., students' names or physiological signals) [40], the constellations of those constraints inevitably brings a discussion around how different kinds of learning analytics can help teachers to provide support for students in the most effective way without trading off student identity. We see this as one of the key challenges in one of the grand themes in Learning Analytics, namely, the ability of learning analytics to support personalised targeted interventions [17, 39].

Moreover, it has been previously reported that there is a generalised misalignment between the learning design and the learning analytics deployed in several education scenarios [26]. Yet, it has also been suggested that when both are aligned the use of such analytics can be more effective [32]. This misalignment issue also emerged in our study. One student questioned the relevance of a question, and respective visualisation, that was concerning the levels of interaction as a group for a task that emphasised individual activity. This emphasises the importance of developing LA solutions that can be adapted to support various learning designs [14]. But this also raises the question about how the EUIs can be configured by the end-users without becoming yet another tool that requires constant support and expertise to be used. A learning design-driven storytelling approach [27] is particularly plausible for addressing this call, but in this work, designers still had to configure the LA interface for teachers to be fully adapted to the learning designs. While creating LA that can provide flexible functionality for teachers to configure them may be ideal, the cost of increased complexity requires further investigation.

### 7.3 Limitations and Future Work

Our illustrative design case already emphasised authentic design challenges. For example, not every question identified can be fully reflected in the LA design. In our case, two questions were not considered in the final dashboard. Q6 (what do I know about students' previous learning?) was not mapped to any visual component because the Zoom system assigns different personal identifiers to students in each newly created breakout room, which makes it challenging to integrate student historic data. This also highlights one of the trade-offs identified during the validation, namely, that additional support for teachers should not come at the expenditure of students' privacy. For Q7 (who is asking for help?), additional work is needed to add functionalities to the communication tool, which can be impossible for the case of closed source tools such as Zoom. Moreover, future work can be done in connecting sessions to capture student behaviours across time. The current LA solution that we proposed is limited to monitoring activities during one session. However, considering behaviours across sessions it would be important to identify potential issues some students may be facing or to model collaborative interactions of groups who may have several online synchronous meetings as a part of a project.

The approach suggested in this paper is illustrated through the example of monitoring synchronous group activities. Although the approach is used to support teachers orchestrating multiple students groups in online classes, it is yet to be validated the extent to which it is applicable for other situations teachers commonly engage in (e.g., formation of students groups). The graduate course in the context of which the approach was illustrated, puts the full load of decision-making on teacher when they engage in formation of students groups for learning activities, with little support of learning analytics. Further studies may explore how such teaching task can be supported with question-driven analytics.

# 8 CONCLUSION

This paper addresses the call for human-centred design practices to create LA interfaces in close collaboration with educational stakeholders. We have proposed a question-driven LA design approach to ensure that end-user LA interfaces *explicitly* address teachers' questions. The approach proposed in the paper was illustrated through a longitudinal study in two parts, namely, design and validation. The first study entails an authentic design case of synchronous online group activities in which teachers, in pairs, needed to orchestrate group tasks using Zoom and Google Docs. This case may be representative of online classes that are currently relying on the use of similar online tools to conduct small group activities, specially during the COVID-19 pandemic. The second study resulted in a functional version of the question-driven interface design being deployed and validated in an authentic university context. The tool was used by two TAs for three consecutive weeks to orchestrate breakout room sessions. A follow up validation of the question-driven LA interface was conducted with eight participants (four TAs and four students, to not only consider the end-user but also the educational stakeholder whose data is under scrutiny). During the validation of the question-driven LA interface, TAs were able to reflect on student groups' progress and relied on data storytelling elements when answering the corresponding questions. This demonstrates the viability of the question-driven learning analytics interface in helping teachers make sense of students progress in learning tasks.

# ACKNOWLEDGMENTS

Roberto Martinez-Maldonado's research is partly funded by Jacobs Foundation.

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