An Institute of

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

Multi-Modal Learning Analytics (MMLA) for Learning Design

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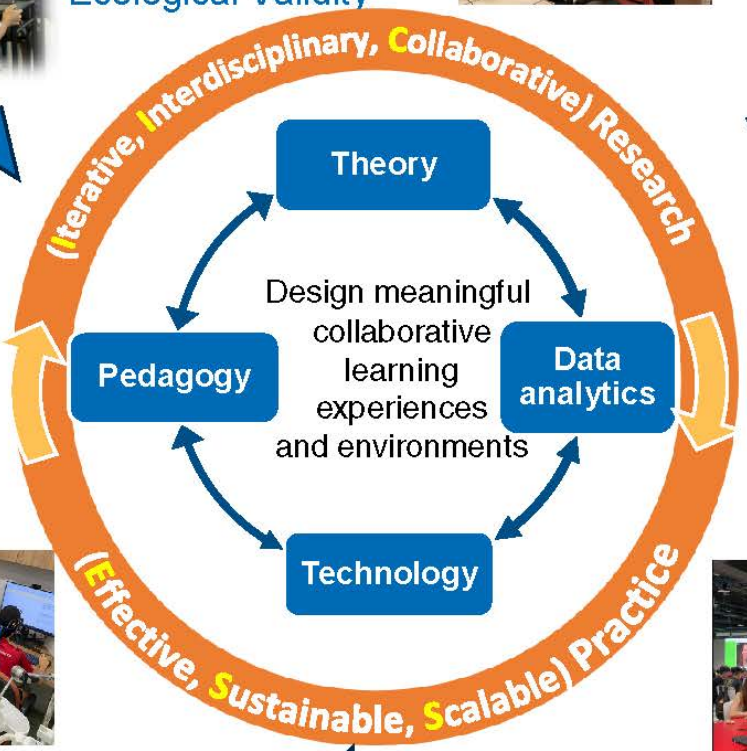
MMLA in Various Learning Environment


SINGAPORE

All secondary school students to get personal laptop or tablet for learning by 2021: Tharman

School classroom-based research

Ecological Validity



Lab-based experiment

Internal Validity

University classroom - based research

External Validity

Context: CSCL

- Collaborative Argumentation (CA)
  - A social process in which individuals work together to construct and critique arguments (Golanics & Nussbaum, 2008)

Scientific explanation

Social Study & History

Language & literature

Learn to Argue

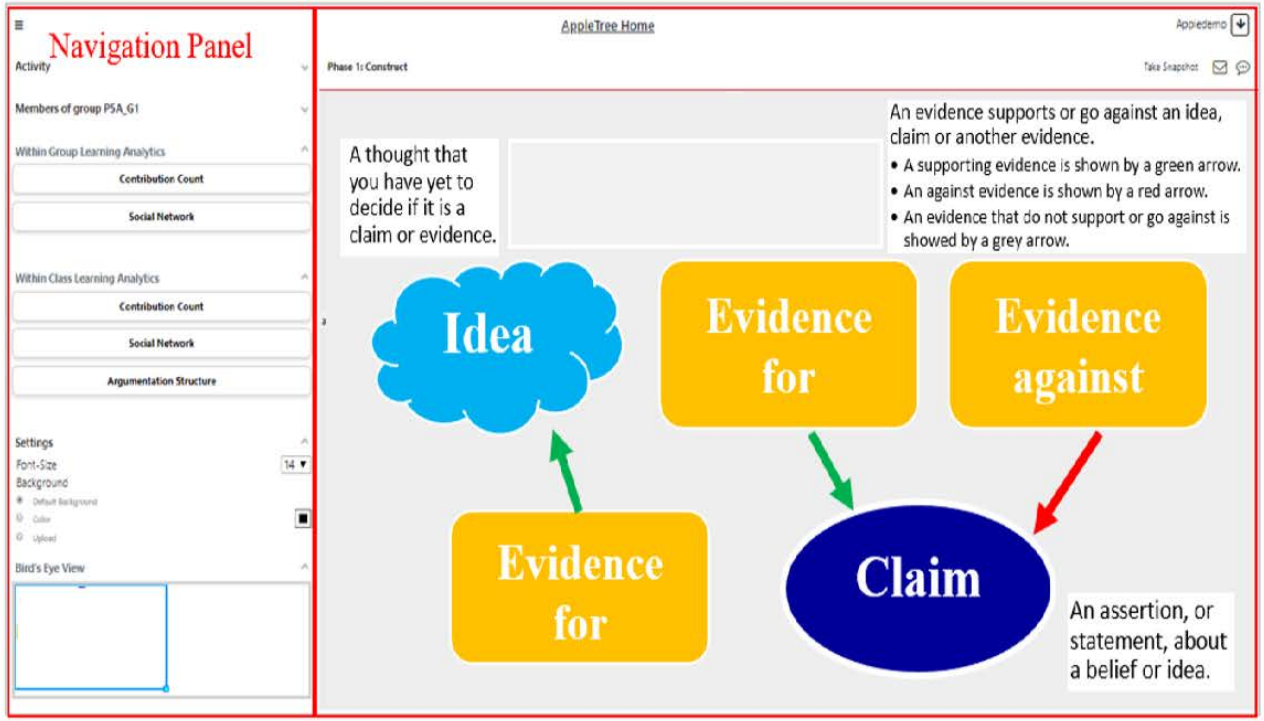
Argue to Learn

  - Techno-pedagogical design to address challenges

Argumentation	Collaborative learning	Analytics and visualization *for* learning
logic reasoning	multiple perspectives	real time
diagram based	improvable ideas	multi-dimensional

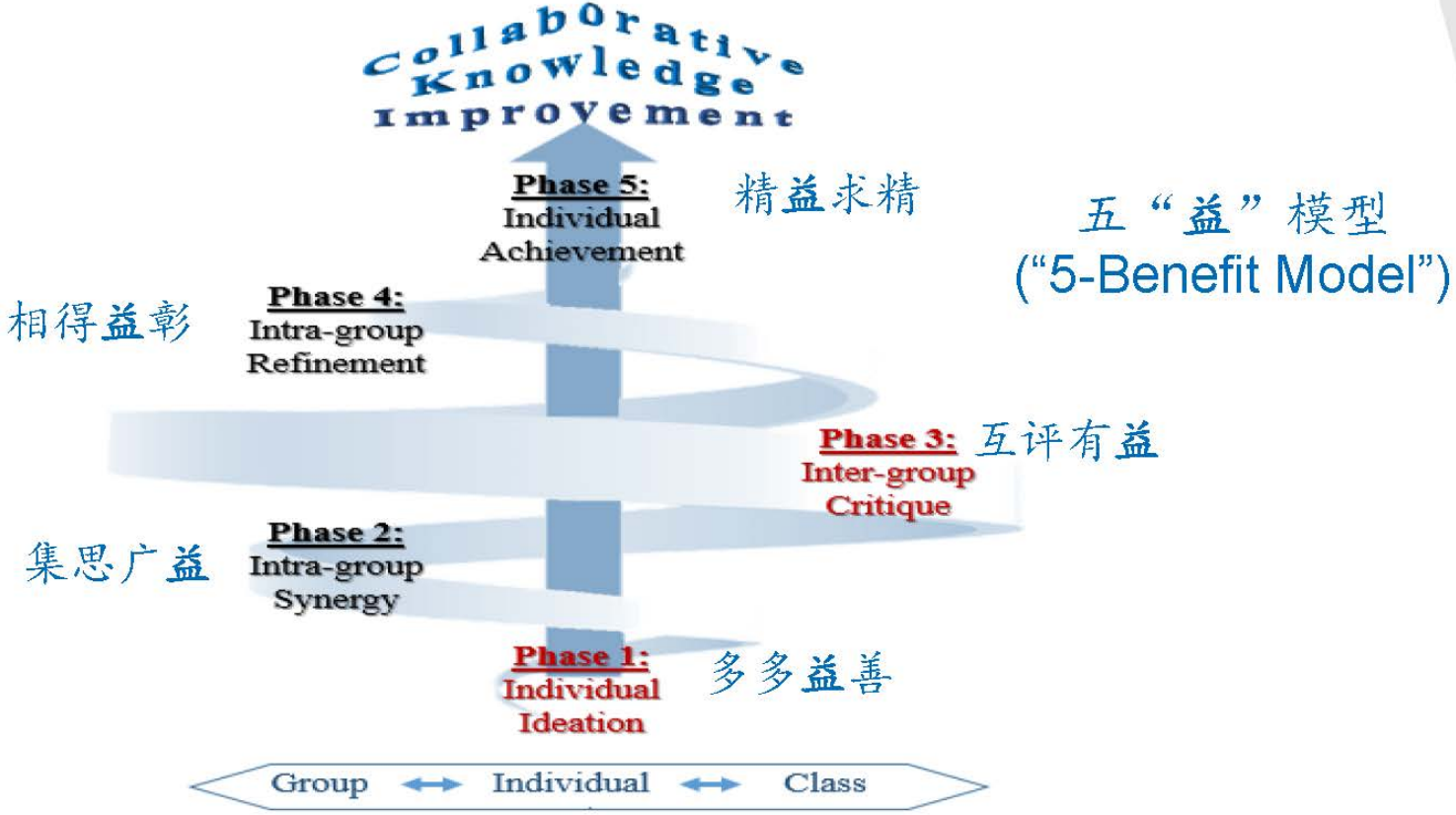
APPLETREE for CSCA

Assessing **P**rocesses and **P**orducts for **LE**arning (APPLE) by **T**racking and **R**eporting **E**fficacy and **E**ffectiveness (TREE)



