MONASH University

Human-Centred Learning Analytics and AI in Education

Reimagining Reflection in Education

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COLAM
Centre for Learning Analytics Monash

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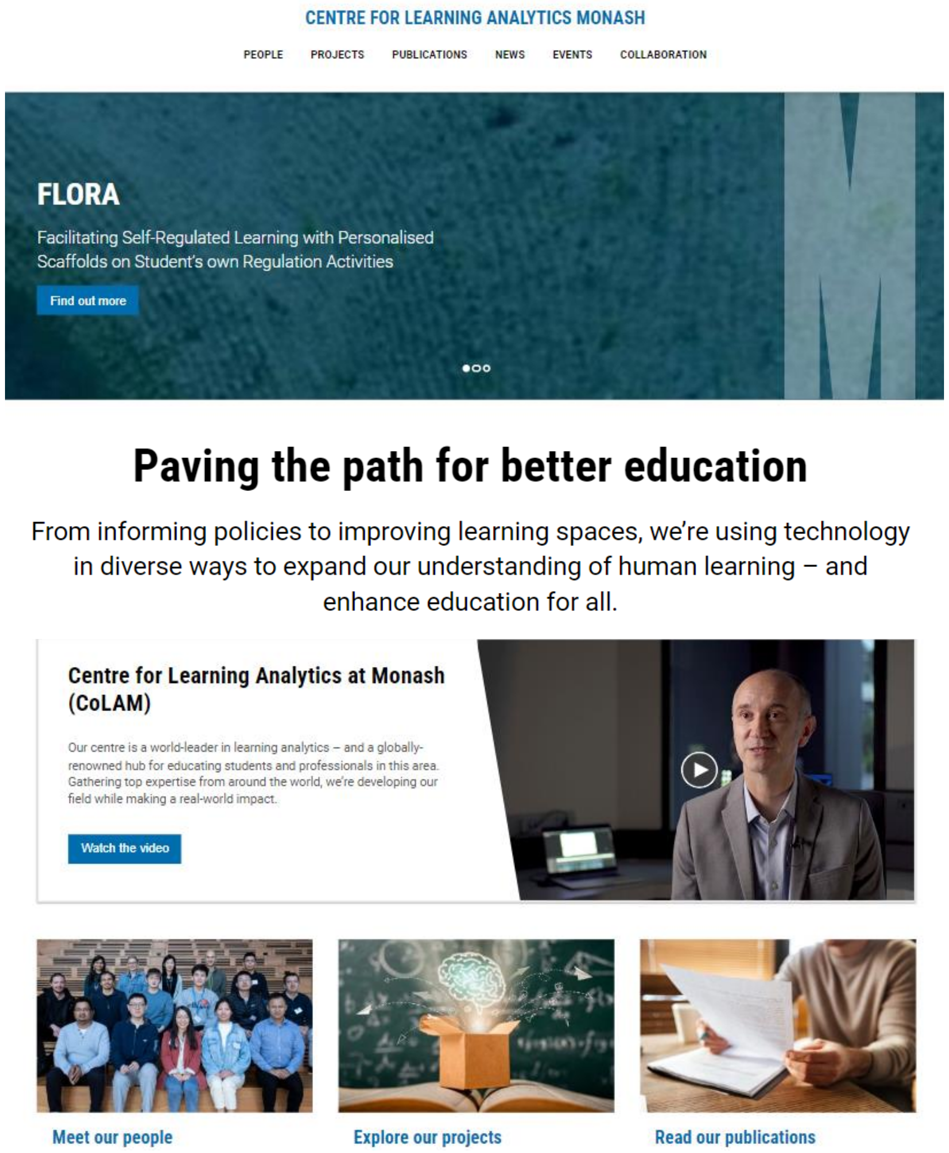


CoLAM Members

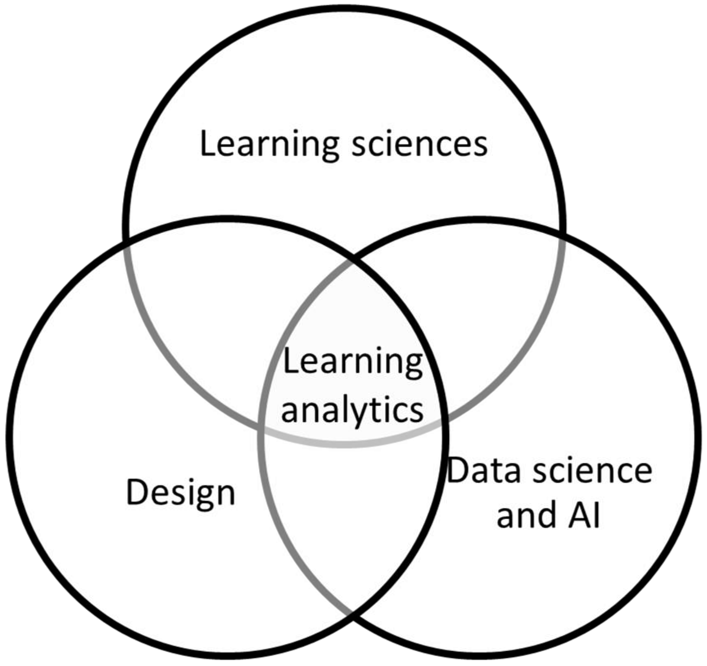
- 12 faculty members
- Four teaching fellows
- Six research fellows
- Five adjunct staff
- Four professional staff
- 30+ full-time PhD students
- 25+ affiliates at Monash
- Largest in the world in LA

COLAM

FOCUS AREAS

Analytics and self-regulated / collaborative learning	Human-centred learning analytics	Analytics and AI for assessment and feedback
Human-AI interaction	Workplace learning and practice analytics	Multimodal learning analytics

CAPABILITIES



C LAM

PARTNERS

Government organisations	General skills	School systems, VET, and TAFE
Industries	Big tech and ed tech	International academic partners

CURRENT FUNDERS

Australian Government
Australian Research Council

VICTORIA State Government
Education and Training

digital health CRC

E·S·R·C ECONOMIC & SOCIAL RESEARCH COUNCIL

Algorand FOUNDATION

NWO

DFG Deutsche Forschungsgemeinschaft

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DARPA

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The British Academy

OUR TEAM

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Yueqiao (Ariel) Jin

PhD Student
Monash University

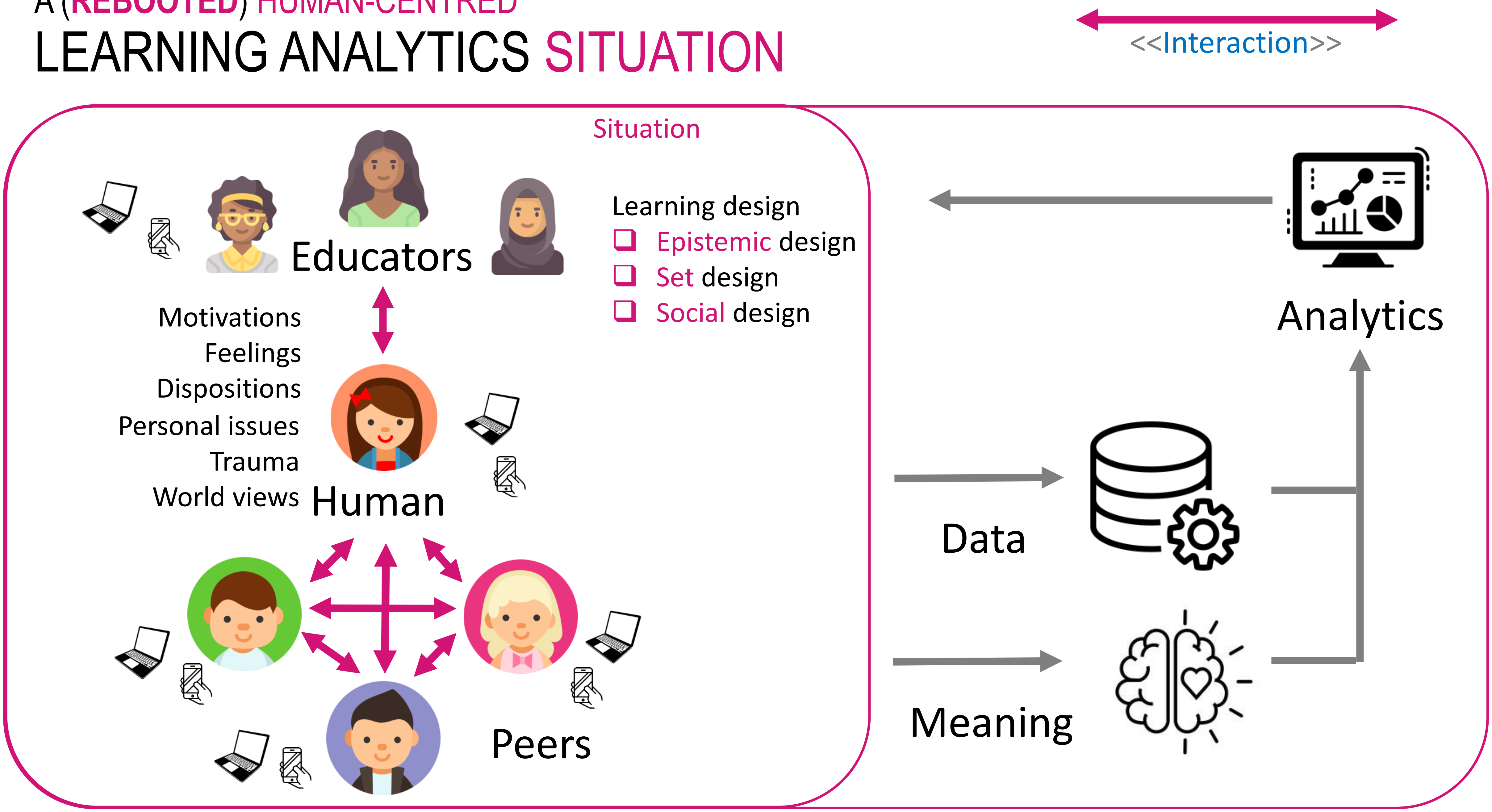
Linxuan Zhao

Research Fellow
Monash University

Mikaela Milesi

PhD Student
Monash University

A (REBOOTED) HUMAN-CENTRED LEARNING ANALYTICS SITUATION

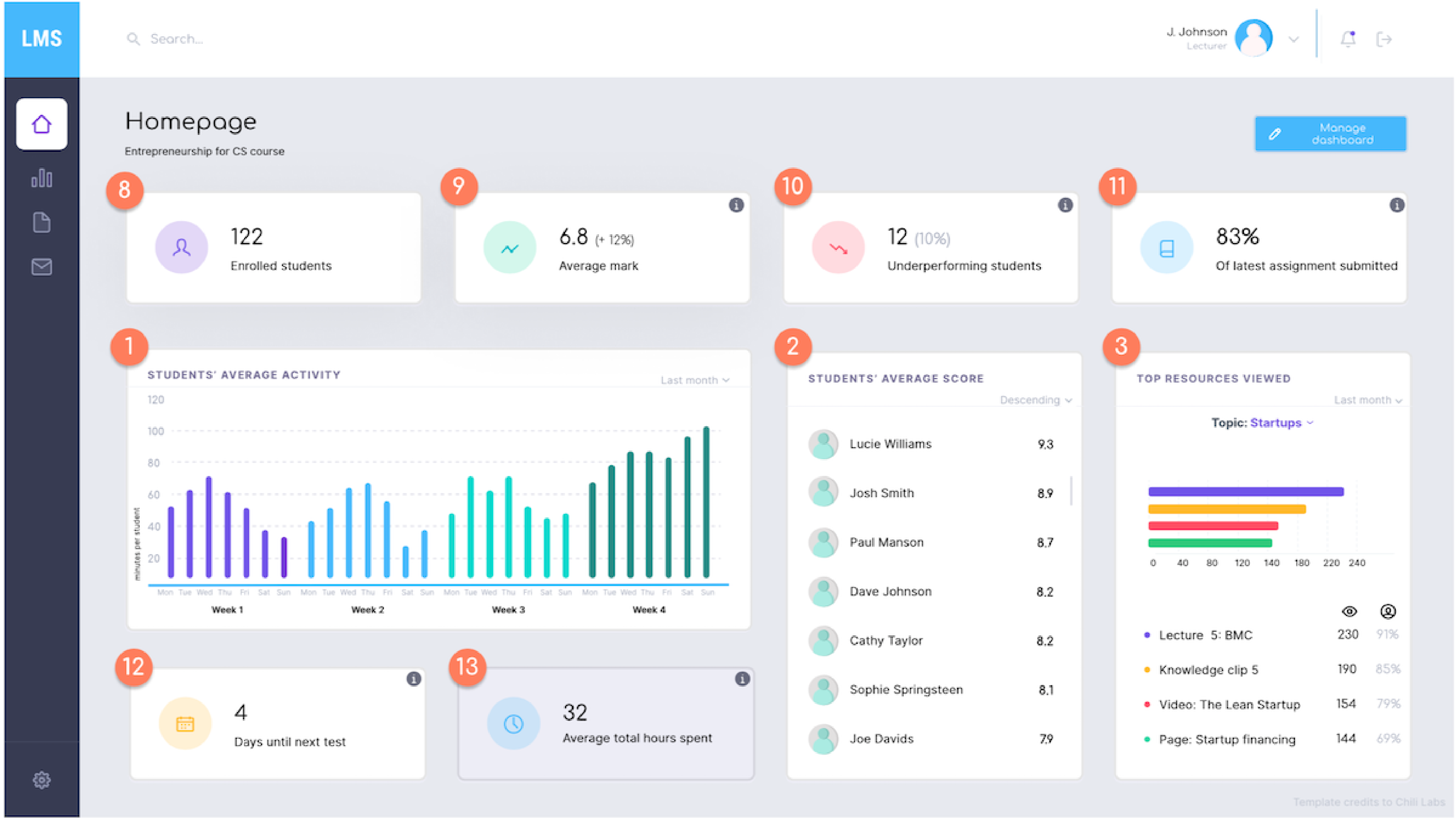


LEARNING ANALYTICS

IN THE CLASSROOM

Within dashboards, visualizations are frequently used to provide a visual representation of education data to support **self-regulated learning, reflection, pedagogical interventions and teacher-student dialogues**.

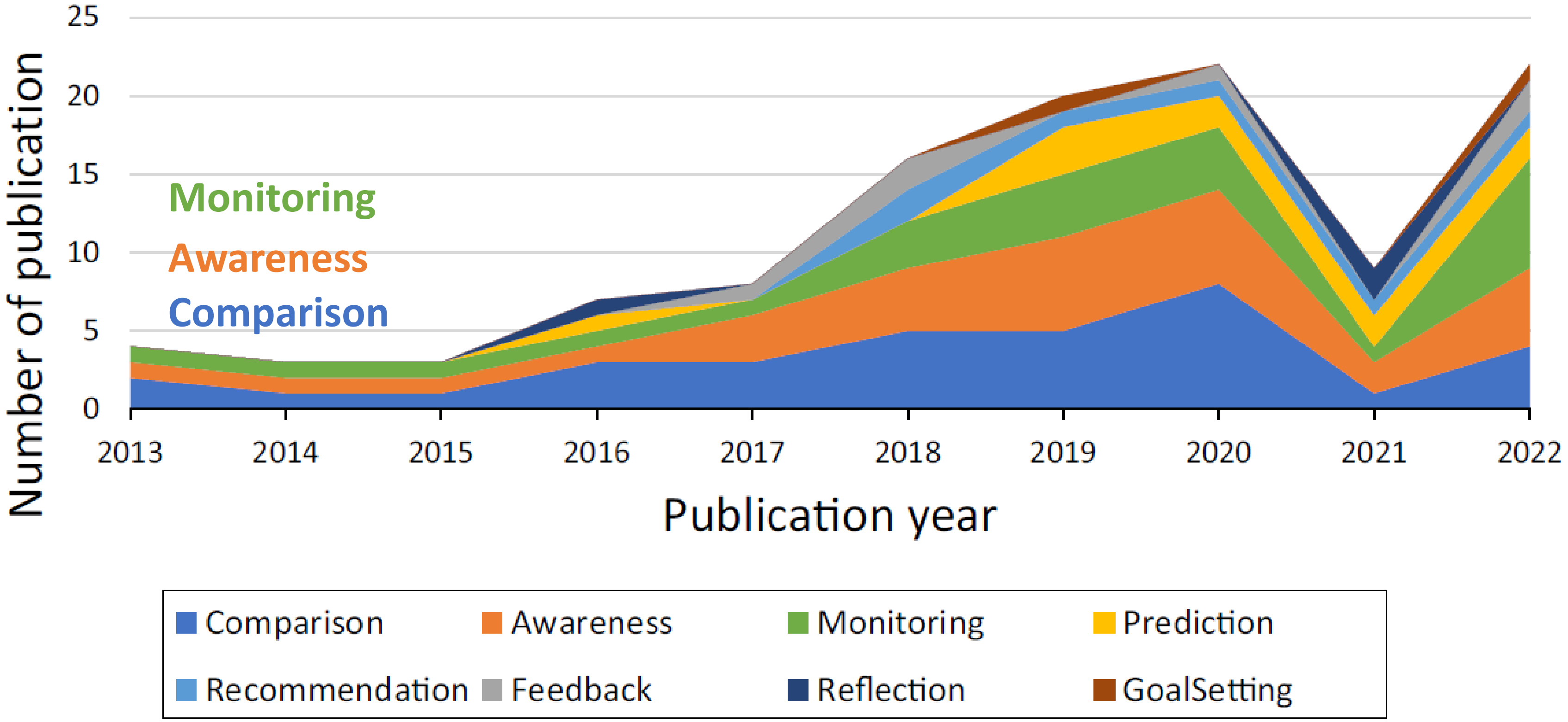
ONLINE
DASHBOARDS



Daryl Zandvliet thesis work. ictinstitute.nl/learning-analytics-research

TO ADDRESS LEARNING,

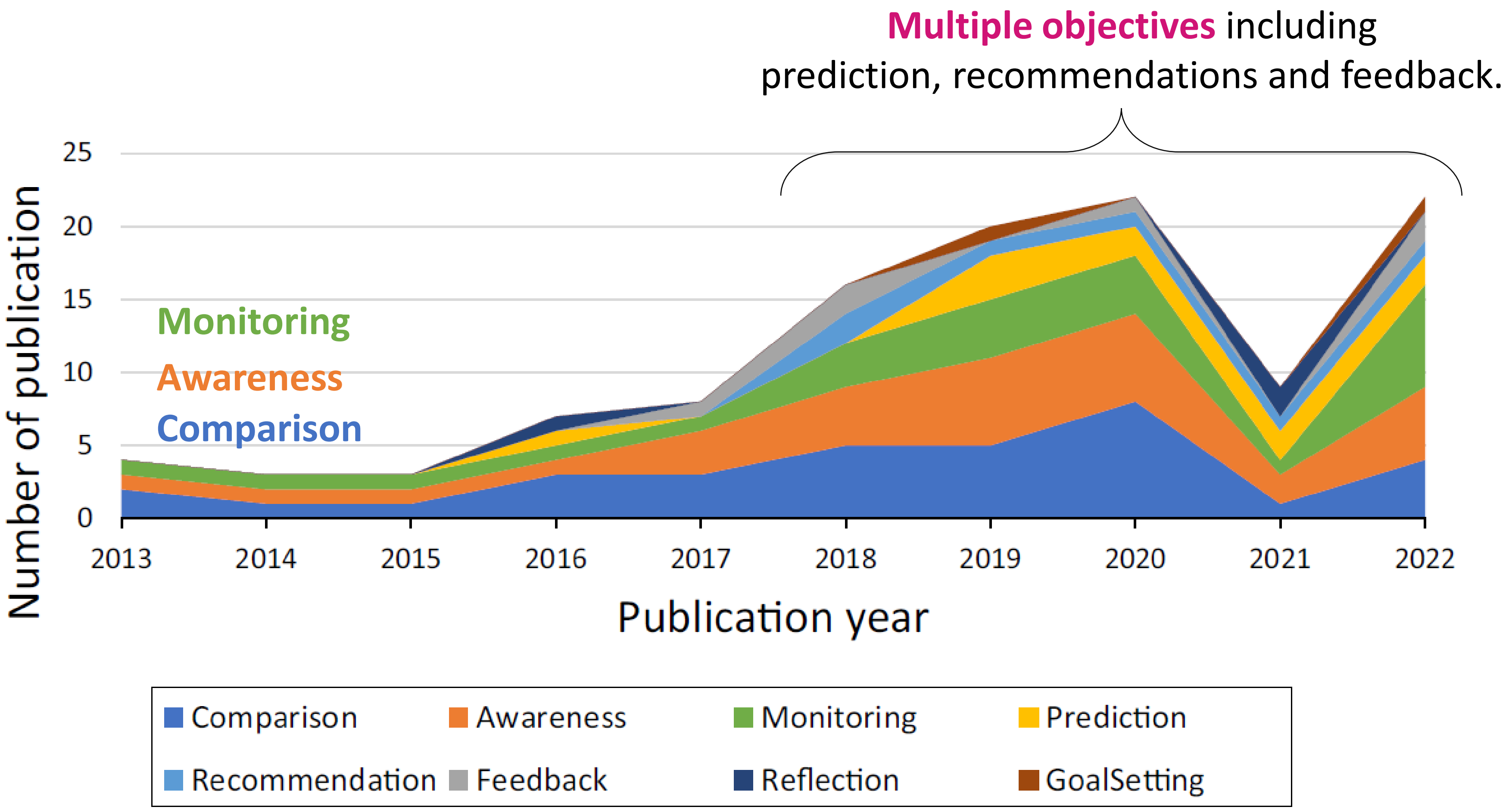
Dashboards are becoming ...



Paulsen, L., & Lindsay, E. (2024). Learning analytics dashboards are increasingly becoming about learning and not just analytics-A systematic review. *Education and Information Technologies*, 1-30.

TO ADDRESS LEARNING,

Dashboards are becoming more complex



Paulsen, L., & Lindsay, E. (2024). Learning analytics dashboards are increasingly becoming about learning and not just analytics-A systematic review. *Education and Information Technologies*, 1-30.

Dashboards

ARE BECOMING MORE **MULTIMODAL**

Education and Information Technologies
https://doi.org/10.1007/s10639-023-12401-4

Check for updates

Learning analytics dashboards are increasingly becoming about learning and not just analytics - A systematic review

Lucas Paulsen[1] · Euan Lindsay[2]

r 2023

merging themes in the design and implementa-
ics dashboards in higher education. Learning
r focusing too much on the analytics, and not
s then guided by an interest in whether these
s-driven or if they have become pedagogically
identified themes of technological maturity,
data sources, and analytical levels over pub-
fies an emerging trajectory towards student-
focused dashboards. These dashboards are informed by theory-oriented frameworks, designed to incorporate affordances that supporting student learning, and realised through integration of more than just activity data from learning management systems – allowing the dashboards to better support students' learnings processes. Based on this emerging trajectory, the review provides a series of design recommendations for student-focused dashboards that are connected to learning sciences as well as analytics.

Keywords Learning analytics · Dashboards · Systematic review · Trajectories · Higher education

Our results imply that external data sources are needed in order to support diagnostic and prescriptive analytics, the types of analytics that we argue are needed in order to support students' learning through affordances such as feedback, reflection and recommendation. Dashboards limited to LMS data are by that nature also restricted in what they can present to students, and to what degree they can understand and support students' learning processes.

Paulsen, L., & Lindsay, E. (**2024**). Learning analytics dashboards are increasingly becoming about learning and not just analytics-A systematic review. *Education and Information Technologies*, 1-30.

DASHBOARDS
ARE NOT DELIVERING THEIR PROMISES

Students find it difficult to interpret/act on data to improve learning (Bodily & Verbert, **2017**; Jivet et al., **2018**; Matcha et al., **2019**; Valle et al., **2021**)

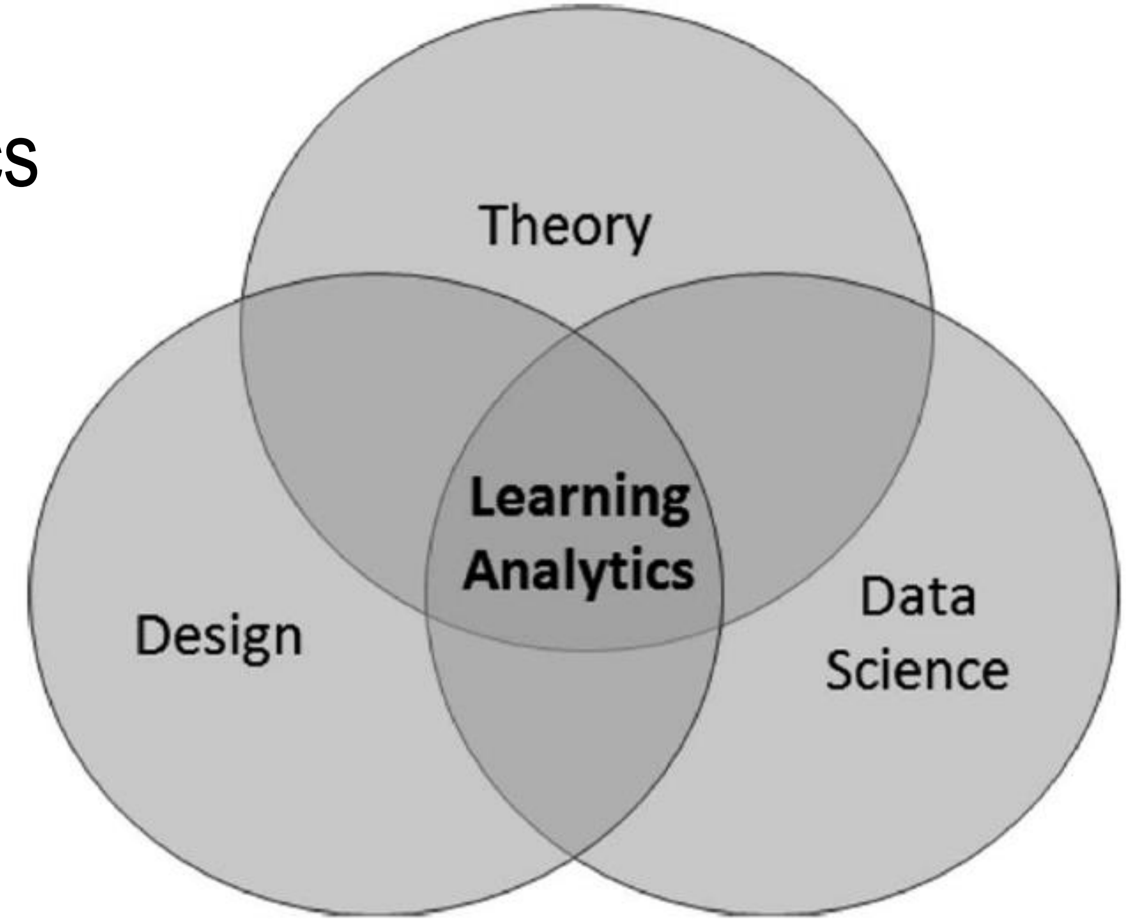
…. and the same applies to **teachers** (Mangaroska & Giannakos, **2018**).

