DAFFI 2020: Designing Automated Feedback for Impact (8-9 Sept. 2020)

Automated Feedback on Collocated Teamwork & Classroom Proxemics

Concepts and co-design methods to bring teachers and students into the feedback design process

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introduction

+ Multimodal analytics mean automated feedback can (in principle) now address *embodied* learning
– But sensors generate very complex data (voice; location/movement; use of physical artifacts; posture; etc…)

How do we move from a mere explosion in data (easy)
to visualisation for researchers (relatively easy)
to designing feedback with impact? (harder)

introduction

Learning contexts

2 learning contexts for this work, and 2 questions to open the discussion:

Can learners make sense of feedback?

How do we know if feedback had an effect?

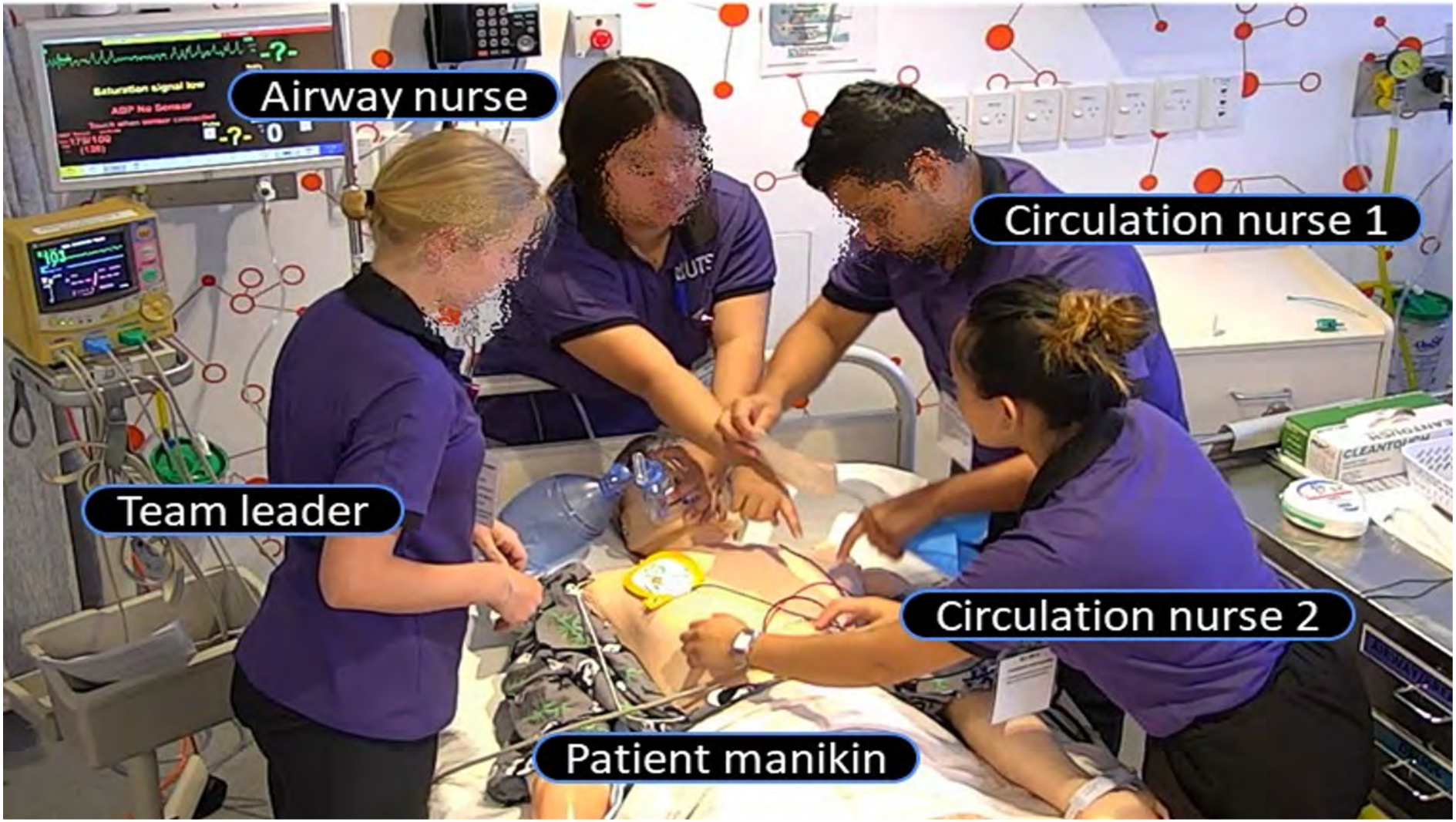
students and teachers commonly are non-data experts

even STEM undergrads find it hard to interpret charts and data visualisations…

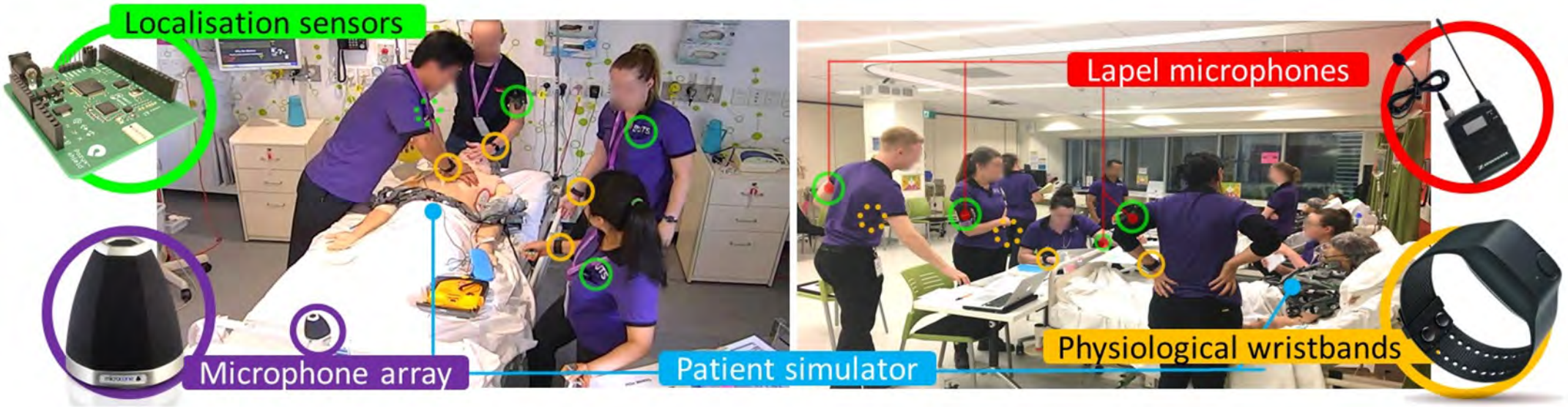
Maltese et al., (2015). Data visualization literacy: Investigating data interpretation along the novice—expert continuum. *Journal of College Science Teaching,* 45(1).

Context 1:
Nursing Simulations

What is going on in the Classrooms?



multimodal learning analytics **vision**



Approaches

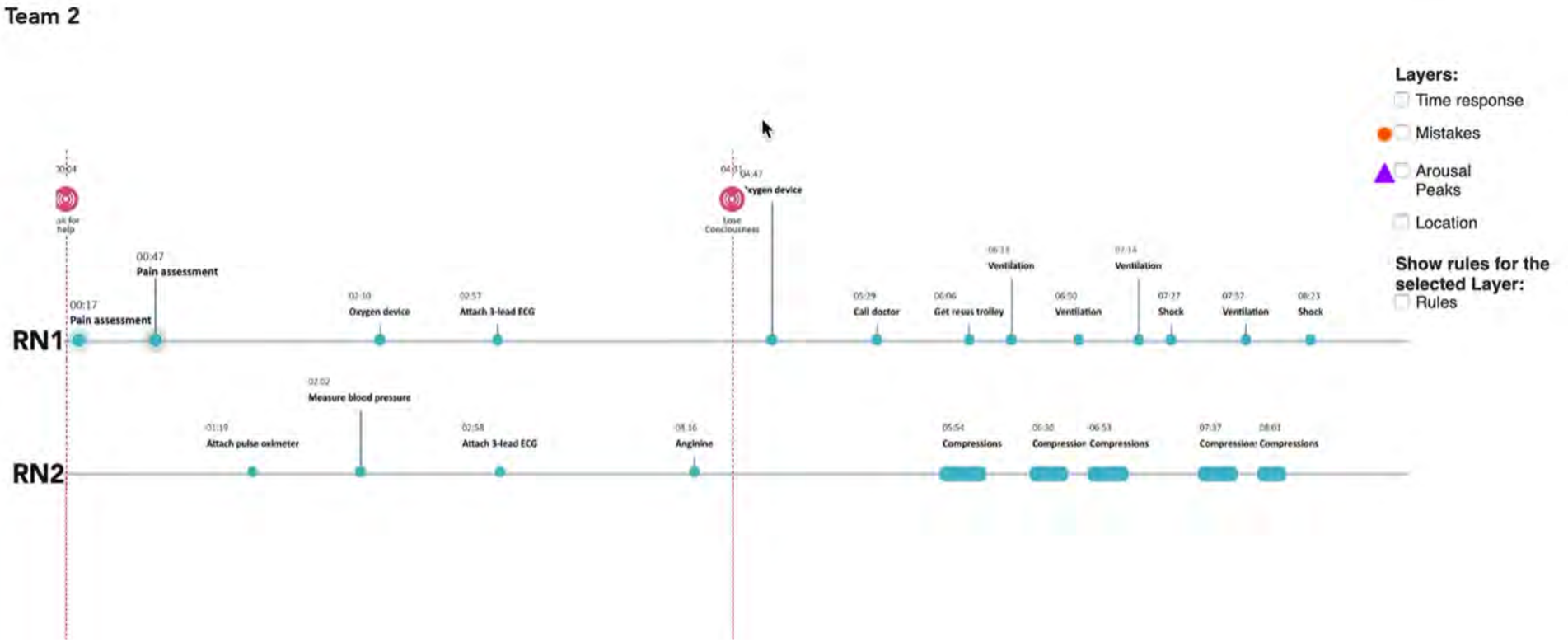
A **Layered Storytelling** Approach for Multimodal Learning Analytics



