ICQE 2019:1st International Conference in Quantitative Ethnography http://icqe19.org • Oct. 20-22, 2019, Madison, WI, USA

The Multimodal Matrix as a Quantitative Ethnography Methodology

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The promise of "Big Data"...

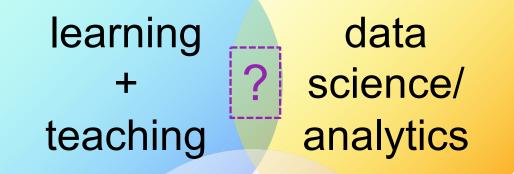
complex societal systems data analysis at speed/scale → timely insight /action The particular systems we're all interested in...

human activity systems data analysis at speed/scale → timely insight /action \rightarrow Raising the key methodological challenge...



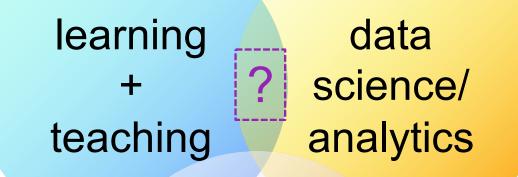
How to handle this intersection with integrity?

\rightarrow The particular context in which we're working...



humancentered design

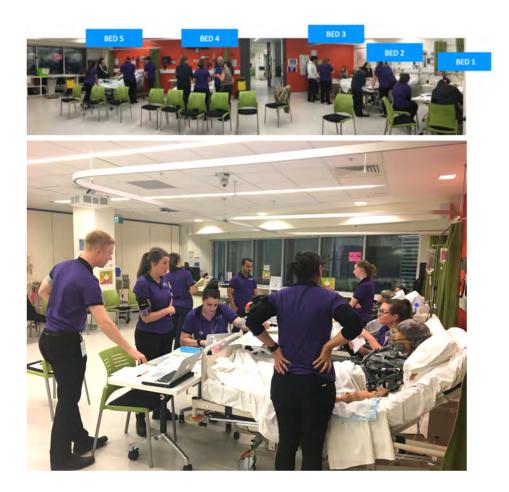
\rightarrow The particular context in which we're working...



humancentered design

education learning sciences assessment sciences

human-computer interaction educational data/AI ethics educ. science and technology studies Training nurses to work respond as a team to a critical change in a patient's condition



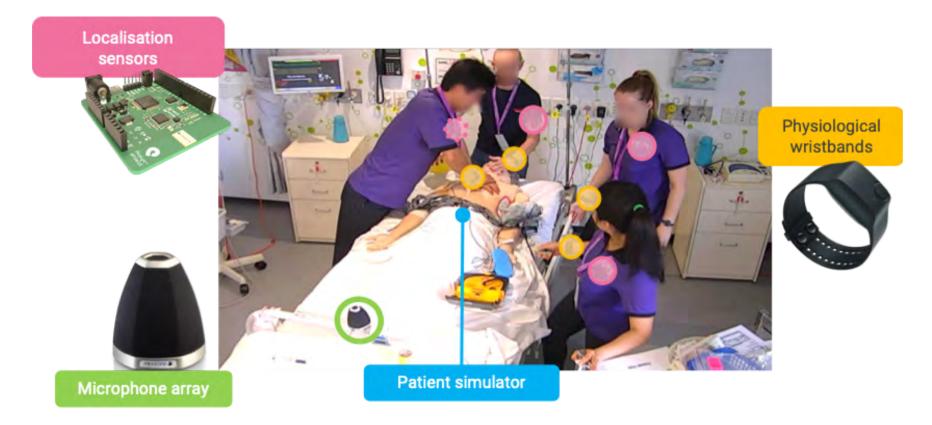
Simulation wards are used widely in universities and hospitals

At UTS, 5-6 teams in action at once

1 instructor coordinating

Intuition: scope to augment feedback to teachers and students using multimodal sensors and analytics?

