

Socio-spatial Learning Analytics for Embodied Collaborative Learning

Presenter: Lixiang (Jimmie) Yan



Agenda

1. Backgrounds
2. Conceptual Framework
3. Illustrative Cases
4. Opportunities and Challenges

Backgrounds

Presenter: Lixiang (Jimmie) Yan



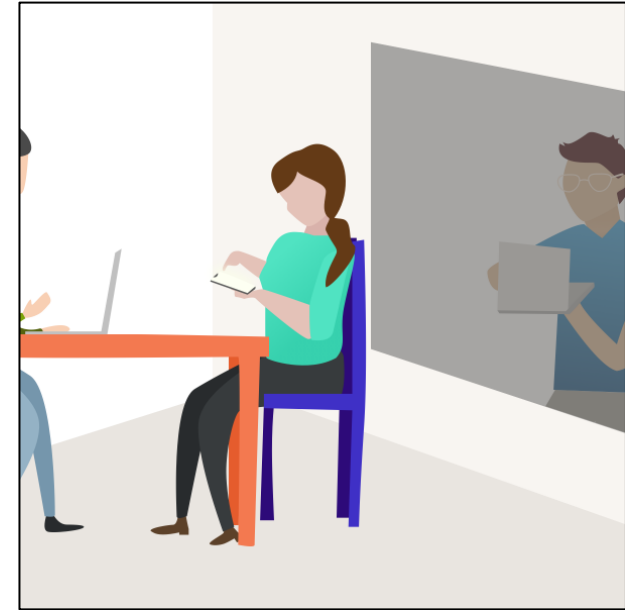
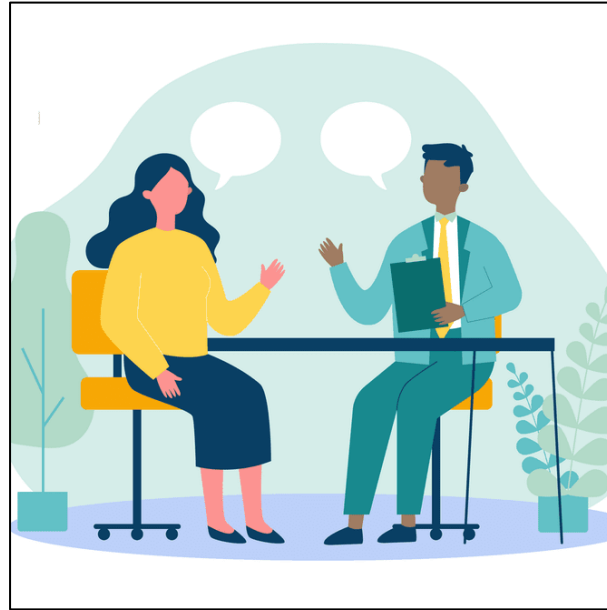
Embodied Collaborative Learning (ECL)

Embodied Collaborative Learning provides unique opportunities for students to practice key procedural and collaboration skills in co-located, physical learning spaces where they need to **interact with others (social)** and **utilise physical and digital resources (spatial)** to achieve a shared goal.

Examples of ECL



Traditional Data Collection Approaches



Multimodal Learning Analytics



Mobile Eye-Tracker



Hand gestures
(leap motion)



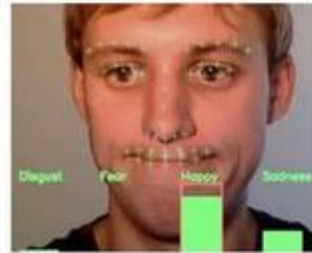
Motion Sensors (Kinect)



Galvanic Skin Response



Machine Learning



Emotion Detection

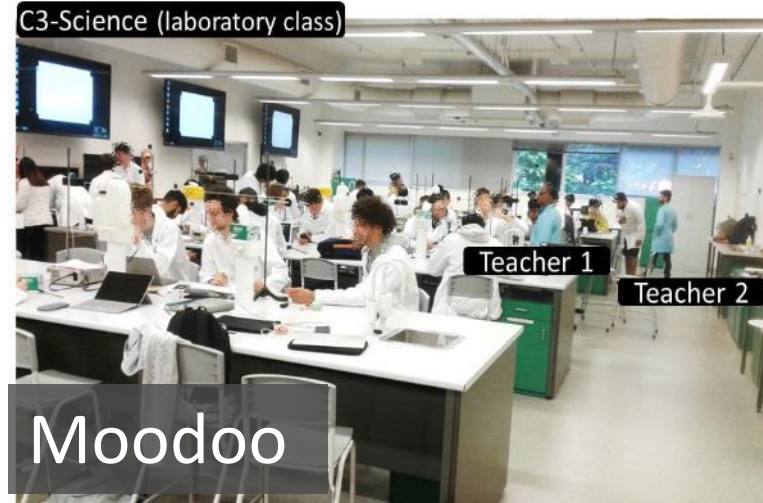


Video and
Speech data



The world's first
\$99 eye tracker

Social and Spatial Aspects of ECL



Martinez-Maldonado, R., Echeverria, V., Schulte, J., Shibani, A., Mangaroska, K., & Shum, S. B. (2020, July). Moodoo: indoor positioning analytics for characterising classroom teaching. In *International Conference on Artificial Intelligence in Education* (pp. 360-373). Springer, Cham.



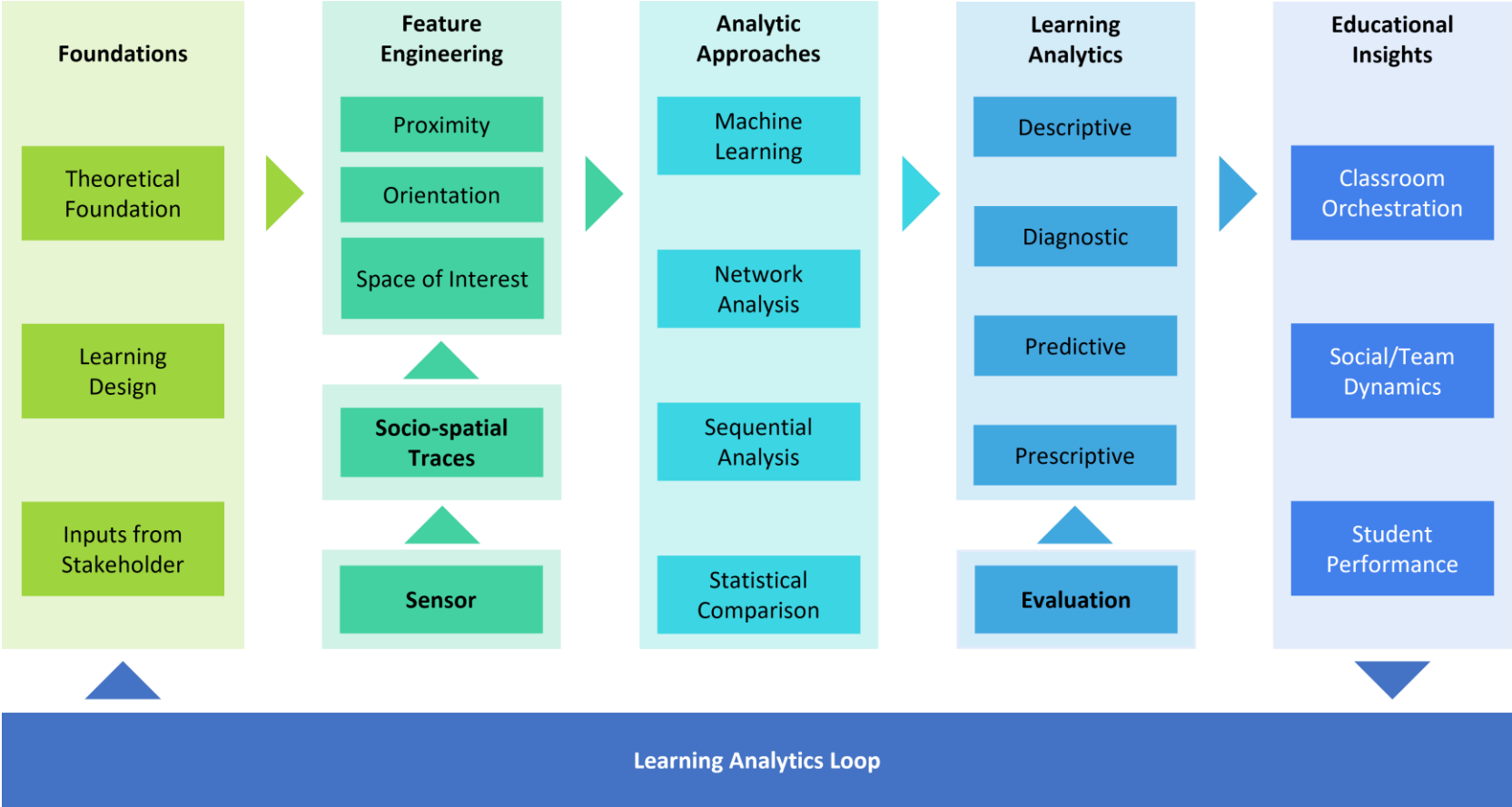
Saquib, N., Bose, A., George, D., & Kamvar, S. (2018). Sensei: sensing educational interaction. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(4), 1-27.

Conceptual Framework

Presenter: Lixiang (Jimmie) Yan



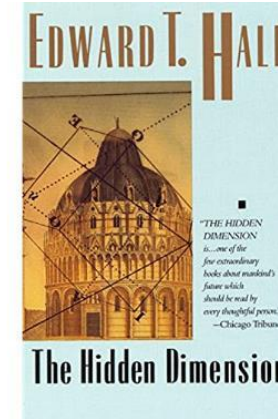
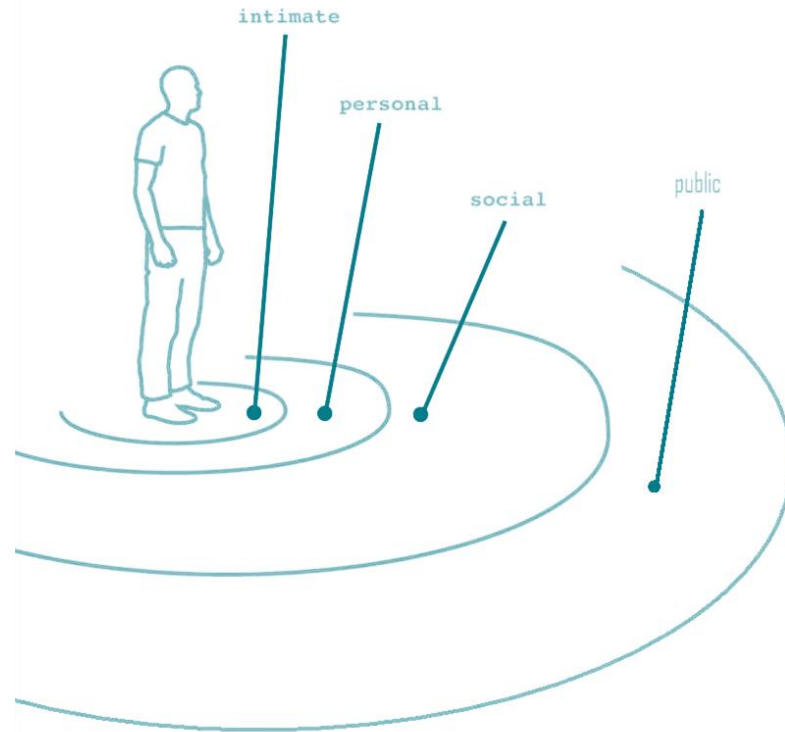
Social-spatial Learning Analytics: Conceptual Framework



Foundation: Theoretical Foundations

Foundations

Theoretical Foundation



Theory of Proxemic

The study of how **physical space** is used during social interactions. (Hall, 1966)

Foundation: Learning Design



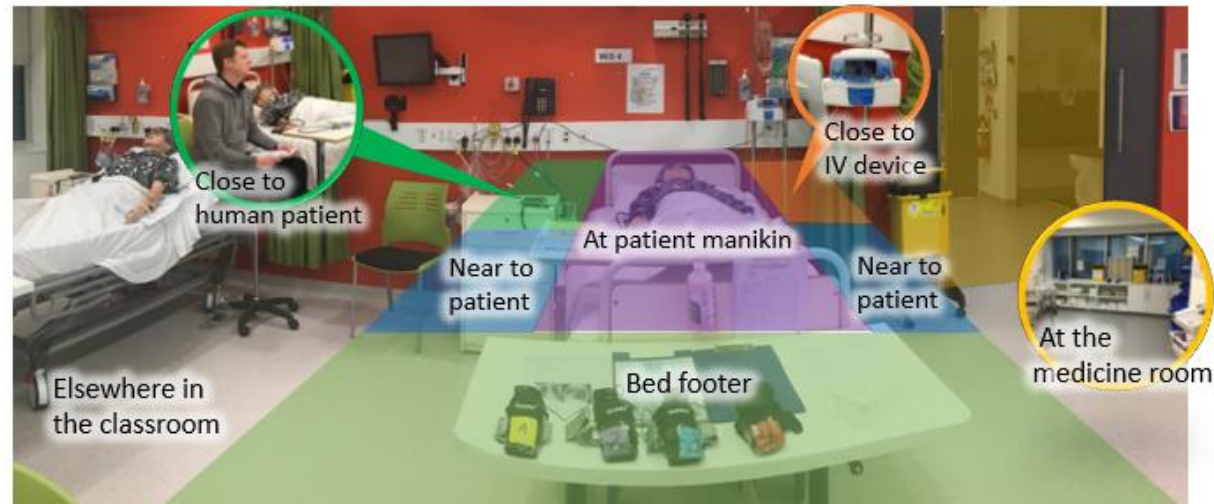
1) educational constructs in interest are strongly associated with students or teachers' **collaborative behaviours** or **interactions with educational resources**, and

2) these behaviours can be **inferred from their spatial movements** in the learning space.