Roberto Martinez-Maldonado, Vanessa Echeverria, Gloria Fernandez Nieto, and Simon Buckingham Shum. 2020. From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (CHI '20).*

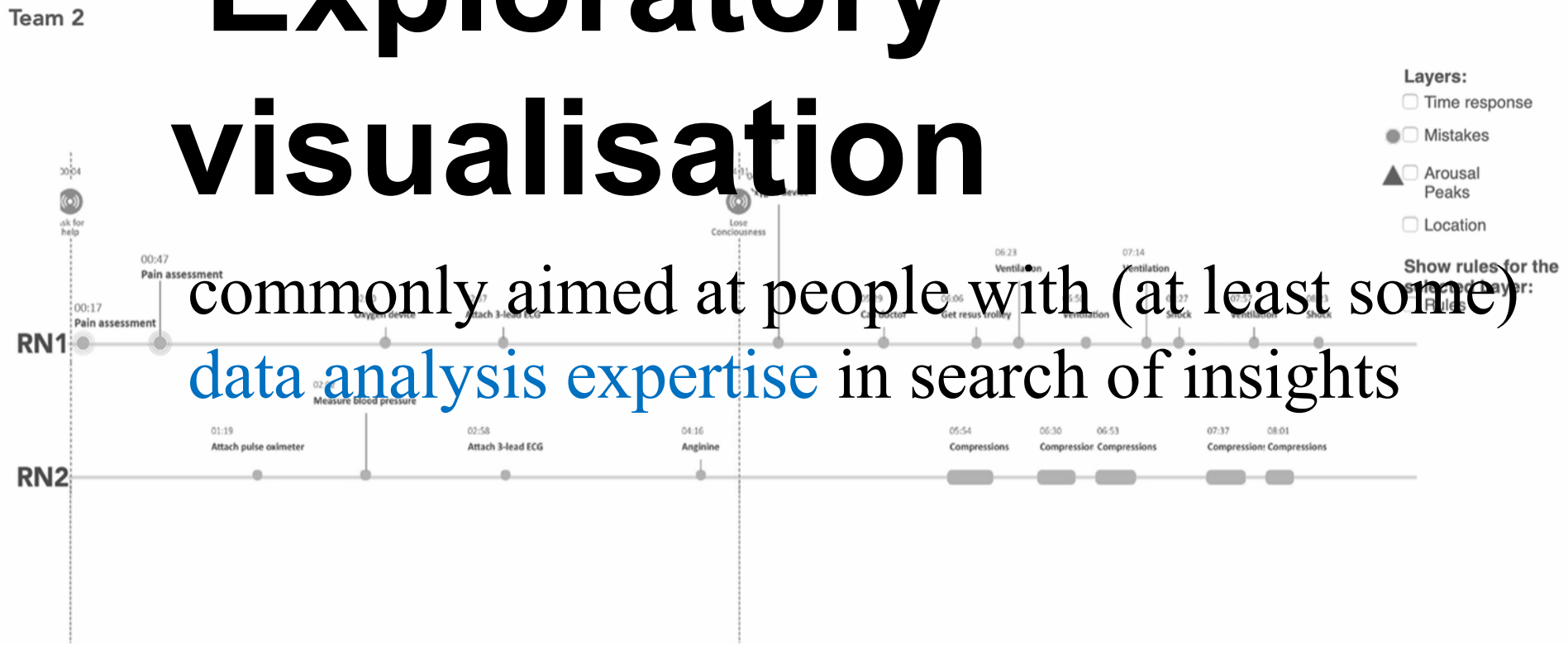
Source: waze. https://www.waze.com/es/livemap

multimodal **storytelling**



Team timeline prototype was co-designed with teachers

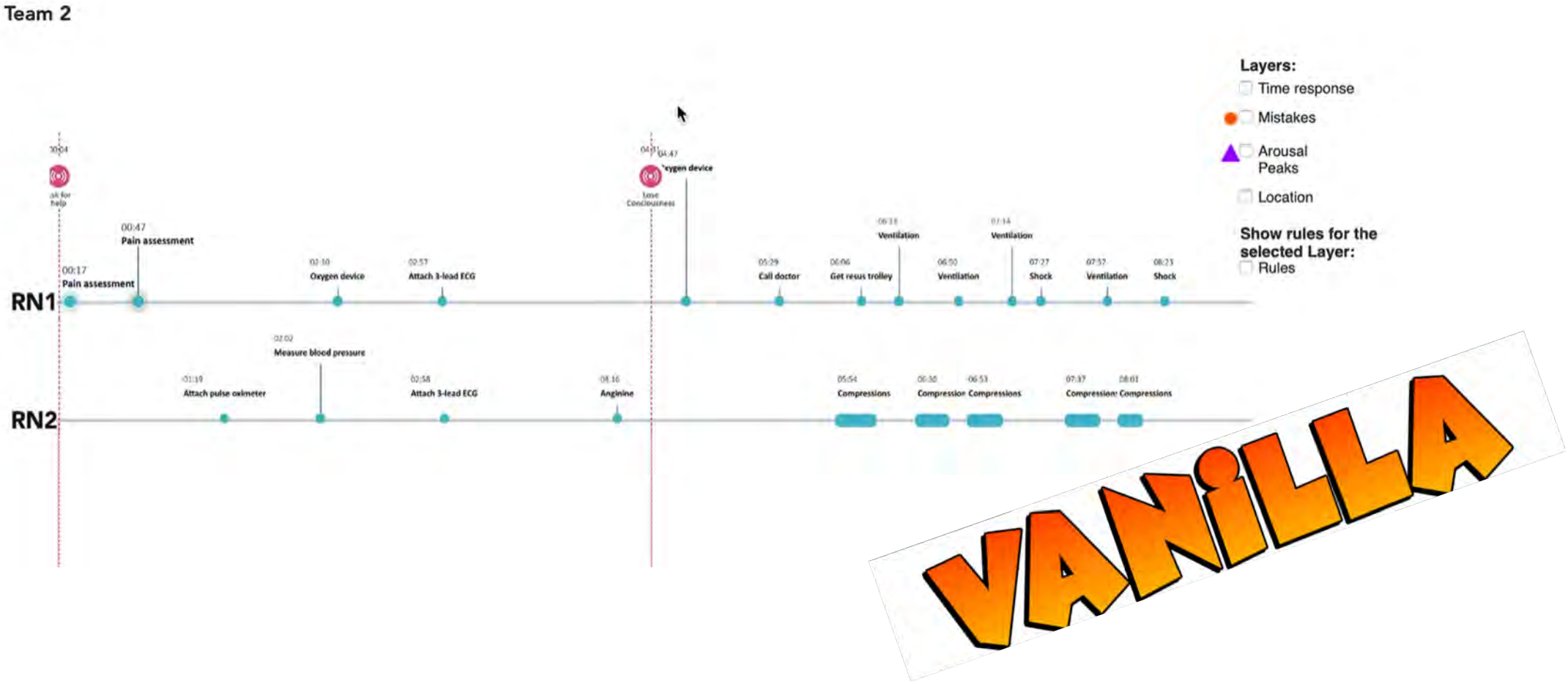
Exploratory visualisation



commonly aimed at people with (at least some) data analysis expertise in search of insights

Young and Wessnitzer. 2016. Descriptive statistics, graphs, and visualisation. In *Modern statistical methods for HCI*, Kaptein M Robertson J. (Ed.)