While capturing collocated teamwork is certainly an **interesting multimodal analytics opportunity**...



...the multimodal data deluge begs the question:

how to make sense of this, and in close to real time?

What contributions can Q.E. make?

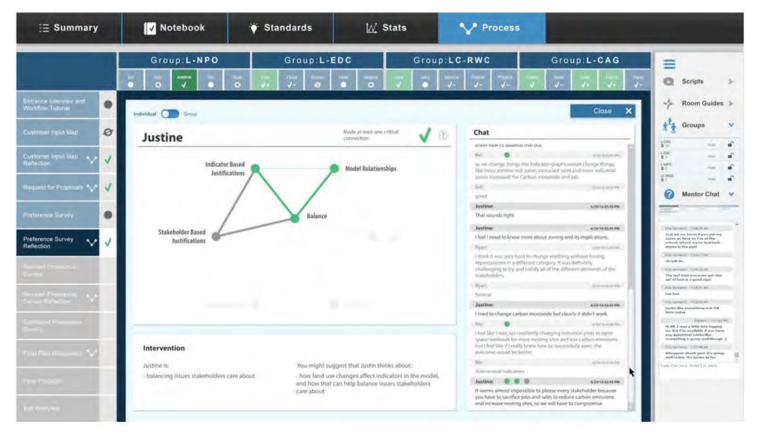




"Meaningful Feedback"

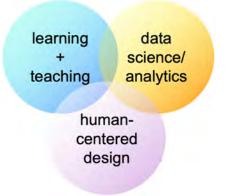
Can this work make contributions back to Q.E.?

Real-time ENA for teachers from online teamwork is possible. QE-enabled feedback for collocated teamwork?



Herder, T. *et al.* (2018). Supporting teachers' interventions in students' virtual collaboration using a network based model. In *LAK'18: International Conference on Learning Analytics and Knowledge*, March 7–9, 2018, Sydney, NSW, Australia. ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3170358.3170394

Understanding the human activity system





Conceptual insights from assessment research

Observation of simulations as they currently run

Educator interviews

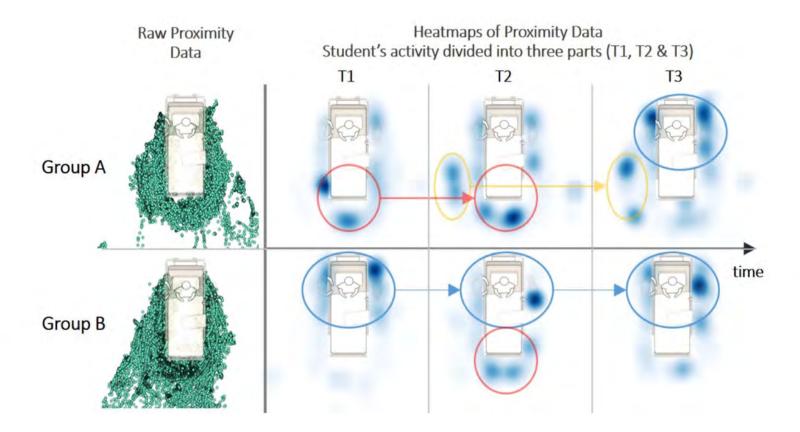
Co-design sessions with educators and students

Co-design techniques to elicit student and educator perspectives (e.g. "Teacher Superpowers", and "Learning/Data Journey mapping" *)



* Prieto-Alvarez, C. G., Anderson, T., Martinez-Maldonado, R., and Buckingham Shum, S. (2018). Mapping Learner/Data Journeys: Evolution of a Visual Co-Design Tool. *Proc. Australian Conference on Human-Computer Interaction*, Melbourne, (ACM, NY), pp.205-214. <u>https://doi.org/10.1145/3292147.3292168</u>