Foundation: Stakeholders' Inputs

Foundations

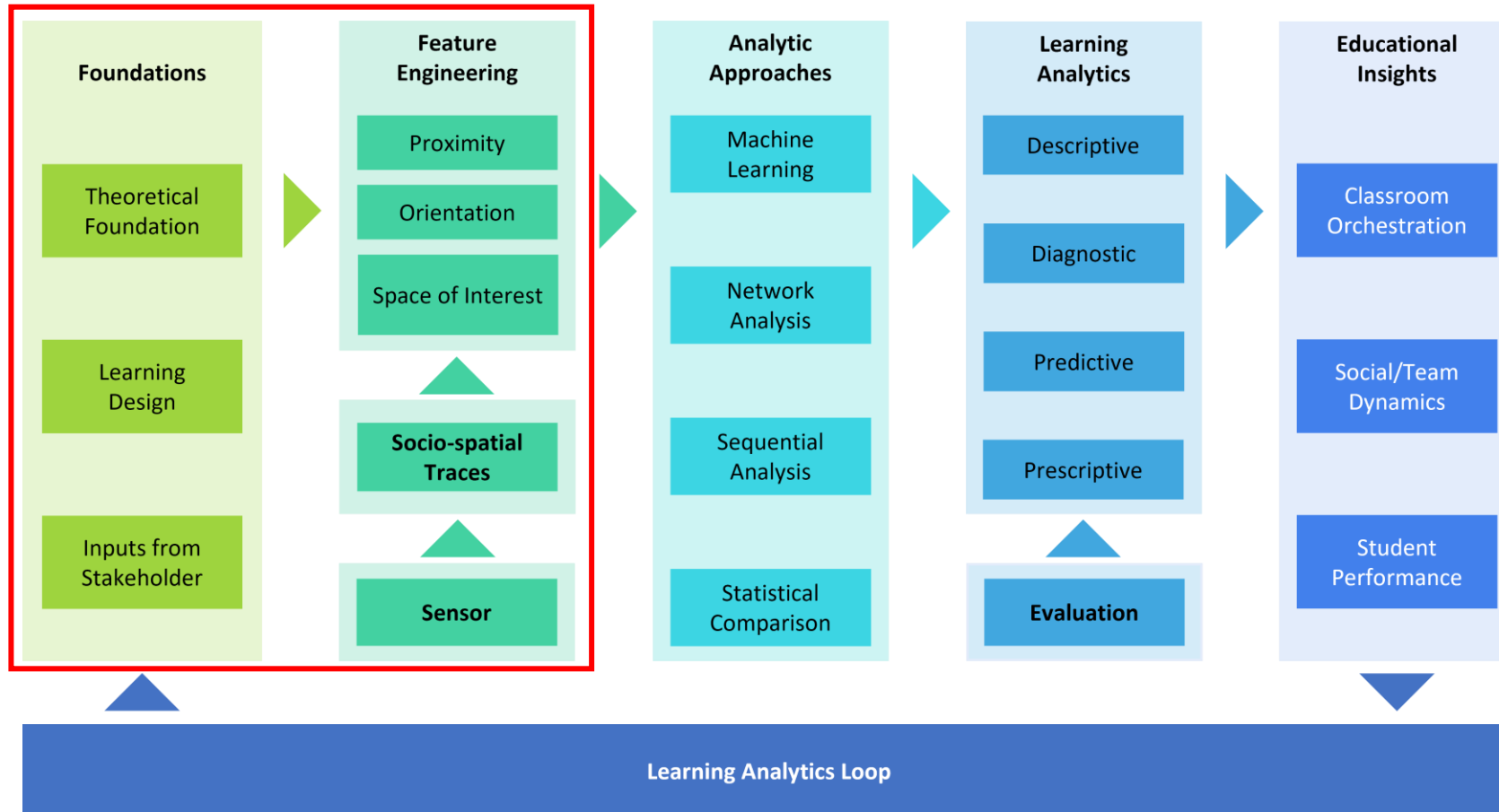
Infuse **Space** with **Meaning**



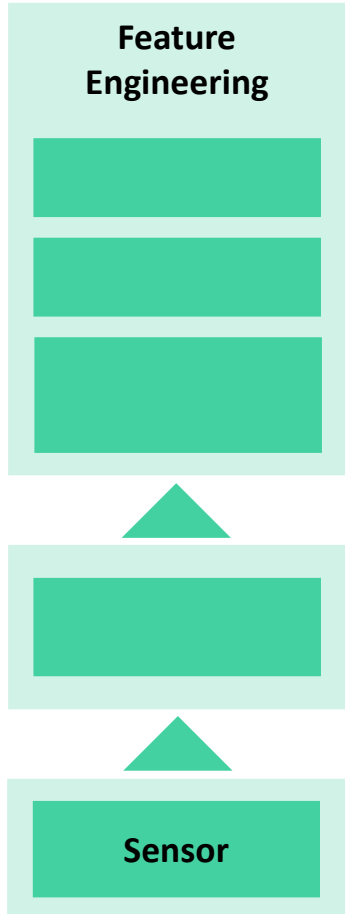
Inputs from Stakeholder

Fernandez-Nieto, G. M., Martinez-Maldonado, R., Kitto, K., & Buckingham Shum, S. (2021, April). Modelling spatial behaviours in clinical team simulations using epistemic network analysis: methodology and teacher evaluation. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 386-396).

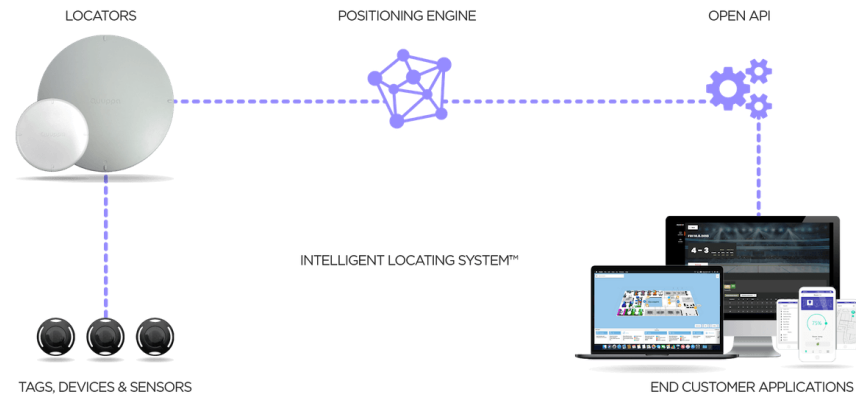
Foundation Informs Feature Engineering



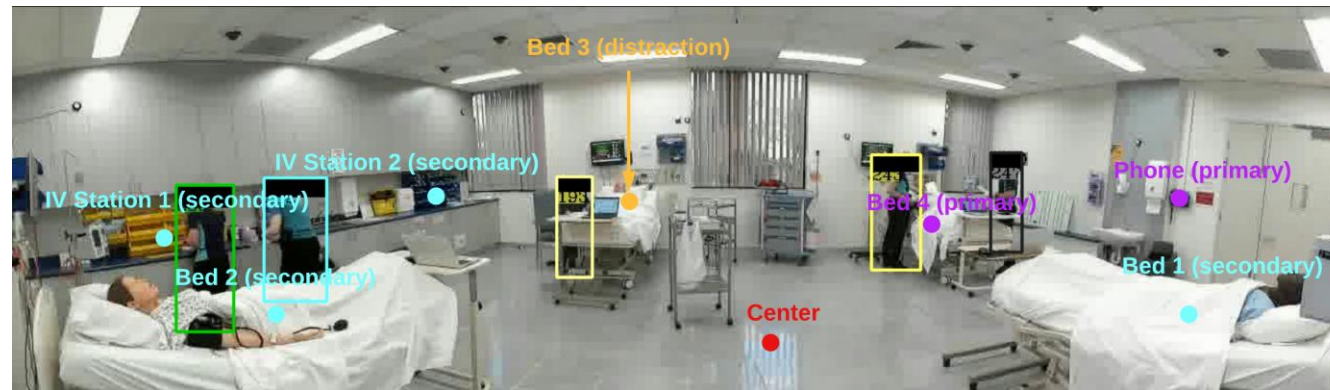
Feature Engineering: Sensor



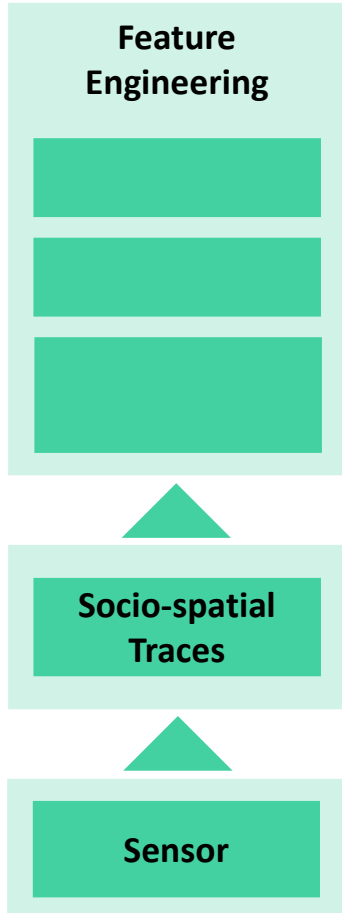
Wearable tracking systems



Computer vision systems



Feature Engineering: Socio-spatial Traces



Raw data (precise location)

Timestamp: 22/07/2019 9:38:24.000

ID: Student0001

x-y coordinates: 5.3775, 17.645

yaw, roll, pitch: 2.08, -1.52, -0.32

Raw data (screen distance)

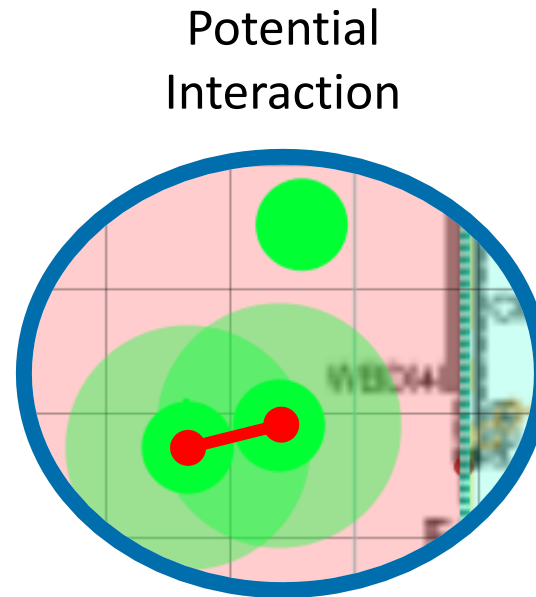
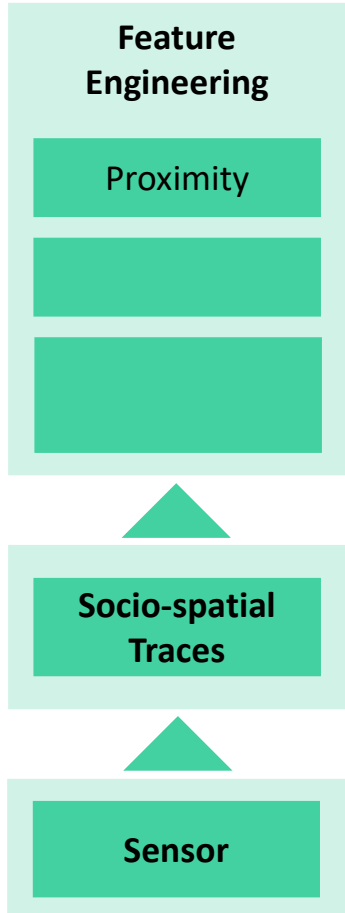
Timestamp: 00:23:58

Screen distance: 51 units

Subject_1: Student0001

Subject_2: Student0002

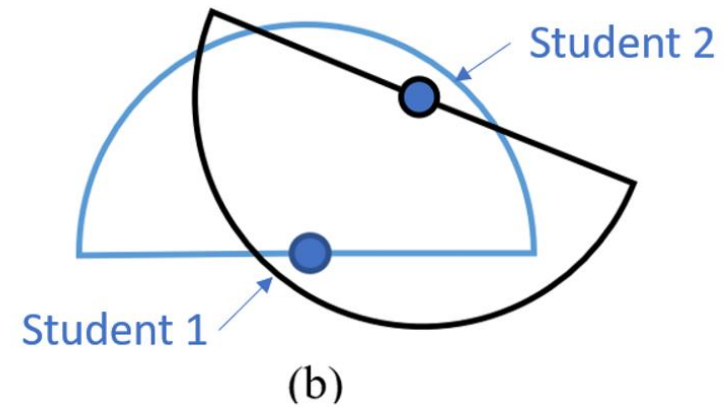
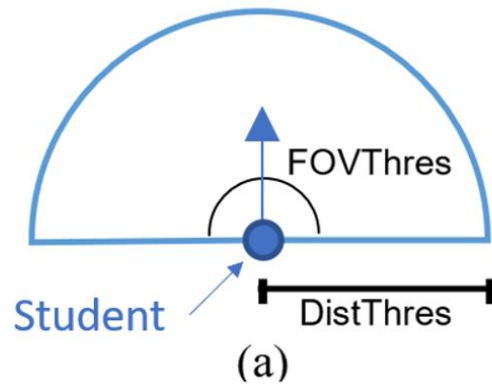
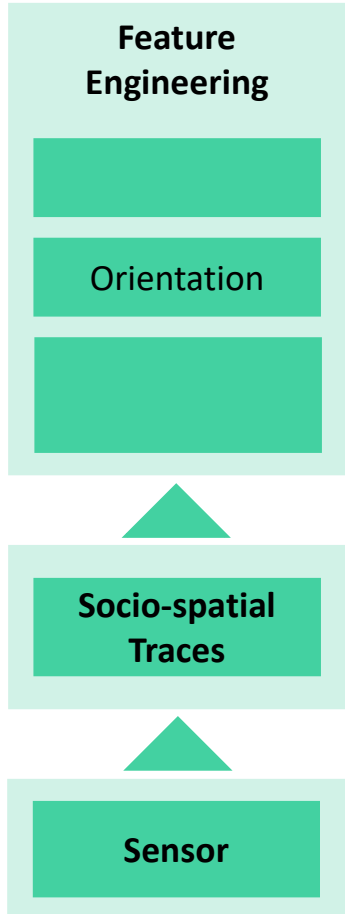
Feature Engineering: Proximity



Distance threshold: within 1-1.5m.