…. most do not address concepts of justice, equity, diversity and inclusion (Williamson & Kizilcec, **2023)**

Bodily, & Verbert (2017). Trends and issues in student-facing learning analytics reporting systems research. LAK'17
Jivet, Scheffel, Specht & Drachsler (2018). License to evaluate: Preparing learning analytics dashboards for educational practice. In LAK'18
Matcha, Gasevic, & Pardo (2019). A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. IEE TLT
Valle, Antonenko, Dawson & Huggins-Manley (2021). Staying on target: A systematic literature review on learner-facing learning analytics dashboards. BJET
Williamson & Kizilcec, R. (2023). A review of learning analytics dashboard research in higher education: Implications for justice, equity, diversity, and inclusion. LAK'22.
Mangaroska & Giannakos (2018). Learning analytics for learning design: A systematic literature review of analytics-driven design to enhance learning. IEEE TLT

THE ROLE OF

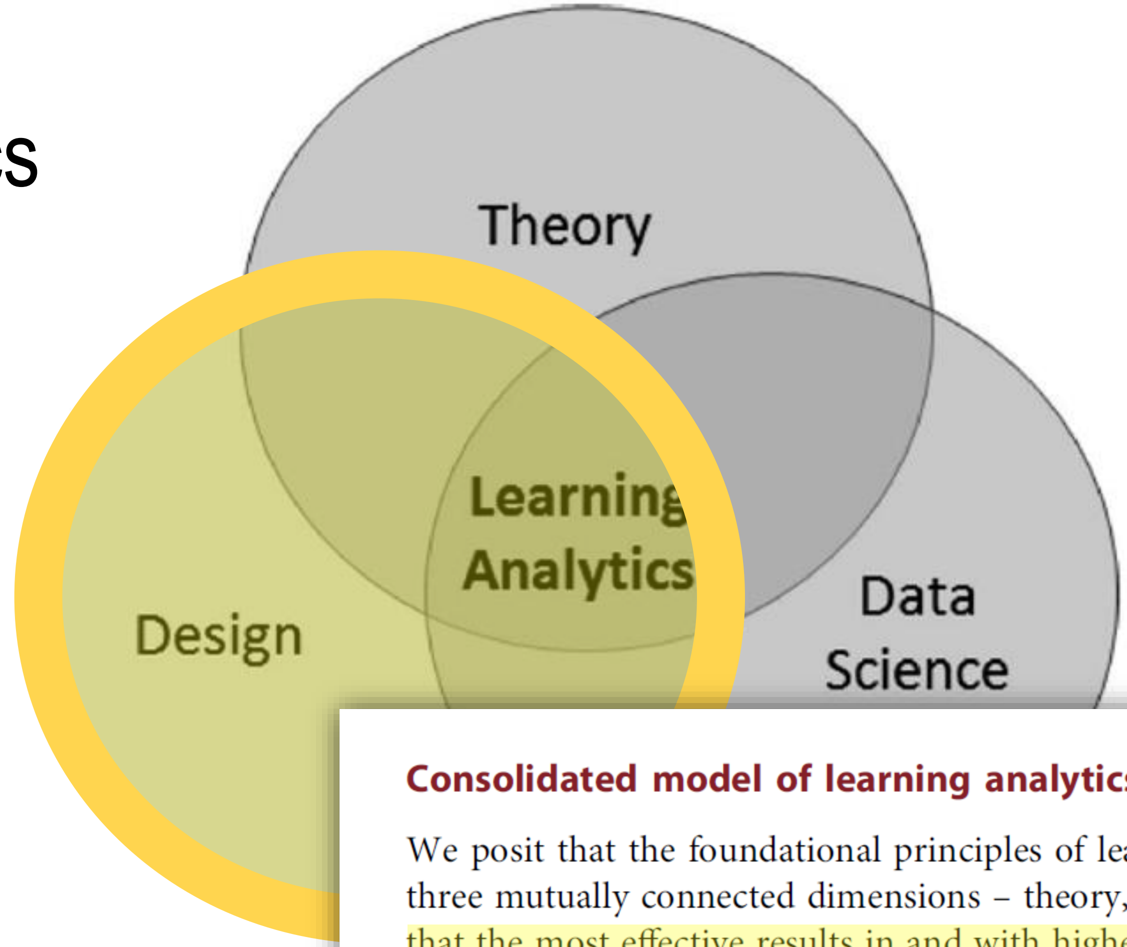
DESIGN in learning analytics



Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: a consolidated model of a field of research and practice. *Learning: Research and Practice, 3*(1).

THE ROLE OF

DESIGN in learning analytics



Consolidated model of learning analytics

We posit that the foundational principles of learning analytics can be grouped around three mutually connected dimensions – theory, design, and data science. We also posit that the most effective results in and with highest validity for research and practice can be achieved only once the principles of all three dimensions are considered. The consolidated model (Figure 1) does not exclude the existing models and frameworks of learning analytics, but rather complements them.

Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: a consolidated model of a field of research and practice. *Learning: Research and Practice, 3*(1).

THE PROBLEM OF ‘DESIGNING FOR’

INSTEAD OF DESIGNING WITH

THIS GROUP OF OLD MEN

is debating the future of women's health care.

Human-Centred Learning Analytics

How is this process done?

WHAT IS HUMAN-CENTRED

LEARNING ANALYTICS?

A balanced working definition of Human-Centred Learning Analytics (HCLA) can be:

the subfield of Learning Analytics focused on developing **trustworthy**, **reliable** systems that **augment** and **support** the capabilities of educational stakeholders, **aligning with their intentions, preferences, interests, and values.**

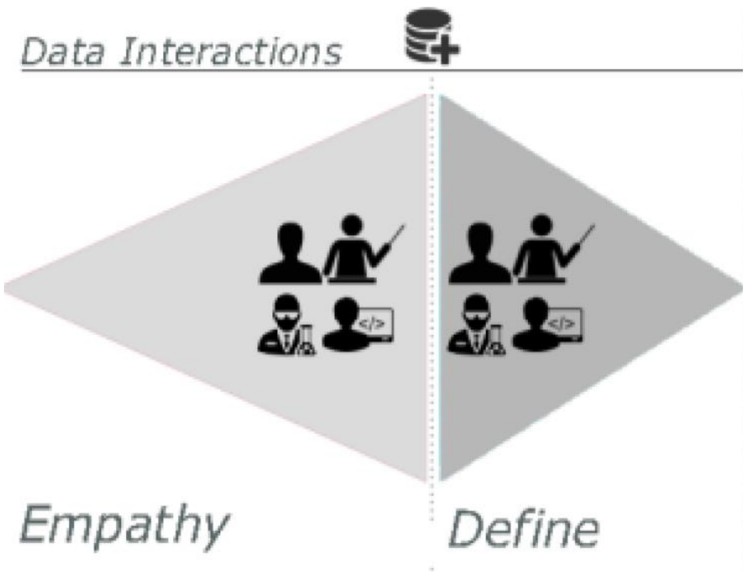
Source: Martinez-Maldonado, R. (2023). Human-centred learning analytics: Four challenges in realising the potential. *Learning Letters*, *1*, 6. https://doi.org/10.59453/FIZJ7007

Human-Centredness
Learning Analytics

DESIGN PHASES IN

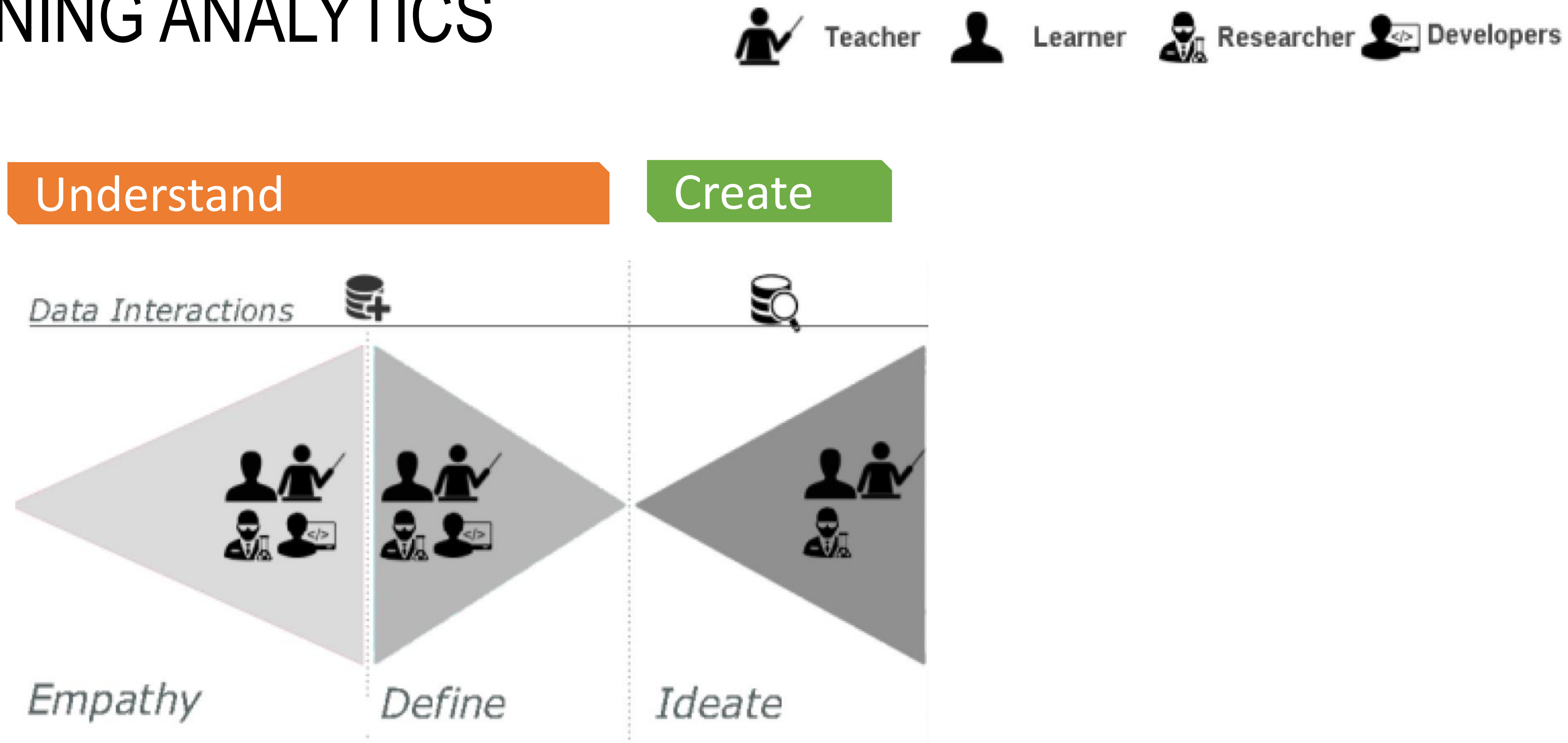
LEARNING ANALYTICS

Understand



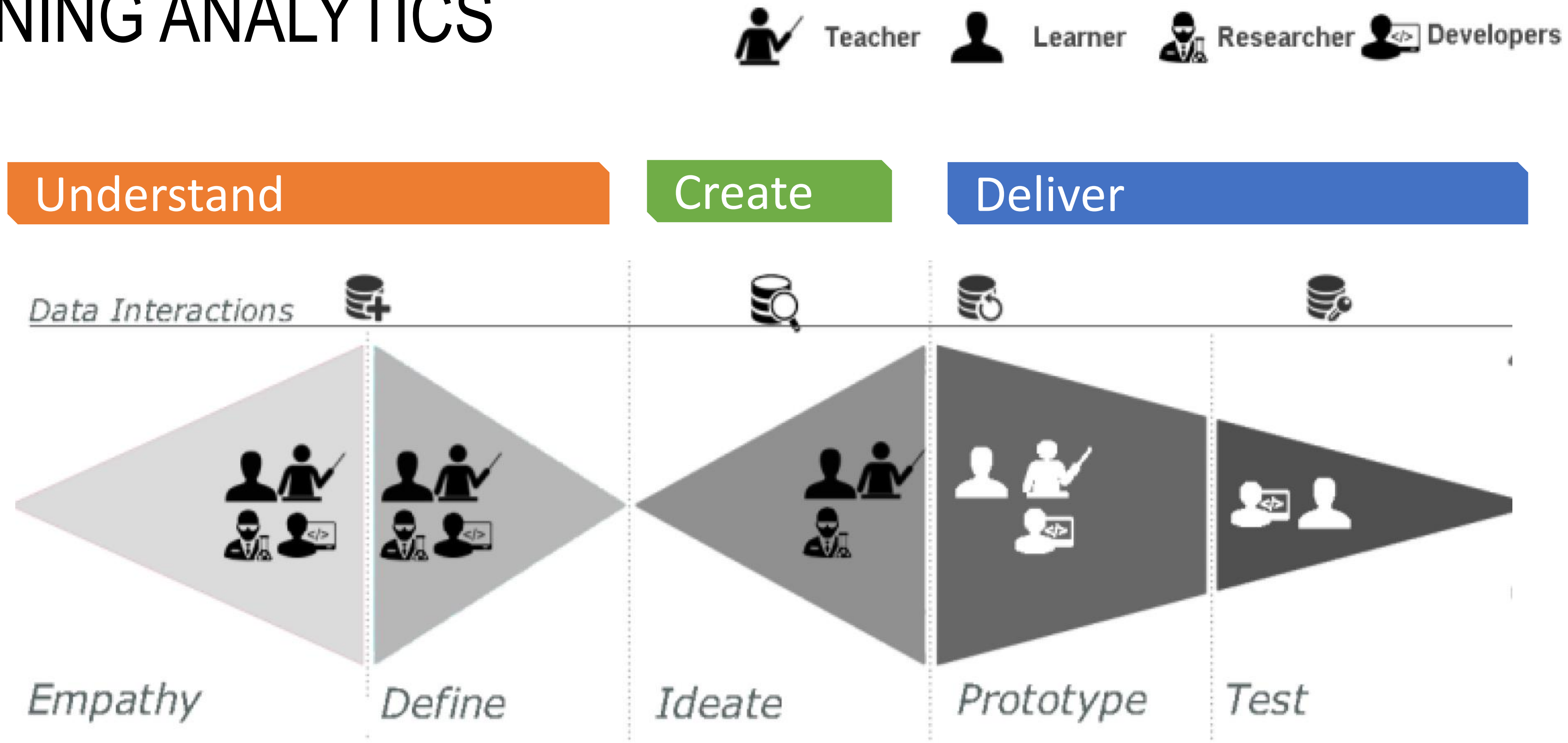
Prieto-Alvarez, C. G., Martinez-Maldonado, R., and Anderson, T. (2018). Co-designing learning analytics tools with learners. In J. M. Lodge, J. C. Horvath, and L. Corrin (Eds.), Learning Analytics in the Classroom.

DESIGN PHASES IN
LEARNING ANALYTICS



Prieto-Alvarez, C. G., Martinez-Maldonado, R., and Anderson, T. (2018). Co-designing learning analytics tools with learners. In J. M. Lodge, J. C. Horvath, and L. Corrin (Eds.), Learning Analytics in the Classroom.

DESIGN THINKING IN
LEARNING ANALYTICS

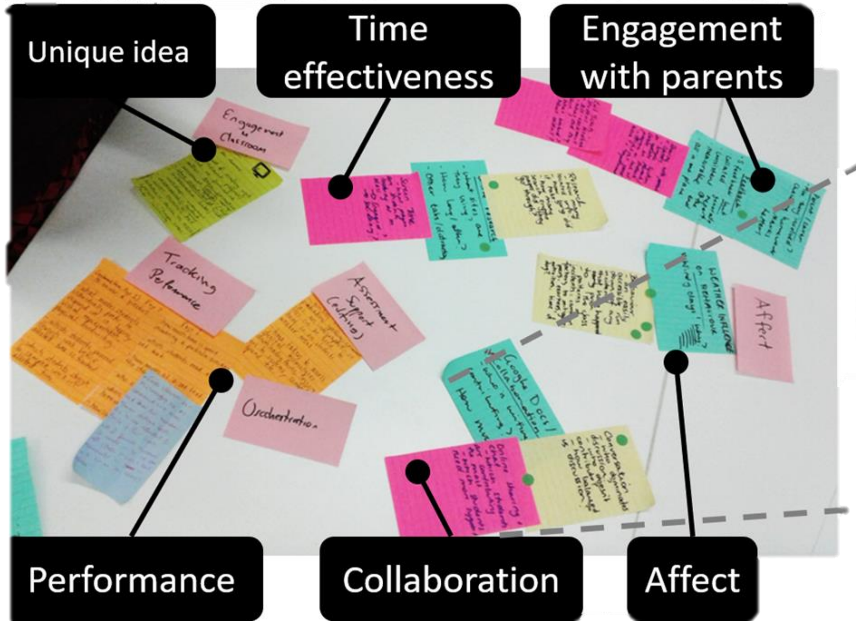


Prieto-Alvarez, C. G., Martinez-Maldonado, R., and Anderson, T. (2018). Co-designing learning analytics tools with learners. In J. M. Lodge, J. C. Horvath, and L. Corrin (Eds.), Learning Analytics in the Classroom.

Understand

USING CARD SORTING AND OTHER
GENERATIVE TOOLS

Question posed to pre-service teachers: “What aspects of the classroom or the learning activity happening in the classroom you would like to make more visible?”



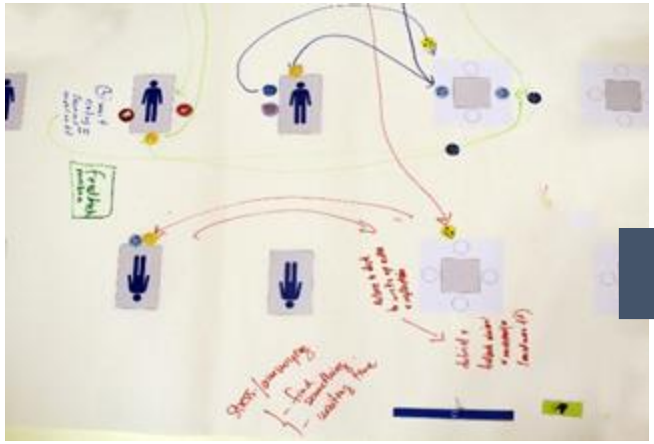
Prestigiacomo, R., et al.. (2020, March). Learning-centred translucence: An approach to understand how teachers talk about classroom data. In *LAK’20*

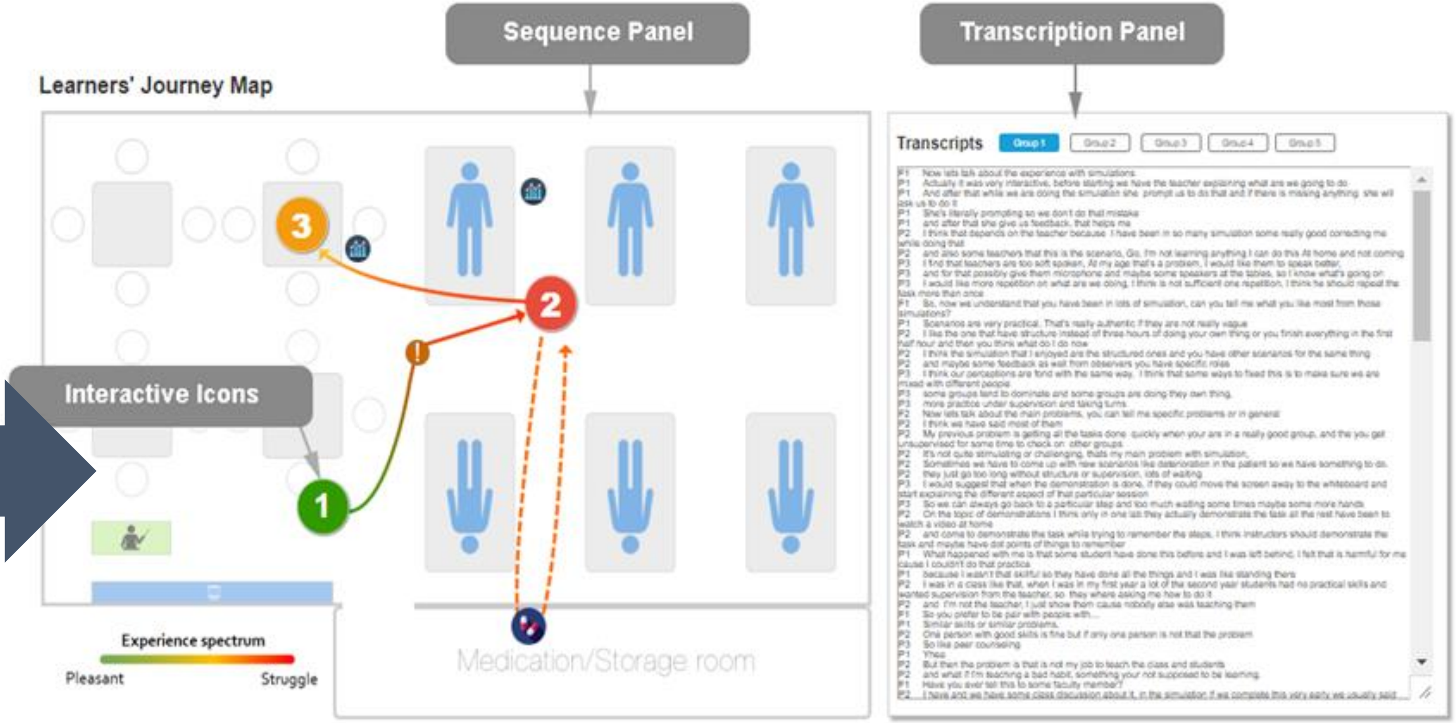
Understand

ADAPTING DESIGN TOOLS SUCH AS

USER JOURNEYS

A three-phase process for crafting **Learner-Data Journey maps** and using them as communication tools to involve other stakeholders in the co-design of a data-intensive educational tools.

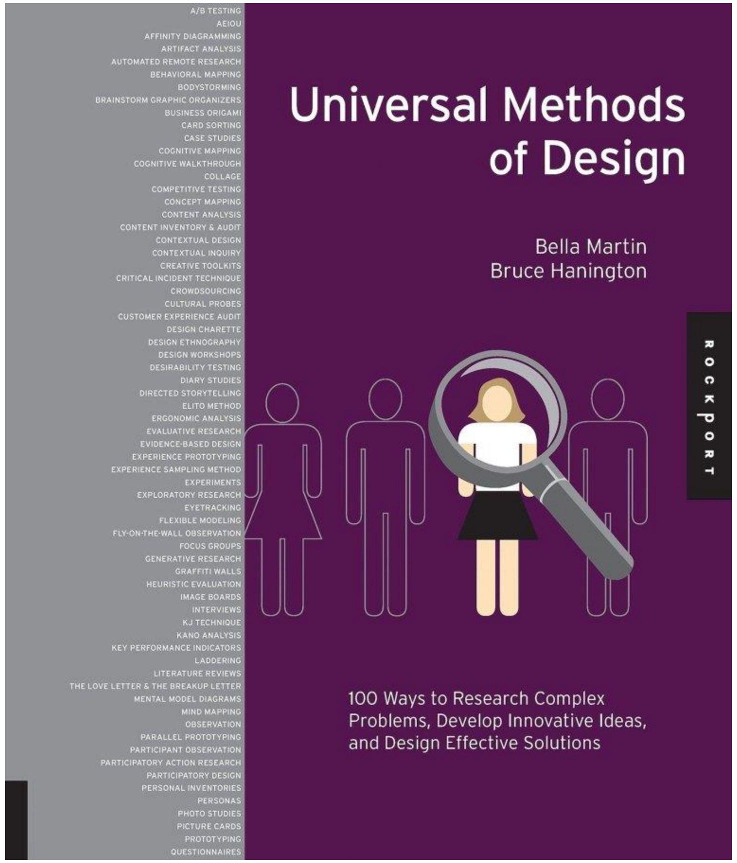




Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Shum, S. B. (2018). Mapping learner-data journeys: Evolution of a visual co-design tool. In *Proceedings of the Australian Conference on Computer-human Interaction*.

WHAT TOOLS CAN WE USE FOR OTHER TASKS?

Martin and Hanington (2012)



Contents

& design phases 1 2 3 4 5

Create

RAPID
PROTOTYPING

Low and high fidelity prototyping with teachers and students.

Prieto-Alvarez, C. G., Martinez-Maldonado, R., & Shum, S. B. (2018). Mapping learner-data journeys: Evolution of a visual co-design tool. In *Proceedings of the Australian Conference on Computer-human Interaction*.