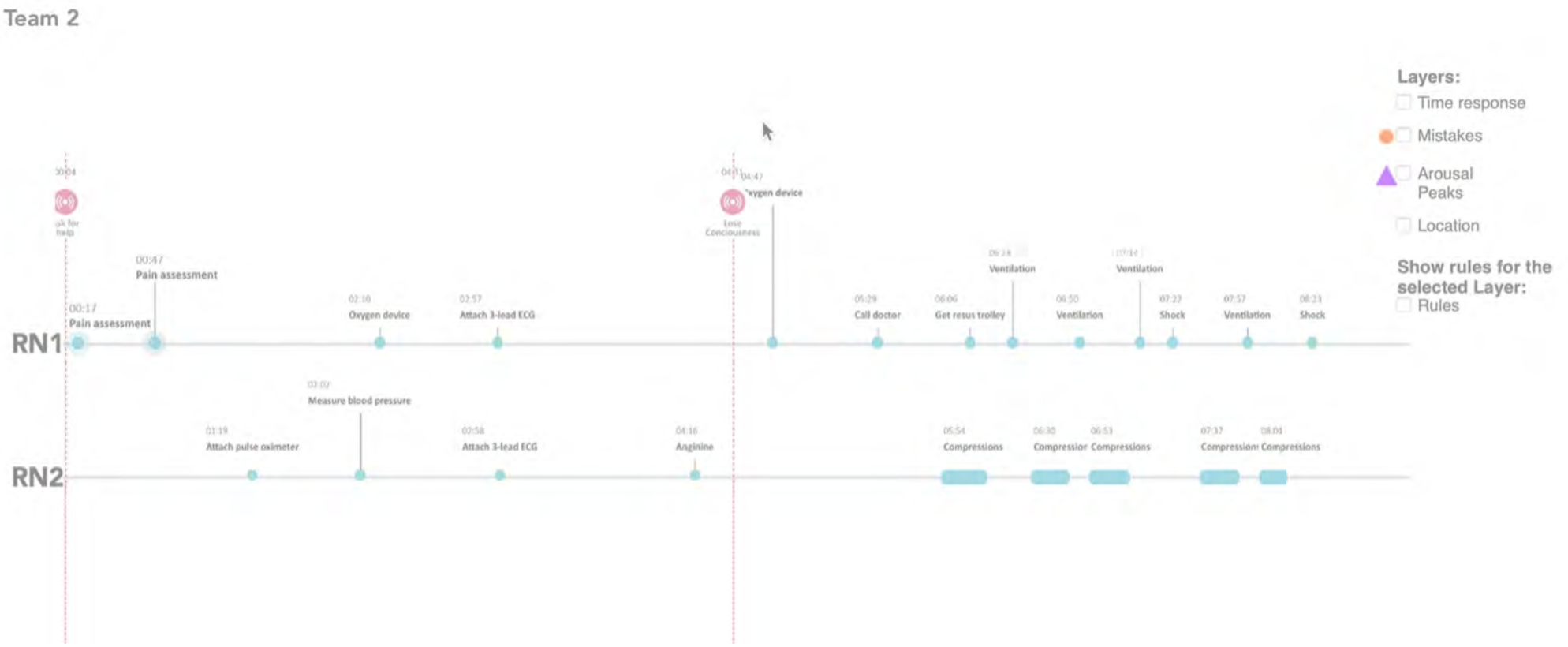
multimodal **storytelling**



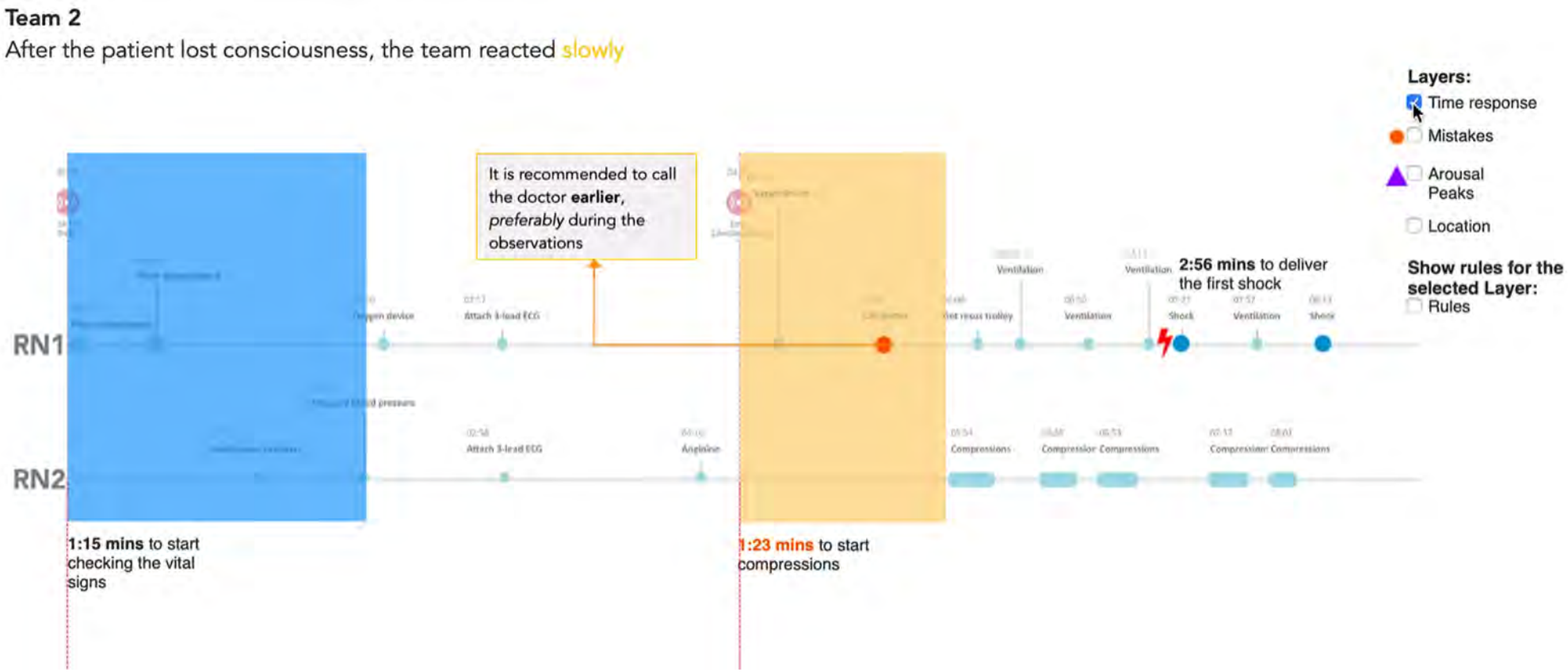
Layered prototype 1

Put to the test with **teachers**

vanilla **timeline**



telling **one story at a time**



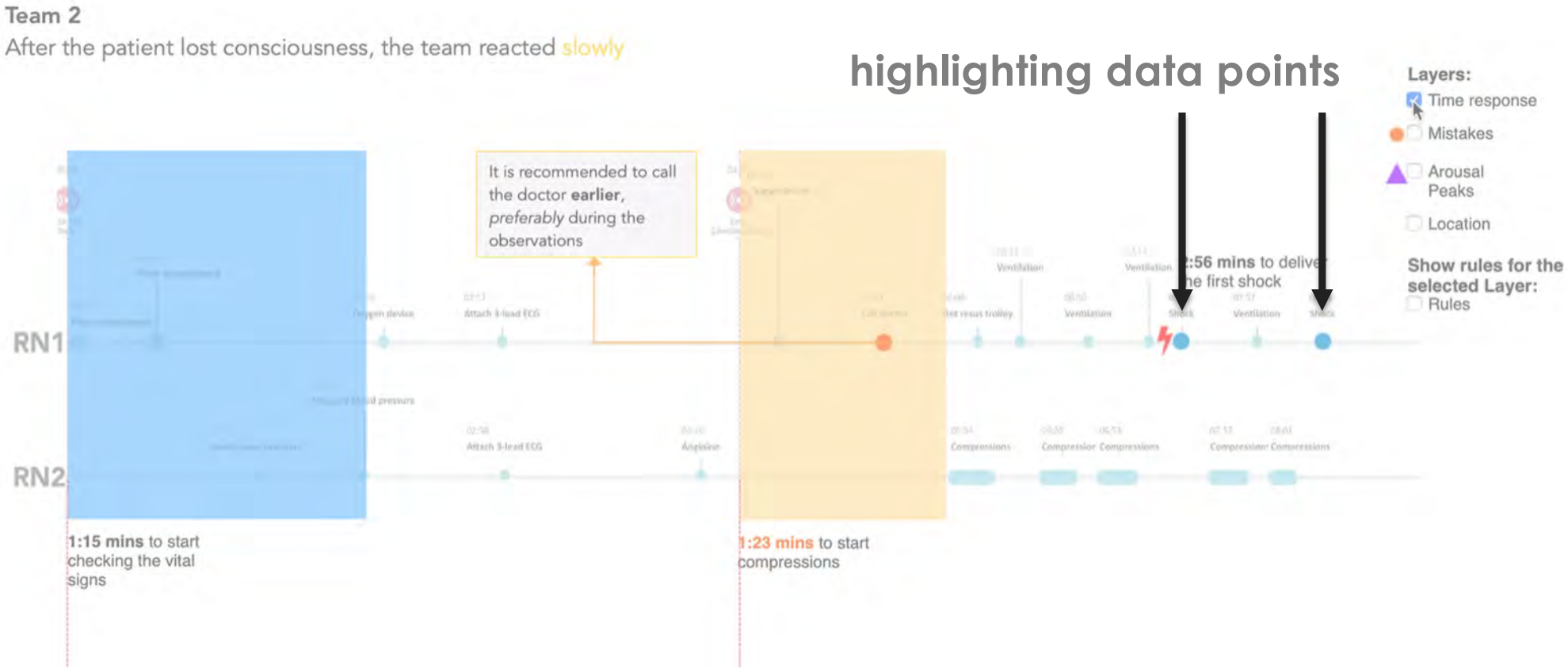
Learning modelling



Data source	Learning intention	Rule pseudocode
Rules used to generate layers in Prototype 1 shown in Figure 4 (left)		
Manikin's logs	The compression depth should be between 5 and 6 cm	if compression_depth < 5: add_annotation("Compressions were shallow. CPR ..") highlight_keyword("shallow", "orange")
Positioning data **Human logs**	A nurse should be located at the top of the bed during CPR	if location_RN != *behind the bed* between(CPR_start_stop): add_annotation(airway) highlight_keyword("behind the bed", "orange")
Physiological data	Nurses should show any arousal state during the activity.	if arousal_peaks(RN) = 0: add_title("RN# did not show any arousal peak") highlight_keyword("arousal peaks", "purple")