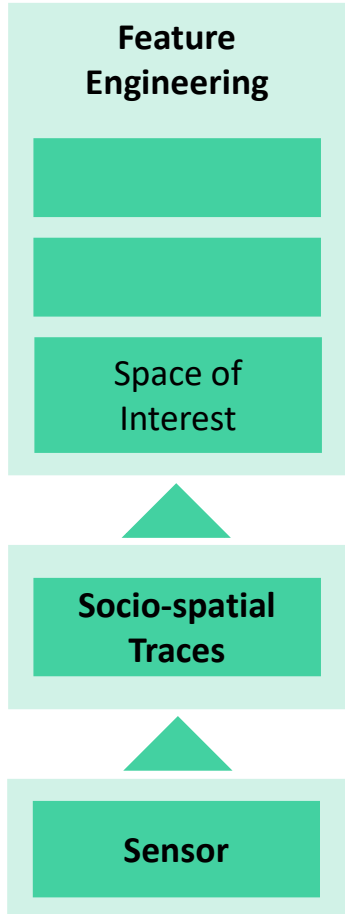
Time threshold: more than 10s

Feature Engineering: Orientation

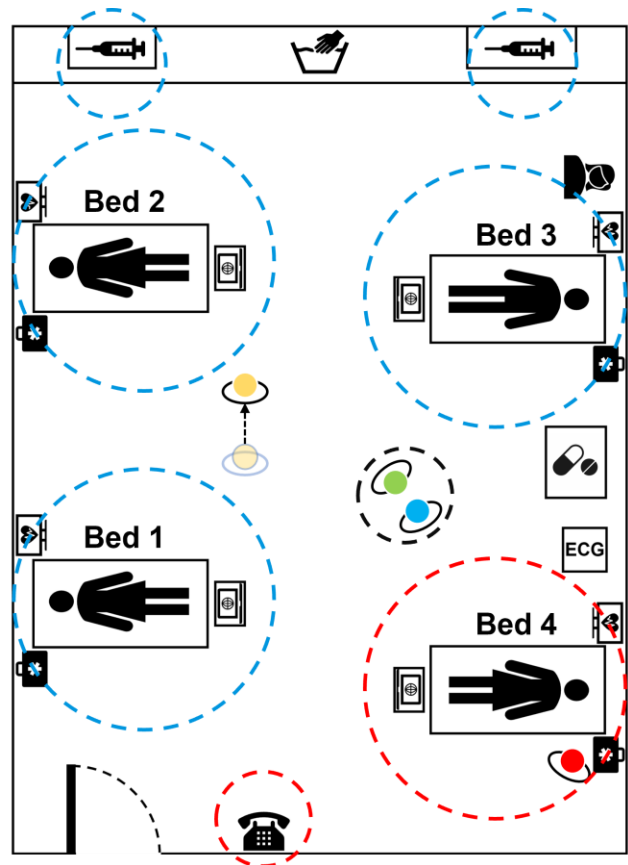


F-formation: when both students are **within a certain proximity threshold** and are **facing toward each others** (Zhao et al., 2022).

Feature Engineering: Space of interests



- Graduate Nurse
- Ward Nurse
- Vital Signs Monitor
- Oxygen Devices
- Laptop
- IV Fluids
- Resus Trolley
- Family Relative
- Phone



Examples of Task Space

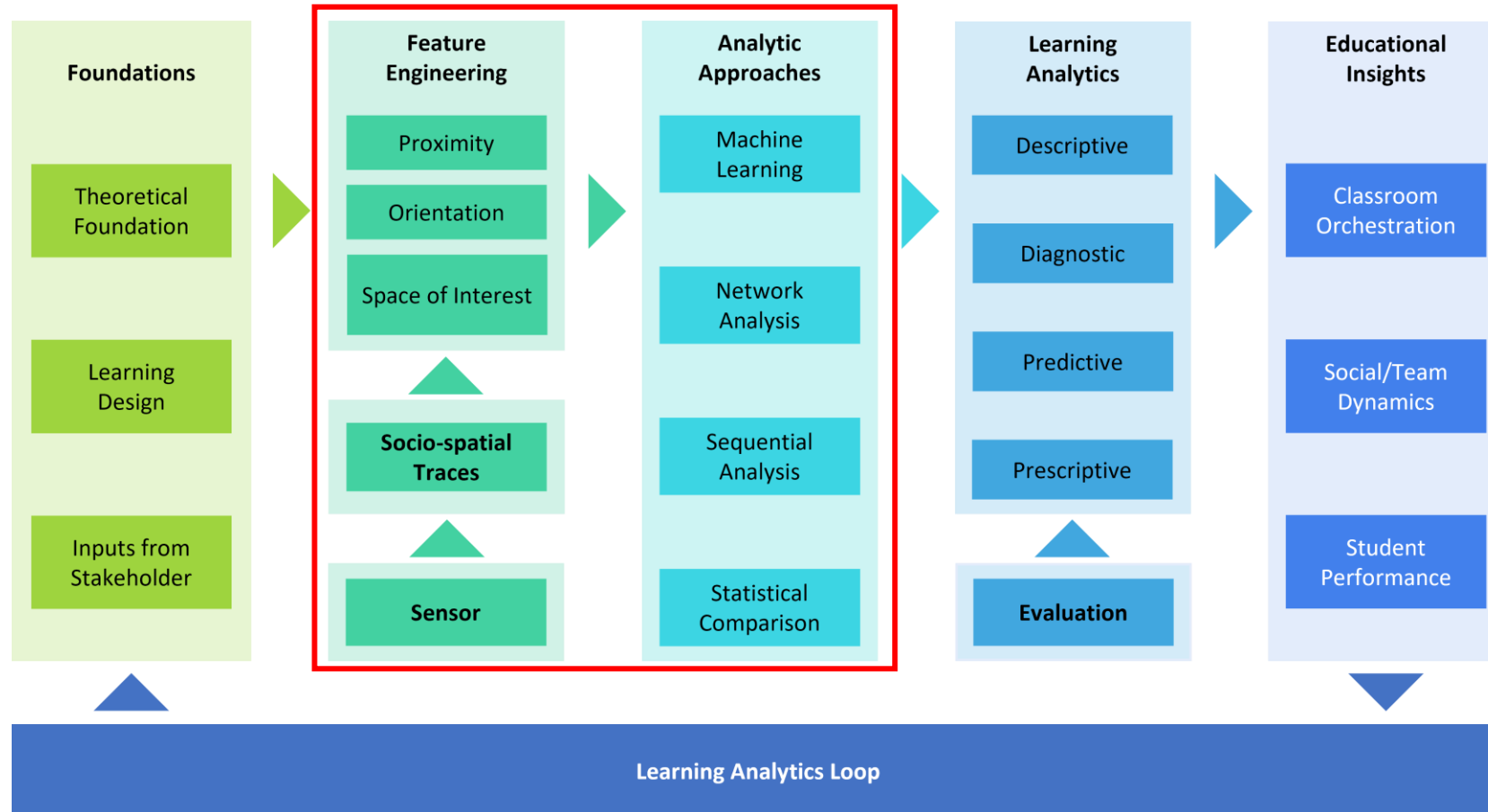
- Primary Task Space
- Secondary Task Space

Examples of Behaviours

- Task Distribution
- Task Transition



Behavioural Features to Analytics Approaches

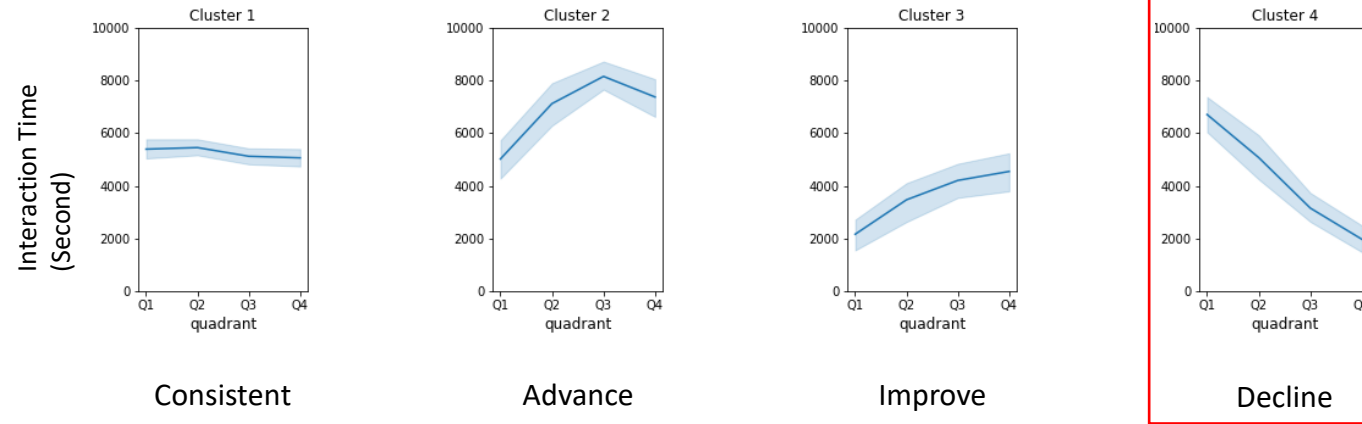


Analytic Approaches: Machine Learning

Analytic Approaches

Machine Learning

Unsupervised methods (e.g., clustering social participation level)

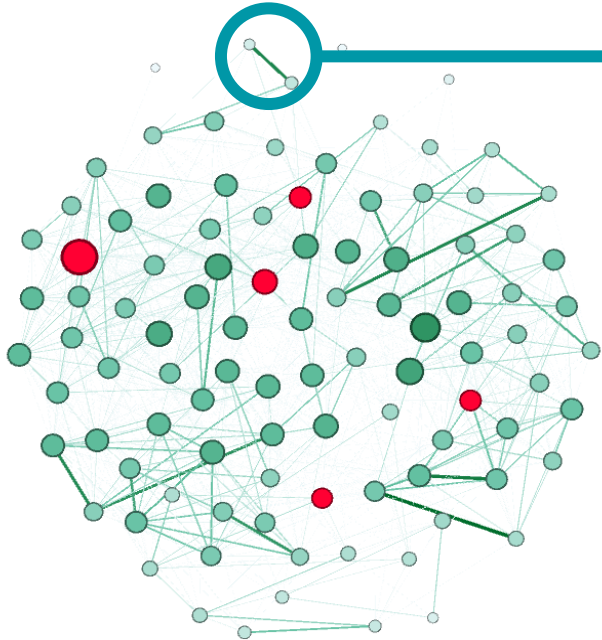


Supervised methods (e.g., predicting students' maths performance)

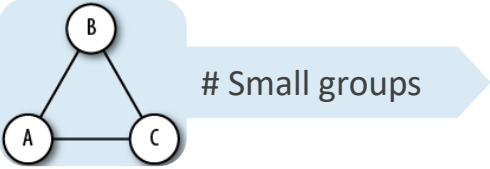
	Accuracy	Precision	Recall	Cohen's <i>k</i>	AUC
LR	0.81 (0.06)	0.71 (0.06)	0.75 (0.06)	0.57 (0.06)	0.79 (0.06)
SVM	0.78 (0.06)	0.66 (0.06)	0.73 (0.06)	0.52 (0.06)	0.77 (0.06)
RF	0.78 (0.06)	0.68 (0.06)	0.67 (0.06)	0.50 (0.06)	0.75 (0.06)
KNN	0.76 (0.06)	0.64 (0.06)	0.68 (0.06)	0.47 (0.06)	0.74 (0.06)
ANN	0.74 (0.06)	0.61 (0.06)	0.66 (0.06)	0.43 (0.06)	0.72 (0.06)