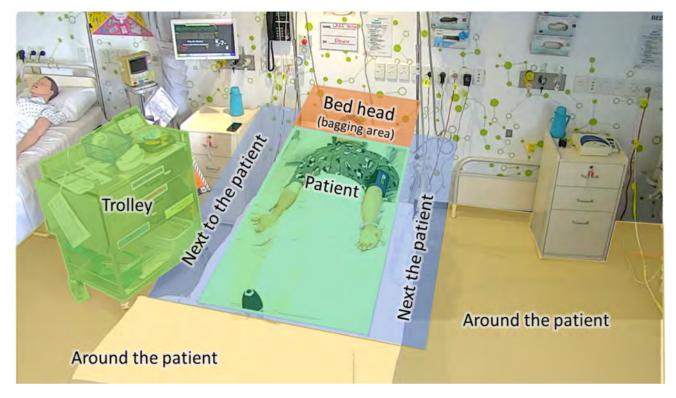
Starting from raw positional data of nurses' movements \rightarrow temporally segmented heatmaps $\rightarrow \dots$



Martinez-Maldonado, R., Yacef, K., Santos, A., Buckingham Shum, S., Echeverria, V., Santos, O. C., and Pechenizkiy, M. (2017) Towards Proximity Tracking and Sensemaking for Supporting Teamwork and Learning. *IEEE International Conference on Advanced Learning Technologies, ICALT 2017, 89-91.*

→ Understanding meaningful zones (= qualitative Codes)

Consultation with nursing educators clarified that there are **5 meaningful zones** for nurses to understand (in these simulations)



- the patient's bed for cases where nurses are located on top of or very close to the patient
- ii) next to patient for cases where nurses are either side of bed
- iii) around the patient for cases where nurses are 1.5 to 3 metres away
- iv) bed head where nurses commonly stand to clear the airway during CPR
- v) trolley area where nurses access medication or equipment

Theoretical lens: key features of collocated collaboration ACAD: Activity-Centred Analysis & Design framework

- The SET physical and digital space and objects; input devices, screens, software, material tools, furniture
- The EPISTEMIC TASKS implicit and explicit knowledge oriented elements that shape the participants' tasks and working methods
- The SOCIAL SITUATION the variety of ways in which people might be grouped together (e.g. dyads, trios); scripted or emerging roles; and divisions of labour
- AFFECTIVE RESPONSES an extension to ACAD, building on evidence from healthcare simulation research

Martinez-Maldonado, R., Goodyear, P., Kay, J., Thompson, K., and Carvalho, L. (2016) An Actionable Approach to Understand Group Experience in Complex, Multi-surface Spaces. *SIGCHI Conference: Human Factors in Computing Systems, CHI 2016, 2062-2074.* <u>https://doi.org/10.1145/2858036.2858213</u> learning + teaching data science/ analytics

humancentered design From multimodal logs (data) \rightarrow higher-order constructs (codes) as proxies \rightarrow meaningful feedback on "patient-centred care" (Codes)