CHALLENGE #1

The challenge: The educational stakeholders participating in a HCLA project may be highly motivated, exceptional individuals, such as high-achieving students or innovative teachers.

This could result in a skewed representation in the participants of the LA design process.

CHALLENGE #1

Potential strategies:

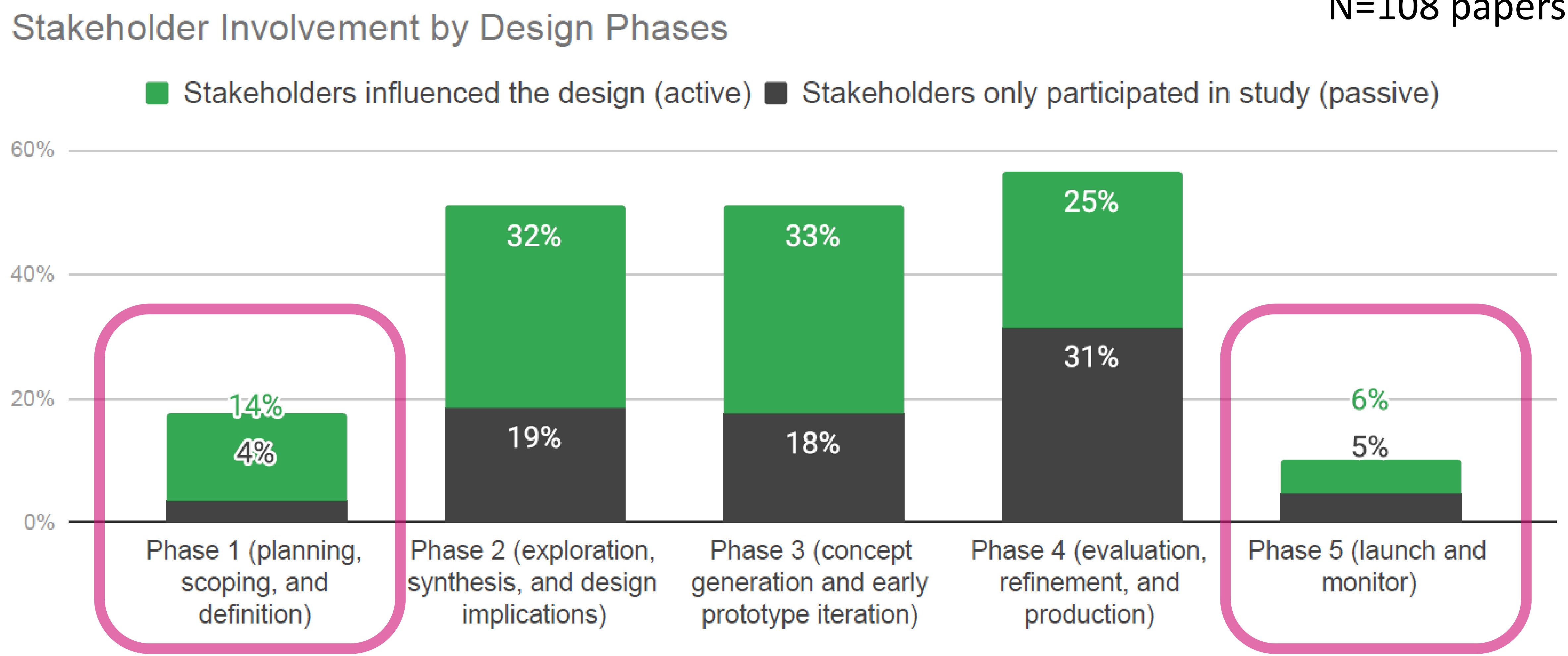
Designing solutions for underrepresented users can often derive breakthroughs that would benefit everyone (Nielsen, 2013)

Make use of inclusive design toolkits (e.g., the Cambridge Inclusive Design Kit) http://www.inclusivedesigntoolkit.com/tools_guidelines/

Nielsen, J. (2013). Usability for Senior Citizens: Improved, But Still Lacking. *En Nielsen Norman Group. Retrieved from:* *https://www.nngroup.com/articles/usability-seniors-improvements*.

THERE HAS BEEN LITTLE STAKEHOLDER INVOLVEMENT IN THE IDEATION AND MONITORING PHASES OF THE DESIGN

N=108 papers

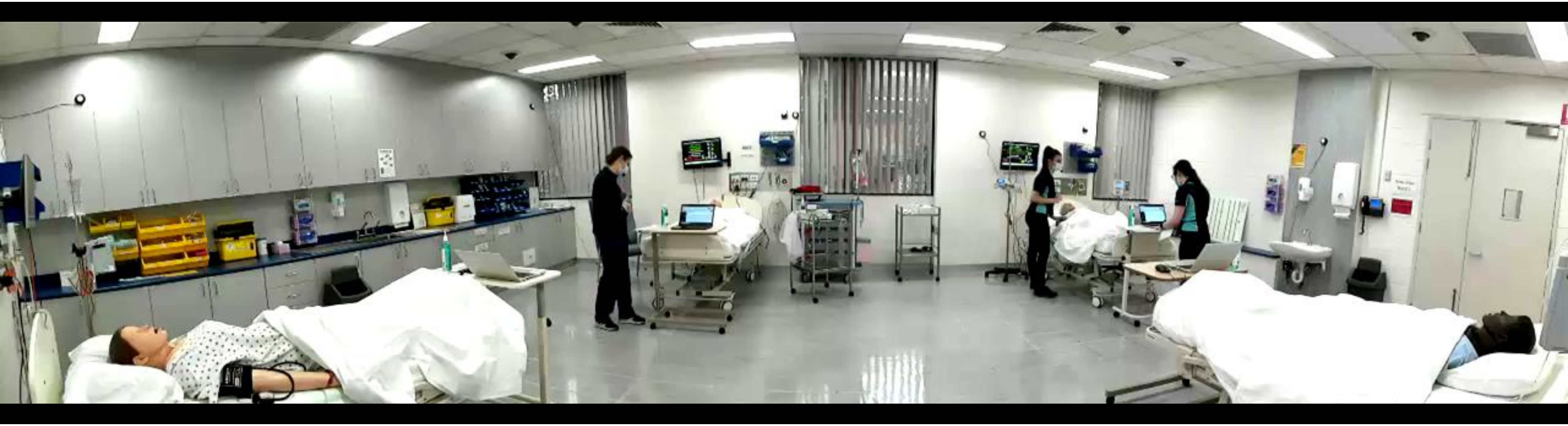


Alfredo et al. (2024) Human-Centred Learning Analytics and AI in Education: a Systematic Literature Review. (under review)

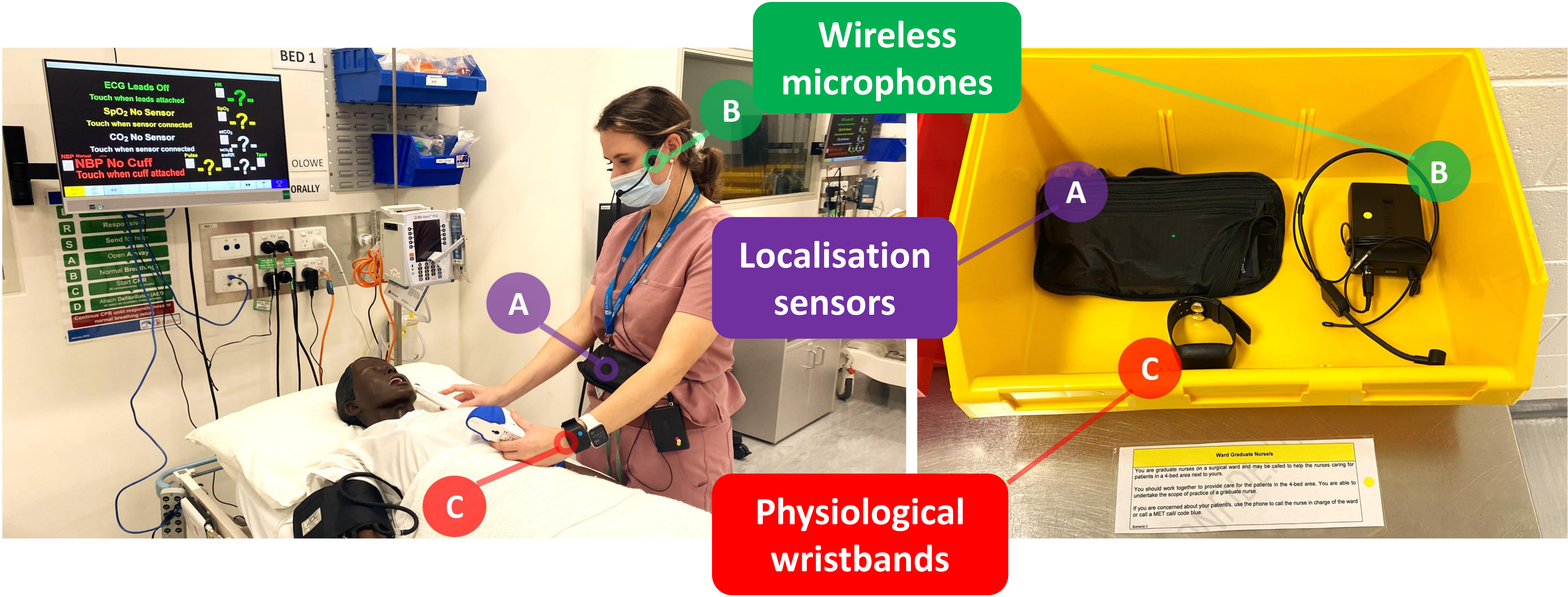
5-YEAR HCLA, MULTIMODAL LEARNING ANALYTICS

CASE STUDY

"**Multimodal data** is used in recognition of the plurality of ways that students may demonstrate or communicate knowledge, interests and intent"

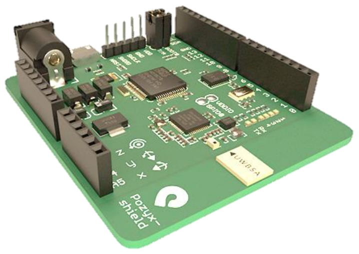


What SENSORS do we use?

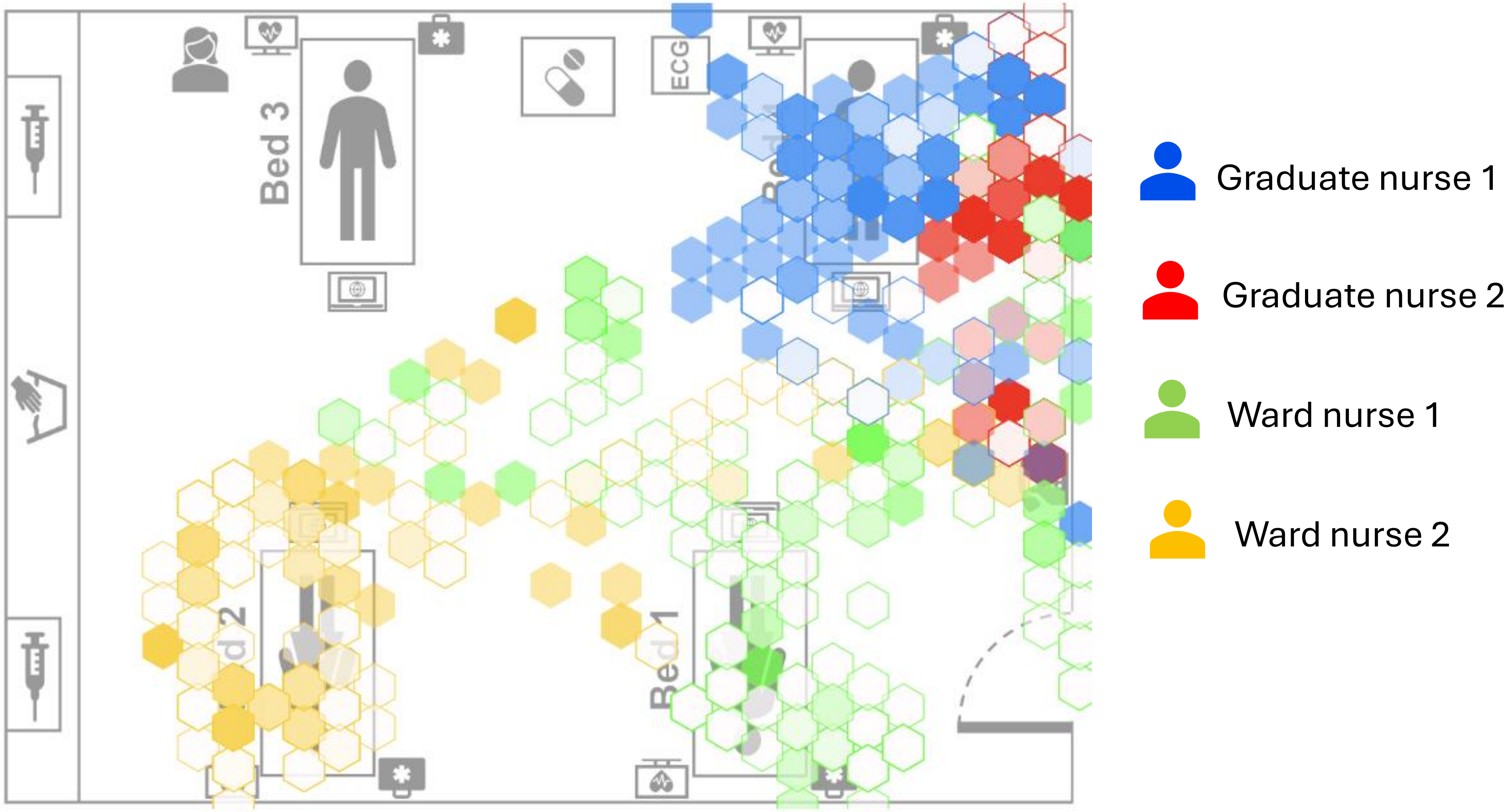


Movement and speech interaction workflows

Localisation sensors



Audio data



LLM-powered conversation analytics

AUDIO DATA STREAMS

TRANSCRIPTS

Speaker 1 (00:12):

So this is Ani. So Ani is a 49-year-old female, four days post his hysterectomy with fibro amani's, AWAI for discharge home. She's called her husband, wasn't able to get hold of him. Mm-Hmm. <affirmative>. So got a past history of Crohn's, um, being stable this shift. Vital signs with their normal limits, just waiting for some discharge instructions with an outpatient appointment and a script for analgesia. Three postop from an

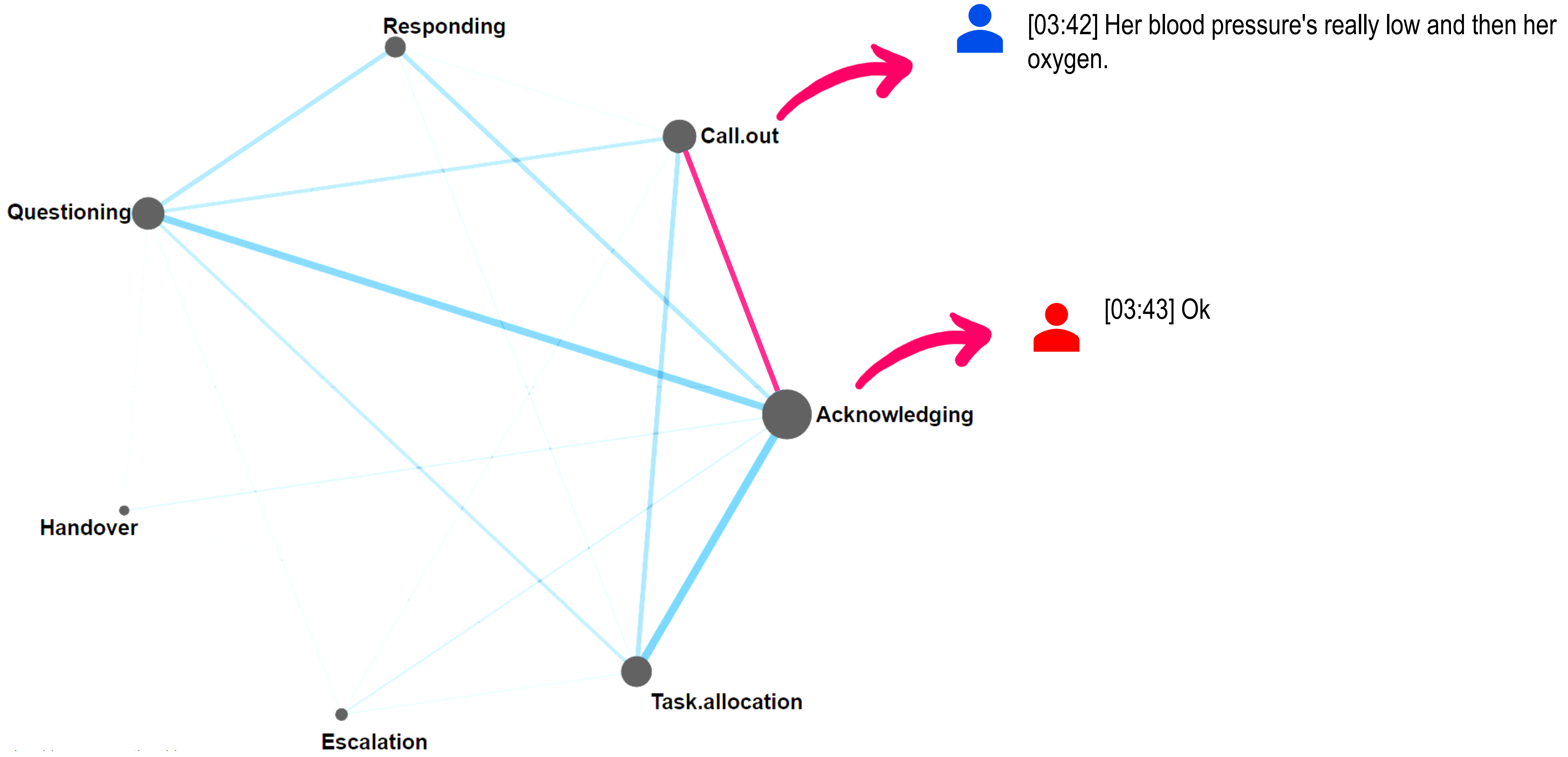
Speaker 2 (00:46):

Ectomy. It's alright, mom. Mom, it's all right. It's, it's alright. Peritonitis. It's all right. It's alright. Mum. She's been on. Excuse me. Excuse me. Can someone come and look at my mom? She can't breathe. Can

TEAMWORK CODES

- Task allocation
- Agreement
- Information sharing
- Situation assessment

Using LLMs, we code nurses' verbal content into team's communication behaviours



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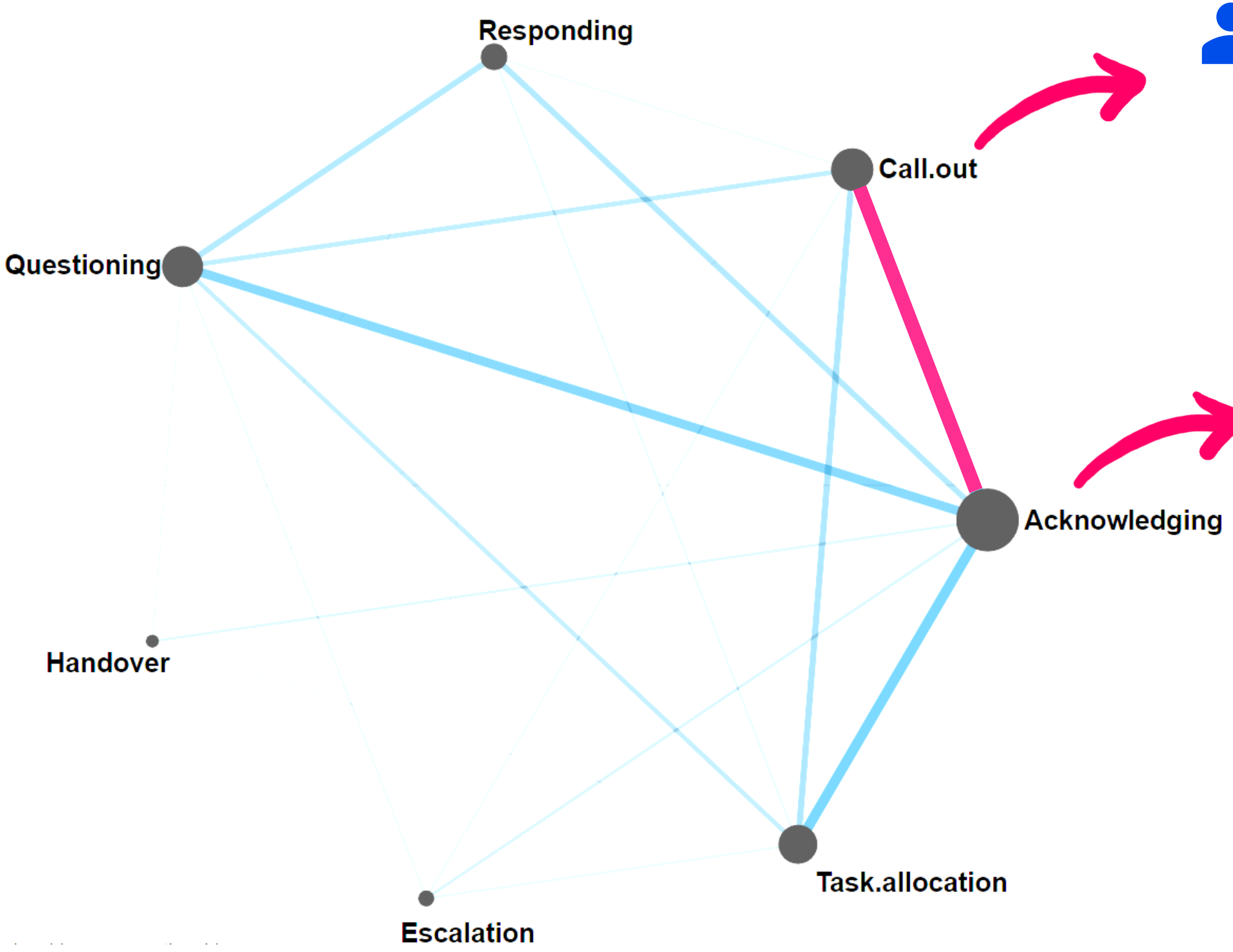
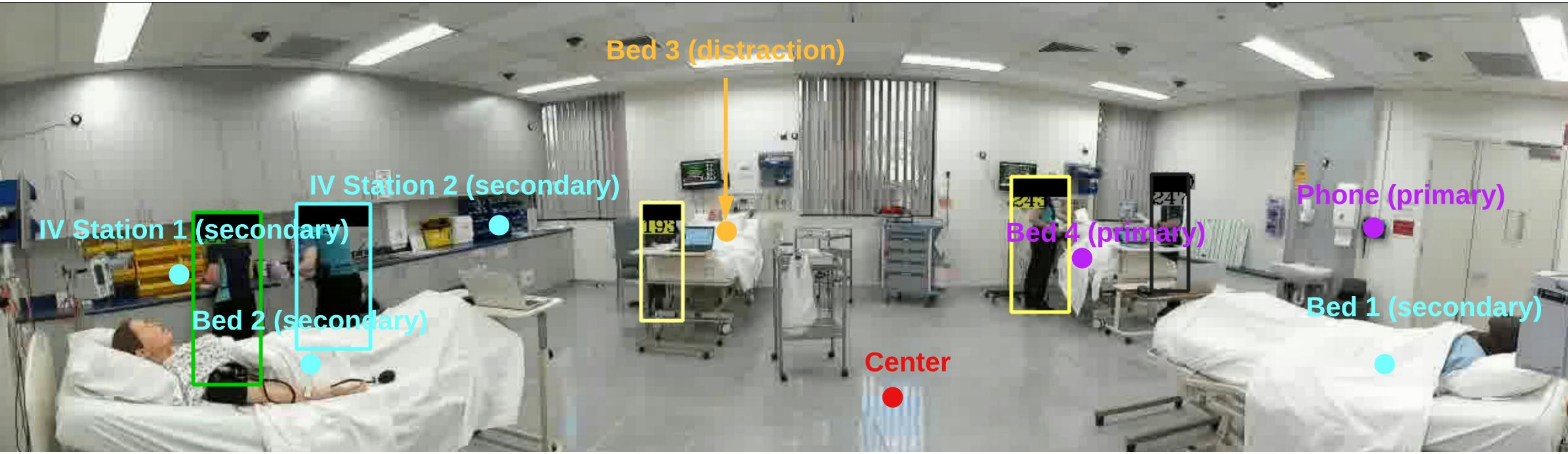


[03:42] Her blood pressure's really low and then her oxygen.
[04:30] Everything seems intact.
[04:31] she's got a lot of pain as well.