Analytic Approaches: Network Analysis

- Analytic Approaches
- Network Analysis



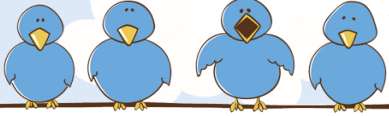
Pair interactions



Small groups

$$\text{Group Cohesion / Density} = \frac{\text{Actual \# of connections}}{\text{All possible connections}}$$

Homophily



Birds of a Feather Flock Together

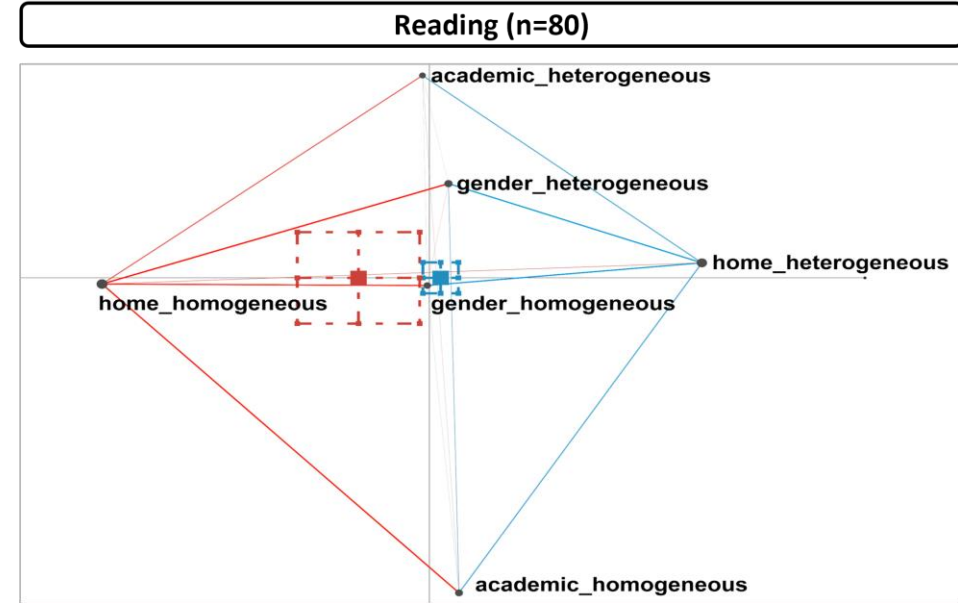
Reading lesson on 22/07/2019 from 10:00am to 11:00am

Analytic Approaches: Sequential and Epistemic Analysis

Analytic Approaches

Sequential Analysis

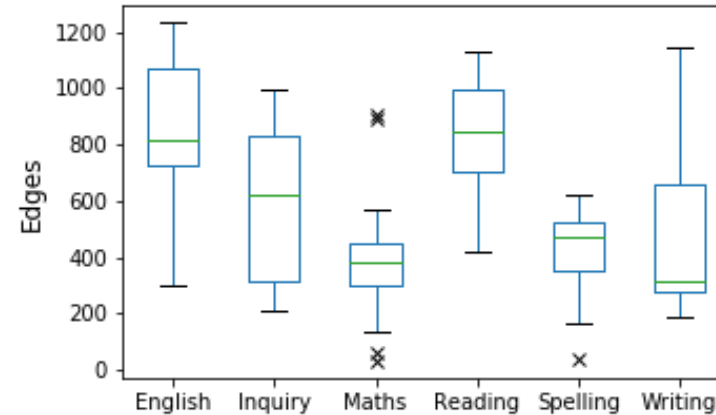
student	gender	gender_homogeneous
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	0
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	0
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1
Student_0002	Female	1



— high-performing students

— low-performing students

Analytic Approaches: Statistical Comparison

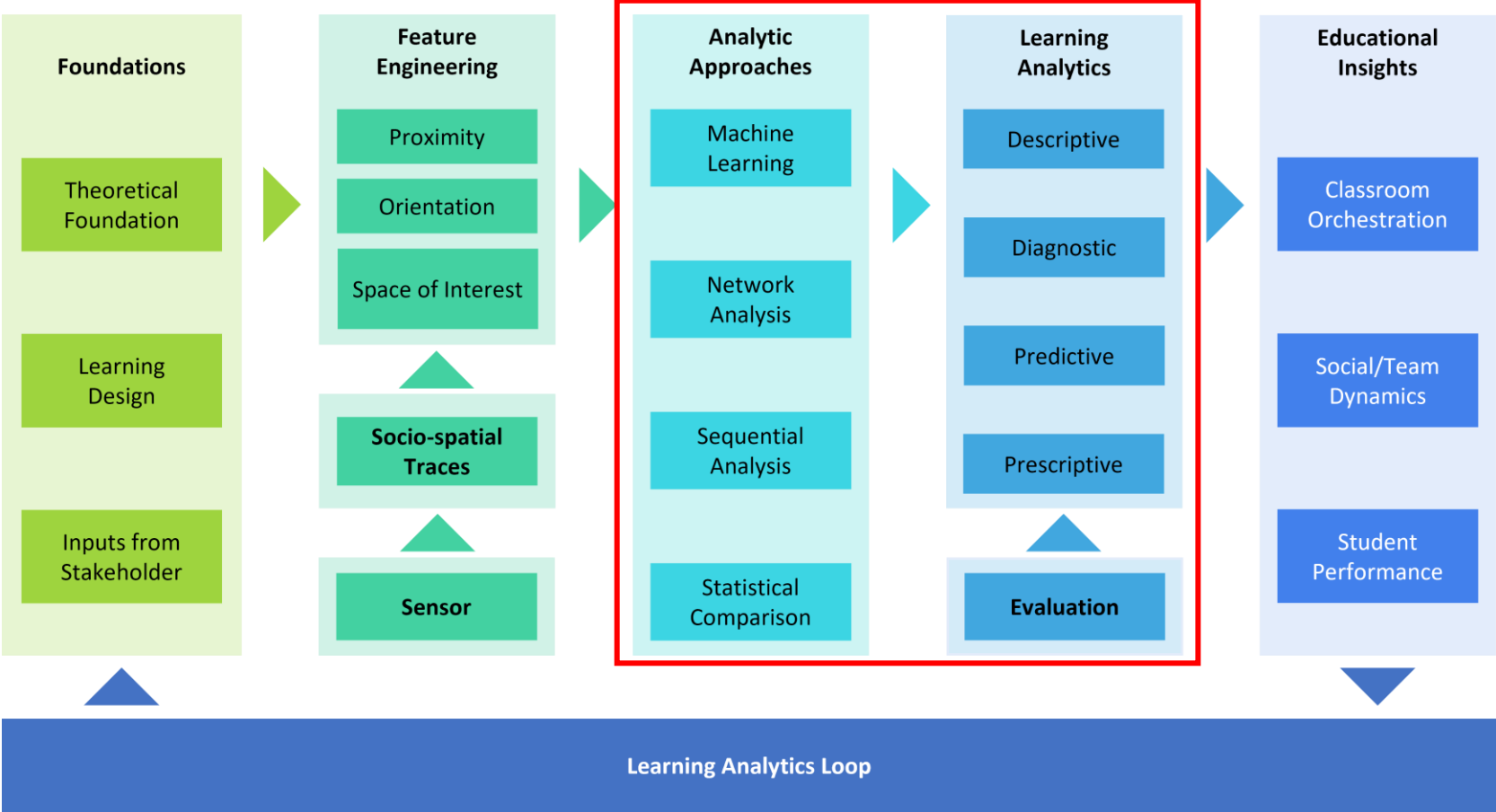


Nonparametric Statistics
(e.g., Mann–Whitney U test)

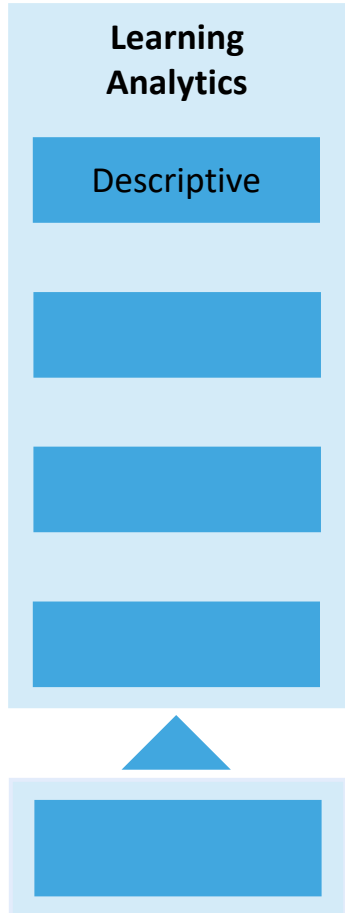
Over

Parametric Statistics
(e.g., Student's t-test)

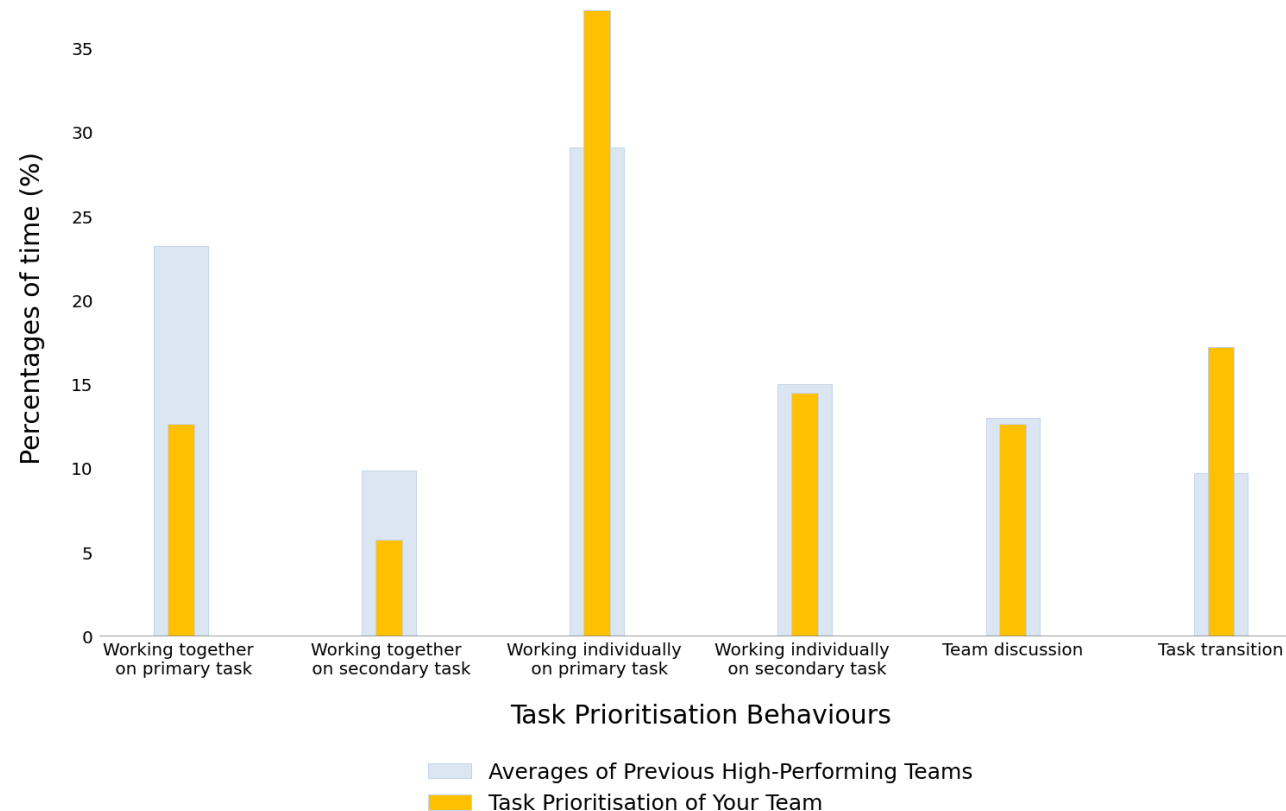
Analytics Approaches to Learning Analytics