Chen, W., Tan, J. S. H., Zhang, S., Pi, Z., & Lyu, Q. (2023). AppleTree system for effective computer-supported collaborative argumentation: An exploratory study. *Educational Technology Research and Development. 71*(5), 2103-2136.

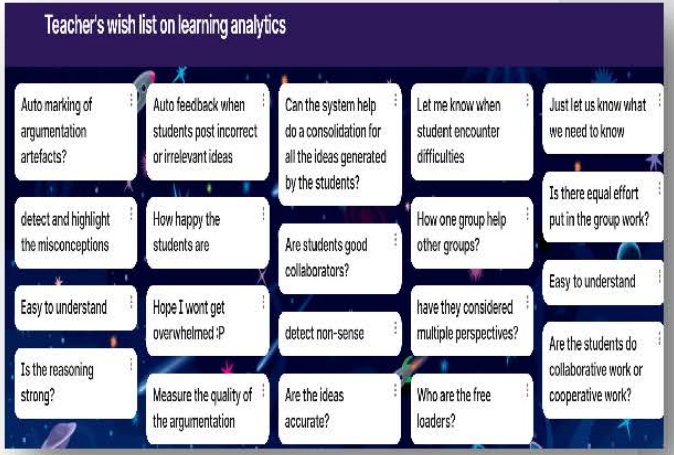
Pedagogical Model to Scaffold Collaborative Learning

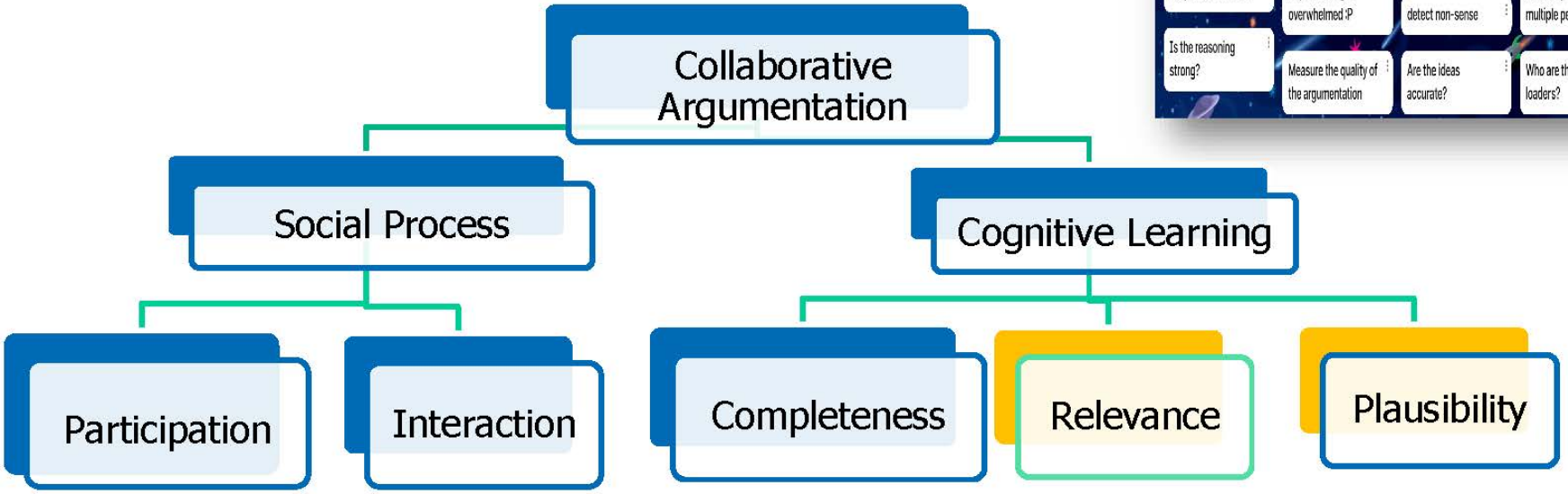


Chen, W., Tan, S.H. J., & Pi, Z. (2021). The spiral model of collaborative knowledge improvement: an exploratory study of a networked collaborative classroom. *International journal of Computer-Supported Collaborative Learning, 16*(1), 7-35.

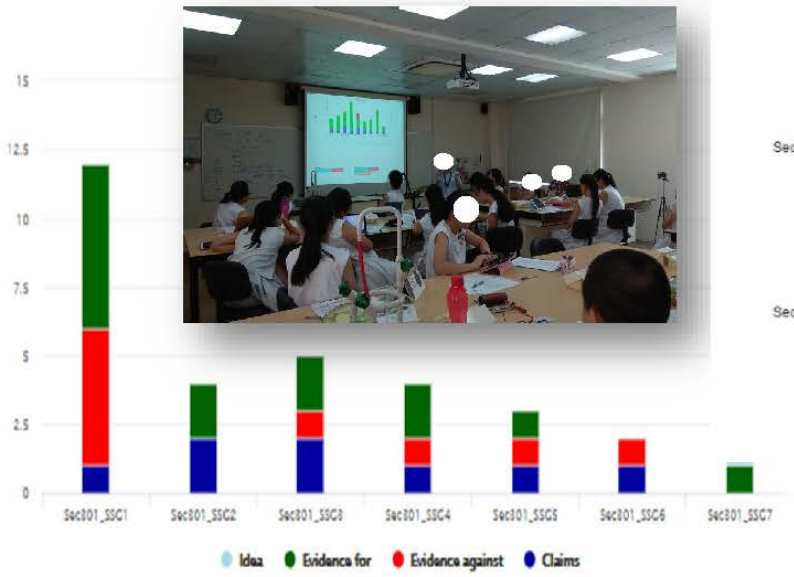
Teacher/Learner - Centered Learning Analytics

- Real time analytics and visualization ***for*** learning
  - To help teachers improvise teaching
  - To help students take agency to reflect and take actions

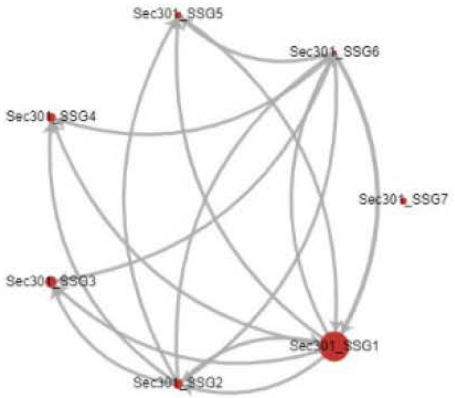




Teacher/Learner - Centered Learning Analytics



Participation



Social Network Analysis

Group Name	Argumentation Count
G1	1
G2	2
G3	1
G4	1
G5	1

Garden Score Explanation

- Golden apple represents a claim with more than two evidences, with at least one supporting and one rebuttal evidence .
- The orange apple represents a claim with one supporting and one rebuttal evidence.
- Red apple represents a claim with at least one evidence.
- Green apple represents a claim without any evidence.

Structural Completeness

Chen, W., & Koh, H. L. E. (2021). Learning Analytics for Education. In Tan., Quek., & Diva (Eds). *Technology for meaningful learning*, (pp. 63-80). Singapore: Springer.