telling **one story at a time**

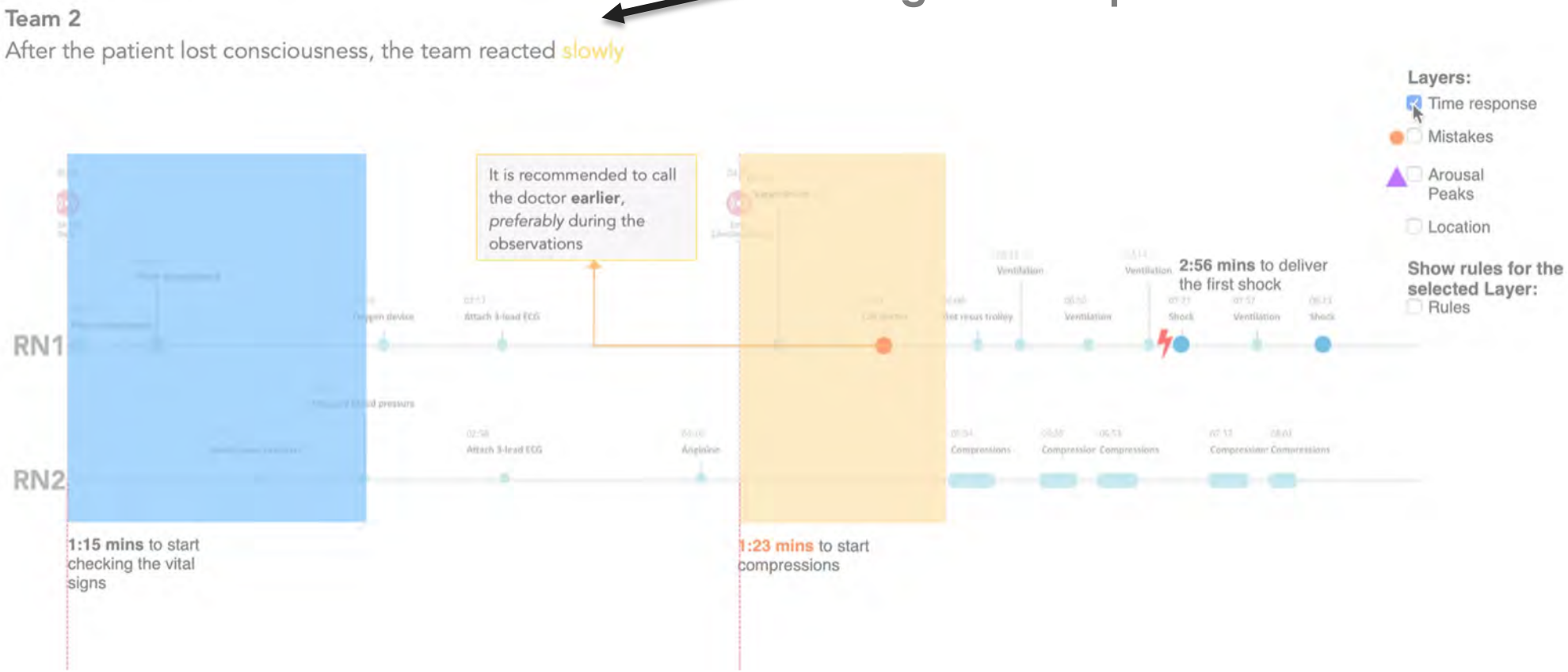
DS
Storytelling principles



telling **one story at a time**

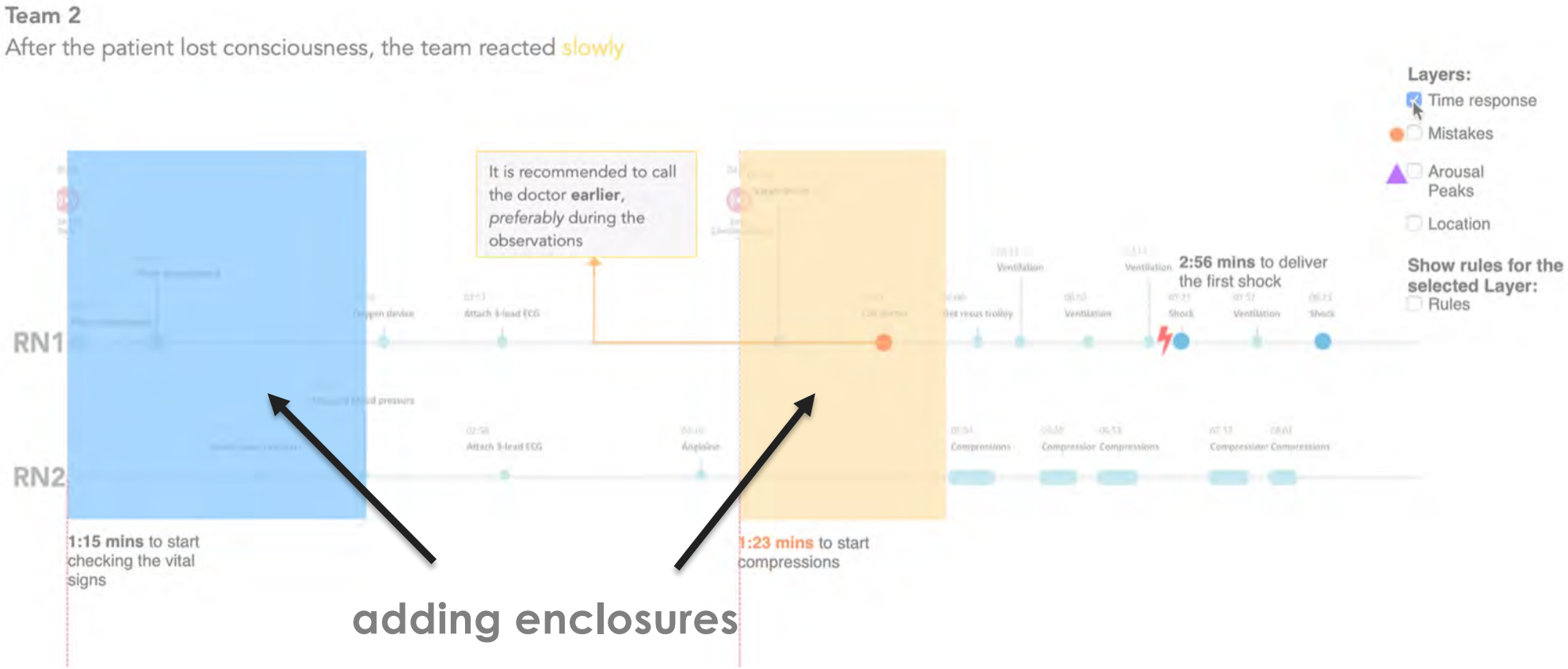
DS
Storytelling principles

adding a descriptive title



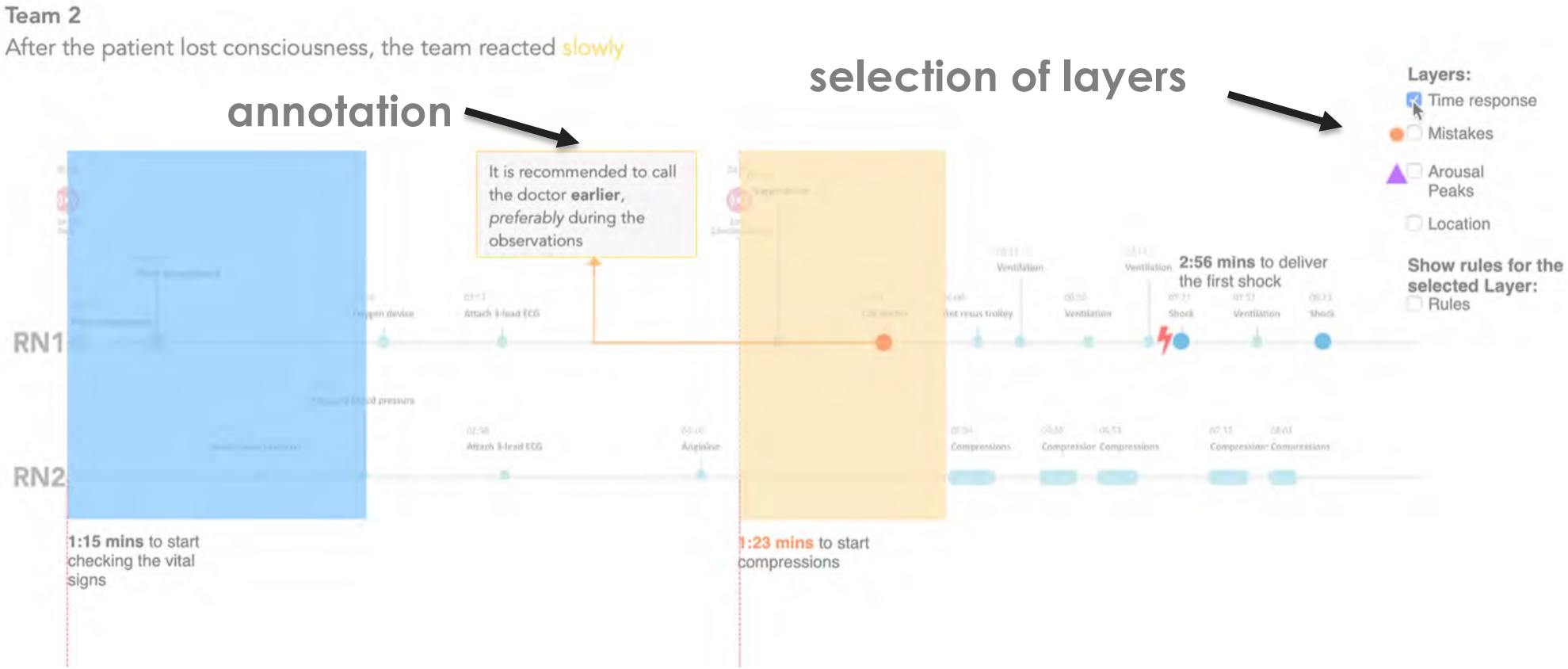
telling **one story at a time**

DS
Storytelling principles



telling **one story at a time**

DS
Storytelling principles

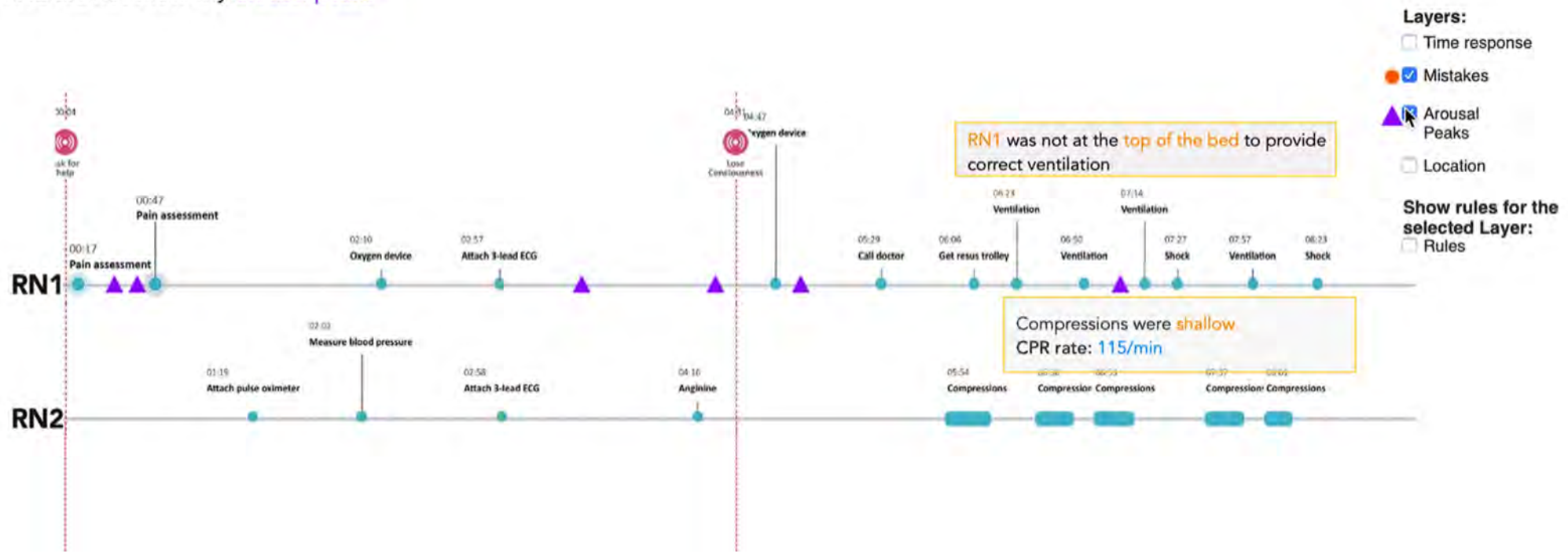


Arousal and errors layer

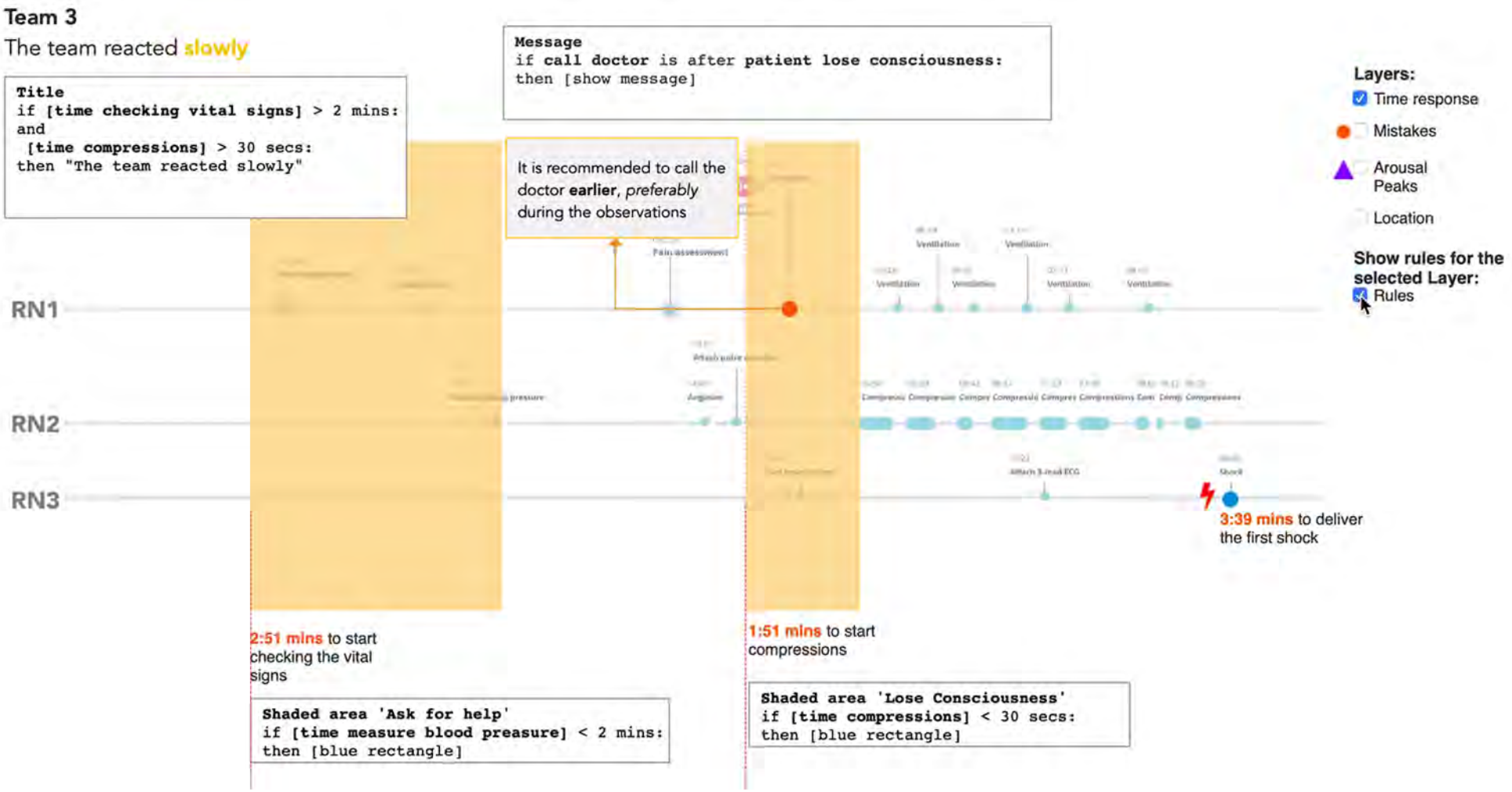


Team 2

RN2 did not show any arousal peaks



opening the black box



Validation with teachers and students regarding

- added value of the layers
- anticipated classroom use
- accountability
- algorithmic transparency.

Martinez-Maldonado, Echeverria, Elliott, Axisa, Power and Buckingham Shum. 2019. Designing translucent learning analytics with teachers: an elicitation process. *Interactive Learning Environments*

Results added value of the layers

Teachers

*"[the layers are] absolutely more valuable, because **each tells a story behind the sim**"*



[Augmented feedback]
*"It's good for students to know that compressions needed to be deeper as shown here If I was there, **I could've only guessed that they were not deep enough"***

Results added value of the layers

Students



"*[data stories] highlight what you didn't do [right]*" (T8, S4); and "*[the data stories] show both what we did and what we were meant to do*" (T8, S4).

"*It's not just that we were late but we were late by that much time, so we can precisely see what we have to improve, and what we have done well. [The data stories] make a big difference*" (T1, S2).

Results in-classroom orchestration opportunities

Teachers