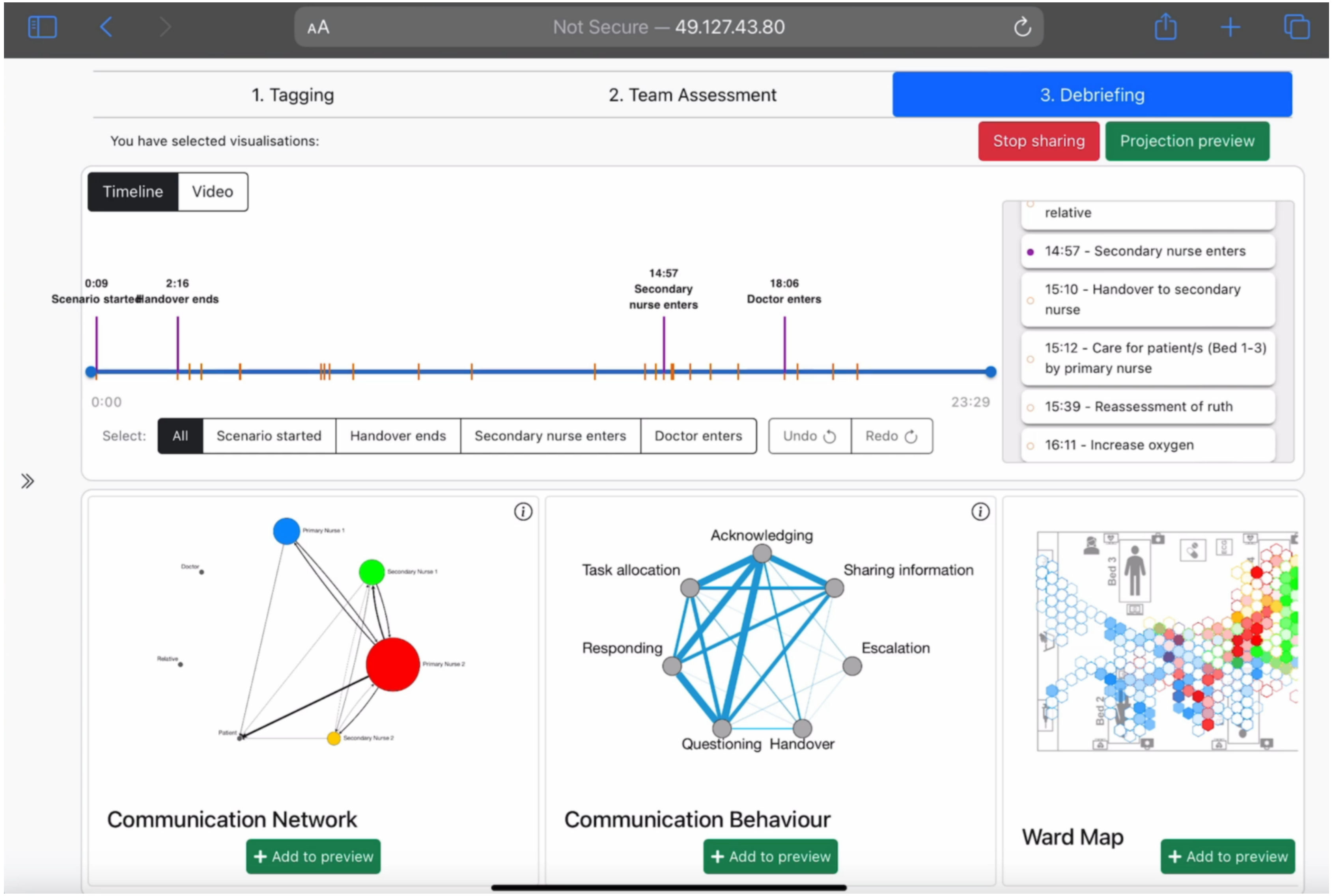
[03:43] Ok
[04:32] I see…

Automated Video Analysis

Using computer vision models, we infer objects and students' location



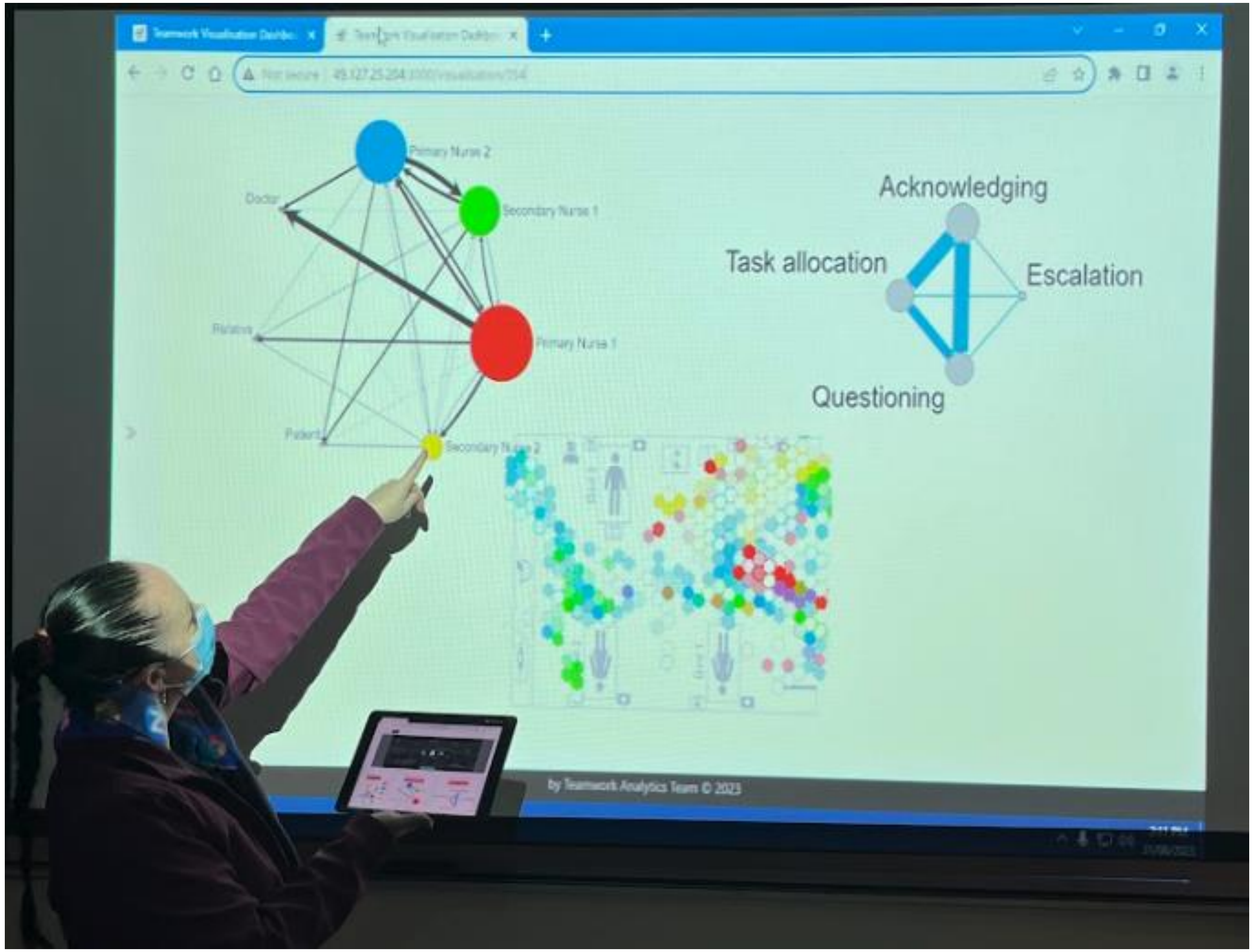
The teachers **co-created a web orchestration application** containing graphs and their own annotations



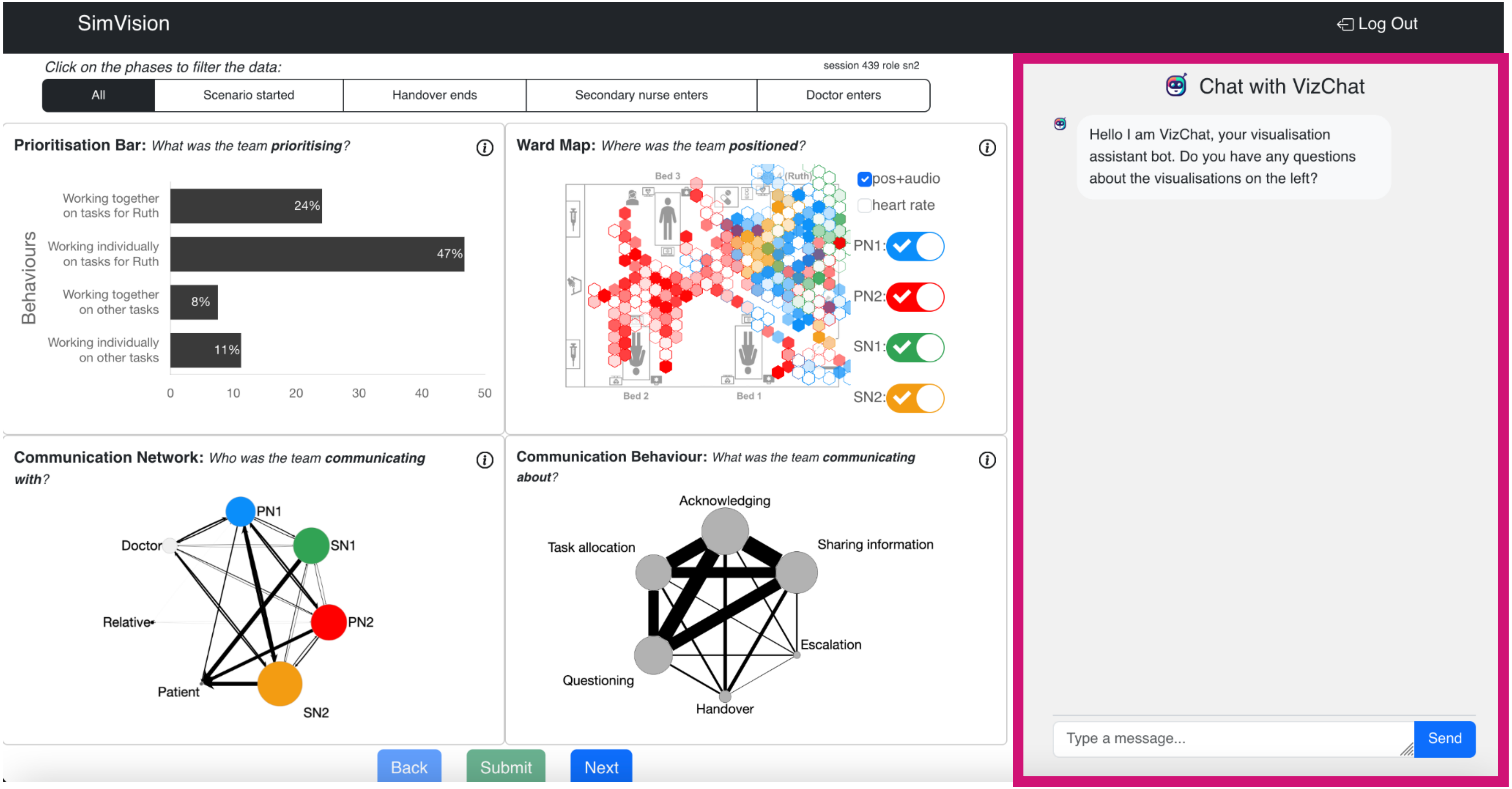
Teachers use the system to annotate critical moments and guide a conversation with their students about team dynamics

ANNOTATIONS DURING THE CLINICAL SIMULATION

TEAMWORK ANALYTICS DURING THE BRIEF



Using GenAI chatbots To guide students' post-hoc reflection



Seeking and

MEMORISING CLARIFICATIONS

Who did I **communicate** with?

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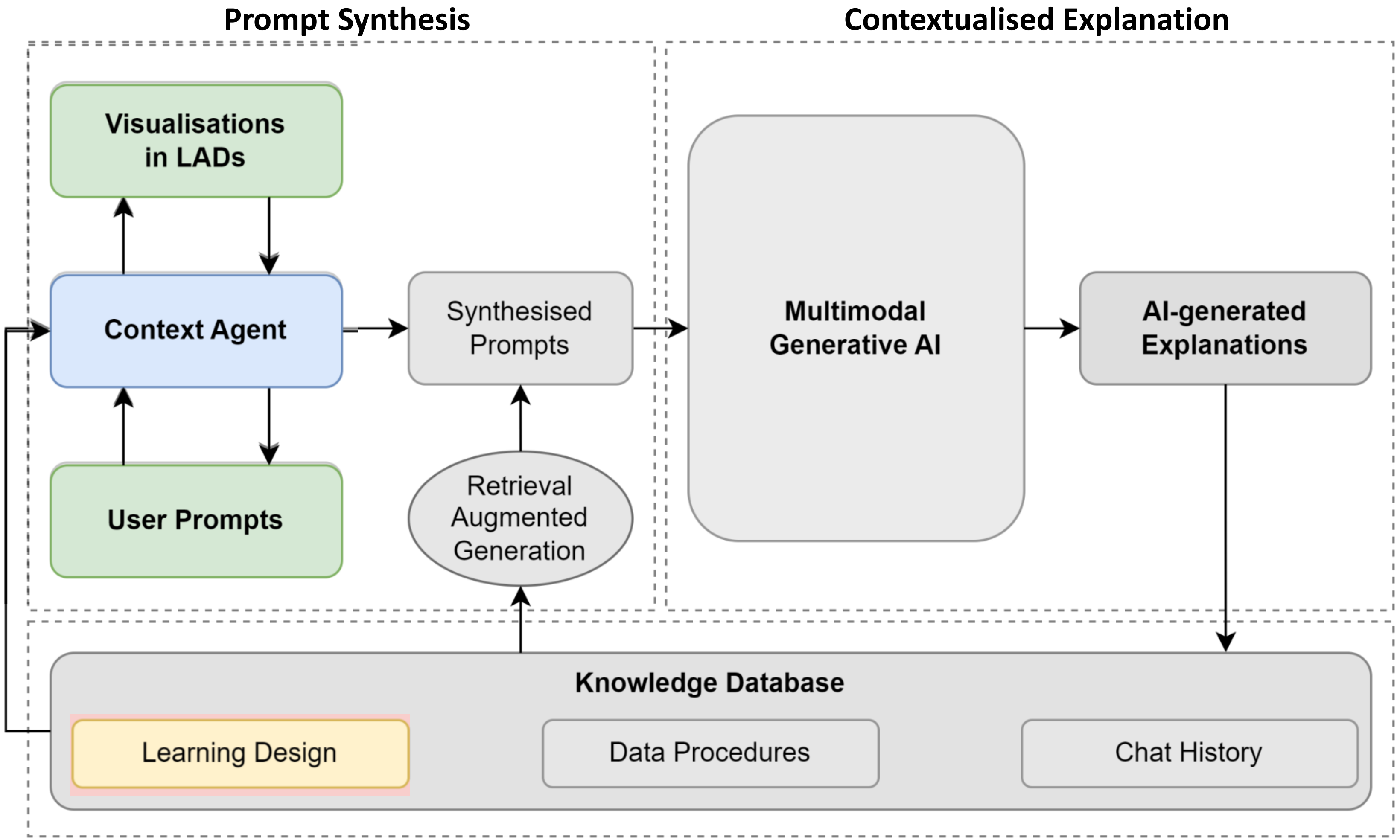
Seeking and

MEMORISING CLARIFICATIONS

Who did I **communicate** with?

To determine who you communicated with, **please provide the name or role** you had during the simulation.

The
VIZCHAT COMPONENTS



Seeking and

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primary nurse 2

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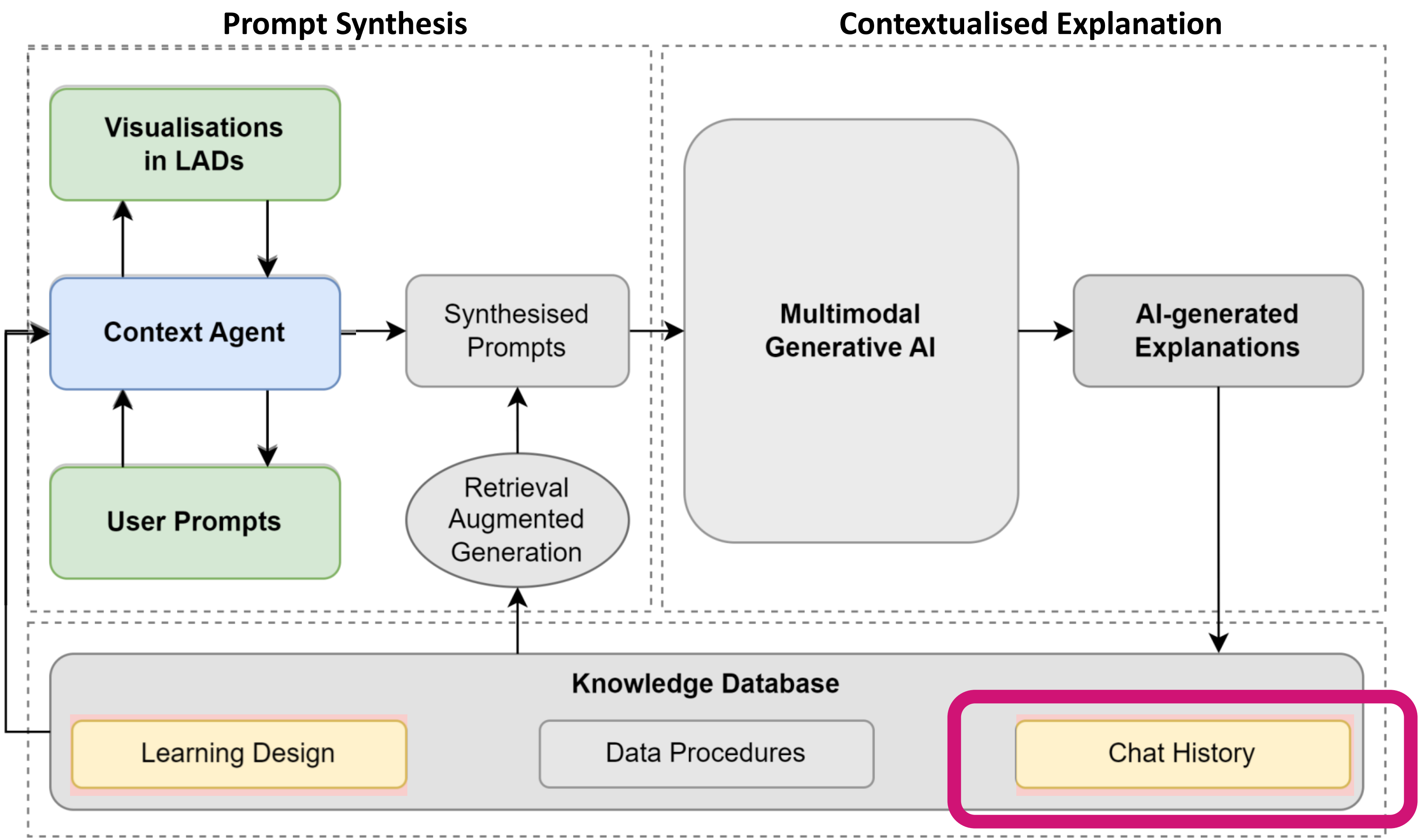
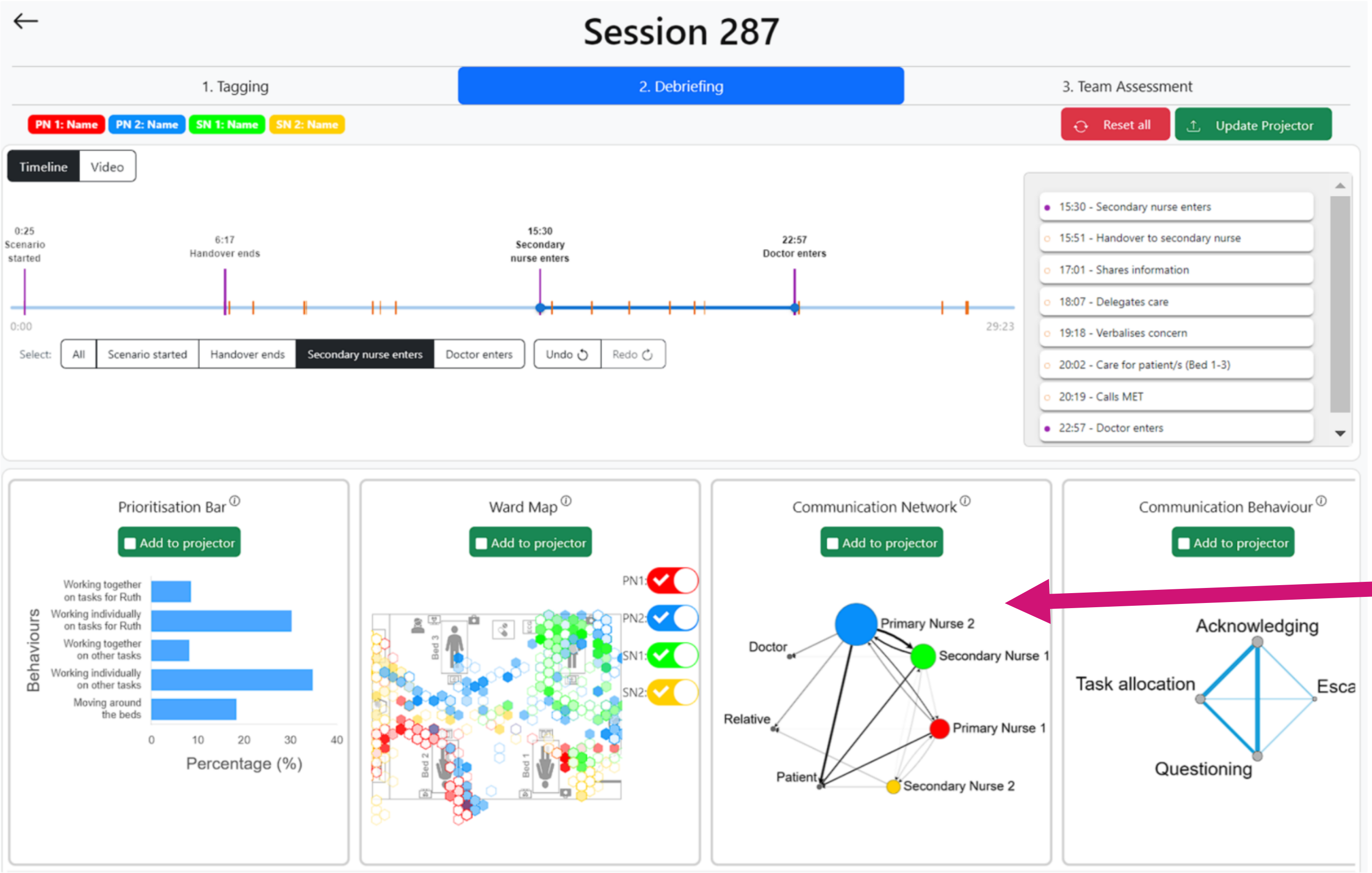
The
VIZCHAT COMPONENTS



Contextualising

RESPONSE



Who did I **communicate** with?

To determine who you communicated with, **please provide the name or role** you had during the simulation.

primary nurse 2

As Primary Nurse 2, you communicated with the doctor, Primary Nurse 1, both Secondary Nurses, and the patients. This is indicated by the **lines connecting** to your icon in the **Communication Network**.

Personalised

RESPONSE

Who did I **communicate** with?

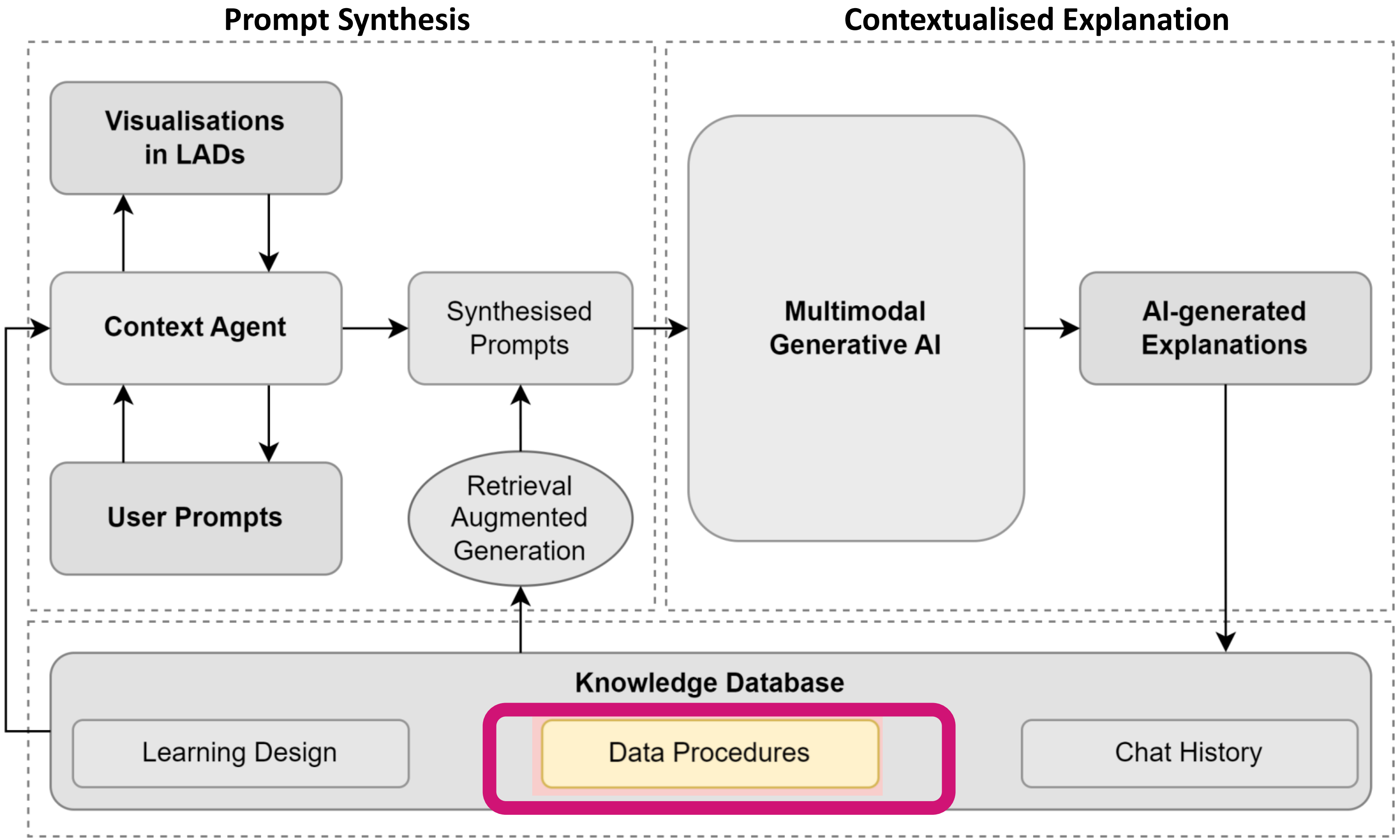
To determine who you communicated with, **please provide the name or role** you had during the simulation.

primary nurse 2

As Primary Nurse 2, you communicated with the doctor, Primary Nurse 1, both Secondary Nurses, and the patients. This is indicated by the **lines connecting** to your icon in the **Communication Network**.