Designing CSCL in University Classrooms

Collaborative lesson design

Tan, J. S., & Chen, W. (2022). Peer feedback to support collaborative knowledge improvement: What kind of feedback feed-forward?. *Computers & Education*, *187*, 104467.

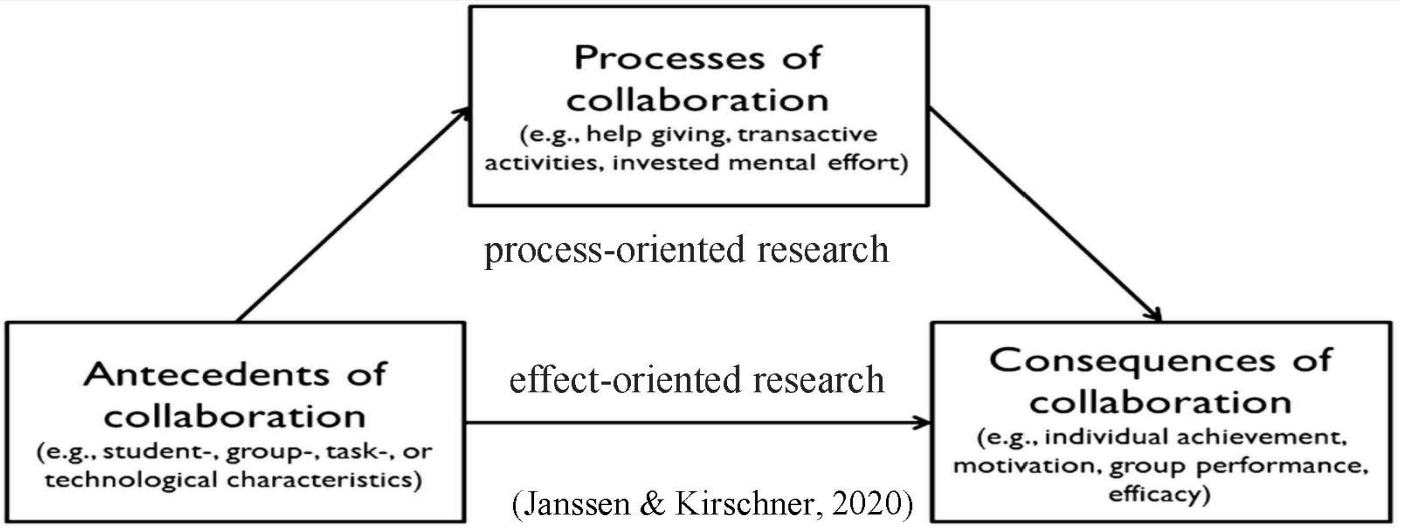
Tan, J. S., Chen, W., Su, J., & Su, G. (2023). The mechanism and effect of class-wide peer feedback on conceptual knowledge improvement: Does different feedback type matter?. *International Journal of Computer-Supported Collaborative Learning*, *18*(3), 393-424.

Interdisciplinary collaborative core courses

Collaborative engineering design

Lyu, Q., Chen, W., Su, J., & Heng, K. H. (2023). Collaborate like expert designers: An exploratory study of the role of individual preparation activity on students' collaborative learning. *The Internet and Higher Education*, *59*, 100920 https://doi.org/10.1016/j.iheduc.2023.100920

Trend in CSCL Research



Measurement, collection, analysis and reporting of data about learners and their contexts

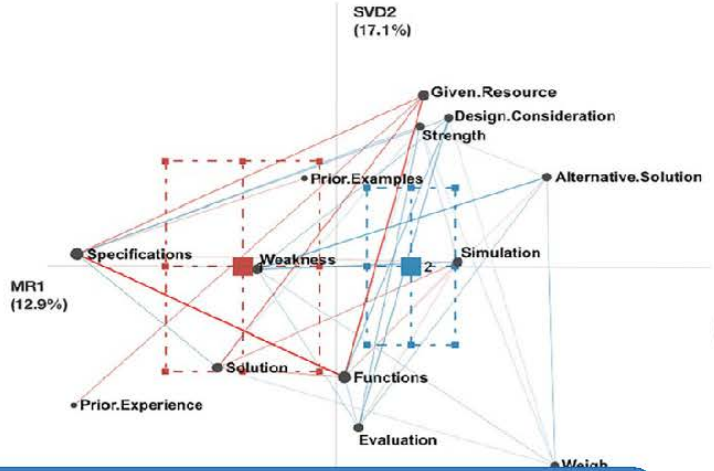
Understand learning experiences and environments

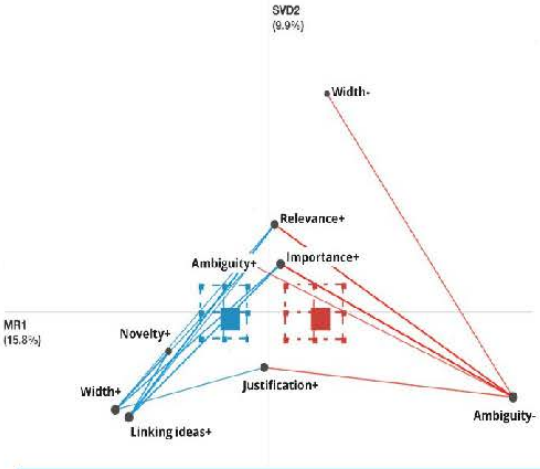
Optimise learning experiences and environments

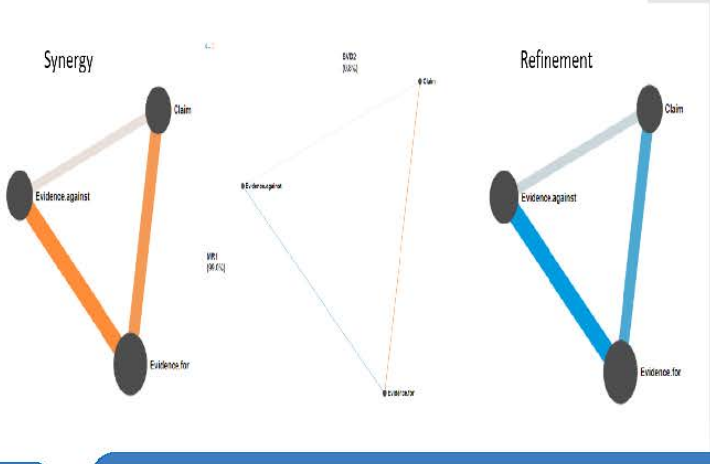
(Long & Siemens, 2011)

Process - Oriented Analysis to Optimize Learning Design

- Epistemic Network Analysis







What are the differences on the characteristics of the student-generated artifacts between two groups?

Lyu, Q., Chen, W., Su J., & Heng, K.H. (2023). Collaborate like Expert Engineers: An Exploratory Study of the Role of Individual Preparation Activity on Students' Collaborative Learning. *The Internet and Higher Education.* https://doi.org/10.1016/j.iheduc.2023.100920

How do students improve their critical thinking through CSCL?

Chen, W., Hu, H., Lyu, Q., & Zheng, L. (2024). Using Peer Feedback to Improve Critical Thinking in Computer-supported Collaborative Argumentation: An Exploratory Study. *Journal of Computer-Assisted Learning.* https://doi.org/10.1111/jcal.13078

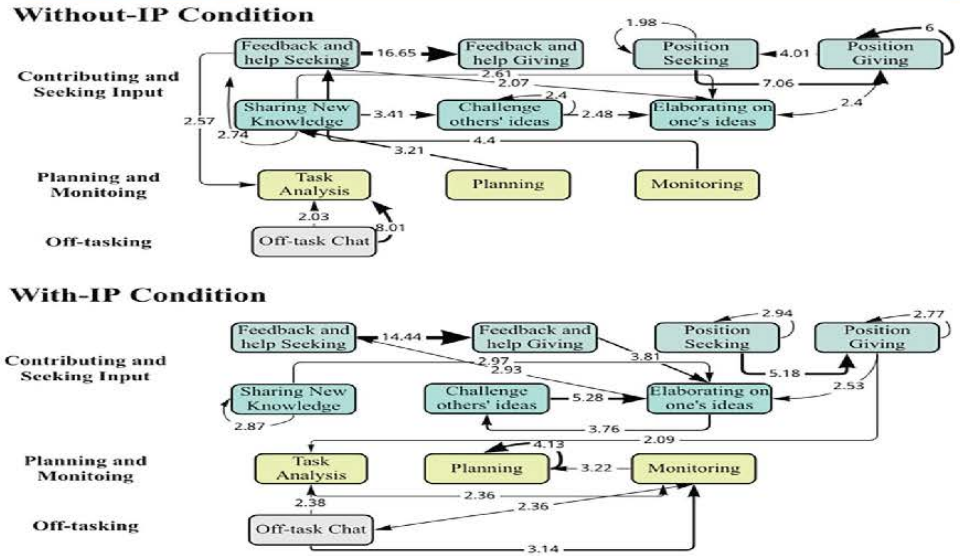
How do students improve their argumentation skills through SMCKI when learning SSI?