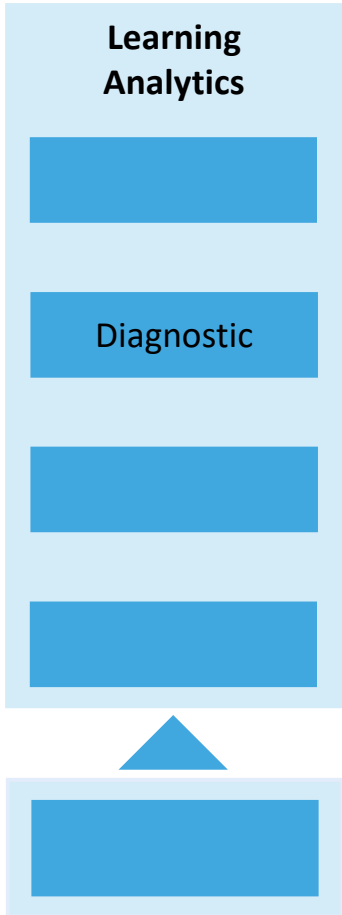
Learning Analytics: Descriptive



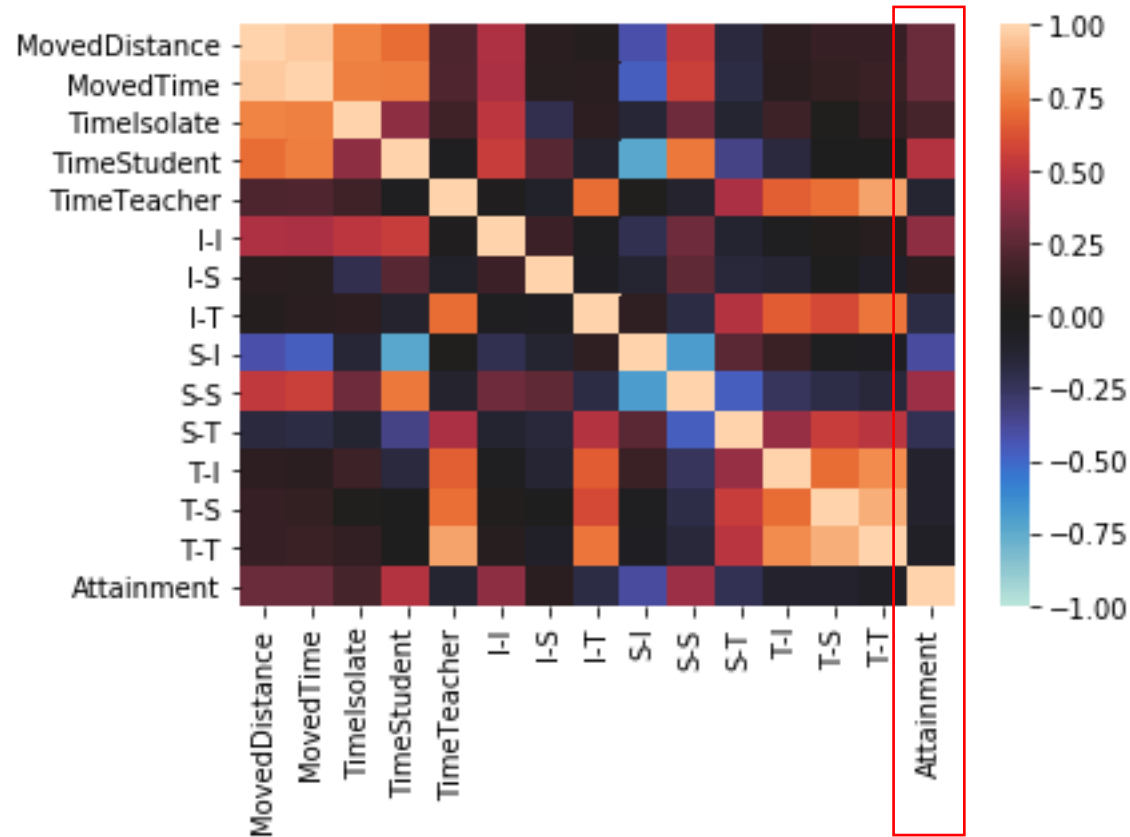
Making **salient** aspects of complex educational constructs **visible** for both teachers and students.



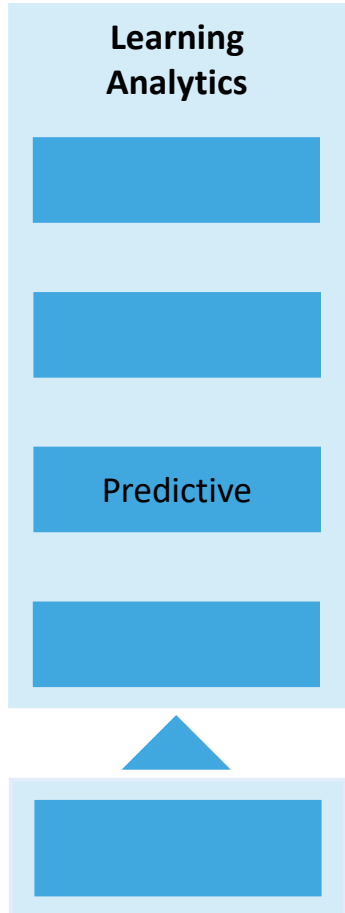
Learning Analytics: Diagnostic



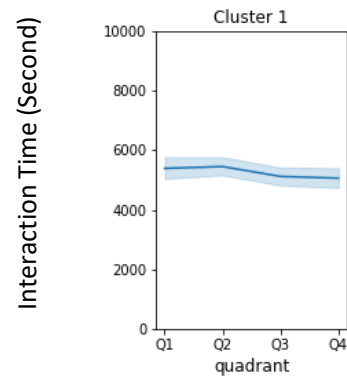
Identifying meaningful **behavioural indicators** of educational constructs based on theoretical assumptions.



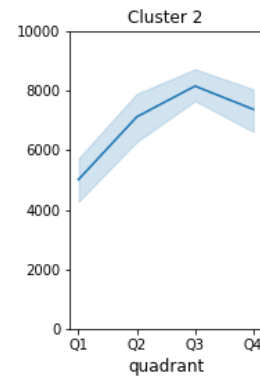
Learning Analytics: Predictive



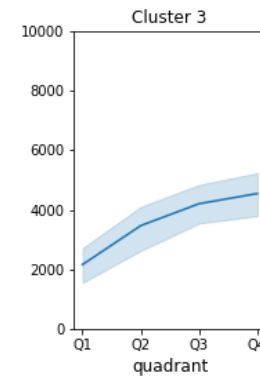
Powering **early detection** technologies that teachers can use to identify and support both socially and academically at-risk students



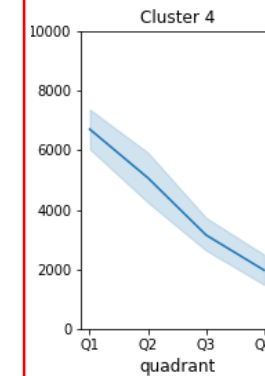
Consistent



Advance

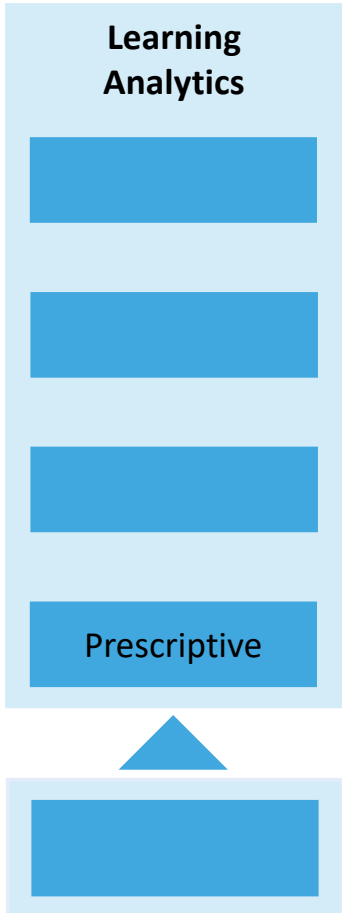


Improve

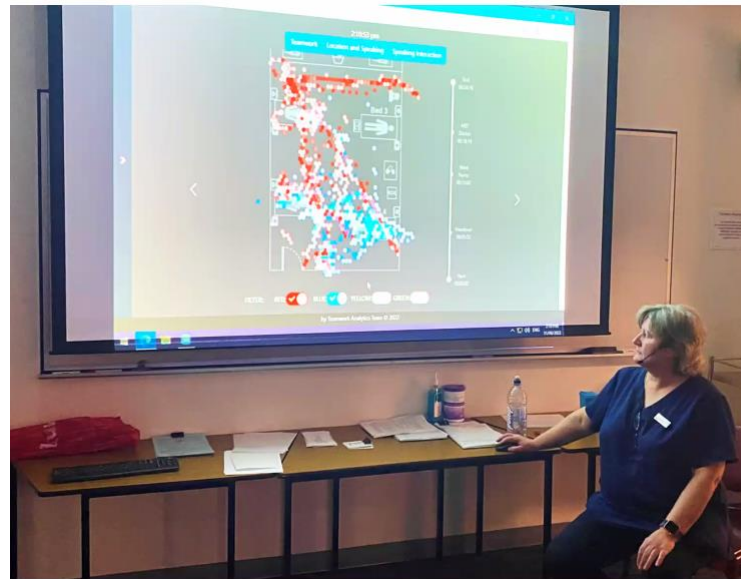


Decline

Learning Analytics: Prescriptive



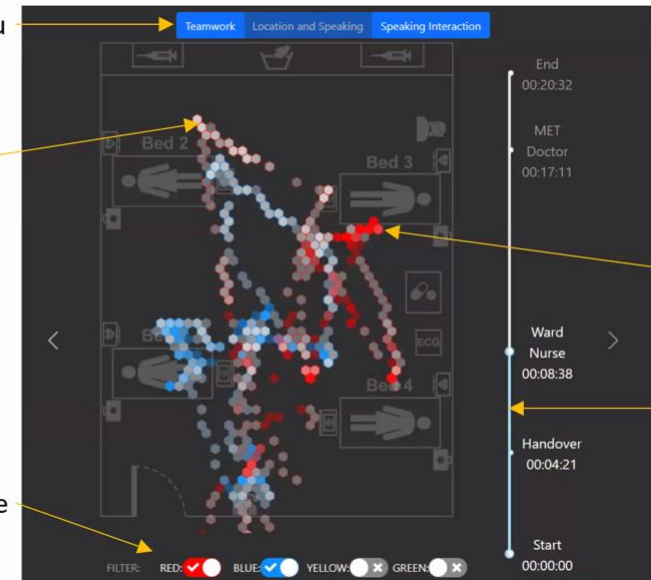
Empirical evidence and **stakeholder endorsements** of the educational values in supporting teachers' decision-making process are emerging.



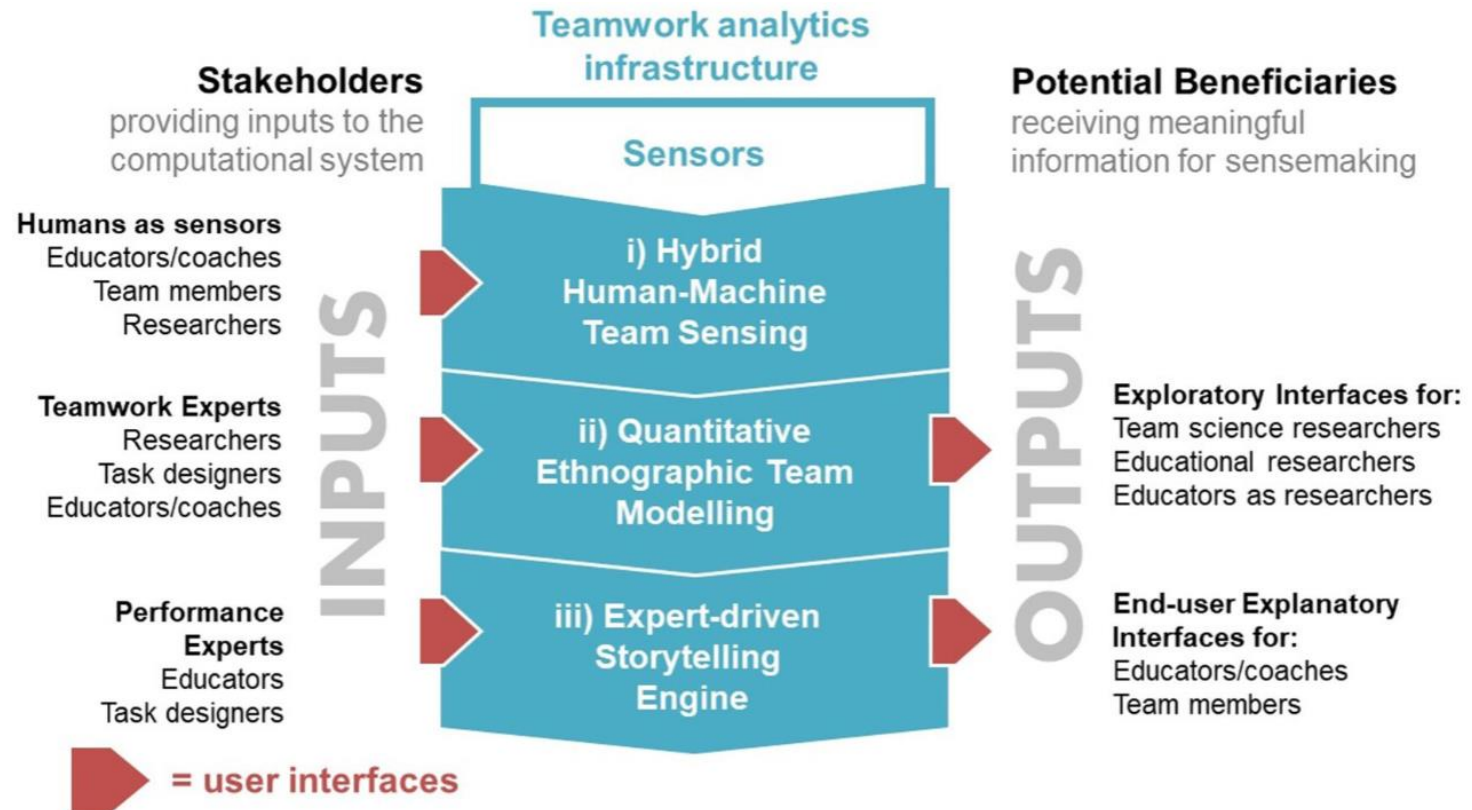
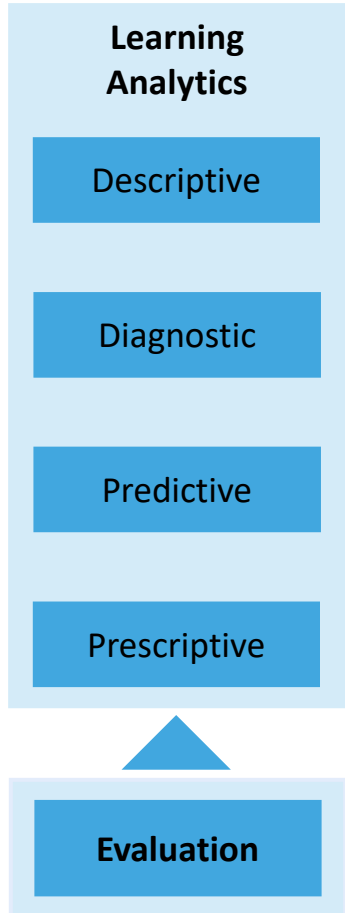
Visualisations' menu