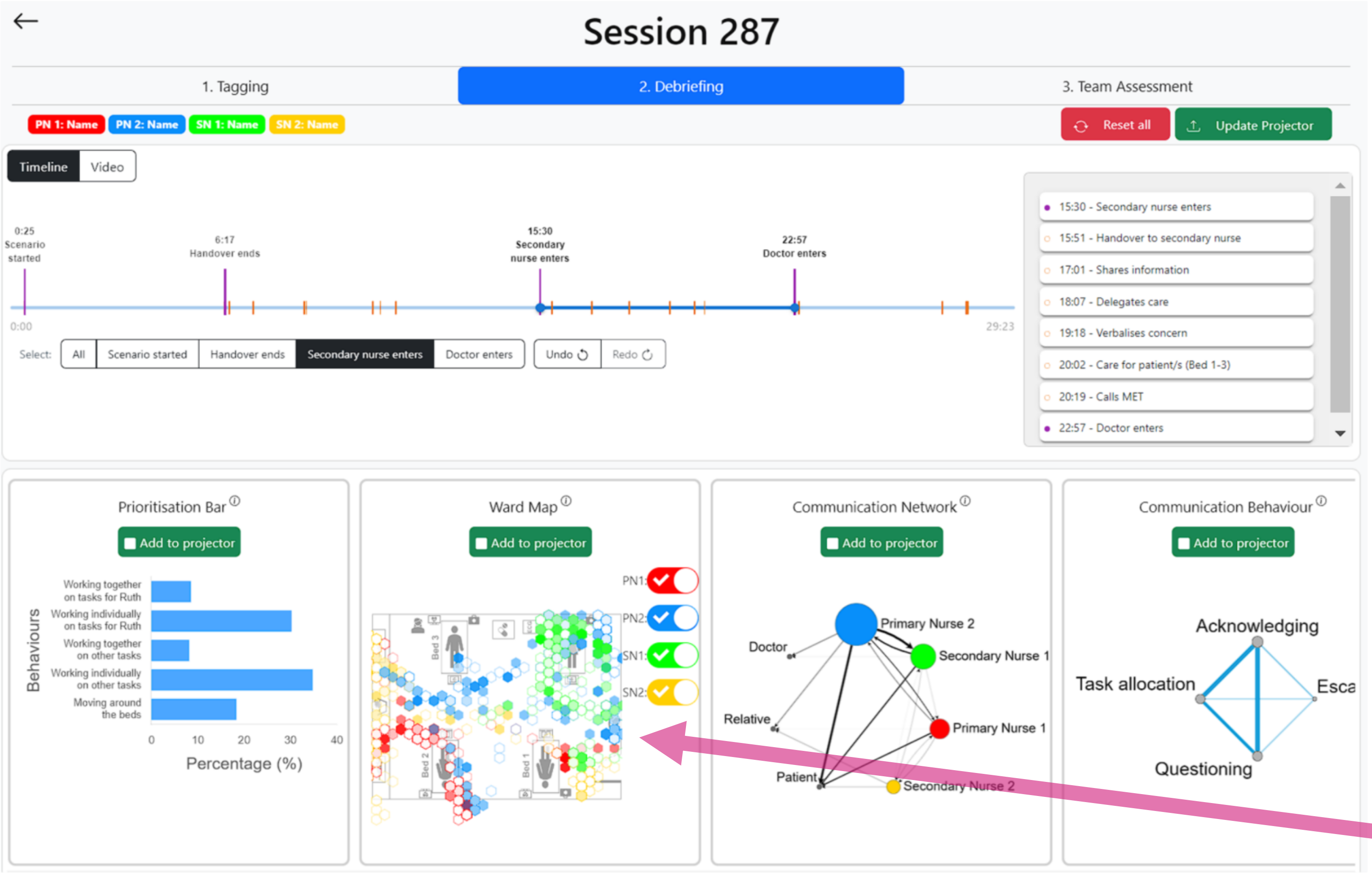
Where did I spend most time?

The
VIZCHAT COMPONENTS



Personalised

RESPONSE



Who did I **communicate** with?

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primary nurse 2

As Primary Nurse 2, you communicated with the doctor, Primary Nurse 1, both Secondary Nurses, and the patients. This is indicated by the **lines connecting** to your icon in the **Communication Network**.

Where did I spend most time?

Primary Nurse 2 spent most time around Bed 4, indicated by the **high concentration of blue hexagons** in that area of the **Ward Map**.

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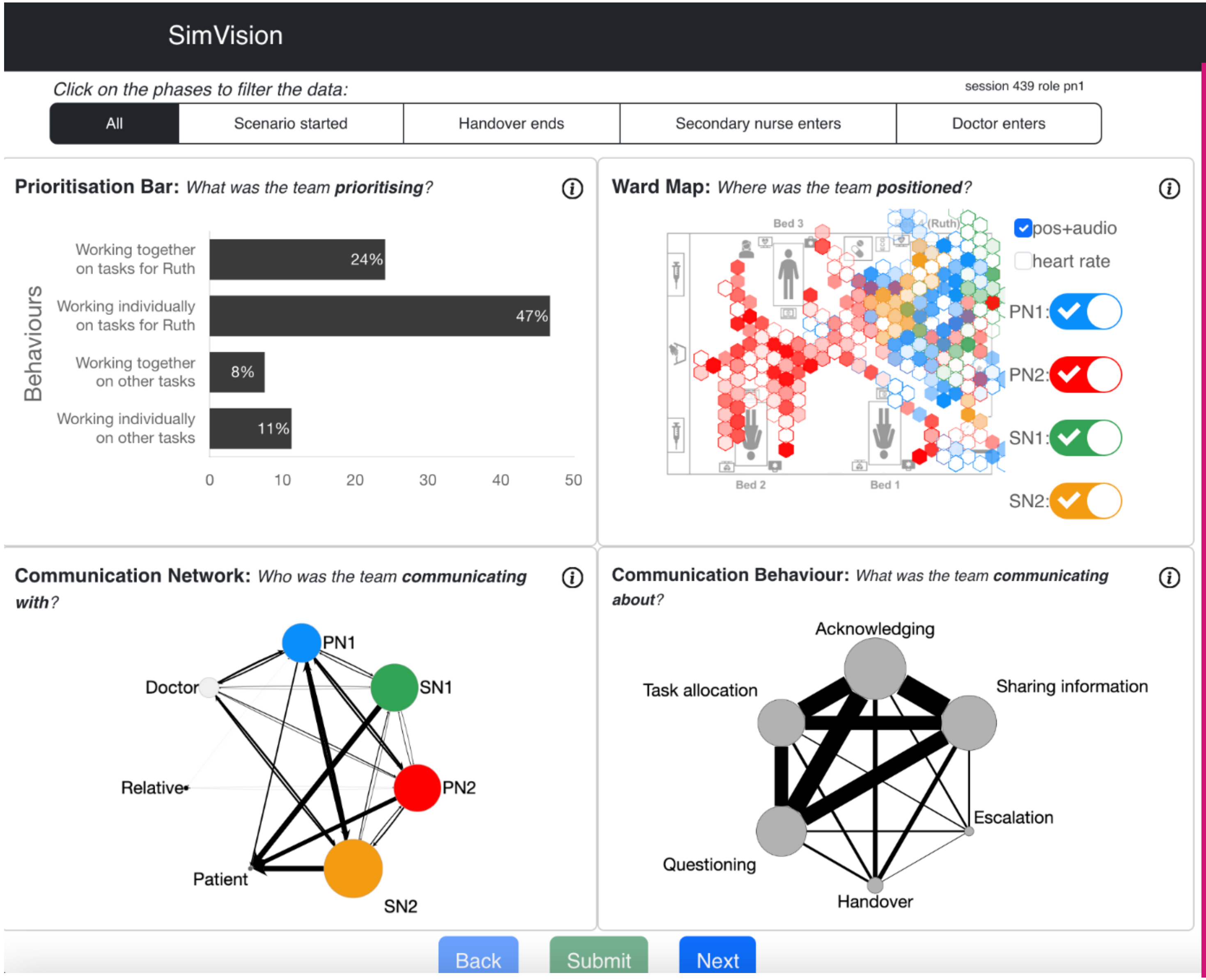
Using AI summary To guide students’ post-hoc reflection

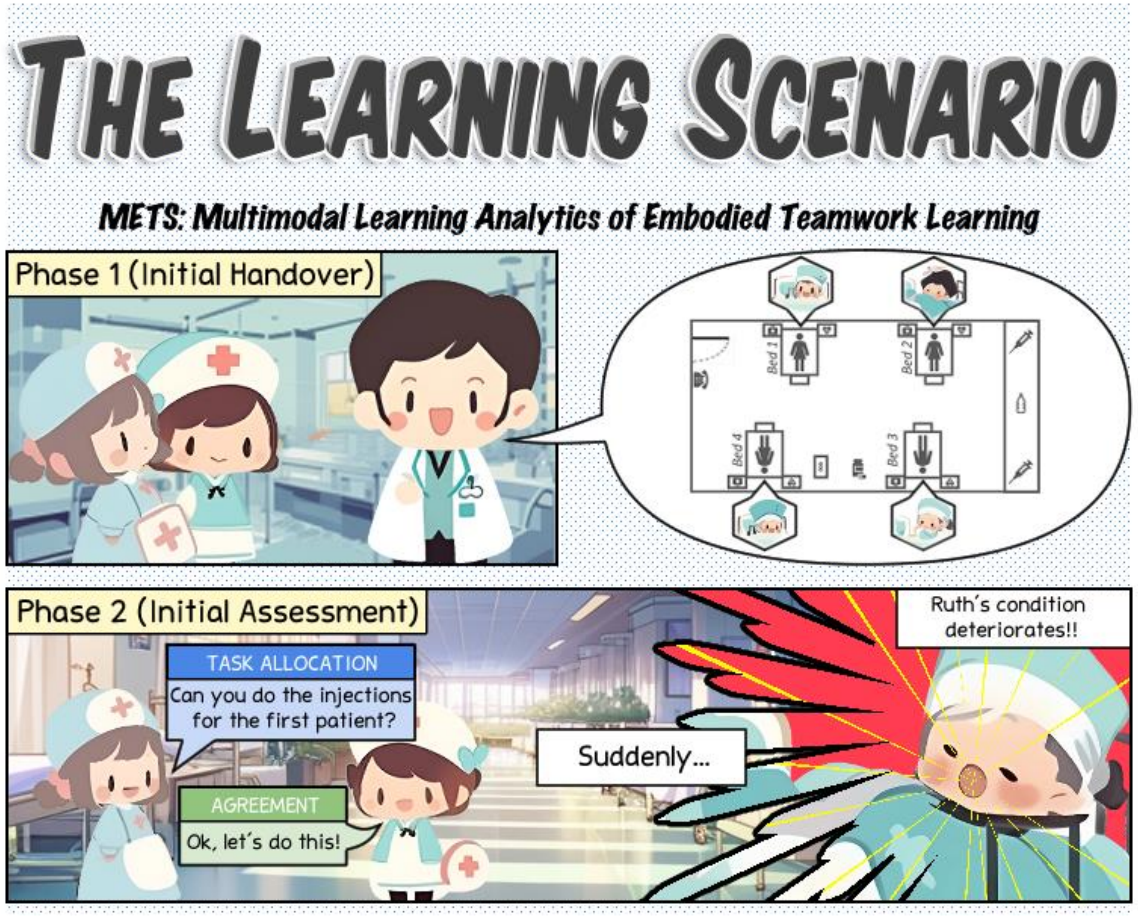


Insights

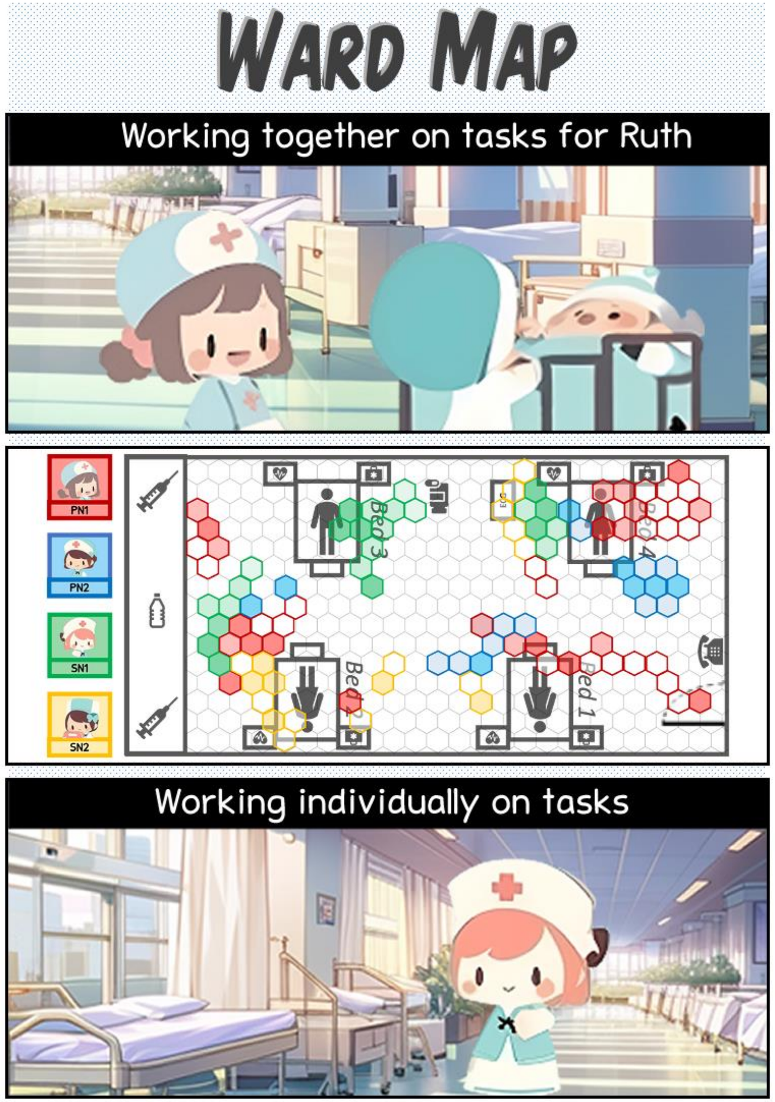
The provided dashboard offers insights into several key constructs:

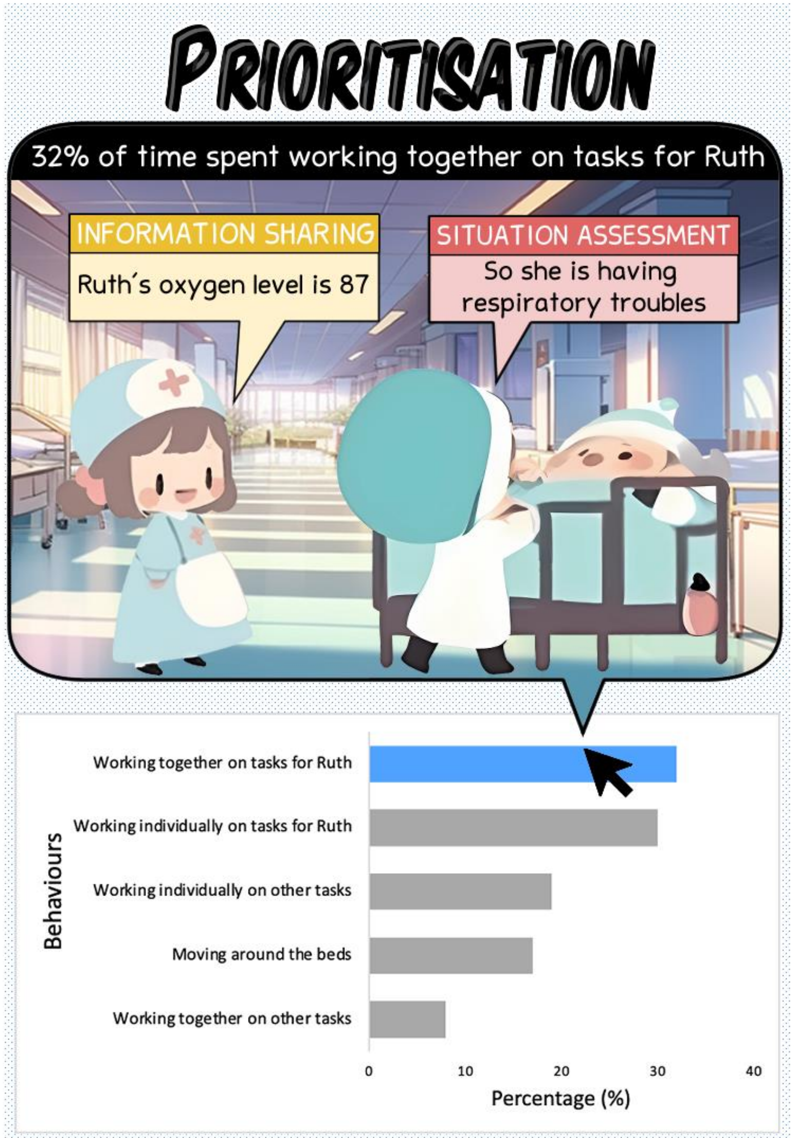
- **Patient Management:**
  - Prioritization: The team prioritized working individually on tasks for Ruth (47%) and working together on Ruth’s tasks (24%), indicating that Ruth's care was a central focus, consistent with the learning objectives.
  - Ward Map: The team was predominantly positioned around Bed 4 (Ruth), with high speech activity, reinforcing the prioritization of Ruth’s care.
- **Contribution to Teamwork:**
  - Communication Network: Primary Nurse 1 (PN1) and Primary Nurse 2 (PN2) had the most extensive communication, indicating active roles in team coordination.
  - Communication Behaviour: Task allocation and information sharing were prominent, showing collaborative efforts in distributing tasks and managing patient care.
- **Communication Strategies:**
  - Communication Network: The thick lines between PN1, SN1, and SN2 highlight significant communication, suggesting a well-connected team structure. The network's design reveals clear hierarchies and interaction patterns essential for effective teamwork.
  - Communication Behaviours: The balanced co-occurrence of acknowledging, sharing information, and escalation indicates a systematic approach to managing both routine tasks and critical situations.

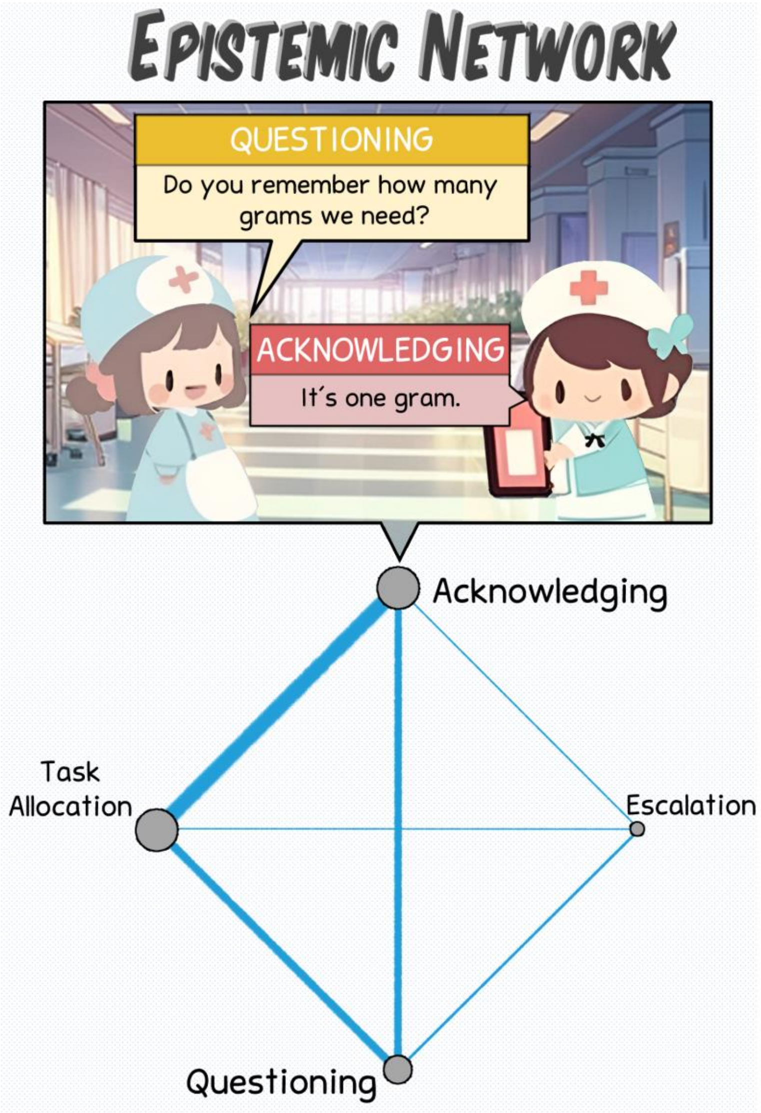
Using Data Comics To present the data to students



Using Data Comics To present the data to students







Moving to the Classroom to present the data about co-teaching

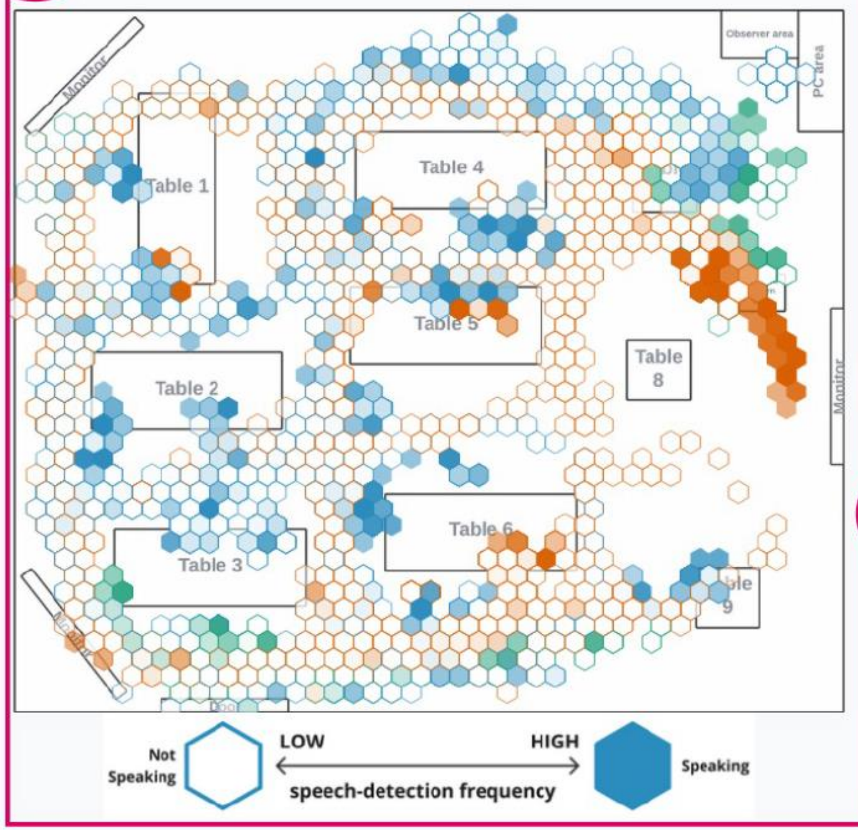
Moving to the Classroom to present the data about co-teaching

Educators (Teachers)	Years of teach. exp.	Num. of sessions:	Pilot		Week 1									Week 2									Week 3									Week 4								
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
T1	19	0	Subject coordinator (no classroom data)																																					
T2	1	8				Blue					Red				Green					Green				Red					Red				Blue					Blue		
T3	8	5			Green																Green								Green	Red									Red	
T4	1	22	Red	Red	Red	Red	Red		Green	Green				Blue	Blue	Blue		Red	Red				Blue	Blue	Blue		Green	Green				Green	Green	Red		Red	Red			
T5	3	4											Red									Blue									Green									Blue
T6	7	13		Blue				Green		Blue			Green				Red		Blue			Green				Blue		Red			Red				Red		Blue			Red
T7	4	9						Red		Red		Red					Green		Green							Green		Blue		Green									Blue	
T8	2	10					Green				Green					Green				Red	Red				Red									Blue	Blue		Green	Red		
T9	9	10	Green	Green	Green	Green								Red	Red								Green	Green								Red	Red							
T10	-	9						Blue	Blue								Blue	Blue								Red	Red				Blue				Green	Green				
T11	-	5							Red									Green									Blue									Blue				Green
T12	-	13	Blue		Blue		Blue				Blue			Green		Red				Blue			Red		Green				Blue			Blue		Green				Green		
T13	-	4										Blue									Blue									Blue									Green	

Moving to the Classroom to present the data to students

Classroom map
with position & audio activity data

1



Spatial pedagogy
observation data

2

ALL	Lecturing	Observing	Interacting	Personal
Red TA	44%	6%	16%	35%
Green TA	36%	5%	10%	49%
Blue TA	15%	11%	31%	43%

3

Co-teaching Strategy

The most common co-teaching strategy was **One Teacher, One Assistant** between:

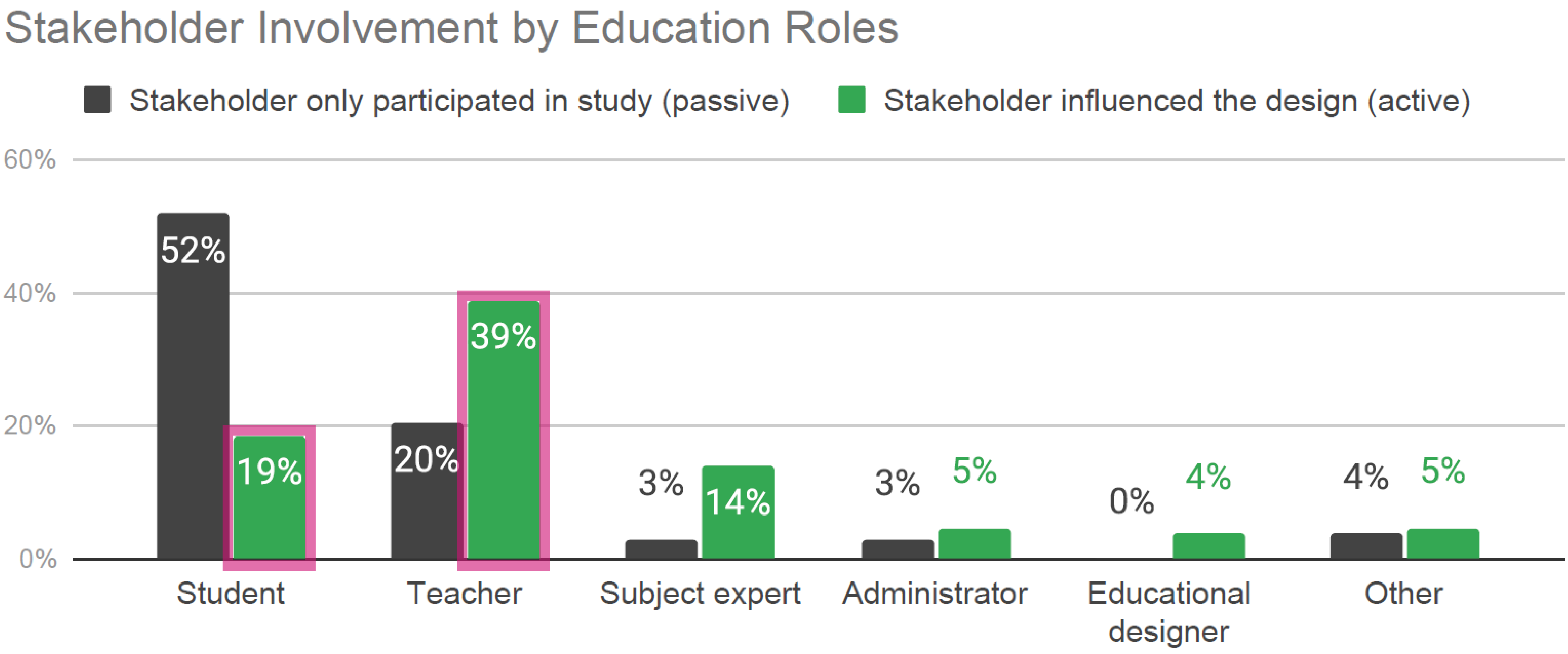
- **Green** and **Red** TAs (26%)
- **Blue** and **Green** TAs (24%)
- **Blue** and **Red** TAs (12%)

*% of the selected period with time slider

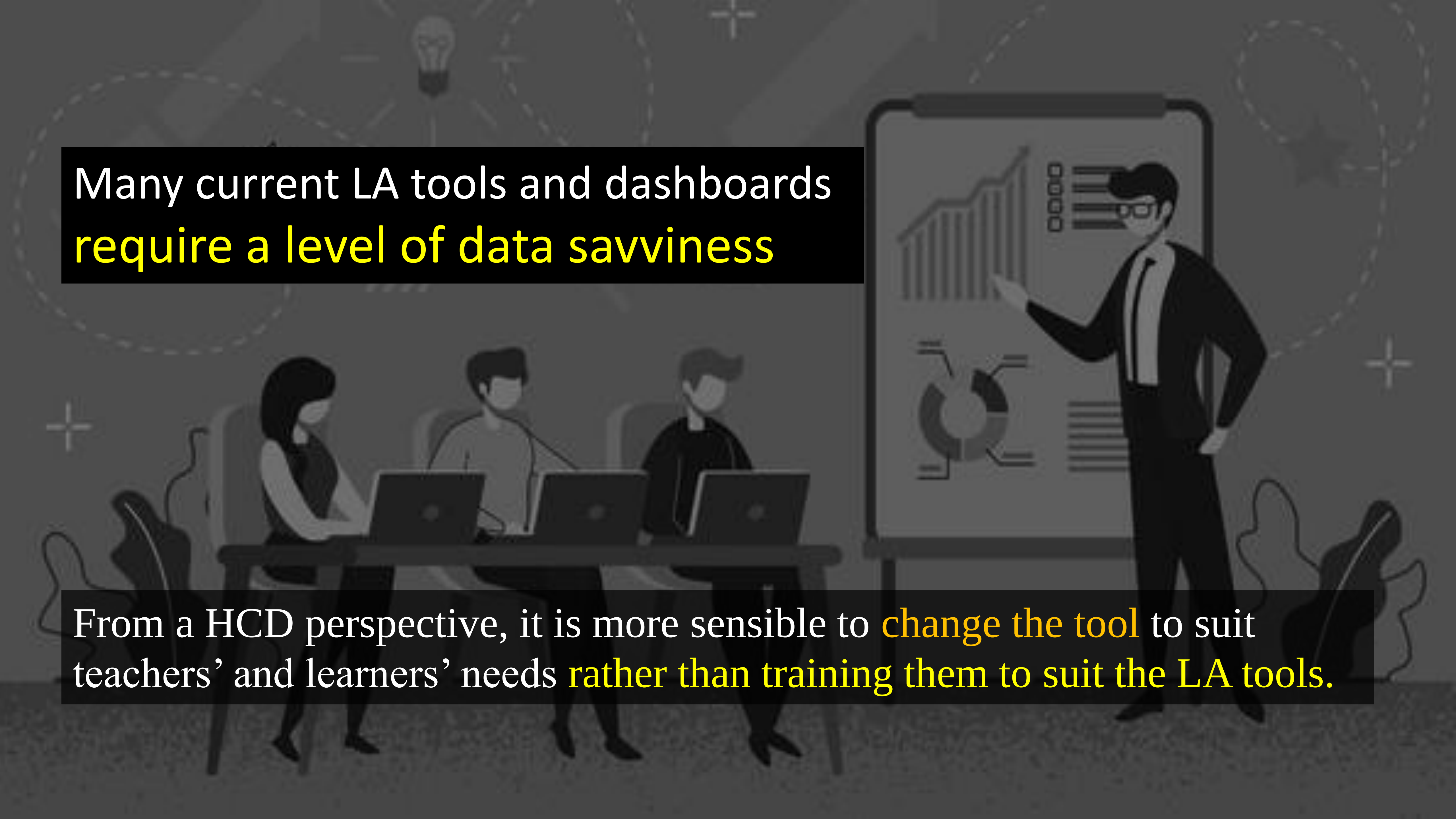
Co-teaching strategy
descriptive data


It may be quite **challenging (challenge #2)** to put yourself in the shoes of others
…designers often commonly cannot **truly** understand what teachers and students really need

THERE HAS BEEN LITTLE ACTIVE INVOLVEMENT OF STUDENTS COMPARED TO TEACHERS



Alfredo et al. (2024) Human-Centred Learning Analytics and AI in Education: a Systematic Literature Review. (under review)

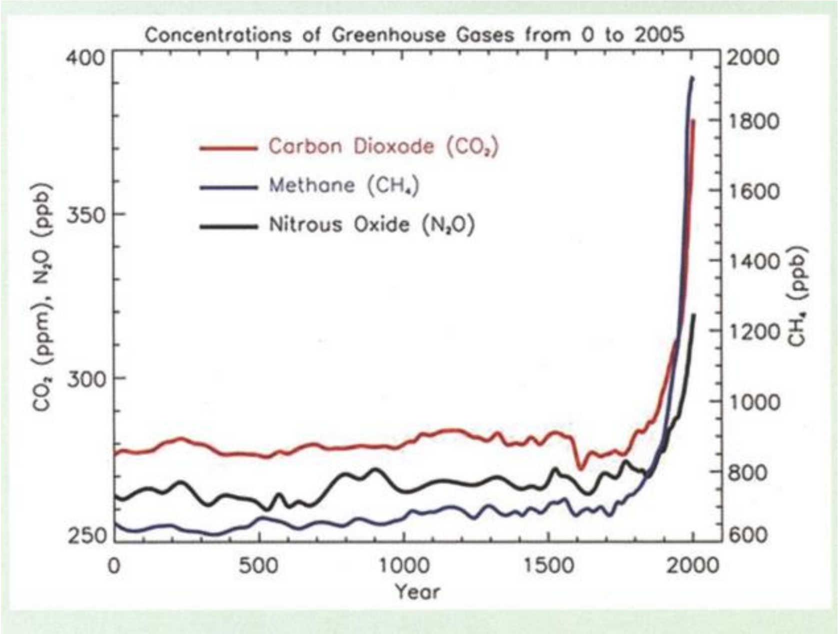


Many current LA tools and dashboards **require a level of data savviness**

From a HCD perspective, it is more sensible to **change the tool** to suit teachers’ and learners’ needs **rather than training them to suit the LA tools.**

TEACHERS AND STUDENTS SHOULD BE CONSIDERED

NON-DATA EXPERTS



HE STEM students find it hard to interpret charts and data visualisations…

"Instructors of undergraduate courses should not expect students to come into courses with high proficiency for understanding, interpreting, and creating data visualizations"(Maltese et al., 2015)

Maltese, Adam V, Joseph A Harsh, and Dubravka Svetina. (2015). Data visualization literacy: Investigating data interpretation along the novice—expert continuum. *Journal of College Science Teaching*, 45(1).

Challenge #3

Non-data experts are unlikely to be aware of the implications of AI design choices

This suggests the need for new methods particularly tailored to engage with teachers and students in the design of data-intensive and pedagogical meaningful LA innovations.

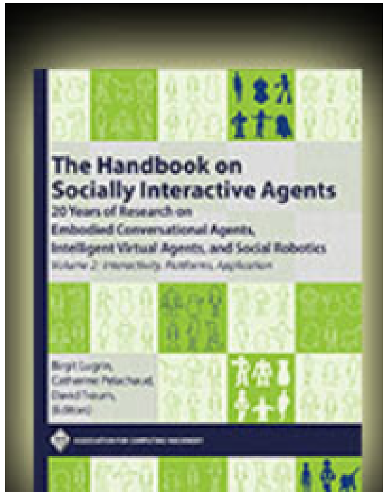
BLOGS

WHY CODESIGNING AI IS DIFFERENT AND DIFFICULT

Authors: Malak Sadek, Rafael Calvo, Céline Mougenot
Posted: Tue, June 27, 2023 - 12:04:00

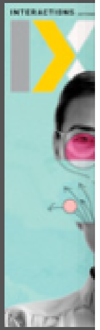
It is estimated that 98 percent of the population are novices with regard to technology (excluding extremes such as infants) [1]. It is this 98 percent, however, that form the main chunk of users and stakeholders affected by AI-based systems. It then makes sense that members of this segment of the population should be involved in designing these systems beyond just the small, homogenous set of experts currently involved.

There have been countless calls for the introduction of a transdisciplinary, participatory design process for AI/ML systems [2,3]. Such a collaborative design (codesign) process has been heralded as especially useful in aiding explainability and transparency [4], embedding values into AI-based systems [5], providing accountability, and mitigating downstream harms arising from several cascading biases and limitations [6]. There have also been calls for collaboration within the entire AI pipeline, including in data creation and selection, instead of having designers at the front end of the process and engineers at the back end [7]. In fact, it has been said that the only way to combat existing structural and



BLOGS

WHY CODESIGNING AI IS DIFFERENT AND DIFFICULT



Ideation and communication

- It is difficult for technical experts to explain to users and nontechnical experts an AI's behavior, what counts as AI, and what it can/cannot do.
- It is also difficult for designers to communicate AI design ideas, interactions, and appropriate use cases/user stories to technical experts, codesign partners, and users. It is also challenging to imagine ways to purposefully use AI to solve a given problem, creating an overall "capability uncertainty" [10].
- It is challenging for designers and developers to understand how to collaborate and co-ideate without a common language or shared boundary objects, especially when designers join late in the project.

back end [7]. In fact, it has been said that the only way to combat existing structural and

The challenge #4:

Power dynamics among researchers, designers, users, and other stakeholders can significantly influence decision-making in the design process.

For instance, it could lead to a situation where researchers, designers, or those stakeholders in positions of power, end up making most, if not all, decisions.

AN EMANCIPATORY PERSPECTIVE FOR LEARNING ANALYTICS

“**Learners are not to be seen as passive beneficiaries of a superior control entity.** With respect to software adaptations, if Learning Analytics has to play a role, it should be limited to one of awareness and recommendation.”

Tchounikine, Pierre. (2019). Learners’ agency and CSCL technologies: towards an emancipatory perspective. *International Journal of Computer-Supported Collaborative Learning,* 14(2).

THE CRITICAL CONCEPTS OF EXPERTISE AND LIVED EXPERIENCE

HCD acknowledges lived experience as a credible form of expertise.

Lived experience refers to a person's experiences, decisions, and knowledge gained from these experiences (Jones, 2013).

A key tenet of co-design is that each stakeholder can contribute with **their own expertise** and, in doing so, there are higher possibilities to design something that addresses authentic needs (McKercher, 2020).

Jones, P. (2013). *Design for care: Innovating healthcare experience*: Rosenfeld Media.

McKercher, K. A. (2020). Beyond sticky notes. *Doing co-design for Real: Mindsets, Methods, and Movements, 1st Edn. Sydney, NSW: Beyond Sticky Notes*.

AI with a Human Touch: within Learning Analytics

Key take aways

- **AI is here to stay**, we need to make sure **WE are also here to stay**
- There is a big difference between **designing with** rather than **designing for**
- **Human-centredness is critical** if we don't want to lose our agency
- **Human-centred AI in Education** has some unique challenges **(casual use, expertise, skewed participation)**

THANKS

DO YOU HAVE ANY QUESTIONS?

CONTACT:
Roberto Martinez-Maldonado
Roberto.MartinezMaldonado.net
Twitter/X: @RobertoResearch

MONASH University

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Open mic

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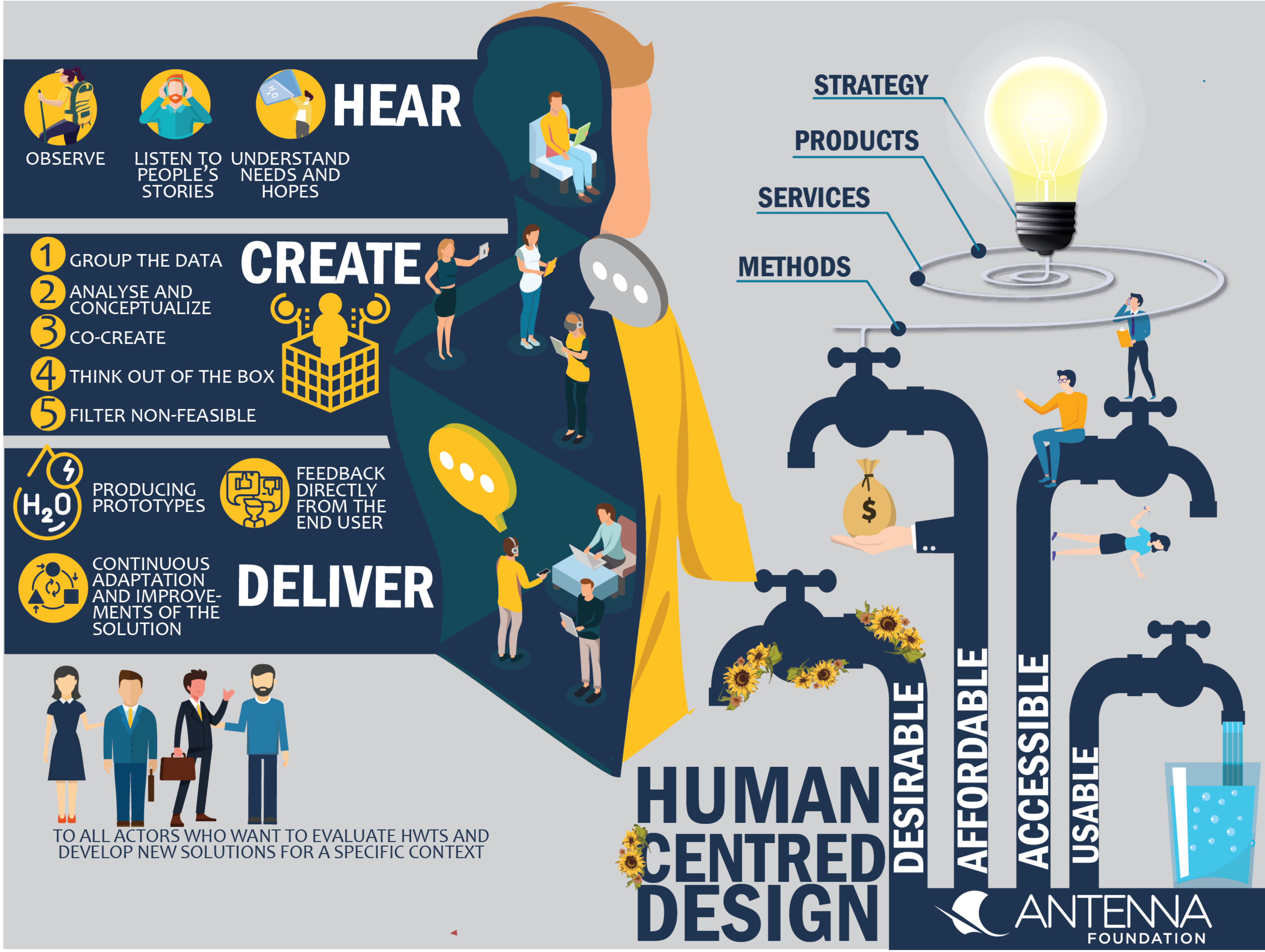
McKercher, K. A. (2020). Beyond sticky notes. *Doing co-design for Real: Mindsets, Methods, and Movements, 1st Edn. Sydney, NSW: Beyond Sticky Notes.*

THE ROLE OF

THE HCD

FACILITATOR



Source: Antenna Foundation ([LINK]())

BUT IS IT CO-DESIGN?

TOOL by KA McKercher.

a. Are people with lived experience, professionals and others involved (e.g. policy-makers, architects) working together?

This could be through researching, sharing and discussing insights, developing ideas, building prototypes or implementing new concepts

- A Yes, people with different experiences are working together
- B Not yet, we're warming up to people being in the same room (for example, trust is low)
- C No, we learn from people with lived experience
- D No, we have seperate advisory groups (e.g. youth advisors)
- E I don't know, show me the next question...

https://g8mvf9i2x72.typeform.com/to/K6PpU2xZ

BUT IS IT CO-DESIGN?

TOOL by KA McKercher.

“ Learning from people (not with them) usually isn't co-design

To get closer to co-design, you might involve people with lived experience in:

- Reviewing data
- Gathering stories
- Developing insights
- Identifying and making ideas
- Testing ideas
- Making decisions

Next question press **Enter** ↵

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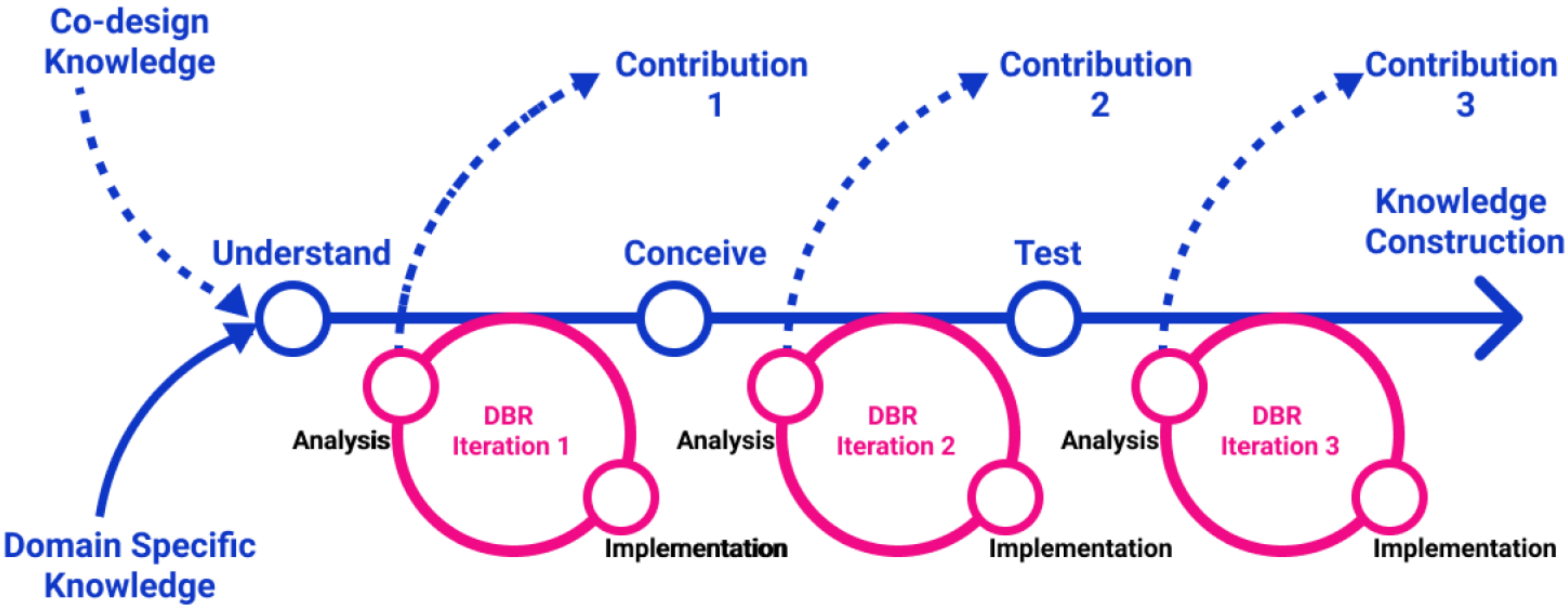
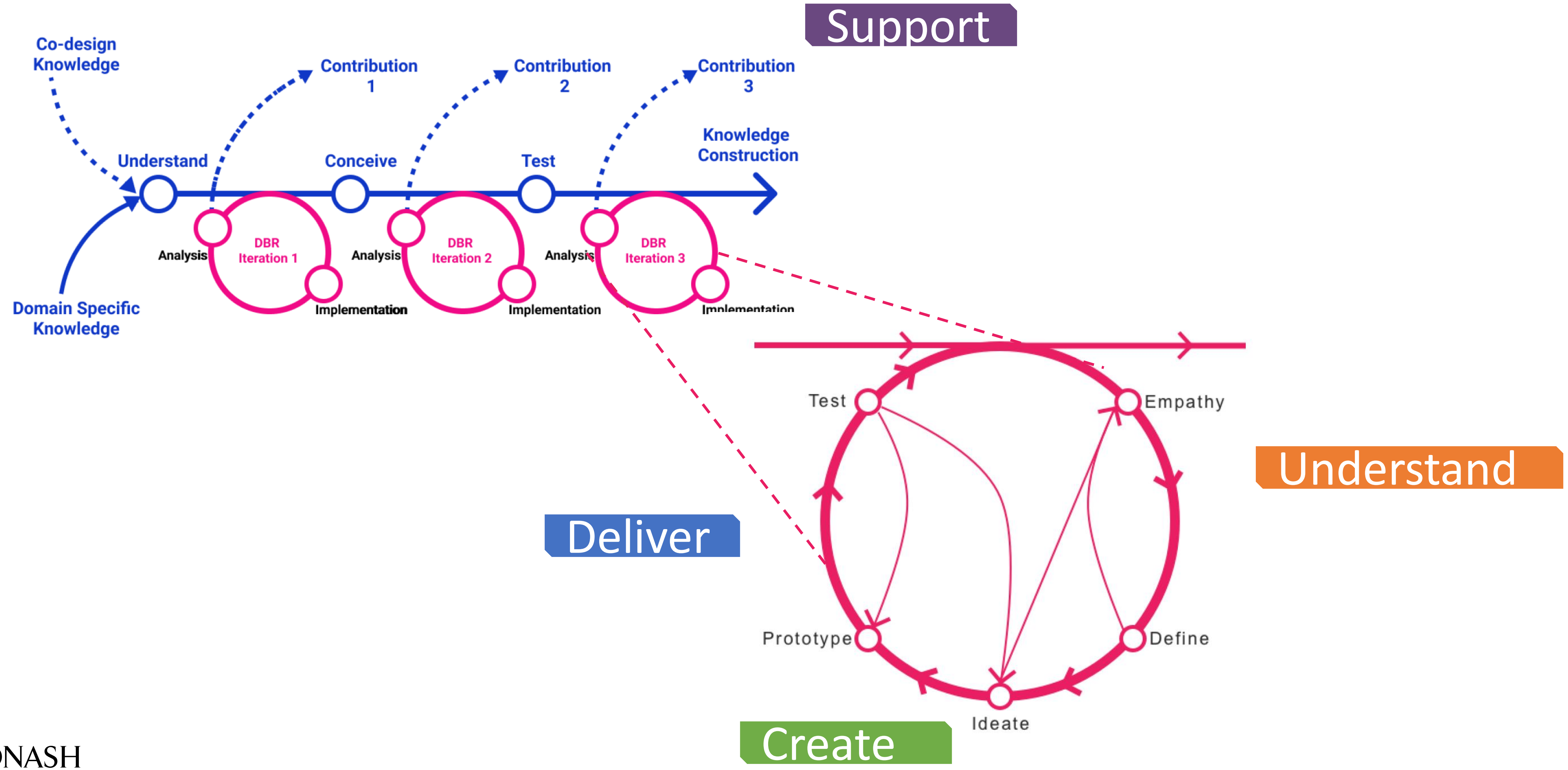
SUPPORTING THE DESIGN PROCESS THROUGHT

DESIGN-BASED RESEARCH CYCLES



EMBEDDING DESIGN THINKING INTO
DBR CYCLES



Prieto Alvarez, Carlos. Engaging stakeholders in the learning analytics design process. PhD Thesis

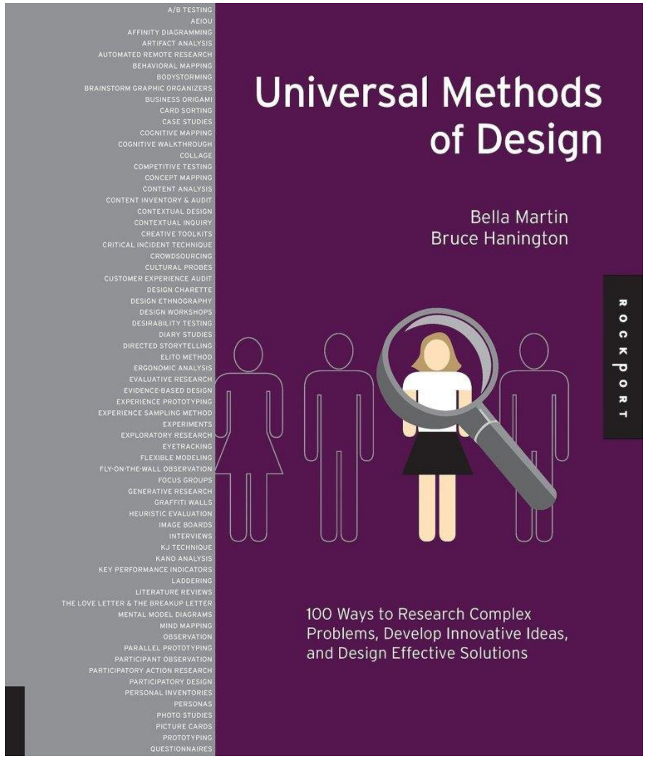
WHAT TOOLS CAN WE USE FOR EMPATHISING AND DEFINING

Giacomin, J. (2014)

Capture of Needs, Desires and Meanings
Verbally based – Ethnographic interviews – Questionnaires – Day-in-the-life analysis – Activity analysis – Cognitive task analysis – The five whys – Conceptual landscape – Word-concept association – Think aloud analysis – Metaphor elicitation – Be your customer – Customer journey – Extreme users – Personas – Scenarios – Brainstorming – Contextual inquiry
Non-verbally based – Game playing – Cultural probes – Visual journals – Error analysis – Fly-on-the-wall observation – Customer shadowing – Body language analysis – Facial coding analysis – Physiological measures – Electroencephalograms

WHAT TOOLS CAN WE USE FOR
OTHER TASKS?