Chen, W., Han, Y., Tan., J., Chai, A., Lyu, Q., & Lyna. (2024). Exploring students' computer supported collaborative argumentation with socio-scientific issues. *Journal of Computer-Assisted Learning.* https://doi.org/10.1111/jcal.13073

Process - Oriented Analysis to Optimize Learning Design

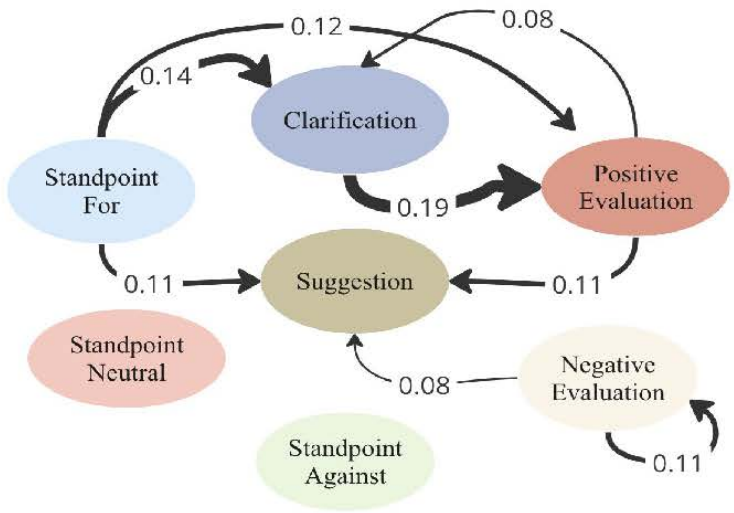
- Lag Sequential Analysis

What are the differences in students' interaction patterns between with-IP and without-IP conditions?



Chen, W., Lyu, Q., & Su, J. (2024). The role of individual preparation before collaboration: An exploratory study on students' Computer-Supported Collaborative Argumentation in a primary classroom. *Journal of the Learning Sciences*, 33(4-5), 757-798. https://doi.org/10.1080/10508406.2024.2397761

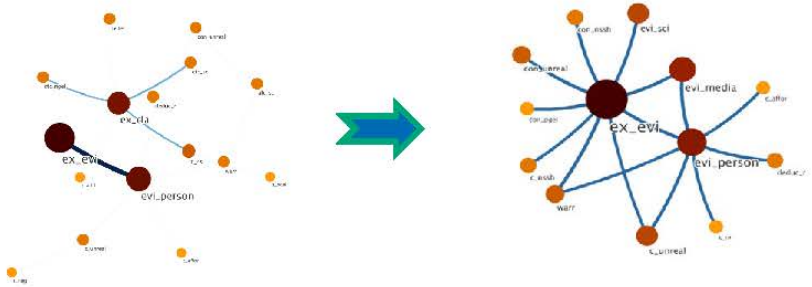
What are the rhetorical moves of students' engagement with peer feedback?



Lyu, Q., Chen, W., Su, J., & Heng, K. H. J. G. (2023). Steps to implementation: The role of peer feedback inner structure on feedback implementation. *Assessment & Evaluation in Higher Education*, 1-14. https://doi.org/10.1080/02602938.2023.2291340

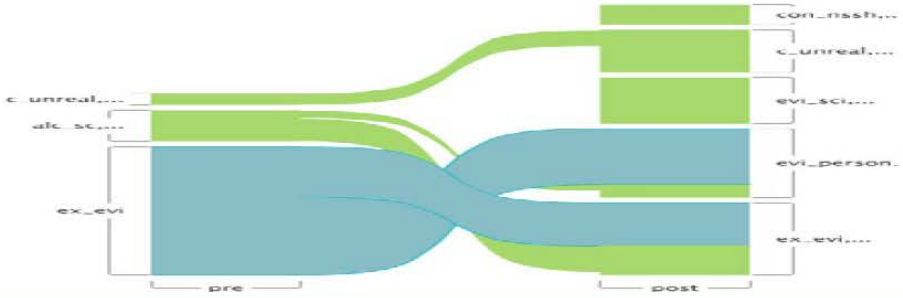
Process - Oriented Analysis to Optimize Learning Design

- Sankey Diagram

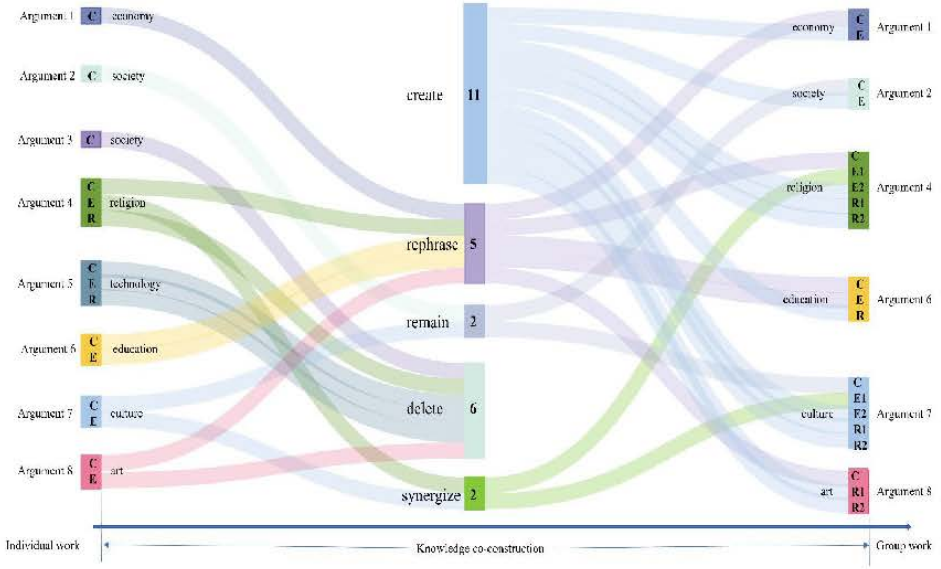


Pre-Intervention

Post-Intervention



Is there any improvement on knowledge after CSCL?

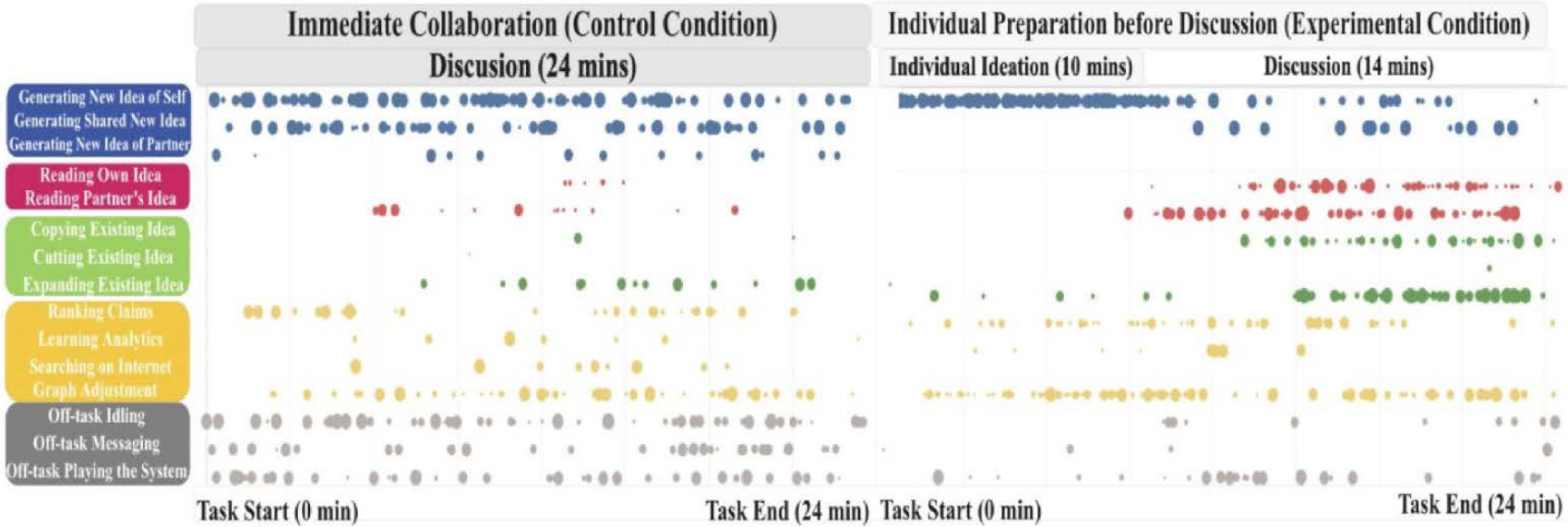


How do students co-construct argumentation?