Student location **without** speaking

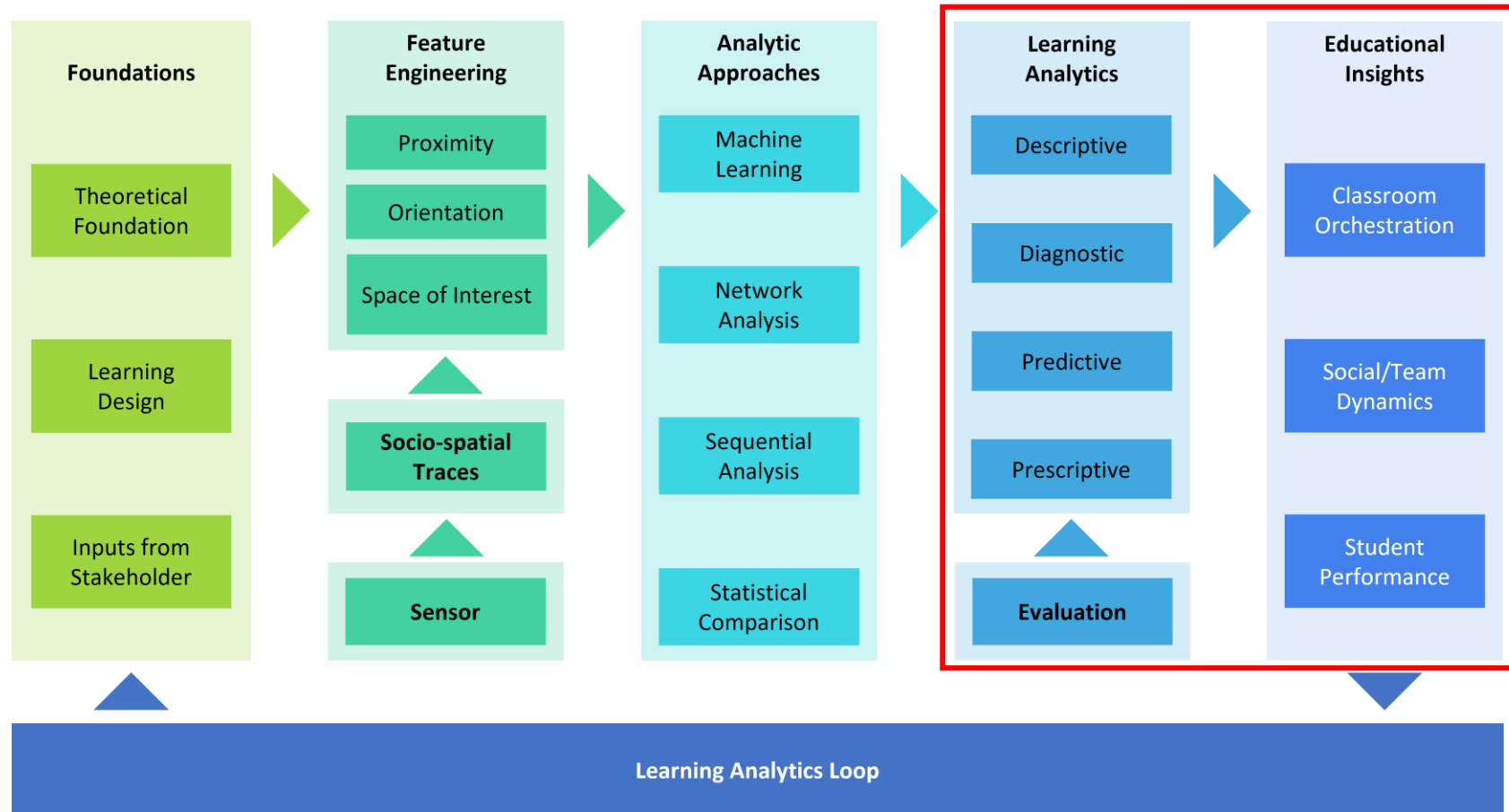
Filter by student role



Learning Analytics: Evaluation



Learning Analytics to Educational Insights



Educational Insights: Classroom Orchestration

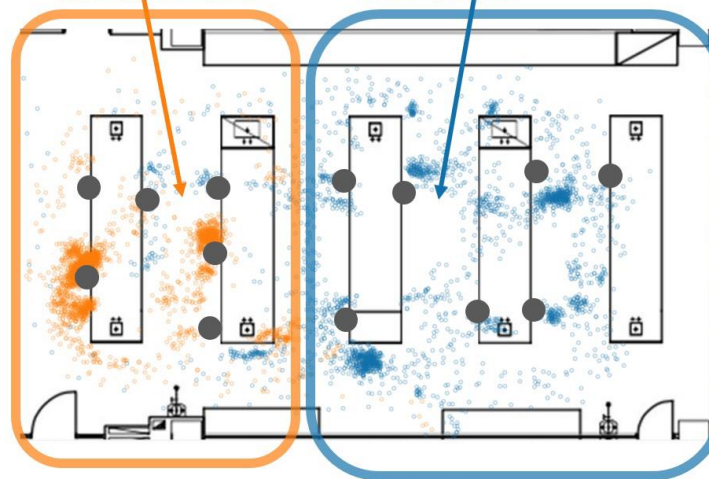
Educational
Insights

Classroom
Orchestration

Helping teachers to **allocate** their time better and ensure every student/group are attended.

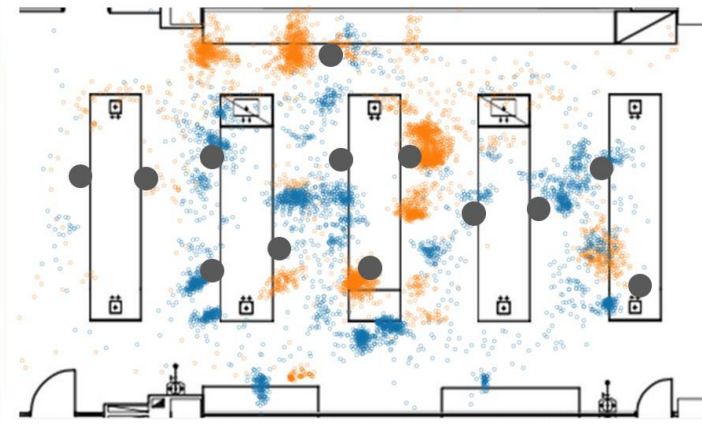
ID1: Prescribed lab (session 3)

Classroom benches distributed between the
teacher assistant and the main teacher



ID2: Project-based lab (session 6)

Both teachers present almost everywhere the classroom

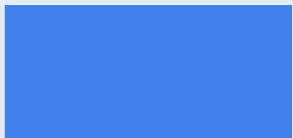


Educational Insights: Social/Team Dynamics

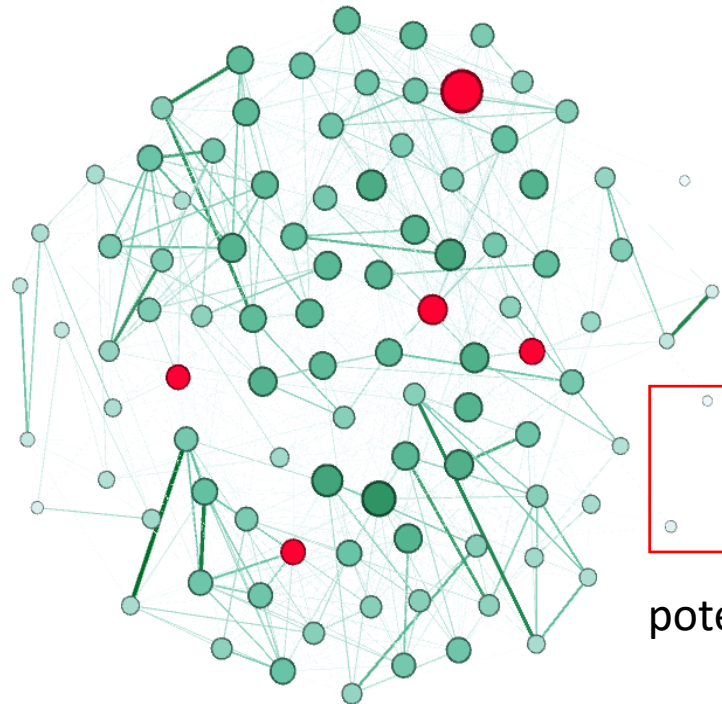
Educational
Insights



Social/Team
Dynamics



Developing learning analytics dashboards that augment teachers' **awareness** of the whole classroom and delivery of evidence-based reflections



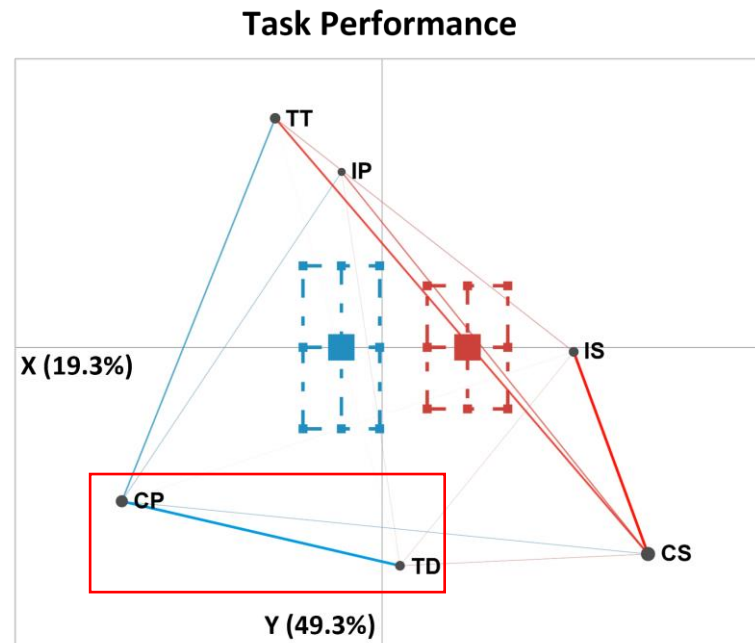
potential socially isolated students

Educational Insights: Student Performance

Educational
Insights

Student
Performance

Supporting researchers and practitioners in **understanding** social and spatial factors related to students' performance in collaborative contexts