“I can tell students: this is what you did well, this is what you did poorly. This is what you can improve, you can do X, Y and Z”



[Feedback based on evidence]
*“I could make **bolder statements that cannot [easily] be disputed**”*

Results in-classroom orchestration opportunities

Students

"*[the data stories] help us to reflect on practical ways to improve and work as a team*" (T3, S5).



"[the data stories] highlighted areas where I need to strengthen my clinical thinking" (T2, S4)

"*The timeline helps the group to recall what we did because sometimes we may forget about the details or the sequences of our own actions*" (T7, S3).

Results accountability

Teachers

“I would only talk about this with the students of my class.”

“students may feel a bit uncomfortable”

“students could focus on comparing their performance with other teams”

Students

Ok to share if it helps in their learning”

“as long as it doesn’t include [their] names”

Results algorithmic transparency and manipulability

Students

“I would like to keep [the parameters] like that”.

*“**teachers would be in a better position** to understand the parameters”*



The potential of the layered storytelling approach

__Reducing complexity__ of analytics interfaces
Deeper reflection based on __objective evidence__
Reviewing __instructional design__
Creating __context specific analytics__

Risk of __bias__
Risk of __false negatives__
Potential and risk of __summative assessment__
Algorithmic transparency
Data ownership, sharing and de-identification

Context 2:
Physics Labs

The learning context

Physics laboratory classroom taught by two teachers while wearing indoor positioning sensors contained in a badge

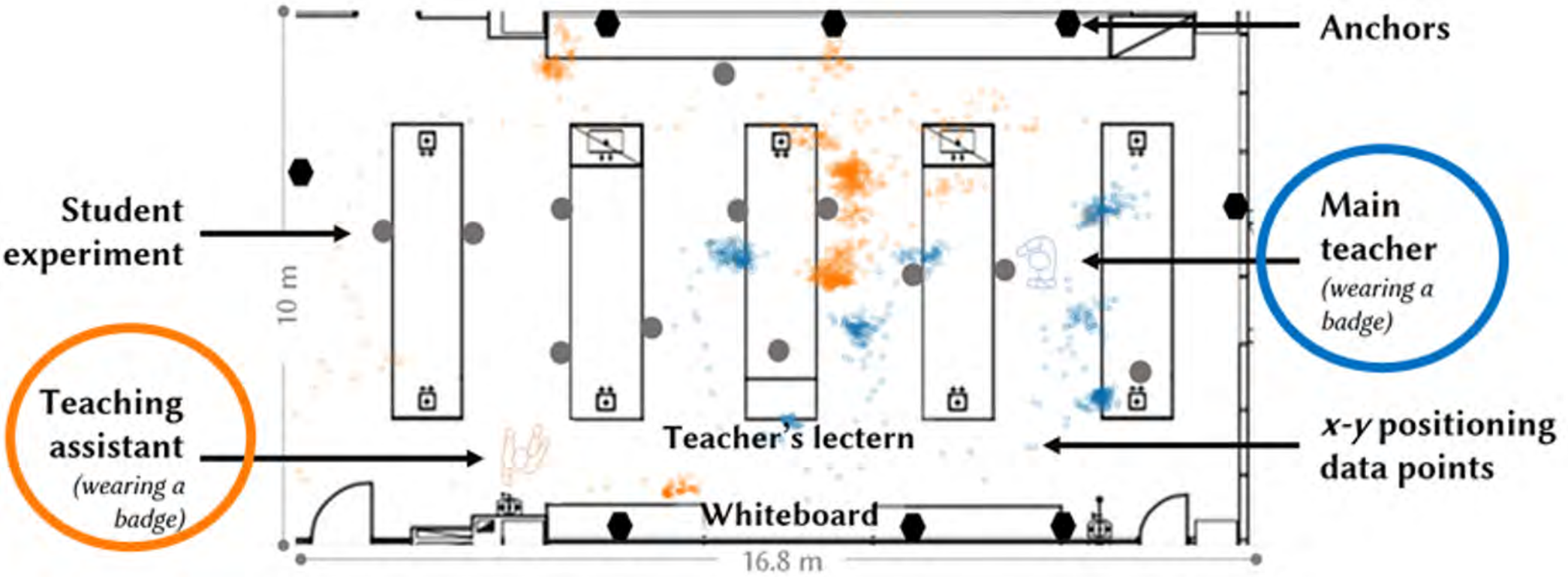


Setup

Positioning data

2Hz avg sampling rate (error rate of ~10 cm)