Chen, W., Su, G., Li, X., Lyu, Q., Su, J., Chai, A., & Ng, E. E. (2023). From Individual Ideation to Group Knowledge Co-Construction: Comparison of High- and Low-performing Groups. *In Proceedings of the 31th International Conference on Computers in Education*. Japan: Matsue.

Process - Oriented Analysis to Optimize Learning Design

- Process mining

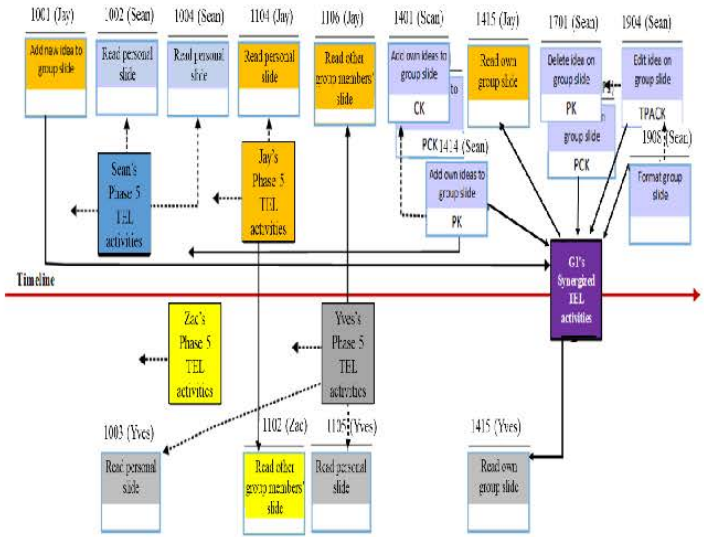


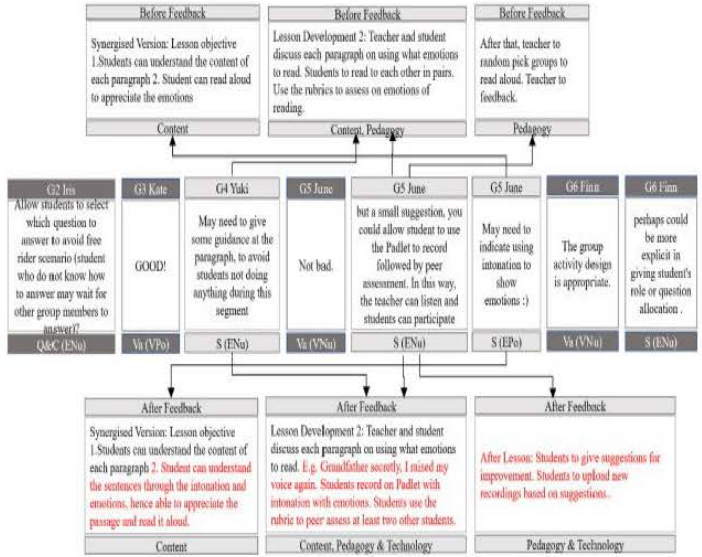
Whether and when different learning behaviours happen?

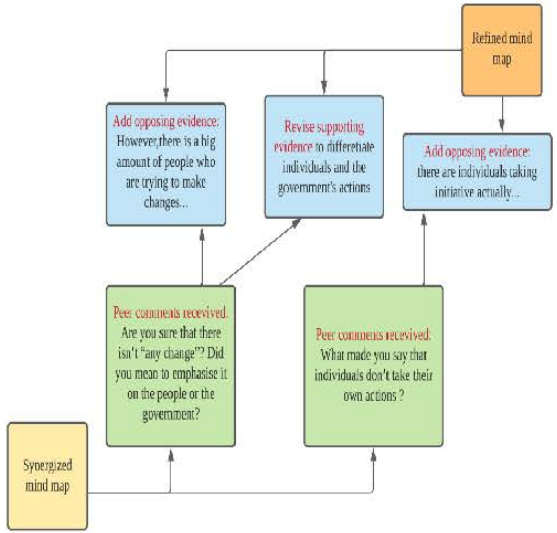
Chen, W., Lyu, Q., & Su, J. (2024). The Role of Individual preparation before collaboration: An exploratory study on students' computer-supported collaborative argumentation in a primary classroom. *Journal of the Learning Sciences*, 33(4-5), 757-798. https://doi.org/10.1080/10508406.2024.2397761

Process - Oriented Analysis to Optimize Learning Design

- Uptake analysis







What are the pivotal moments in collaborative ideation?

What are the pivotal moments in peer feedback?

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Tan, S. H. J., & Chen, W. (2022). Peer feedback to support collaborative knowledge improvement: What kind of feedback feed-forward? *Computers & Education, 187,* 104467. https://doi.org/10.1016/j.compedu.2022.104467

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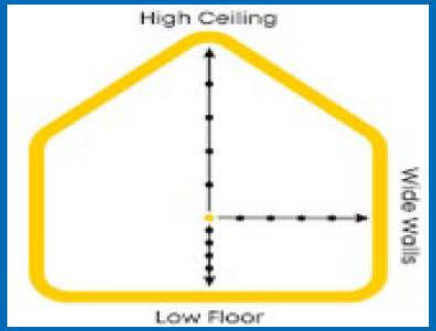
What are the missed opportunities?

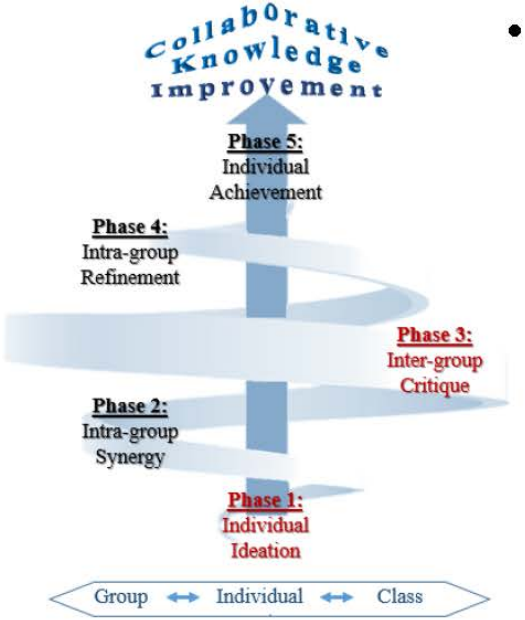
Task Design: When task is too simple or too close-ended



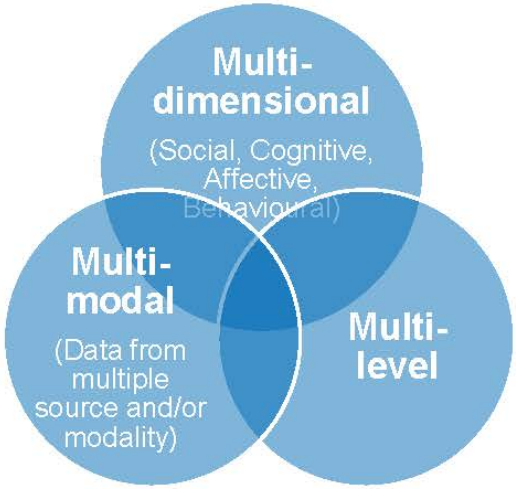
Time allocation: When time allocated is too short or too long