Martin and Hanington (2012)



Contents

& design phases 1 2 3 4 5

A **SKEPTICAL** VIEW OF

HCLA @ LAK'23

RESEARCH-ARTICLE

Learning Analytics and Stakeholder Inclusion: What do We Mean When We Say "Human-Centered"?

Authors: Charles Lang, Laura Davis Authors Info & Claims

LAK2023: LAK23: 13th International Learn

417 • https://doi.org/10.1145/3576050.35

Human-centeredness seems to rest on the idea that stakeholders have access to knowledge that researchers and designers do not, and access to this knowledge will create better research and design products. This may be true, but there is no reason why it must be true, or even true a majority of the time. Especially within a field such as learning analytics where tools, data and people are interacting in new ways. It seems more likely that such a context would be unfamiliar to all stakeholders, from researchers to users.

WHY
HUMAN-CENTRED DESIGN?

"Eric Von Hippel of the MIT Business School has noted that "70% to 80% of new product development that fails does so not for lack of advanced technology, but because of a **failure to understand users' needs**."

Joseph Giacomin, 2012 seminar

Von Hippel, E. 2007, An emerging hotbed of user-centered innovation, Breakthrough ideas for 2007, Harvard Business Review, Article R0702A, February

DON NORMAN's ESSAY ON

HCD

Human-Centered Design Considered Harmful

By Donald A. Norman > Nielsen Norman Group > norman@nngroup.com

Human-centered design has become such a dominant theme in design that it is now accepted by interface and application designers automatically, without thought, let alone criticism. That's a dangerous state—when things are treated as accepted wisdom. The purpose of this essay is to provoke thought, discussion, and reconsideration of some of the fundamental principles of human-centered design. These principles, I suggest, can be helpful, misleading, or wrong. At times, they might even be harmful. Activity-centered design might be superior.

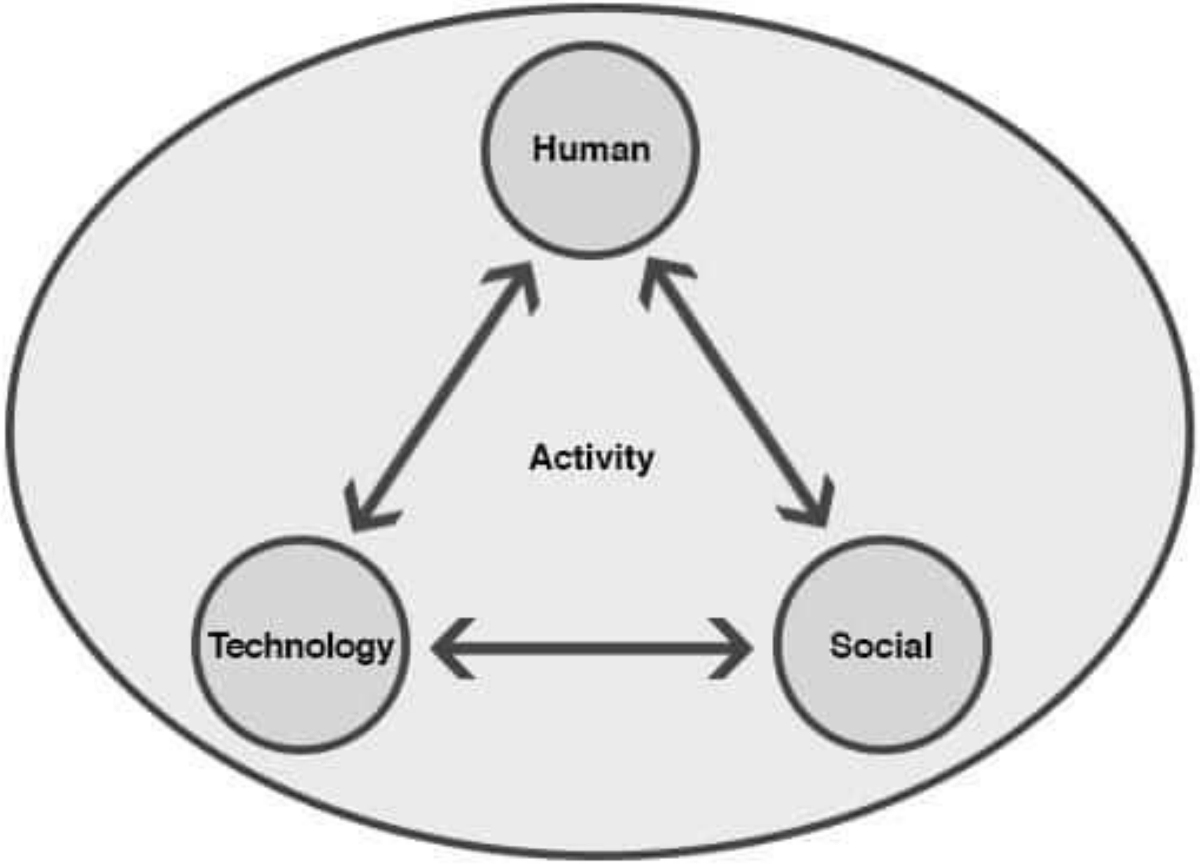
Most items in the world have been designed without the benefit of user studies and the methods of human-centered design. Yet they do quite well. Moreover, these include some of the most successful objects of our modern, technological worlds. Consider two representative examples:

The Automobile. People all over the world learn to drive quite successfully with roughly the same configuration of controls. There were no systematic studies of users. Rather, early automobiles tried a variety of configurations, initially copying the seat-

SOURCE: https://arl.human.cornell.edu/linked%20docs/HCD%20considred%20Harmful.pdf

HUMAN-**CENTRED** IS NOT THE SAME AS

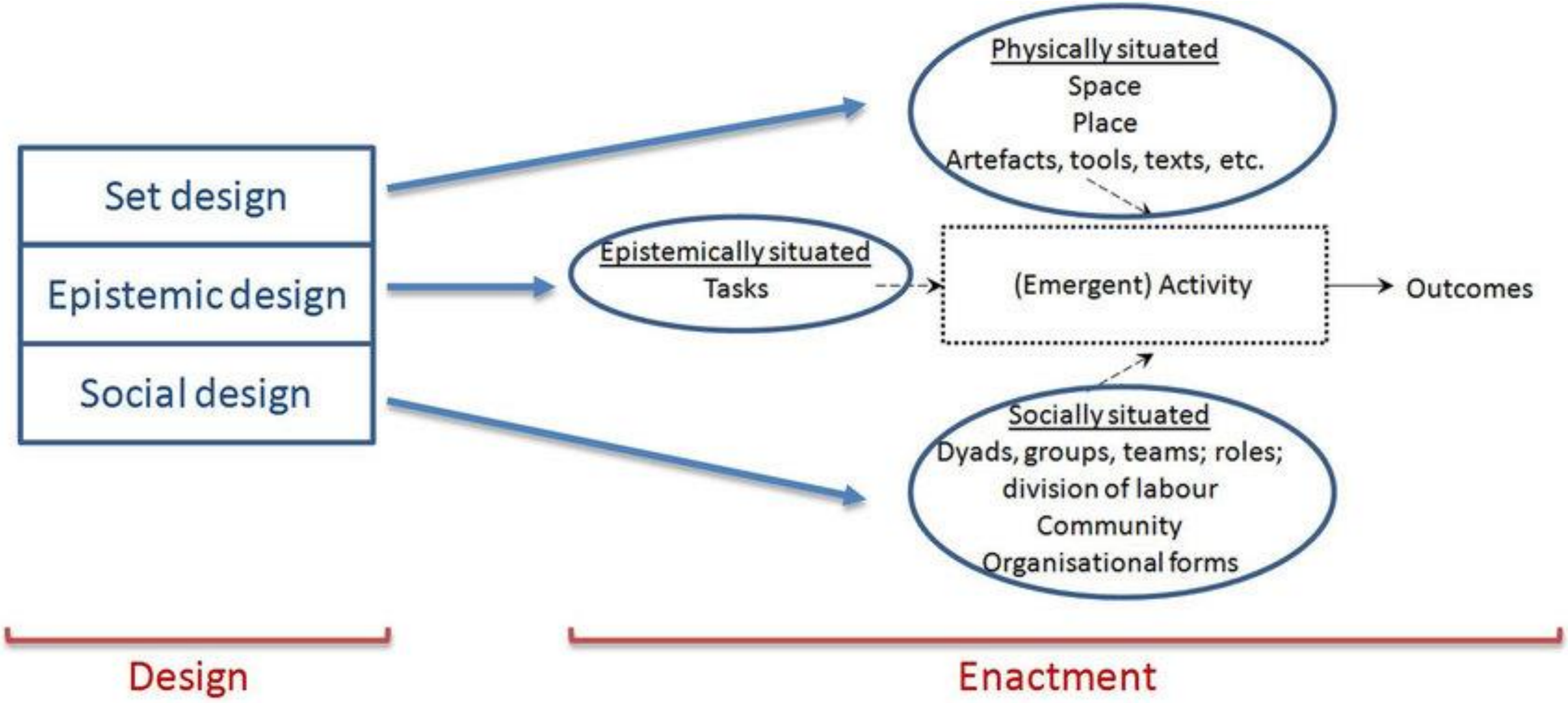
HUMAN CENTRIC



Human centredness includes all the human factors, social factors and technology factors interact together under the human activity umbrella.

Winograd and Woods. 1997. *The challenge of human-centered design*. Human-centered systems: information, interactivity, and intelligence.

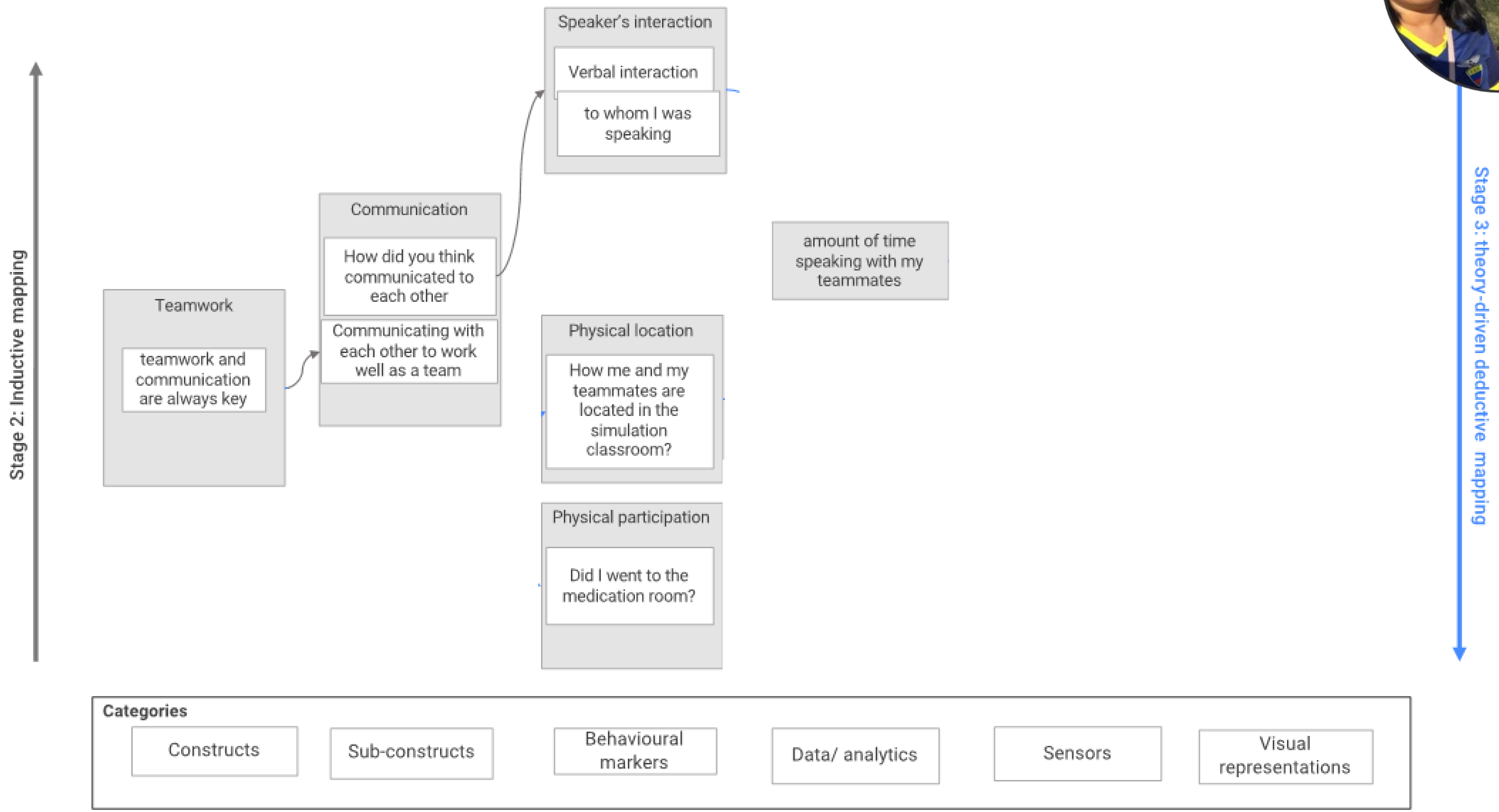
USING
ACTIVITY-CENTRED DESIGN



Muñoz-Cristóbal, J. A., Hernández-Leo, D., Carvalho, L., Martinez-Maldonado, R., Thompson, K., Wardak, D., & Goodyear, P. (2018). 4FAD: A framework for mapping the evolution of artefacts in the learning design process. Australasian Journal of Educational Technology, 34(2).