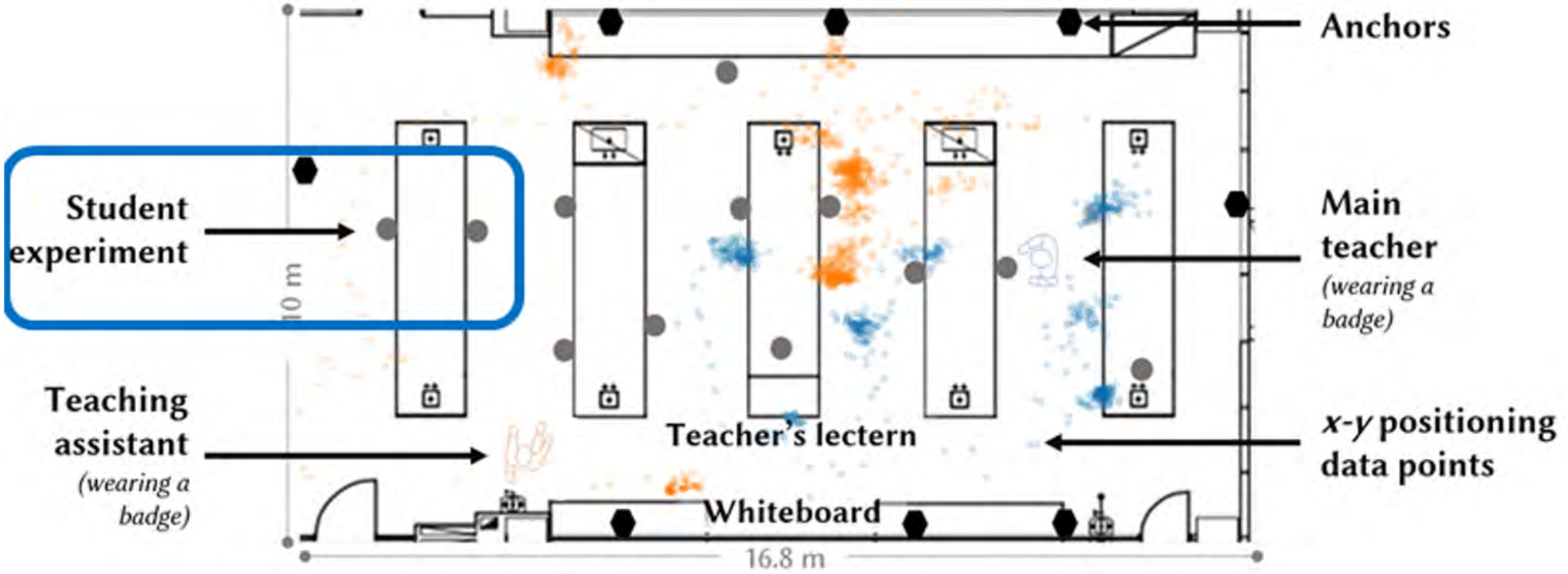
835,033 datapoints



Setup

Student positions

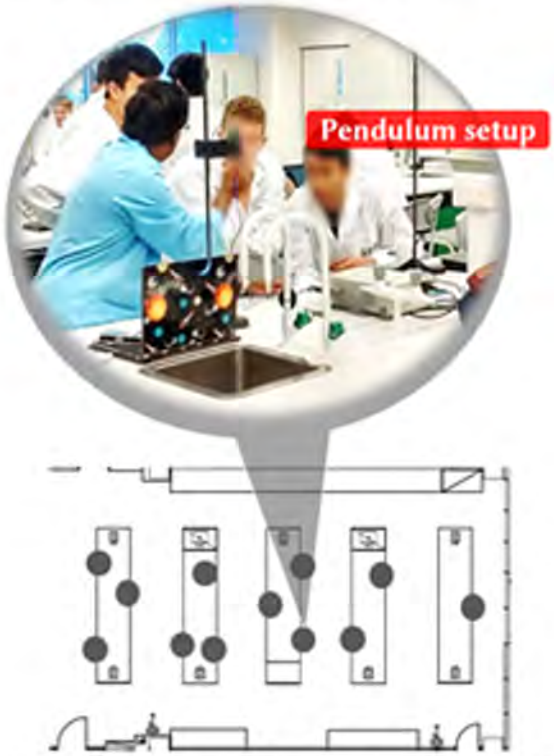
Manually captured based on experiment positions



Three learning designs (6 x 3 authentic classes)

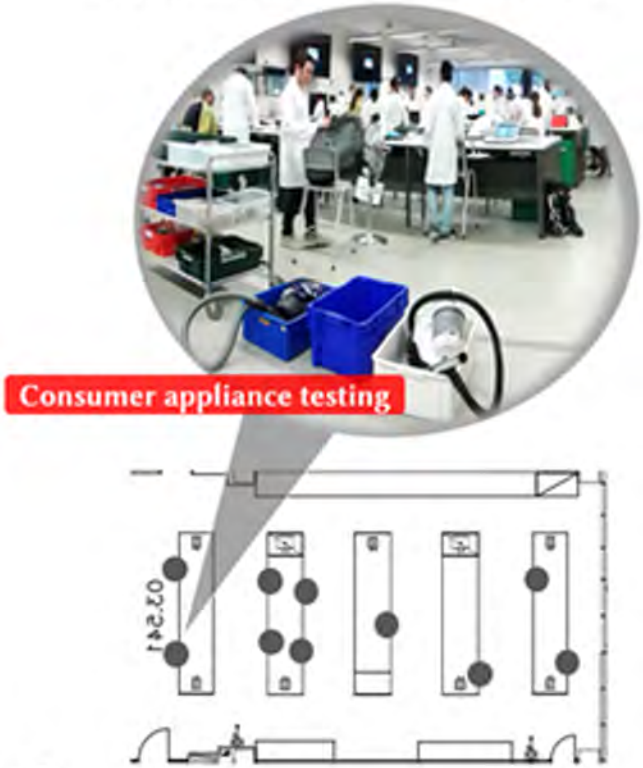
LD1: Prescribed.Lab

Each team doing the same experiment



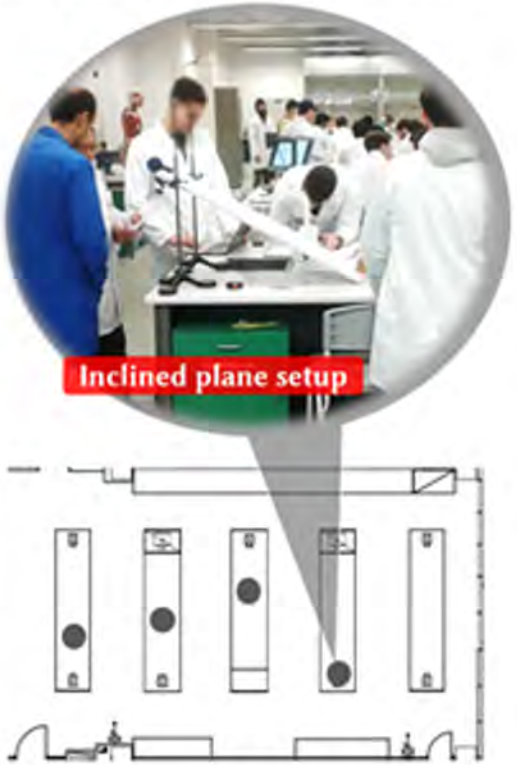
LD2: Project.Lab

Each team works with a different project



LD3: Theory.Lab

Teams rotating around four experiments

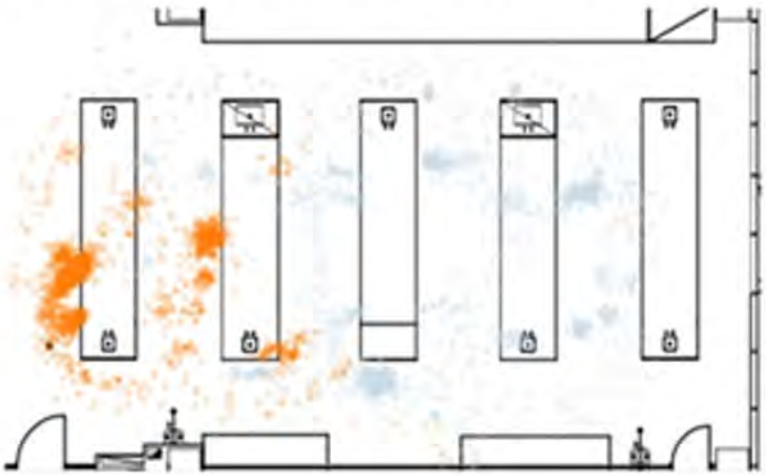


Locations of students' experiments marked as: ●

Characterising teaching strategies

T6 - Highly focused assistant

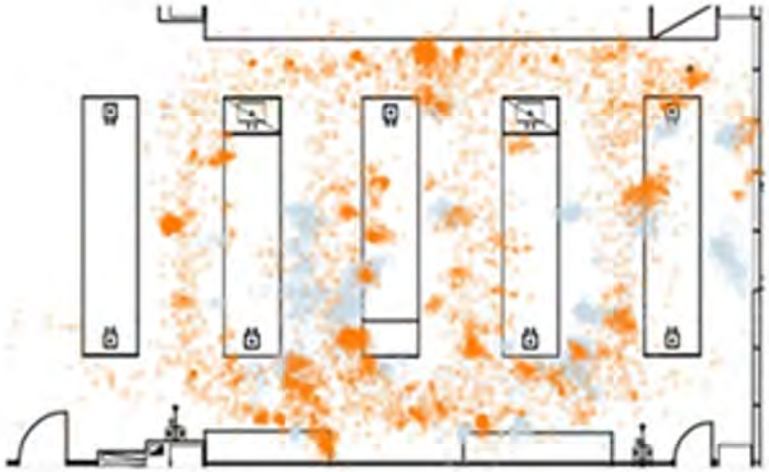
(within students' inter-personal zones)