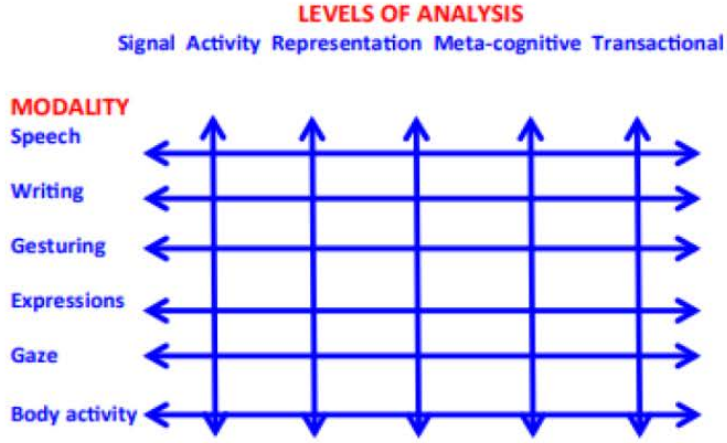
- **Asymmetrical participation**
- Focus on **completing rather than improving** the work
- **Lack inter-dependence** in group processes
- **Quick consensus:** Questions and comments are absent or ignored without deep-thinking
- **Poor conflict management:** Disagreement, conflict and competition issue
- **Difficulties in knowledge integration:** Integrating multiple ideas from various perspectives

Evidence Based Research to Optimize Learning Design



- MMLA approach for more nuanced understanding of students' engagement in different learning designs
  - extend the breadth and depth of research
  - examine the process of learning on a moment-by-moment basis as temporal approach is more reliably calibrate learning process



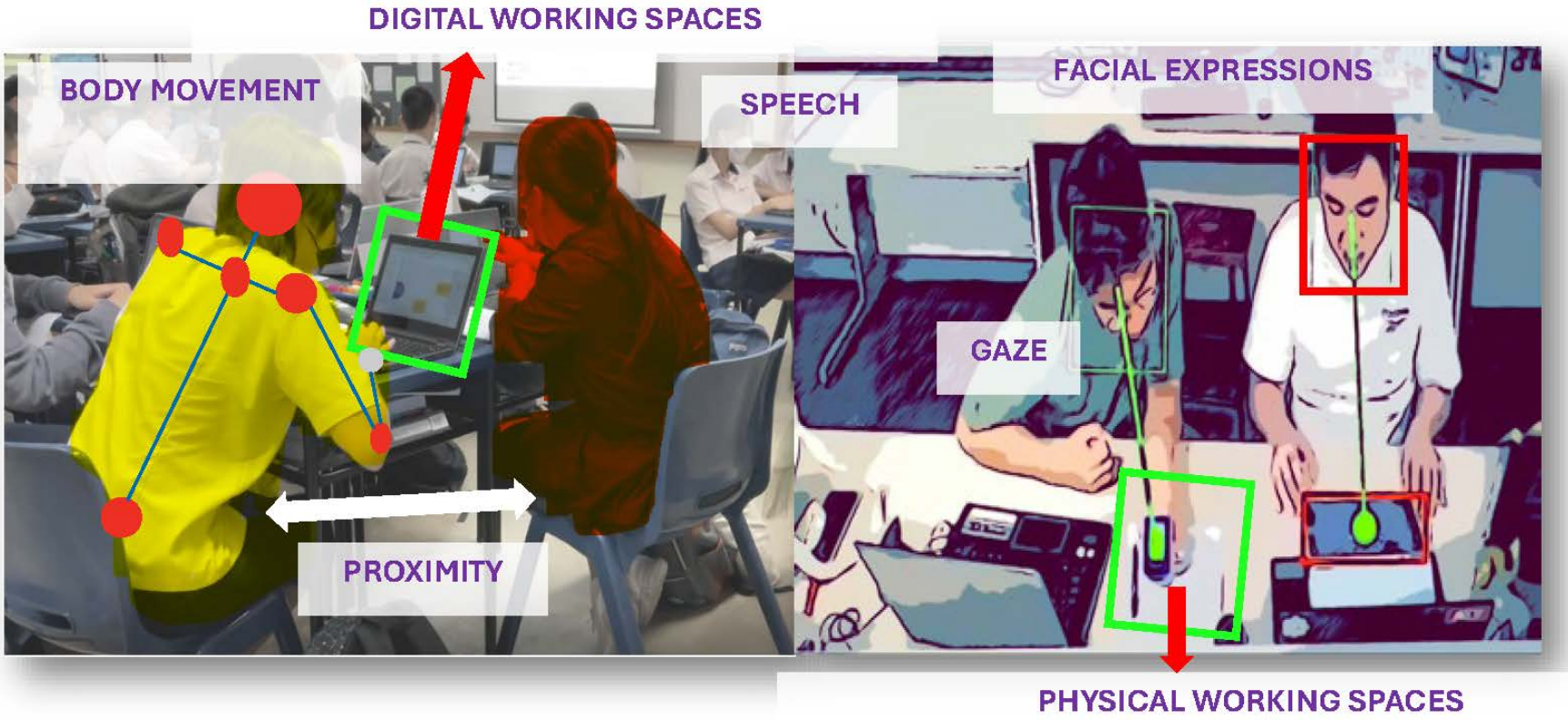


(Oviatt et al, 2018)

macromicro

Multi-Modal Data in Classrooms

- Multimodal data entails streams of data from several sources/ modalities.



Taxonomy of Multimodal Data

(Di Mitri et al., 2018)

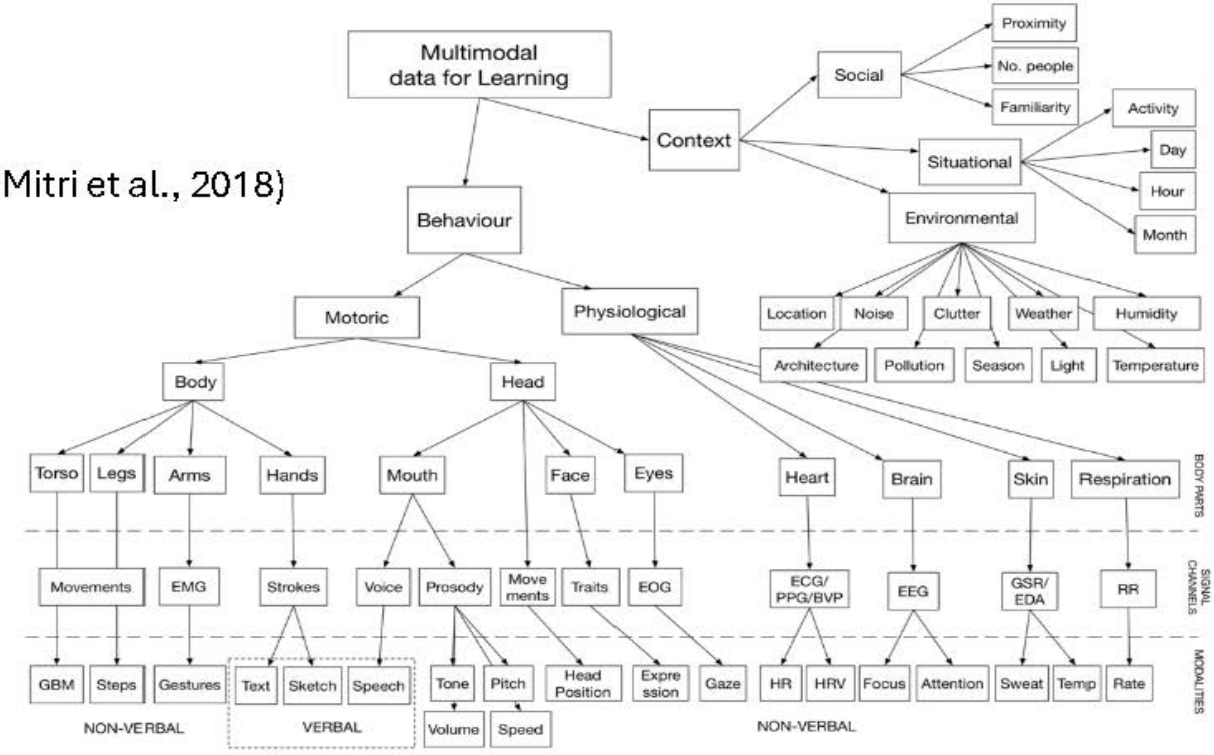
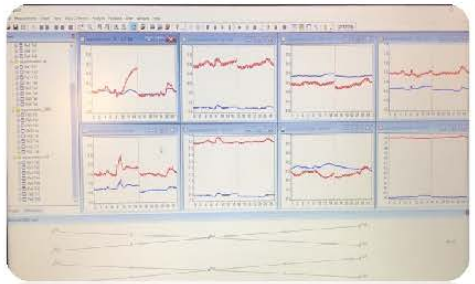