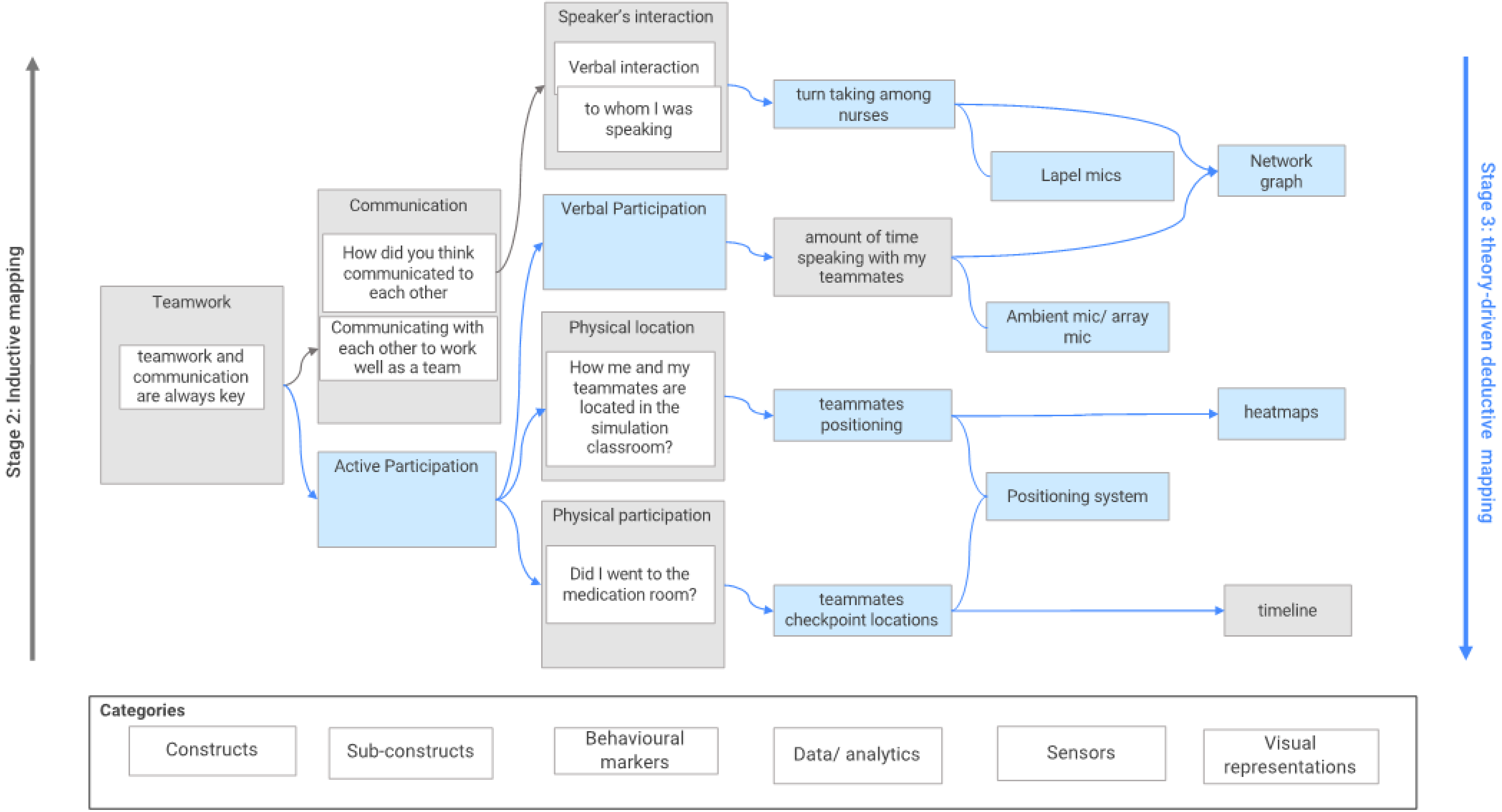
Human-Centred
Learning Analytics

INDUCTIVE
STEP WITH TEACHERS



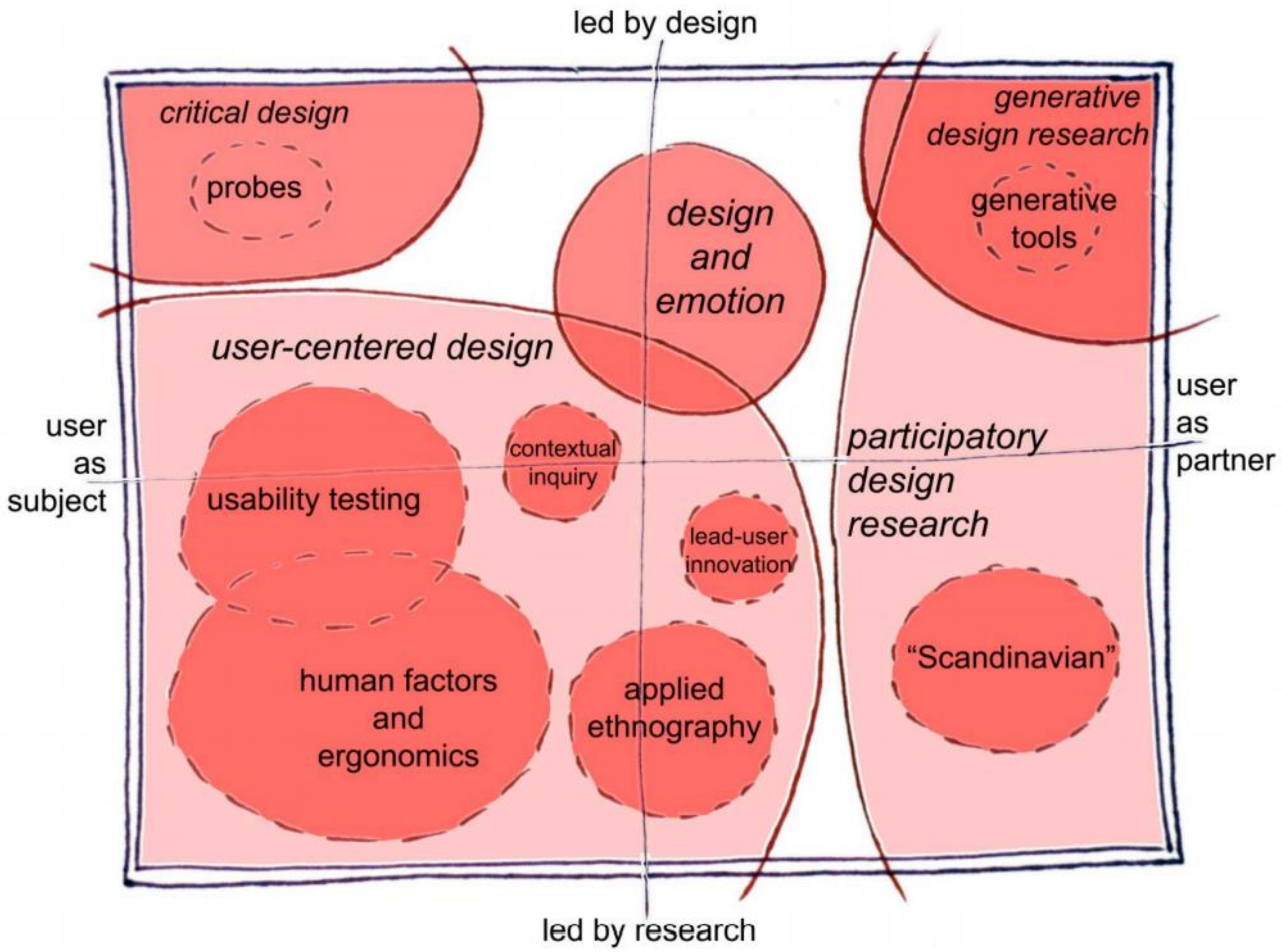
DEDUCTIVE

STEP: FILLING THE GAPS USING THEORY



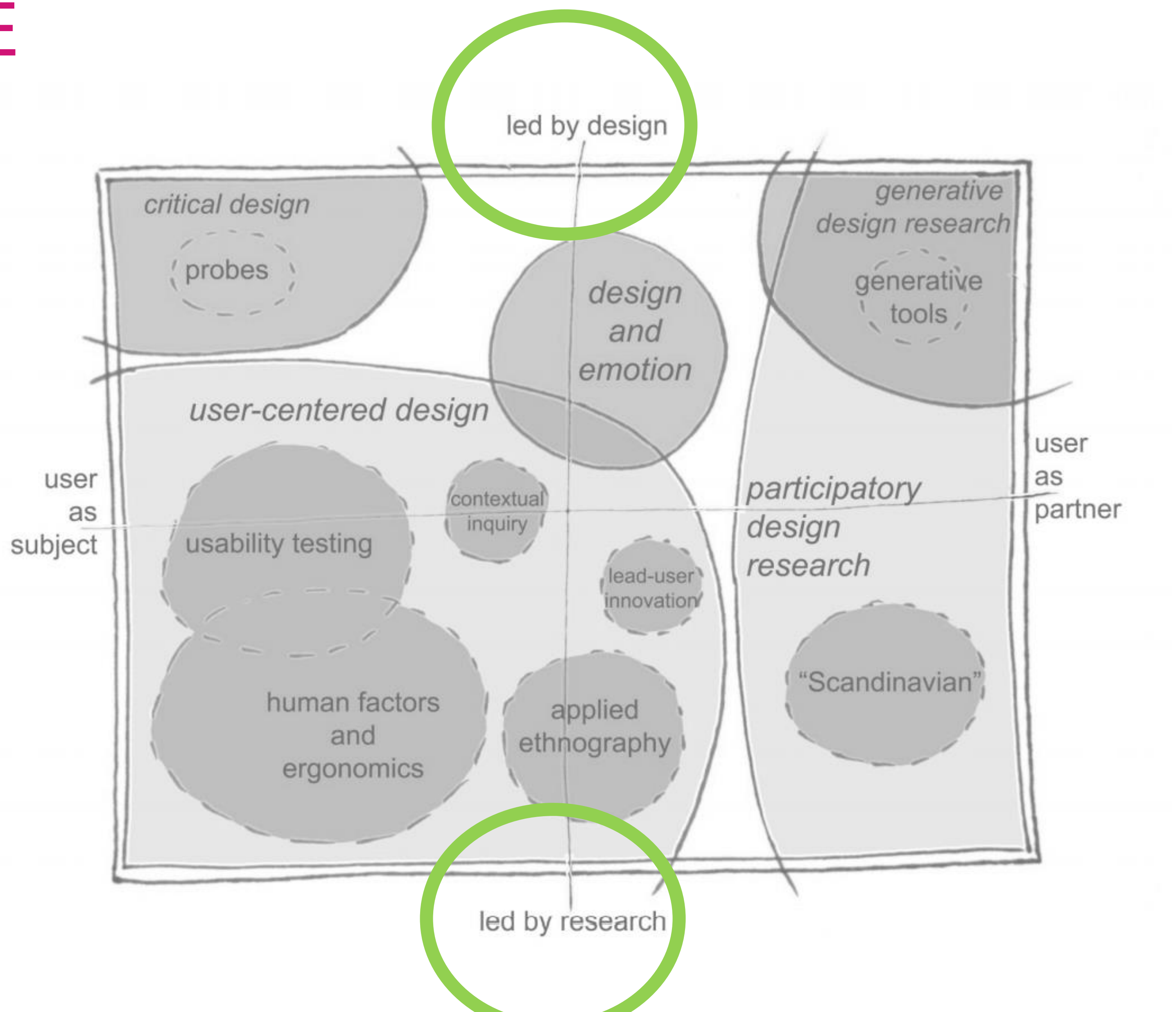
THE HUMAN-CENTRED DESIGN

LANDSCAPE



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

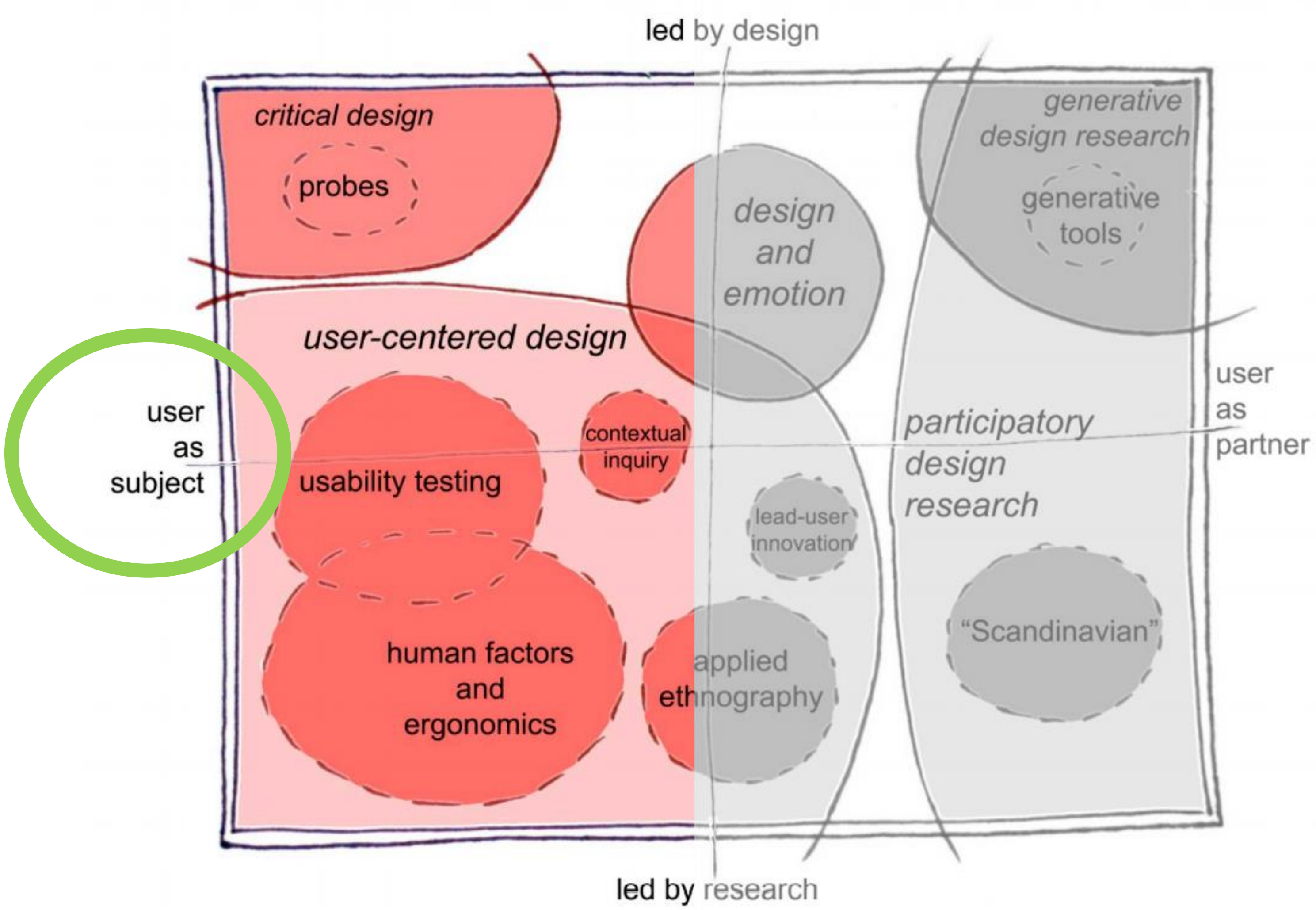
THE HUMAN-CENTRED DESIGN
LANDSCAPE



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

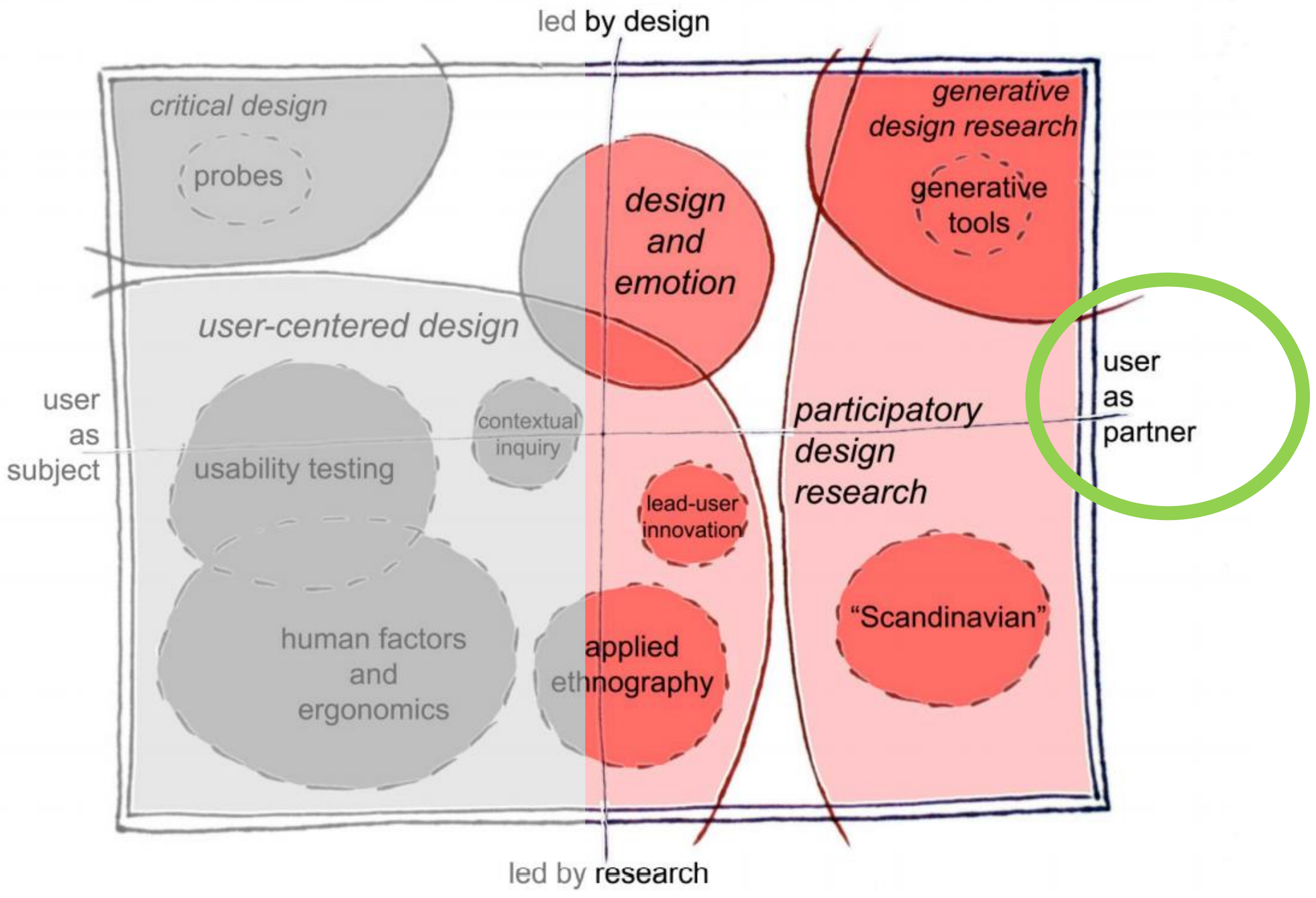
THE HUMAN-CENTRED DESIGN

LANDSCAPE



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

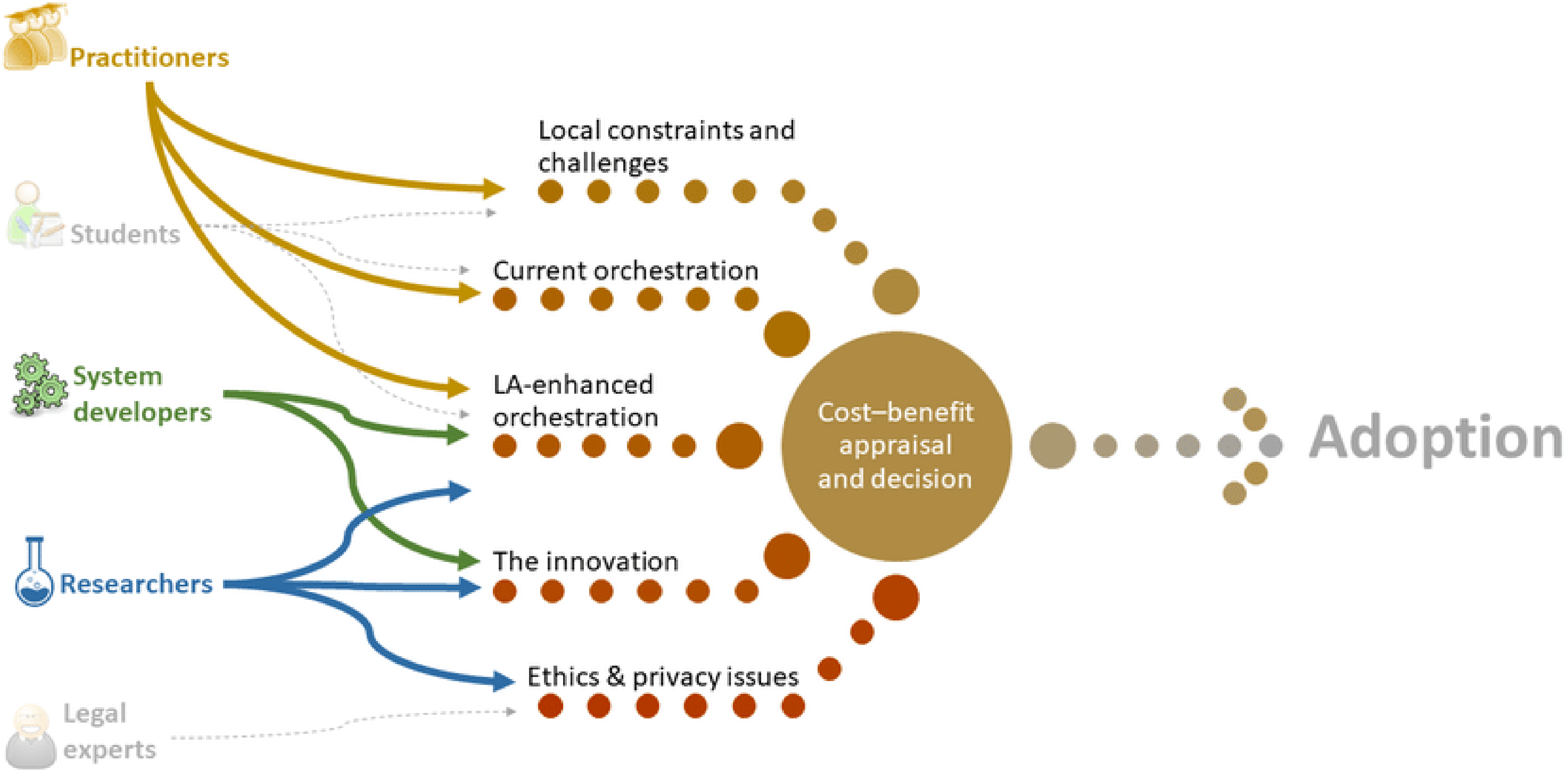
THE HUMAN-CENTRED DESIGN
LANDSCAPE



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

THE

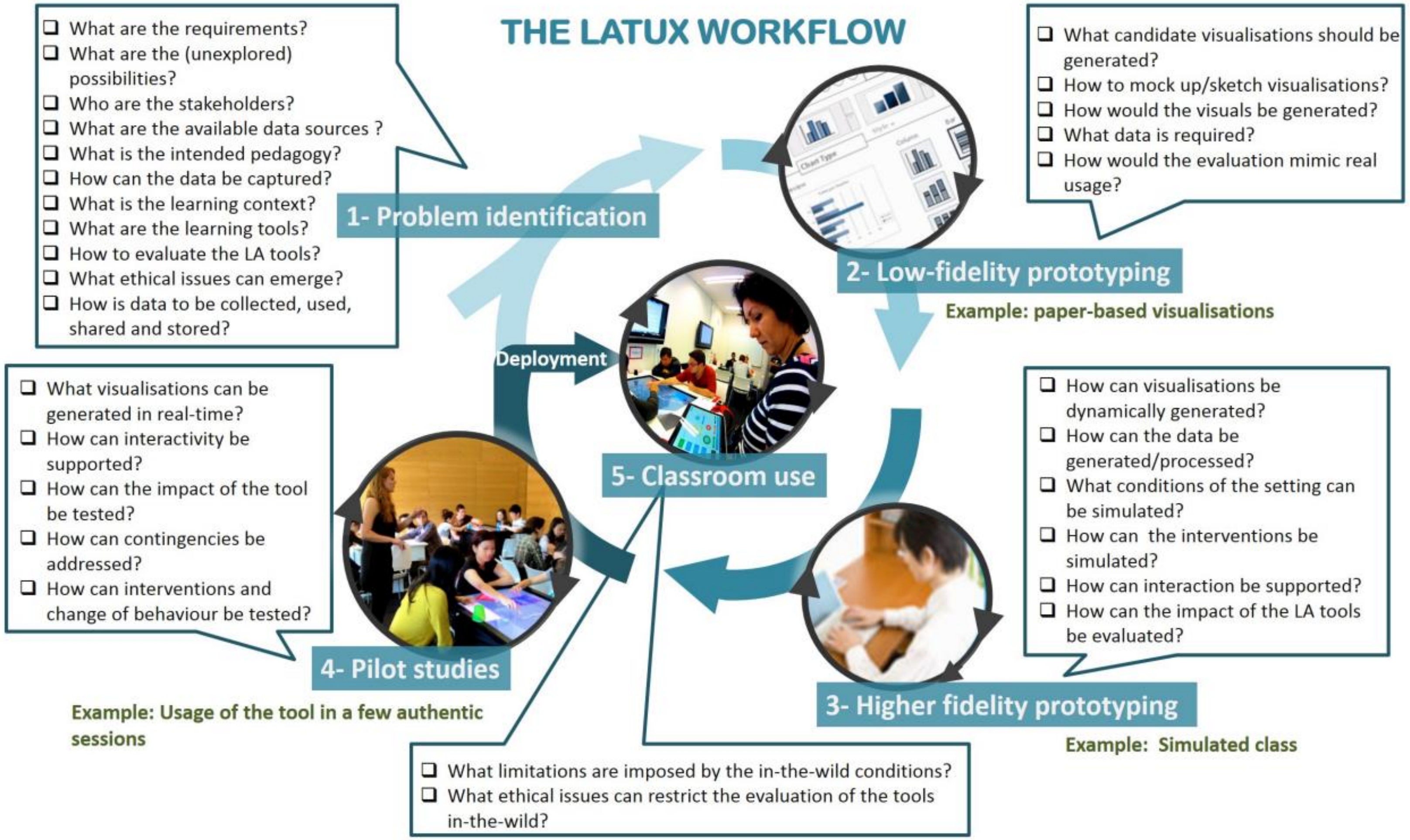
ORLA FRAMEWORK



Prieto, L. P., Rodríguez-Triana, M. J., Martínez-Maldonado, R., Dimitriadis, Y., & Gašević, D. (2019). Orchestrating learning analytics (OrLA): Supporting inter-stakeholder communication about adoption of learning analytics at the classroom level. *Australasian Journal of Educational Technology.*

THE

LATUX WORKFLOW



Martinez-Maldonado, R., Pardo, A., Mirriahi, N., Yacef, K., Kay, J. and Clayphan, A. (2016) LATUX: an Iterative Workflow for Designing, Validating and Deploying Learning Analytics Visualisations. International Journal on Learning Analytics, JLA, 2(3)

LEARNING ANALYTICS ARE ABOUT LEARNERS AND EDUCATORS

Chapter 1: Theory and Learning Analytics

Simon Knight, Simon Buckingham Shum

Connected Intelligence Centre, University of Technology Sydney, Australia

DOI: 10.18608/hla17.001

ABSTRACT

The challenge of understanding how theory and analytics relate is to move "from clicks to constructs" in a principled way. Learning analytics are a specific incarnation of the bigger shift to an algorithmically pervaded society, and their wider impact on education needs careful consideration. In this chapter, we argue that by design – or else by accident – the use of a learning analytics tool is always aligned with assessment regimes, which are in turn grounded in epistemological assumptions and pedagogical practices. Fundamentally then, we argue that deploying a given learning analytics tool expresses a commitment to a particular educational worldview, designed to nurture particular kinds of learners. We outline some key provocations in the development of learning analytic techniques, key questions to draw out the purpose and assumptions built into learning analytics. We suggest that using "claims analysis" – analysis of the implicit or explicit stances taken in the design and deploying of technologies – is a productive human-centred method to address these key questions, and we offer some examples of the method applied to those provocations.

Keywords: Theory, assessment regime, claims analysis

In what has become a well-cited, popular article in *Wired* magazine, in the new era of petabyte-scale data and analytics, Anderson (2008) envisaged the death of theory, models, and the scientific method. No longer do we need to create theories about how the world works, because the data will tell us directly as we discern, in almost real time, the impacts of probes and changes we make.

This high profile article and somewhat extreme conclusion, along with others (see, for example, Mayer-Schönberger & Cukier, 2013), has, not surprisingly, attracted criticism (boyd & Crawford, 2011; Pietsch, 2014).

Educational *researchers* are one community interested in the application of "big data" approaches in the form of learning analytics. A critical question turns on exactly how theory could, or should shape research in this new paradigm. Equally, a critical view is needed on how the new tools of the trade enhance/constrain theorizing by virtue of what they draw attention to, and what they ignore or downplay. Returning to our opening provocation from Anderson, the opposite conclusion is drawn by Wise and Shaffer (2015, p. 6):

> What counts as a meaningful finding when the number of data points is so large that something will always be significant? [...] In sum, when working with big data, theory is actually more important, not less, in interpreting results and identifying meaningful, actionable results. For this reason we have offered Data Geology (Shaffer, 2011; Arastoopour et al., 2014) and Data Archeology (Wise, 2014) as more appropriate metaphors than Data Mining for thinking about how we sift through the new masses of data while attending to underlying conceptual relationships and the situational context.

Data-intensive methods are having, and will continue to have, a transformative impact on scientific inquiry (Hey, Tansley, & Tolle, 2009), with familiar "big science" examples including genetics, astronomy, and high energy physics. The BRCA2 *gene*, *Red Dwarf* stars, and the Higgs bosun do not hold strong views on being computationally modelled, or who does what with the results. However, when people become aware that their behaviour is under surveillance, with potentially important consequences, they may choose to adapt or distort their behaviour to camouflage activity, or to game the system. Learning analytics researchers aiming to study learning using such tools must do so aware that they have adopted a particular set of lenses

Let us turn now to *educators and learners*. The potential of learning analytics is arguably far more significant than as an enabler of data-intensive educational research, exciting as this is. The new possibility is that educators and learners – the stakeholders who constitute the learning system studied for so long by researchers – are for the first time able to see their own processes and progress rendered in ways that until now were the preserve of researchers outside the system. Data gathering, analysis, interpretation, and even intervention (in the case of adaptive software) is no longer the preserve of the researcher, but shifts to embedded sociotechnical educational infrastructure. So, for *educators and learners*, the interest turns on the ability to gain insight in a timely manner that could improve outcomes.

Buckingham Shum. "Theory and learning analytics." Handbook of learning analytics (2017): 17-22.

SOME CURRENT
HCLA LITERATURE AND RESOURCES

Special issue editorial

- Buckingham Shum, S., Ferguson, R. and Martinez-Maldonado R. (2019). Human-Centred Learning Analytics. JLA.

SOLAR Webinar

- Alyssa Wise. Designing Learning Analytics for Humans with Humans. LINK

SOME CURRENT

HCLA LITERATURE AND RESOURCES

Special issue editorial

- ❑ Buckingham Shum, S., Ferguson, R. and Martinez-Maldonado R. (2019). Human-Centred Learning Analytics. JLA.

SOLAR Webinar

- ❑ Alyssa Wise. Designing Learning Analytics for Humans with Humans. LINK

Some key papers

- Dimitriadis, Y., Martínez-Maldonado, R., & Wiley, K. (2021). Human-Centered Design Principles for Actionable Learning Analytics. Book chapter
- Barreiros, C., Leitner, P., Ebner, M., Veas, E., & Lindstaedt, S. (2023). Students in Focus–Moving Towards Human-Centred Learning Analytics. Book chapter
- Ahn, J., Campos, F., Hays, M., & DiGiacomo, D. (2019). Designing in Context: Reaching beyond Usability in Learning Analytics Dashboard Design. *JLA.*
- Sarmiento, J. P., & Wise, A. F. (2022, March). Participatory and Co-Design of Learning Analytics: An Initial Review of the Literature. In LAK22.
- Dollinger, M., Liu, D., Arthars, N., & Lodge, J. (2019). Working Together in Learning Analytics Towards the Co-Creation of Value. Journal of Learning Analytics, 6(2), 10–26.
- Lawrence, L., …, Rummel, N., & Aleven, V. (2022). Process to co-design AI-based orchestration tools to support dynamic transitions: Design narratives through Conjecture Mapping. In CSCL conference.
- Carlos G. Prieto-Alvarez et al., Co-designing learning analytics tools with learners. Book Chapter

British Journal of Educational Technology

Call for submissions for 2023 Special Section:

Human-Centred Design of Learning Analytics

Guest Editors

- **Simon Buckingham Shum** (University of Technology Sydney, Australia)
  Corresponding Guest Editor: Simon.BuckinghamShum@uts.edu.au
- **Roberto Martínez-Maldonado** (Monash University, Australia)
- **Yannis Dimitriadis** (Universidad de Valladolid, Spain)
- **Patricia Santos** (Universitat Pompeu Fabra, Spain)

Link to the call

British Journal of Educational Technology

Call for submissions for 2023 Special Section:

Topic questions:

- ❑ Can design processes from other disciplines, such as **HCI, Co-Design and Participatory design**, be unproblematically adopted for HCLA, or do they require adaptation?
- ❑ What are the **obstacles to the adoption** of HCLA design processes?
- ❑ How can the **voice of students** be taken more into account, besides the dominant thread of involving teachers? (a gap identified in the 2019 JLA special issue)
- ❑ What are the **lessons learnt from mid-to-long term HCLA studies** and how do they inform the aforementioned topic of adoption?
- ❑ To what extent can the **design tools** used in other areas be adopted or adapted for the purpose of LA design?
- ❑ Human-AI **complementarity**.

TALKS RELATED TO HCLA
@ LAK'23

Keynote

Keynote: Human-Centred Learning Tools: Empowering vs Analysing Students?

Wed Mar 15, 2023 9:00 AM - 10:00 AM

SEIR 298
Speakers: Yvonne Rogers

Invited Panel

Session 4A-02: Invited Panel: How Universal Design for Learning can inform human-centered design in learning analytics

Thu Mar 16, 2023 10:50 AM - 11:50 AM

SEIR 298

PAPERS RELATED TO HCLA
@ LAK'23

Full

Session 8B-03: Learning Analytics and Stakeholder Inclusion: What do We Mean When We Say "Human Centered"?

Fri Mar 17, 2023 1:40 PM - 2:00 PM

SEIR 198
Speakers: Charles Lang

Practitioner

Session 8B-04: A peer in the loop: The human touch that analytics needs

Fri Mar 17, 2023 2:00 PM - 2:20 PM

SEIR 198
Speakers: Jenna Matthews

What SENSORS do we use?