≠

T5 - Highly un-focused assistant

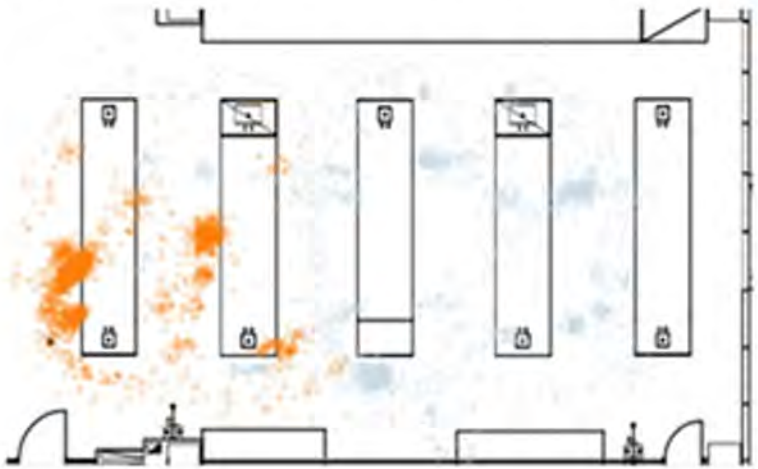
(constantly walking-supervising)



Insight: T6 evidently moved less than T5

T6 - Highly focused assistant

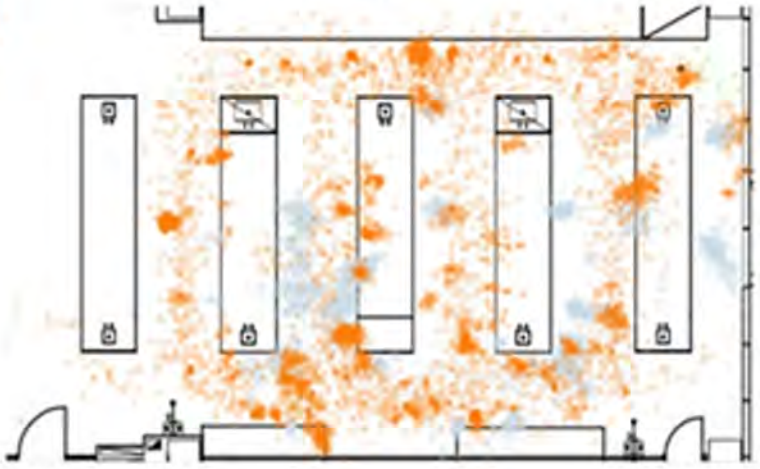
(within students' inter-personal zones)



25 *Stops* **46**

T5 - Highly un-focused assistant

(constantly walking-supervising)

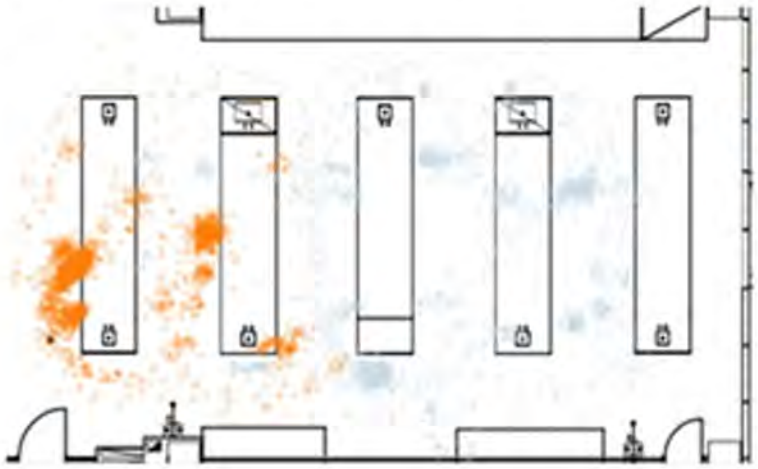


Characterising teaching strategies

Insight: T6 and the main teacher in his class tended to divide the classroom among themselves.

T6 - Highly focused assistant

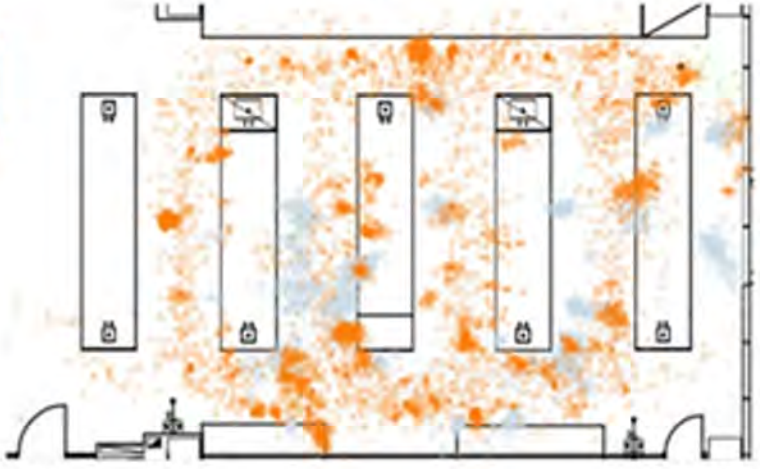
(within students' inter-personal zones)



25	*Stops*	46
3	*Instances of co-teaching*	10

T5 - Highly un-focused assistant

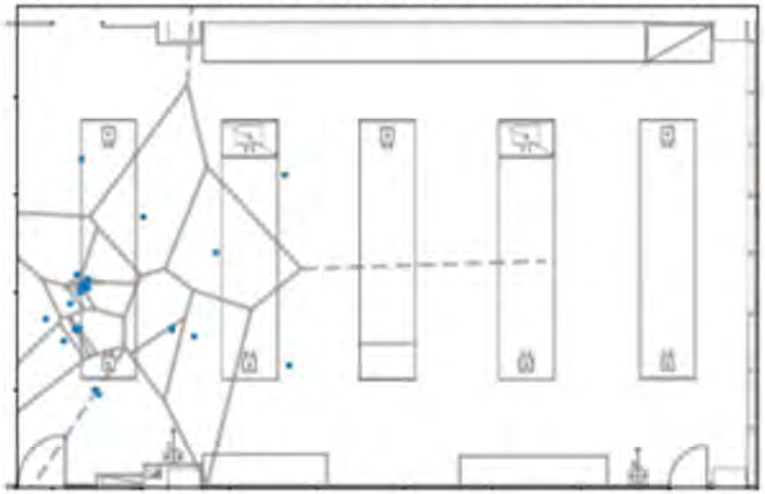
(constantly walking-supervising)



Modelling spatial entropy

T6 - Highly focused assistant

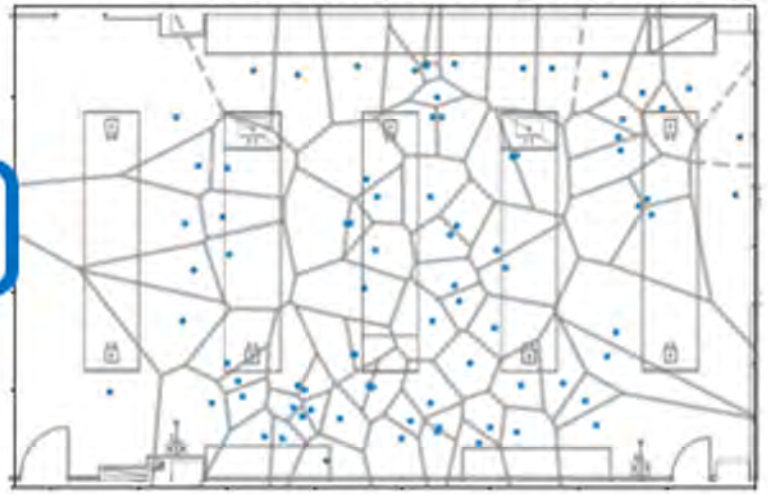
(within students' inter-personal zones)



25	*Stops*	**46**
3	*Instances of co-teaching*	**10**
3.2 (focused)	*Entropy* (bits)	**6.2** (unfocused)

T5 - Highly un-focused assistant

(constantly walking-supervising)



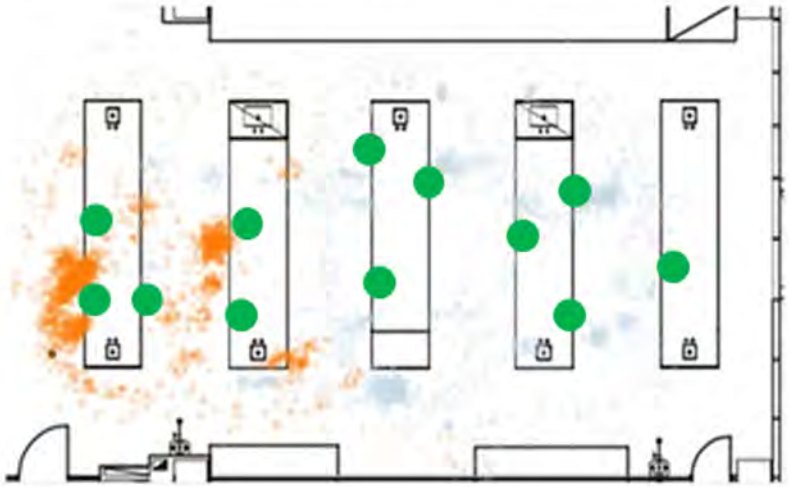
teams of students (marked as: ●)

Insight: T6 attended a smaller set of teams for a longer time.

Student-teacher attention time was higher and focused.