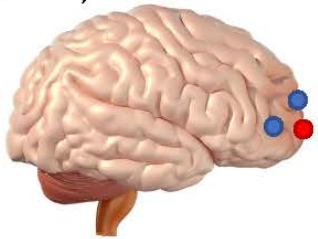
FIGURE 3 Taxonomy of multimodal data for learning. EMG: electormyogram; ECG: electrocardiogram; PPG: photoplethysmography; EEG: electroencephalogram; GSR: galvanic skin response; GBM: gross body movement; HR: heart rate; HRV: heart rate variability; EOG: Electrooculogram; BVP: Blood volume pulse; EDA: Electro dermal activity; RR: Respiration rate

Lab - Based Experiment

(Impact of Pedagogical Scaffold for CSCA)

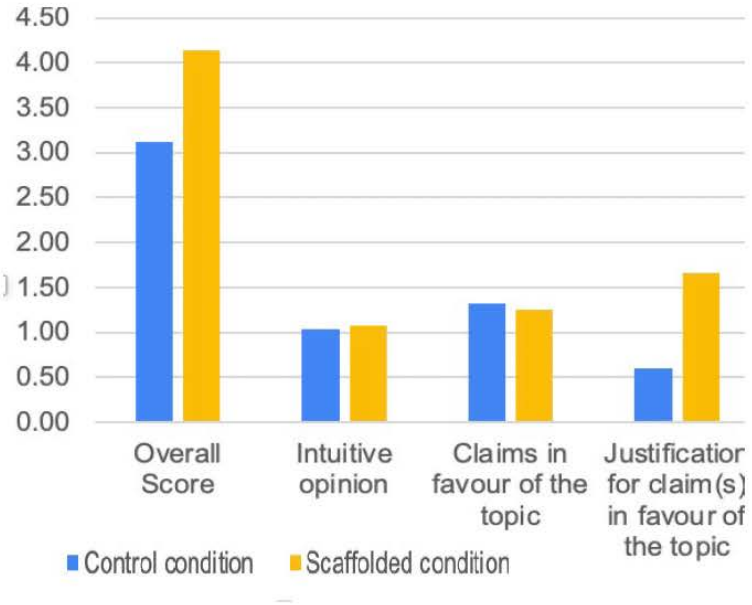


- Functional near-infrared spectroscopy (fNIRS)
  - Portable neuroimaging technique
  - Measures brain activity by detecting the changes in cortical hemodynamic activity as a result of neural activation
  - This study measures hemodynamic response of the Prefrontal Cortex (PFC)
    - Strong relationship between PFC and cognitive workload (Gateau et al., 2015; Çakır et al., 2016).

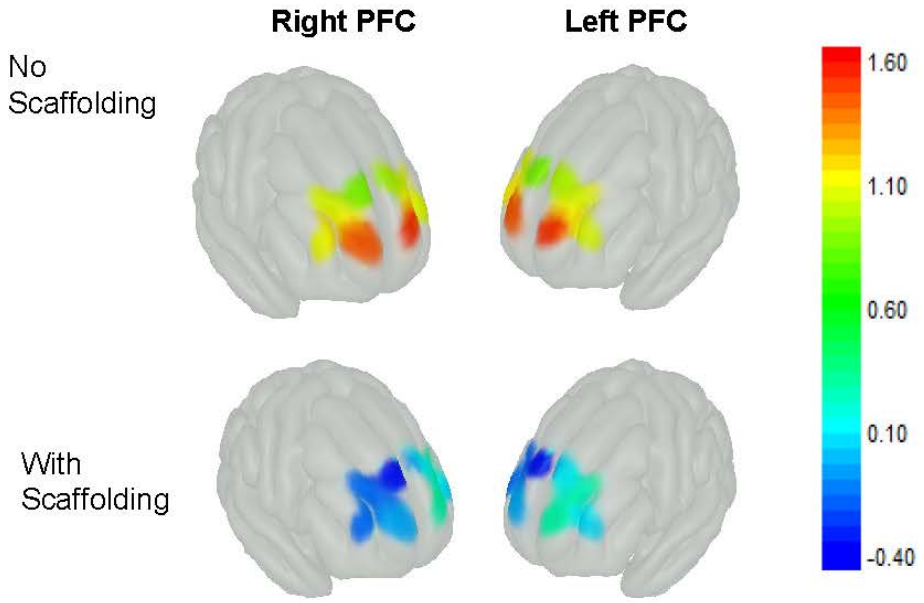


Impact of Argumentation Scaffold on Cognitive Load

- Argumentation artefact quality

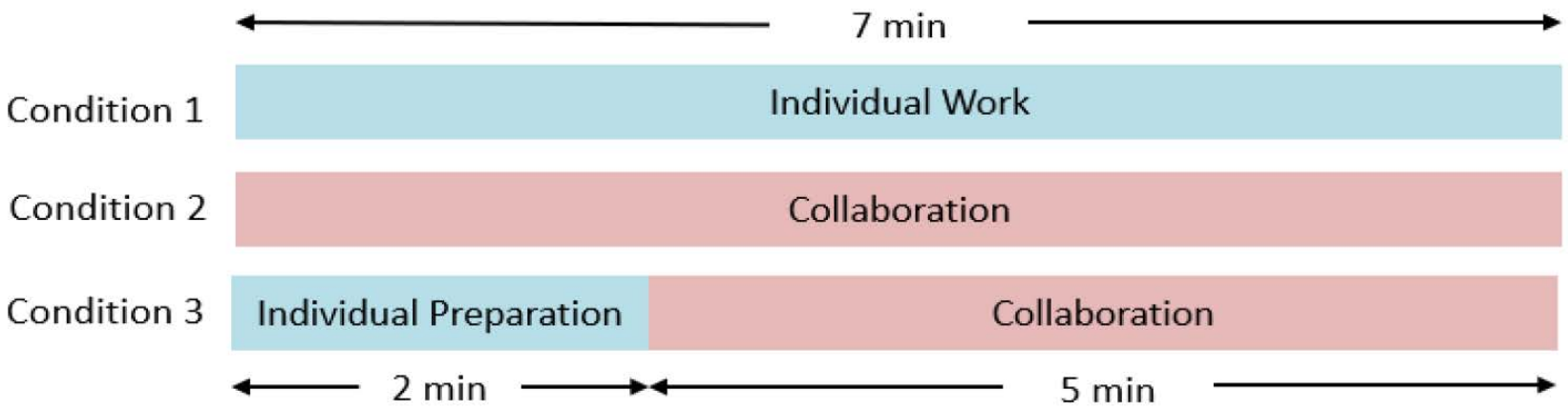


- Brain activation



Lab - Based Experiment

(Impact of Individual Preparation Before Collaboration)



- Collaboration activity: Dyad-based product ideation task

Multi-Modal Data Collection

(Bowden, Tickle, & Naumann, 2021)

1 fNIRS

- Individual: Functional connectivity
- Group: Inter-brain synchrony (IBS)

5 Student-generated artefact

2 Eye-Gaze

- Selecting
  Time to first fixation/entry time
- Organizing
  Dwell time, Fixation duration
- Integrating
  number of visits or re-reading
- Group: Joint attention

3 Behavior

- Verbal
- Online
- Facial Expression
- Body movement

4 Survey/ Interview

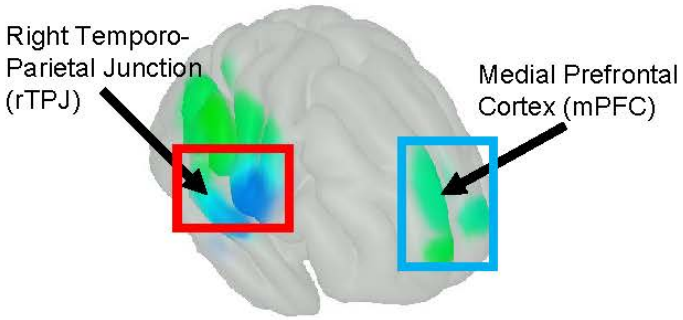
- Cognitive load, Emotion states, Group preference
- Perception