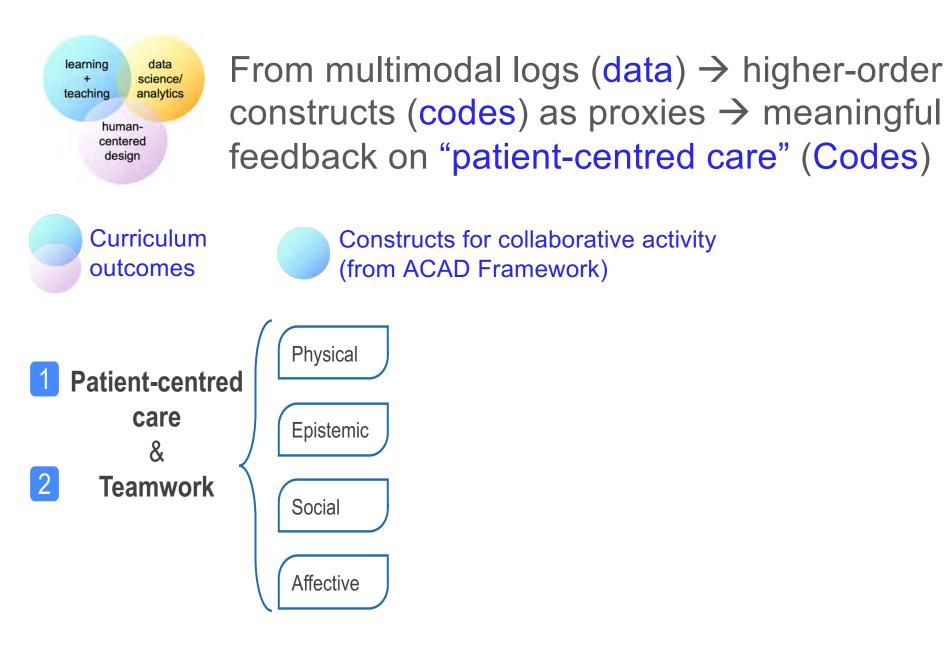


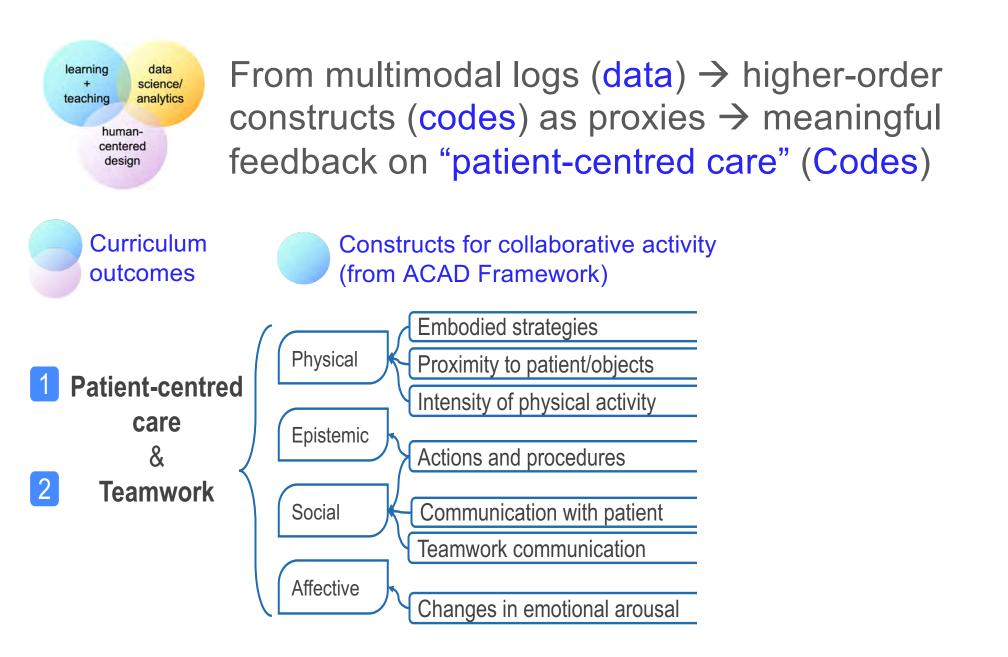
From multimodal logs (data) \rightarrow higher-order constructs (codes) as proxies \rightarrow meaningful feedback on "patient-centred care" (Codes)