— high-performing teams

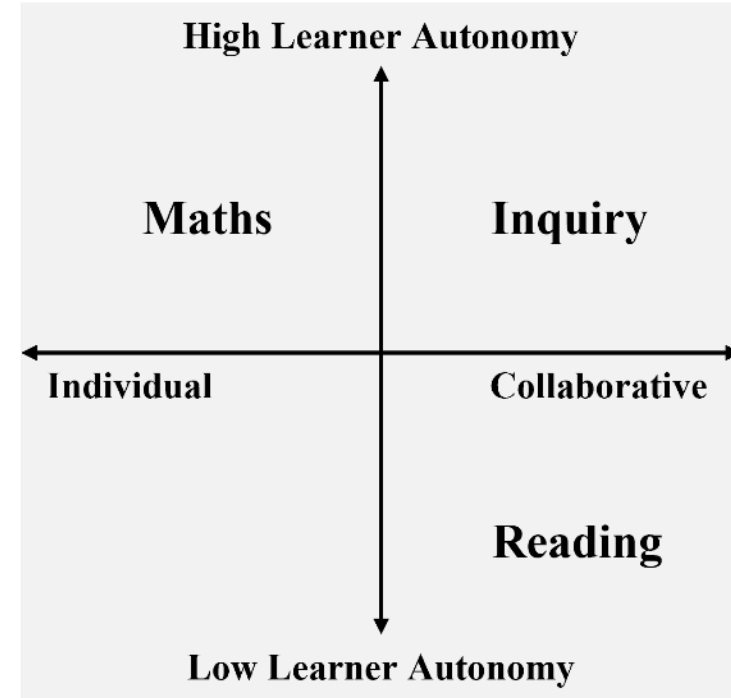
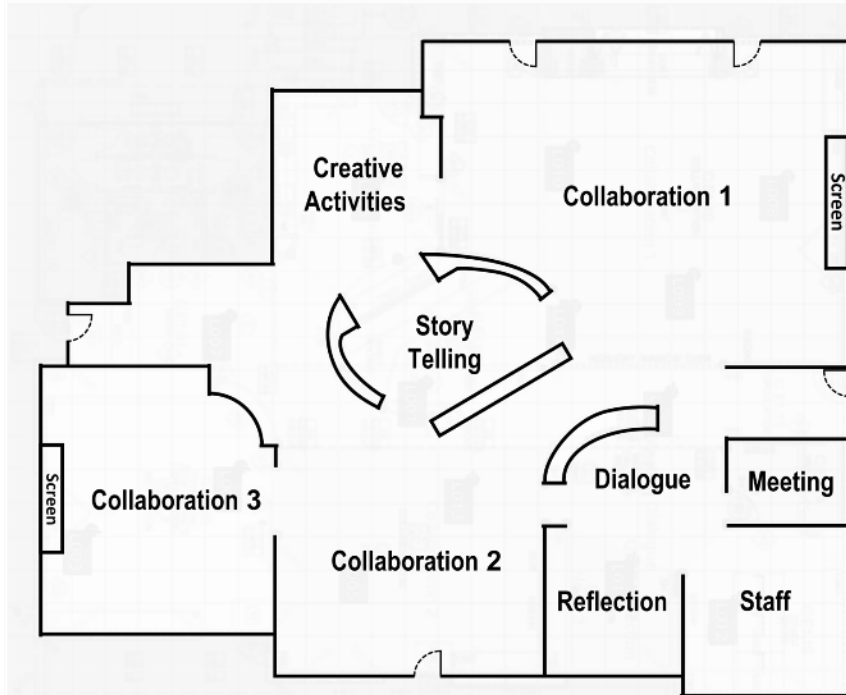
— low-performing teams

Illustrative Cases

Presenter: Lixiang (Jimmie) Yan



Case 1: Open Learning Space



Case 1: In-the-wild Study with Indoor Positioning System

8 Weeks

35 Maths Sessions

23 Reading Sessions

14 Inquiry Sessions

77.15m Data Points

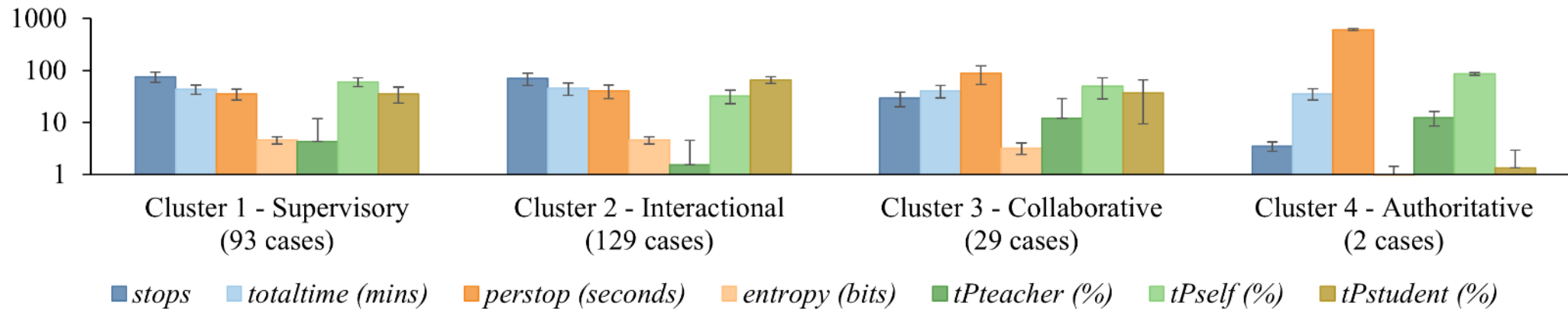


Case 1: Socio-spatial Features

Table 1: Teachers' Socio-spatial Metrics with the Corresponding Unit and Description.

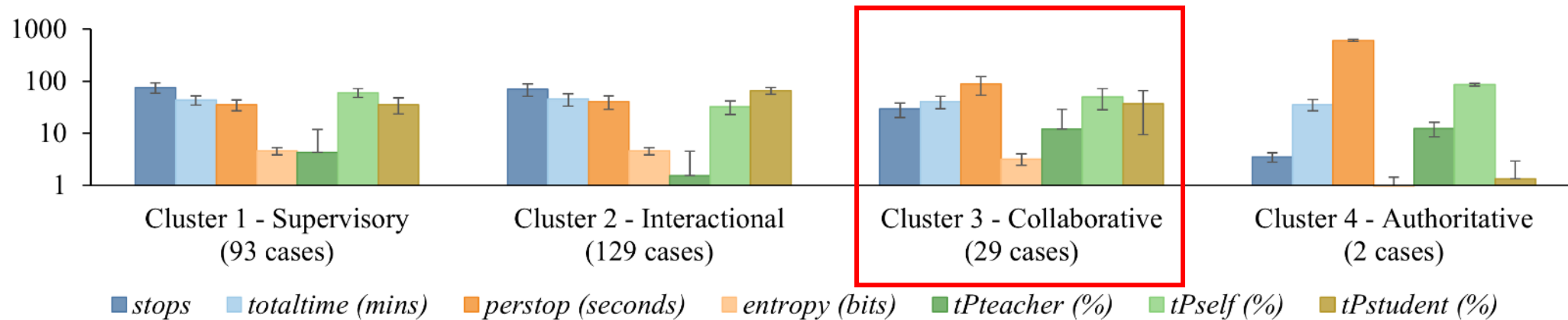
Metric	Unit	Description
<i>stops</i>	instances	The number of stops made by a teacher per session.
<i>totaltime</i>	minutes	The total stopping time of a teacher per session.
<i>perstop</i>	seconds	The duration of each stop made by a teacher per session.
<i>entropy</i>	bits	The information density of a teacher's spatial data per session.
<i>tPteacher</i>	percent	The percentage of time a teacher spent near other teachers per session.
<i>tPself</i>	percent	The percentage of time a teacher spent by her/himself per session.
<i>tPstudent</i>	percent	The percentage of time a teacher spent near students per session.

Case 1: Teachers' Spatial Pedagogy



Teachers' socio-spatial behaviours based on the four types of pedagogical approaches proposed by Lim et al.'s theory of spatial pedagogy (interactional, supervisory, authoritative, personal).

Case 1: Teachers' Spatial Pedagogy



Teachers' socio-spatial behaviours based on the four types of pedagogical approaches proposed by Lim et al.'s theory of spatial pedagogy (interactional, supervisory, authoritative, personal).