T6 - Highly focused assistant

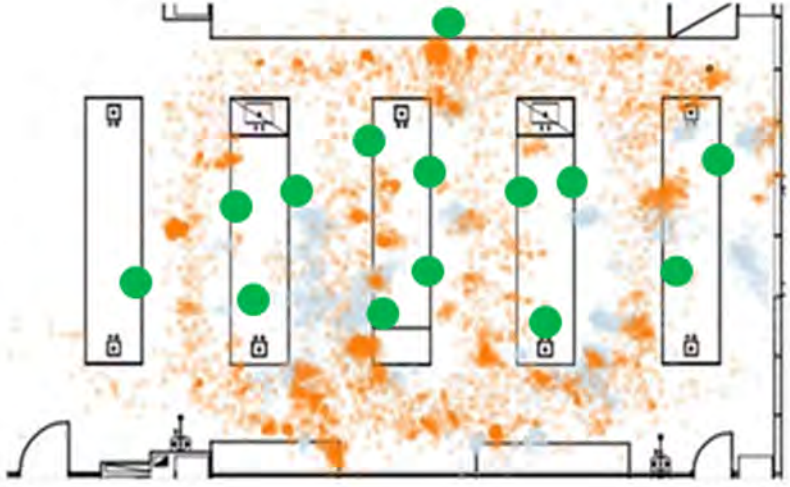
(within students' inter-personal zones)



25	*Stops*	**46**
3	*Instances of co-teaching*	**10**
3.2 (focused)	*Entropy* (bits)	**6.2** (unfocused)
0.83 (unbalanced)	*Gini*	**0.14** (egalitarian)
40	*Attention to students (min)*	**25**

T5 - Highly un-focused assistant

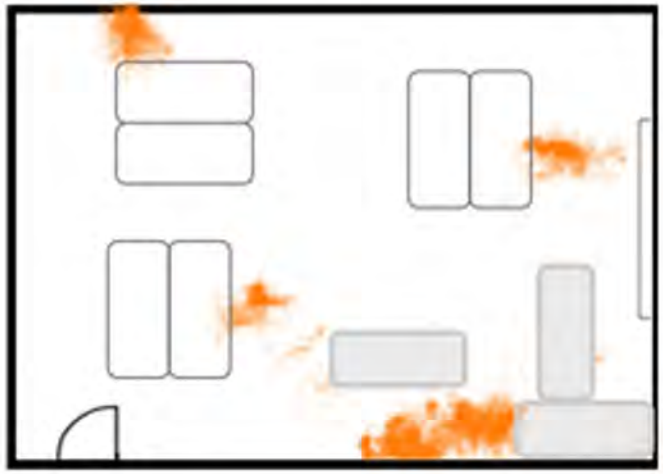
(constantly walking-supervising)



LAK'19

Pilot study: a design HE classroom

Heatmaps



A live teacher's dashboard



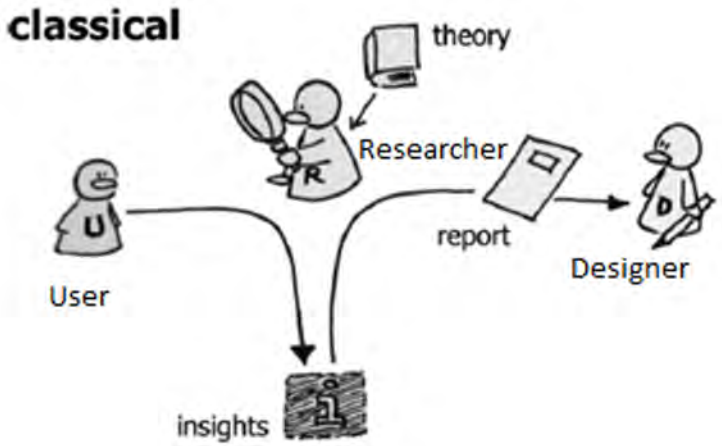
discussion (1/4)

A **key part of the analytics infrastructure is to map from low level data to language that is meaningful to educators and students**



discussion (2/4)

User-centred design



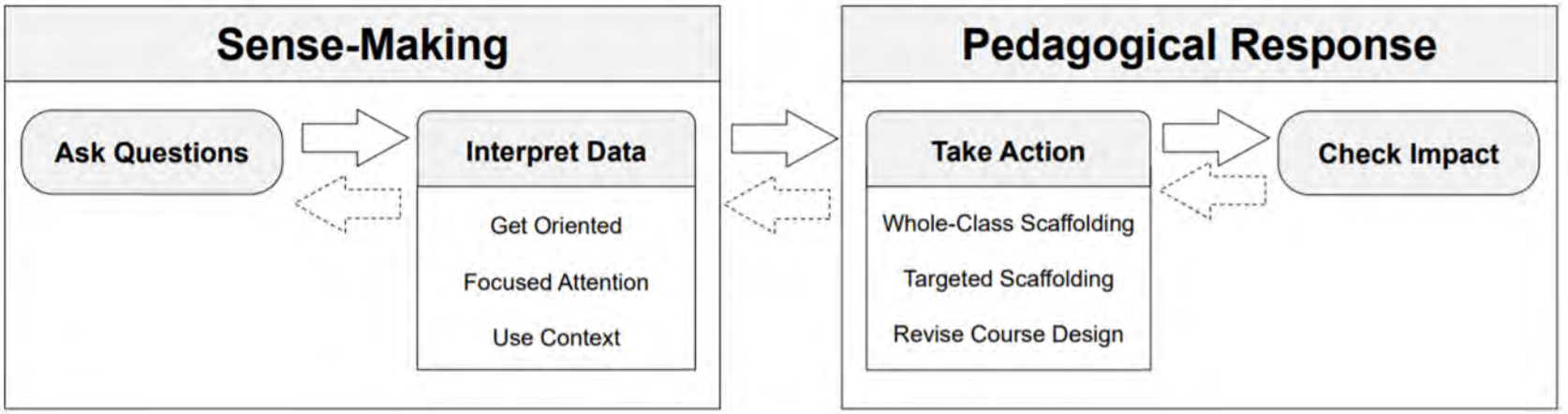
Co-creation (co-design)



Sanders, E. B. N., & Stappers, P. J. (2008). Co-creation and the new landscapes of design. *Co-design*, *4*(1), 5-18.

discussion (3/4)

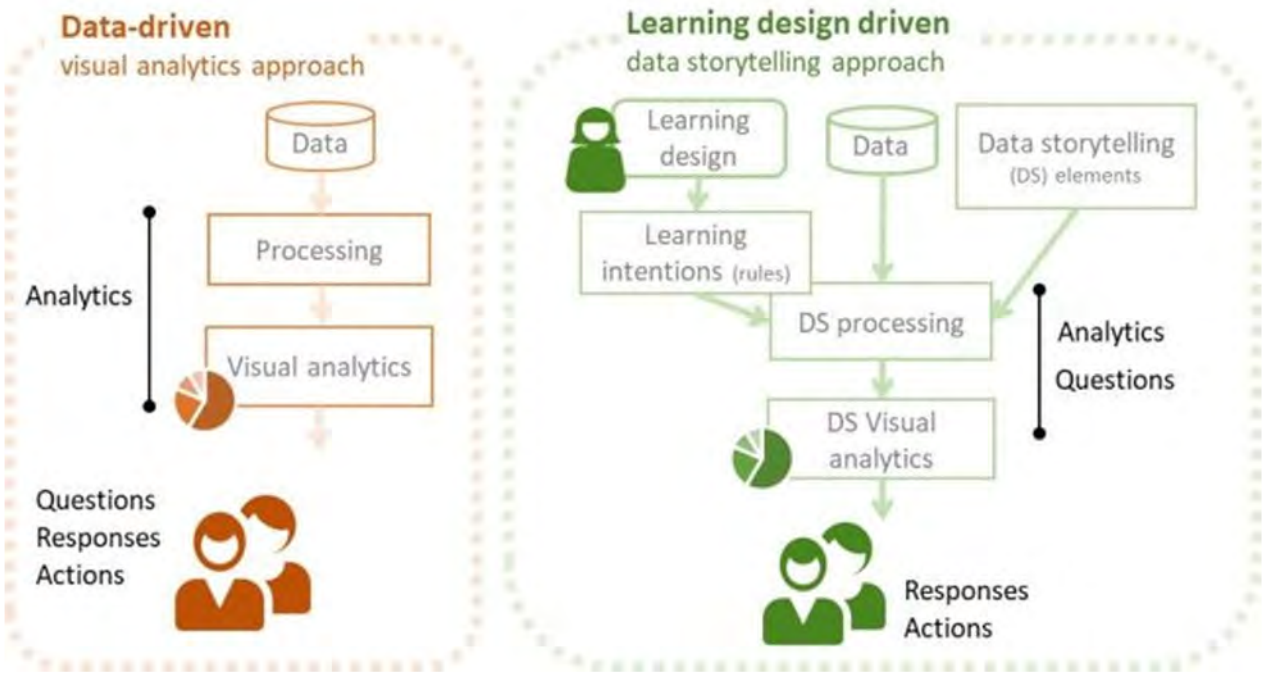
methodologies to measure the impact of visualisations/analytics



Wise, A. F., & Jung, Y. (2019). Teaching with analytics: Towards a situated model of instructional decision-making. *Journal of Learning Analytics*, *6*(2), 53-69.

discussion (4/4)

data storytelling (paradigm)



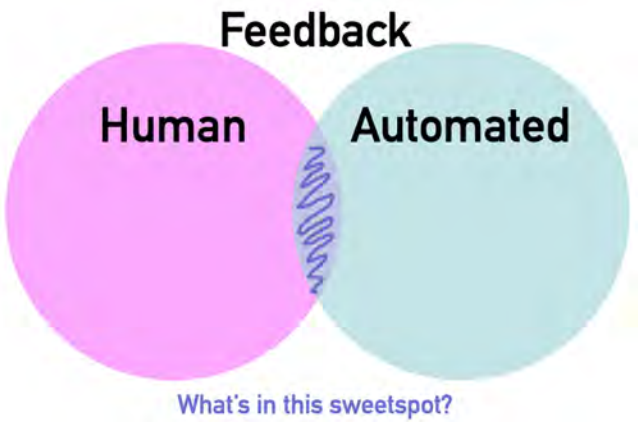
Summary

Learning contexts

2 learning contexts for this work, illuminating 2 questions:

Can learners make sense of feedback?

How do we know if feedback had an effect?



Contributions to the sweetspot from Human-Centred Learning Analytics

HCI: Participatory Design & UI Evaluation methodologies

Information Visualisation: Guidance & Data Storytelling

Theory-informed Learning Analytics: modelling "from clicks to constructs"

Open microphone