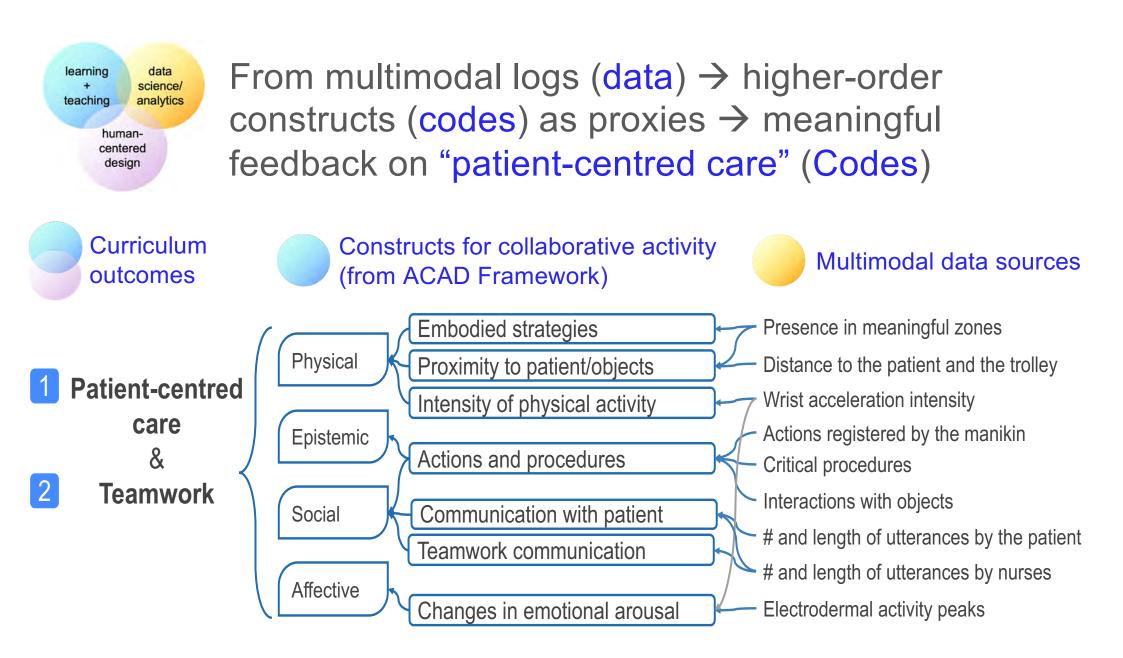


Curriculum

outcomes







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stanza

Task

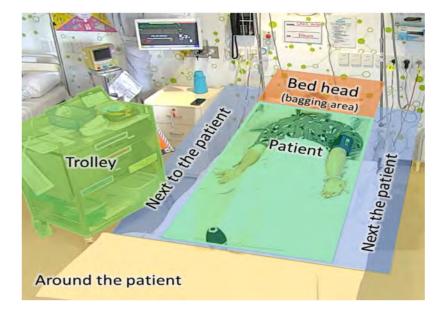
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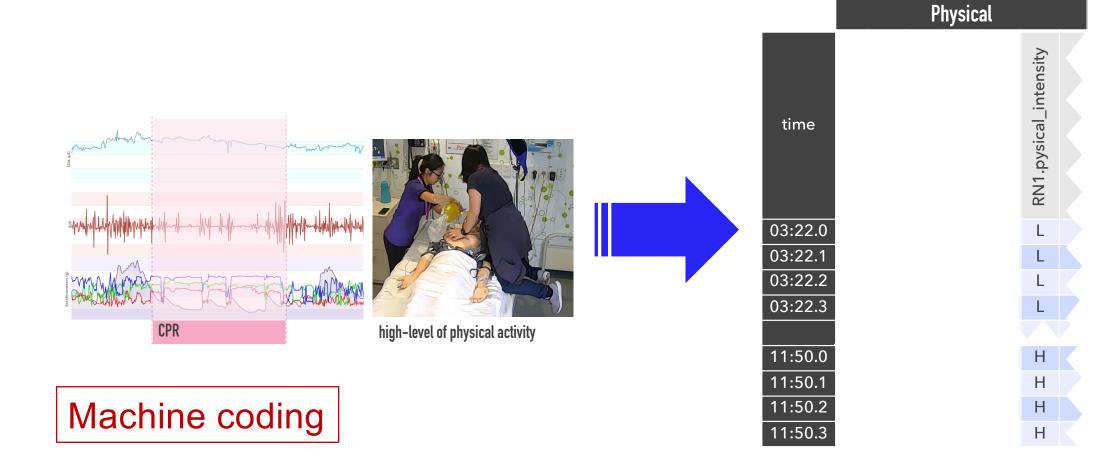
Mapping from positional Codes to digital codes in the Multimodal Matrix