Case 1: Context-specific Spatial Pedagogy

Fixed-sitting Classroom

- Interactional
- Supervisory

Open Learning Space

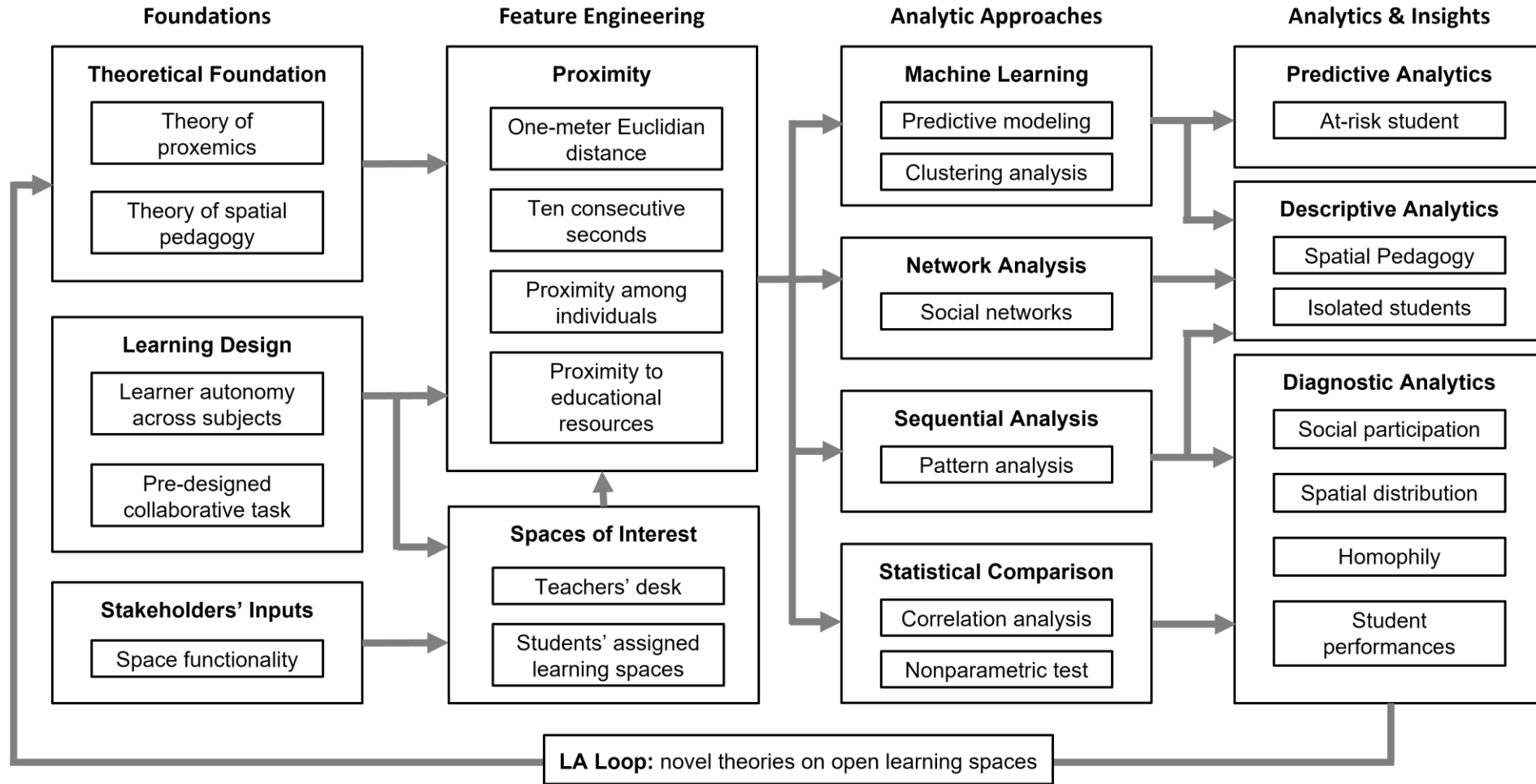
- Interactional
- Supervisory

- Authoritative
- Personal

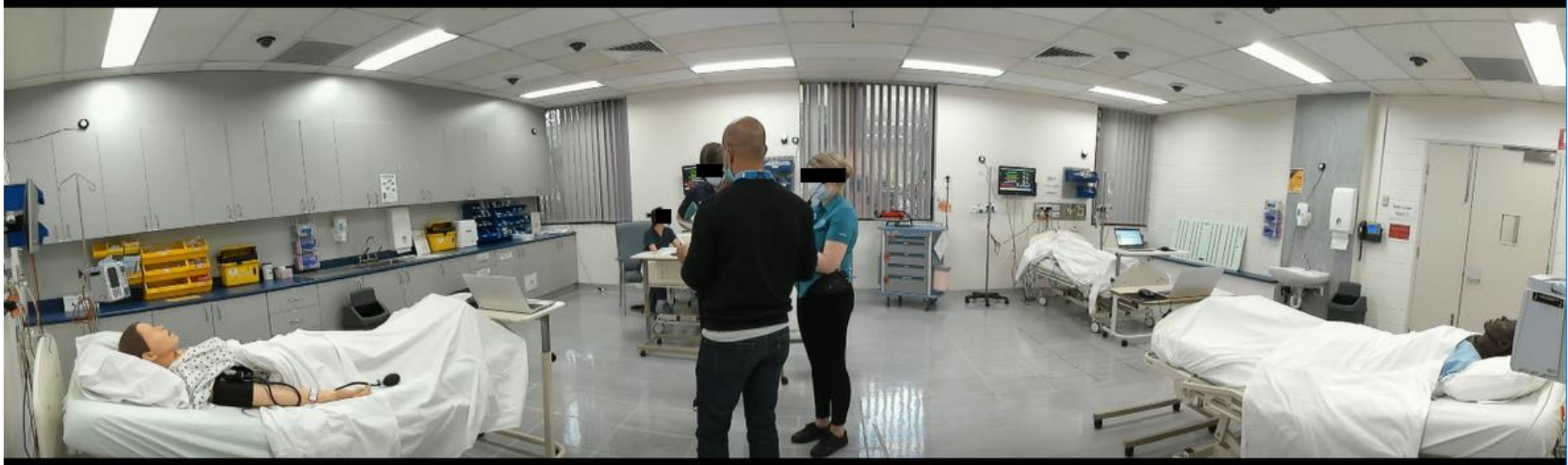


- Authoritative/Personal
- Collaborative

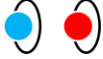








Case 1: Framework in Action

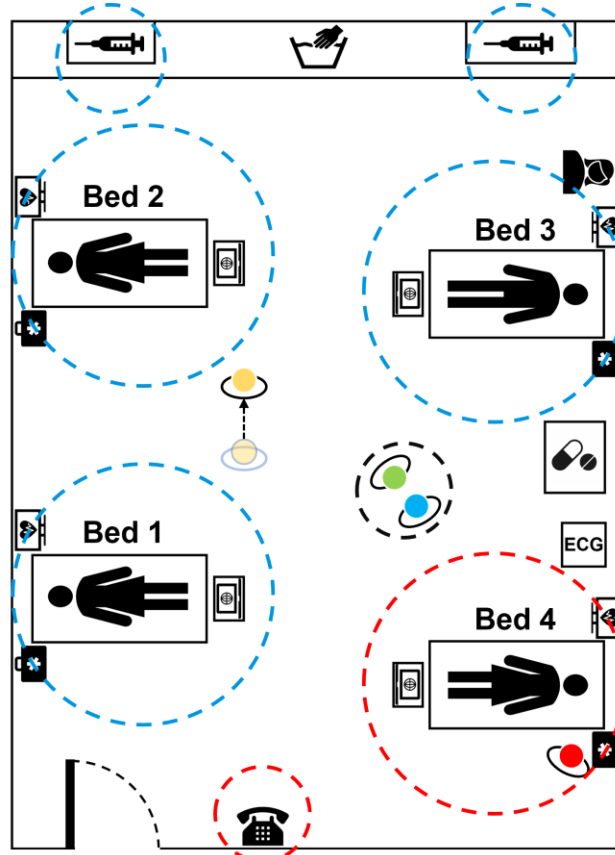


Case 2: Team-based Clinical Simulation





Case 2: Floor Plan and Task Spaces



-  Graduate Nurse
-  Ward Nurse
-  Vital Signs Monitor
-  Oxygen Devices
-  Laptop
-  IV Fluids
-  Resus Trolley
-  Family Relative
-  Phone



Examples of Task Space

-  Primary Task Space
-  Secondary Task Space

Examples of Behaviours

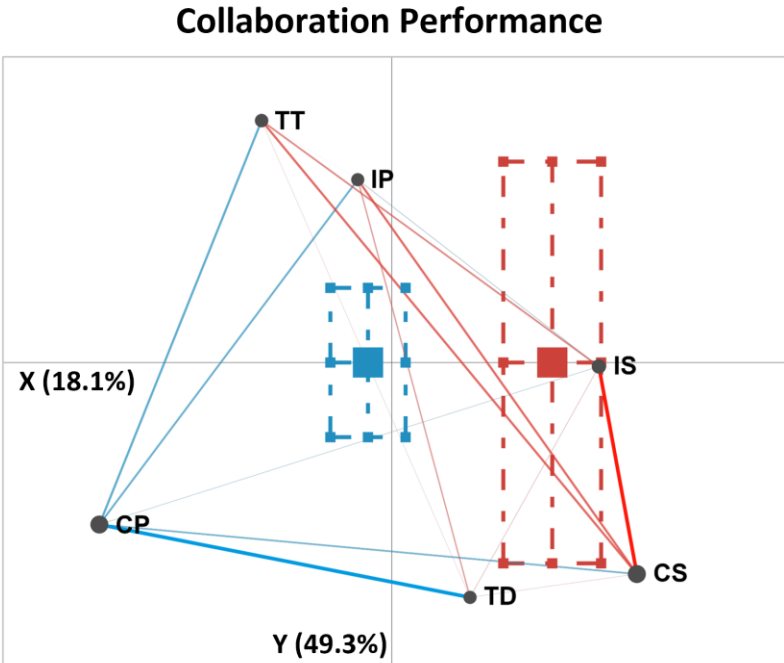
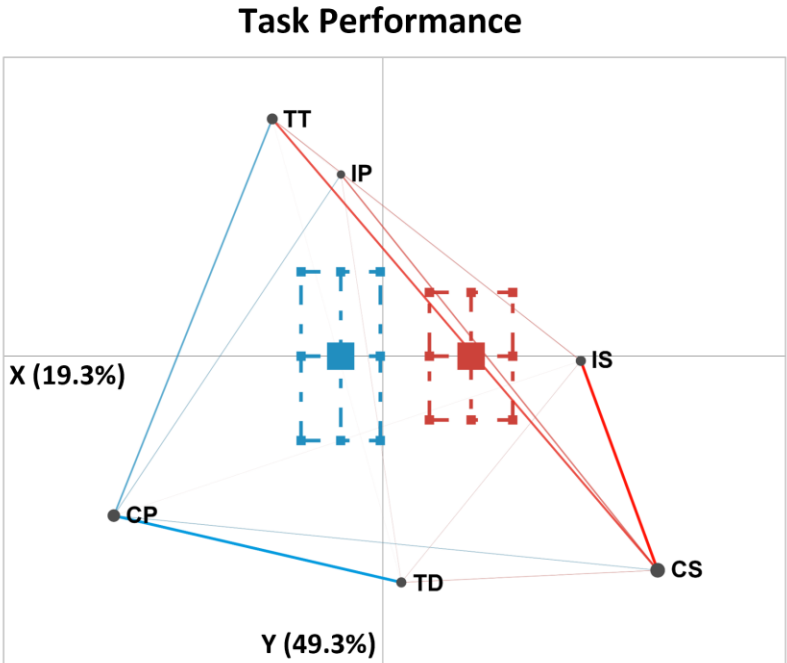
-  Task Distribution
-  Task Transition

Case 2: Socio-spatial Features

TABLE 2 Spatial-procedural behavioural features (percentage).

Features	Spatial-procedural Behaviours
<i>Collaborate_Primary (CP)</i>	Students working on the primary tasks collaboratively.
<i>Independent_Primary (IP)</i>	Students working on the primary tasks individually.
<i>Collaborate_Secondary (CS)</i>	Students working on the secondary task collaboratively.
<i>Independent_Secondary (IS)</i>	Students working on the secondary task individually.
<i>Task_Distribution (TD)</i>	Students distributing the responsibility of different tasks.
<i>Task_Transition (TT)</i>	Students transiting from one task to another task.

Case 2: Epistemic Network Analysis



- high-performing teams
- low-performing teams

Case 2: Educational Value — Supporting Reflective Practices

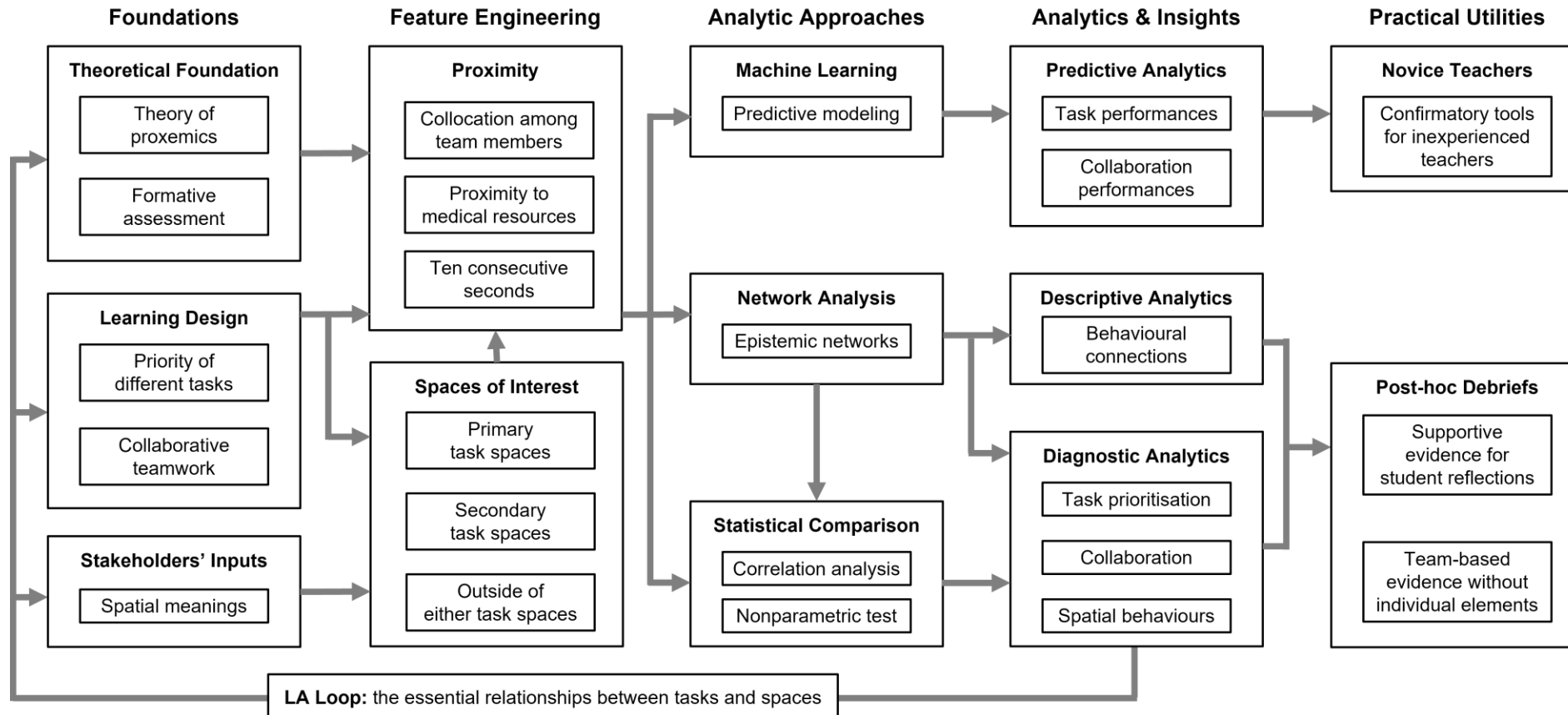
“This [epistemic network] would allow us to have a little bit of data to support what happened so that we can have a really good discussion in the debrief”

— Teacher_02

“I agree completely. Taking the students through something like you just did with us [explaining the epistemic networks] is a really good visual to then open up the discussion about, okay, tell me what was happening”

— Teacher_01

Case 2: Framework in Action



Opportunities and Challenges

Presenter: Lixiang (Jimmie) Yan



Opportunities for Educational Research

1. A potentially **more reliable and less biased** method to re-investigate previously found relationships between socio-spatial behaviours and educational constructs.
2. Data with greater **temporal and spatial precision** making advanced data analytic techniques more viable, which could benefit research into contemporary educational theories.
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Methodological and Practical Challenges

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Ethical Challenges

consent privacy
labelling surveillance data
stability misuse explainable
transparency personal
algorithmic biases accuracy
trustworthiness

Key Takeaways

Presenter: Lixiang (Jimmie) Yan



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1. The value of socio-spatial analytics is **context-dependent**
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References and Reading List

- Yan, L., Martinez-Maldonado, R., Cordoba, B. G., Deppeler, J., Corrigan, D., Nieto, G. F., & Gasevic, D. (2021, April). **Footprints at school: Modelling in-class social dynamics from students' physical positioning traces.** In LAK21: 11th international learning analytics and knowledge conference (pp. 43-54).
- Yan, L., Martinez-Maldonado, R., Zhao, L., Dix, S., Jaggard, H., Wotherspoon, R., ... & Gašević, D. (2022). **The role of indoor positioning analytics in assessment of simulation-based learning.** British Journal of Educational Technology.
- Yan, L., Martinez-Maldonado, R., Zhao, L., Deppeler, J., Corrigan, D., & Gasevic, D. (2022, March). **How do teachers use open learning spaces? Mapping from teachers' socio-spatial data to spatial pedagogy.** In LAK22: 12th International Learning Analytics and Knowledge Conference (pp. 87-97).
- Yan, L., Martinez-Maldonado, R., Gallo Cordoba, B., Deppeler, J., Corrigan, D., & Gašević, D. (2022). **Mapping from proximity traces to socio-spatial behaviours and student progression at the school.** British Journal of Educational Technology, 53(6), 1645-1664.
- Zhao, L., Yan, L., Gasevic, D., Dix, S., Jaggard, H., Wotherspoon, R., ... & Martinez-Maldonado, R. (2022, March). **Modelling co-located team communication from voice detection and positioning data in healthcare simulation.** In LAK22: 12th International Learning Analytics and Knowledge Conference (pp. 370-380).
- ZHAO, L., SWIECKI, Z., GAŠEVIĆ, D., YAN, L., DIX, S., JAGGARD, H., ... & MARTINEZ-MALDONADO, R.(2023). **METS: Multimodal Learning Analytics of Embodied Teamwork Learning.**
- Echeverria, V., Martinez-Maldonado, R., Yan, L., Zhao, L., Fernandez-Nieto, G., Gašević, D., & Shum, S. B. (2022). **HuCETA: A Framework for Human-Centered Embodied Teamwork Analytics.** IEEE Pervasive Computing.

FOR MORE INFORMATION CONTACT: LIXIANG YAN

Email: Lixiang.Yan@monash.edu

LinkedIn: Lixiang (Jimmie) Yan

Twitter: [@jimmie_yan](https://twitter.com/jimmie_yan)