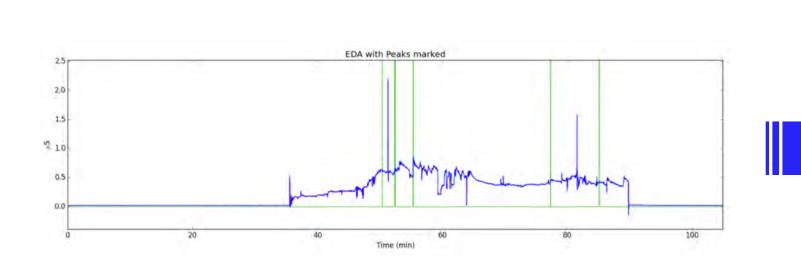


	Physical												
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03:22.2	0	1	0	0	0								
03:22.3	0	1	0	0	0								
11:50.0	1	0	0	0	0								
11:50.1	1	0	0	0	0								
11:50.2	1	0	0	0	0								
11:50.3	1	0	0	0	0								

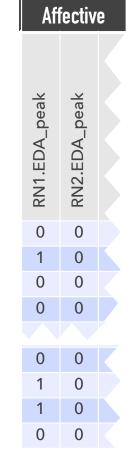
Classifying raw accelerometer data → low/medium/high physical activity



Thresholding raw EDA traces to focus on what's interesting: EDA peaks + low physical activity



Machine coding



Observers (e.g. researchers or students) use a tablet-based annotation tool to log key actions

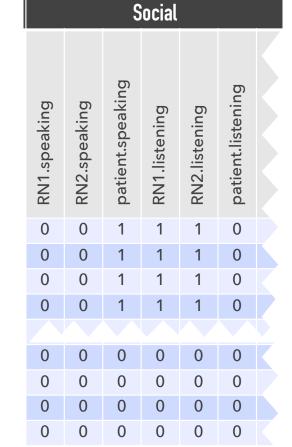
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Microphones failed (too noisy) so researcher had to analyse video to code who is speaking and listening/sec.

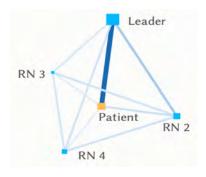




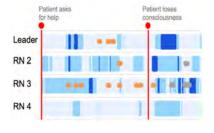
Human coding

Multimodal Matrix \rightarrow visual analytics for researchers, educators and students

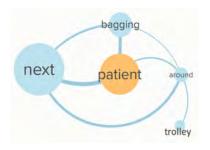
NB: social/physical/spatial/temporal relationships are key



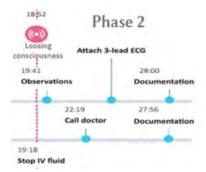
Patient-centred verbal communication, and within nursing team



Affective/cognitive arousal via EDA peaks



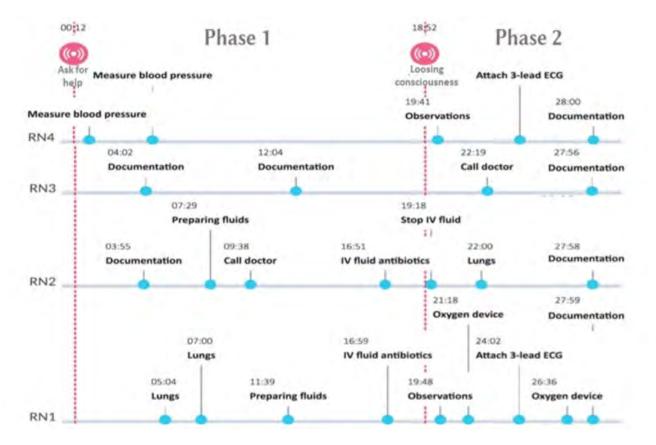
Patient-centred movement around the simulation zones



Critical actions performed by nurses

Echeverria, V., Martinez-Maldonado, R. and Buckingham Shum, S. (2019). Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proceedings of ACM CHI Conference (CHI'19)*. ACM, New York, NY, USA. <u>https://doi.org/10.1145/3290605.3300269</u>

Team Timeline can be generated within a few minutes of a simulation to assist debriefing (user studies now under way)



Echeverria, V., Martinez-Maldonado, R. and Buckingham Shum, S. (2019). Towards Collaboration Translucence: Giving Meaning to Multimodal Group Data. In *Proceedings of ACM CHI Conference (CHI'19)*. ACM, New York, NY, USA. <u>https://doi.org/10.1145/3290605.3300269</u>

How close are we to fully automated workflow?

RN 3

next

RN 4

Call docts

19-38 Stop IV fluid

	Collaboration Proxy	Data source	Manual interventions		Automated
Patient RN 2 RN 4	Patient- centred speech interaction	Audio from video recording	Speech interaction manually annotated	\rightarrow	Sociograms generated from speech onset/offset logs
patient must	Patient- centred movement	X,Y positions and pre- defined zones using indoor localization		\rightarrow	Zone transition networks generated from localisation data
	Physical Intensity and Affective reaction	EDA and accelerometer from Empatica wristband	Wristband data download	\rightarrow	EDA timelines generated from wristband data
Phase 2 Attach 3-lead ECG 28:00 Dosumentation 19 10 deater 27:50 Documentation	Teamwork Timeline	Timestamped actions from observation tool	Nursing actions logged by an observer	\rightarrow	Timelines generated from action logs

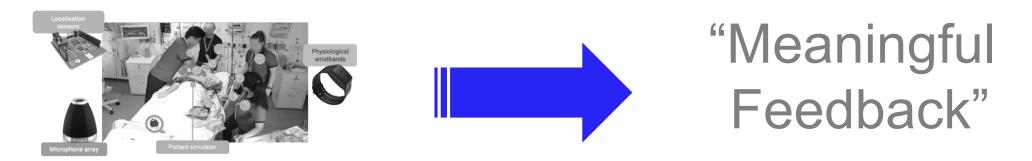
To conclude...

human activity systems data analysis at speed/scale → timely insight /action

How to handle this intersection with integrity?

To conclude...

What contributions can Q.E. make? Principles underpinning the MM



Can this work make contributions back to Q.E.? MM may assist other Q.E. research Exemplifies Q.E. for rapid <u>collocated</u> activity analysis

To conclude...

We propose that this work builds on and augments QE as follows...

- Understand the human activity system (Discourse + Codes)
 → expert interviews + theory + co-design including <u>envisioned</u> practices
- Integrate qualitative and quantitative data (discourse + codes)
 → integrated by the Multimodal Matrix to handle multimodal data streams
- Analysis techniques read from + write to a common data representation
 → human + machine analysis can contribute coded data to the MM
- 4. Enable semi/fully automated analysis at scale, and visualize for users
 → partially automated analytics workflow to generate visual analytics

Buckingham Shum, S., Echeverria, V. & Martinez-Maldonado, R. (2019). The Multimodal Matrix as a Quantitative Ethnography Methodology. In: Eagan B., Misfeldt, M. & Siebert-Evenstone, A. (Eds.), *Advances in Quantitative Ethnography*. Communications in Computer and Information Science, Vol. 1112. Springer: Cham, pp.26-40. DOI: https://doi.org/10.1007/978-3-030-33232-7_3