Experimental Set Up

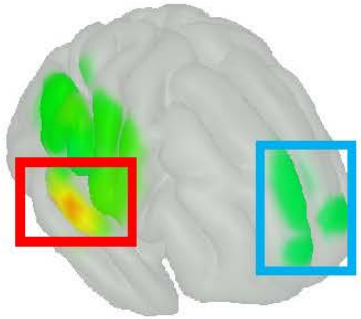
Hyperscanning : allows investigation of real-time dynamics between ≥ 2

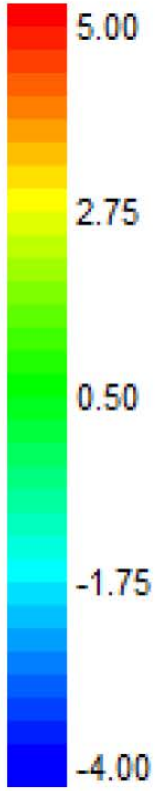
Findings on Brain Activation

- Individual learning

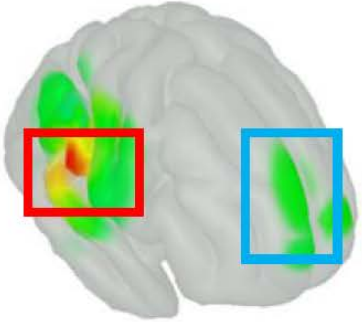


- Collaborative learning



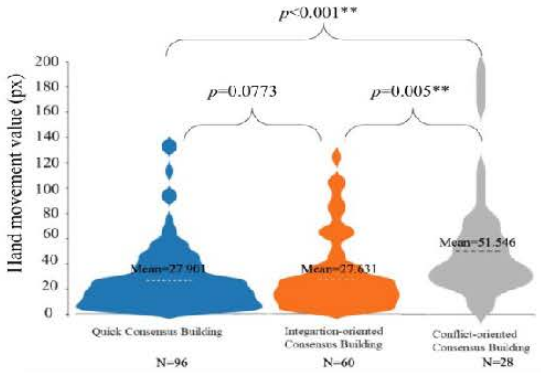


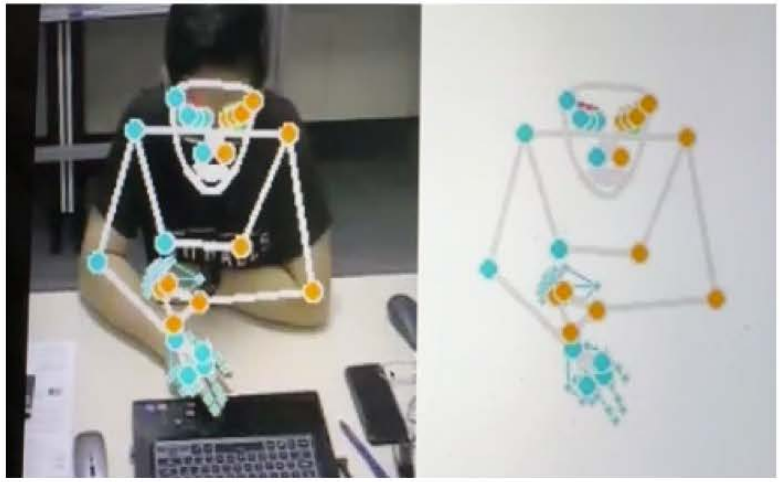
- Individual Preparation + Collaborative



AI-Empowered Analytics on Body Movement

- How do students apply **bodily engagement** for collaborative learning?
  - **Machine learning model**: MediaPipe
  - **Input**: video file
  - **Output**: moment-by-moment body landmarks





PhD student
Qianru LYU's work

- More hand movement in conflict-oriented consensus building than quick consensus building.
- More bodily engagement was applied during idea negotiation than superficial discussions.

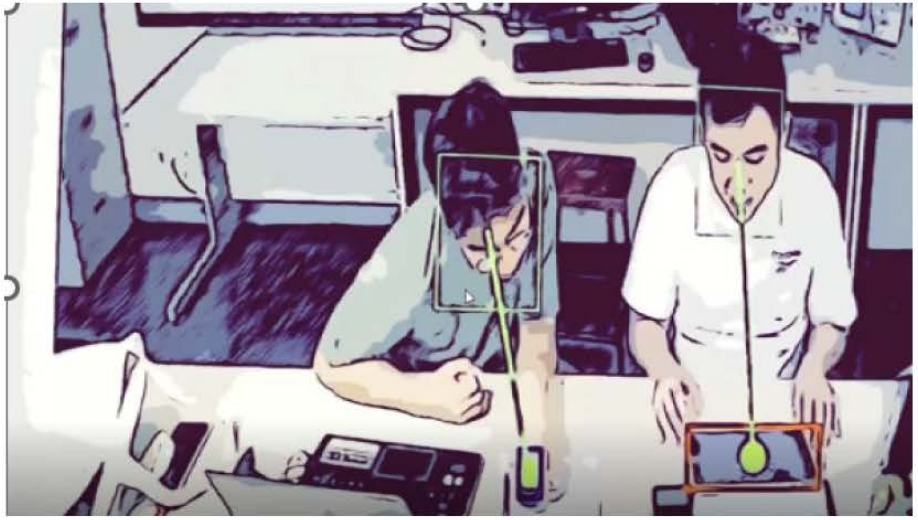
Lyu, Q., Chen, W., Su, J., Heng, K.H.J.G., Liu, S. (2023). How peers communicate without words-An exploratory study of hand movements in collaborative learning using computer-vision-based body recognition techniques. In: Wang, N., Rebolledo-Mendez, G., Matsuda, N., Santos, O.C., Dimitrova, V. (eds) Artificial Intelligence in Education. AIED 2023. Lecture Notes in Computer Science, vol 13916. Springer.

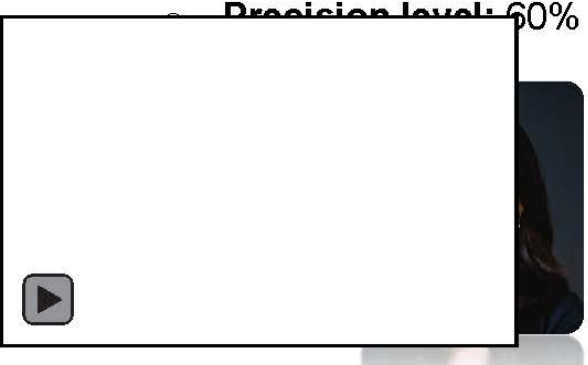
Lyu, Q., Chen, W., & Yeo, Amilia. (2024). Hands-on consensus building: Leveraging deep learning models to unveil hand gestures in consensus building discourses. Accepted by Cognition and Instruction.

AI-Empowered Analytics on Joint Attention

- How students apply **joint attention** (synchronized gazing detection) for collaborative learning?

  - **Machine learning model**: gazing detection, object detection (YOLOv7)
  - **Input**: video file
  - **Output**: moment-by-moment gazing detection and object detection
  - **Precision level**: 60% - 89%





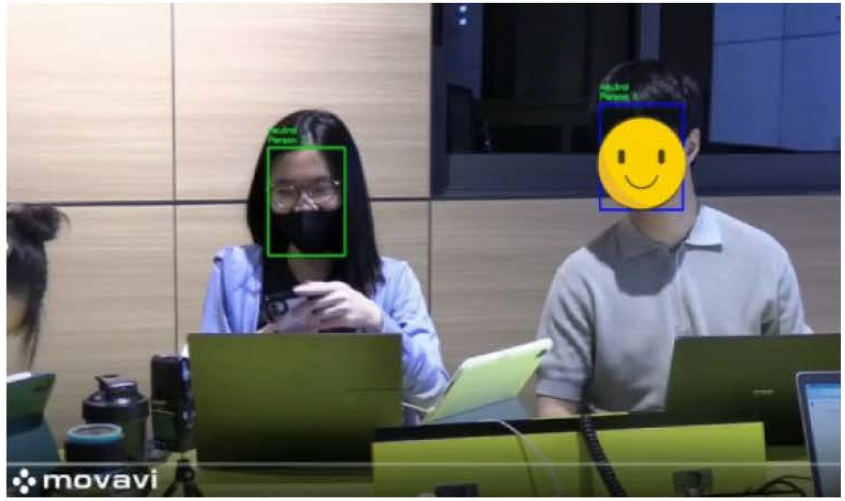
PhD student
Qianru LYU's work

AI-Empowered Analytics on Facial Expression

- The interplay of socio-cognitive and socio-emotional processes

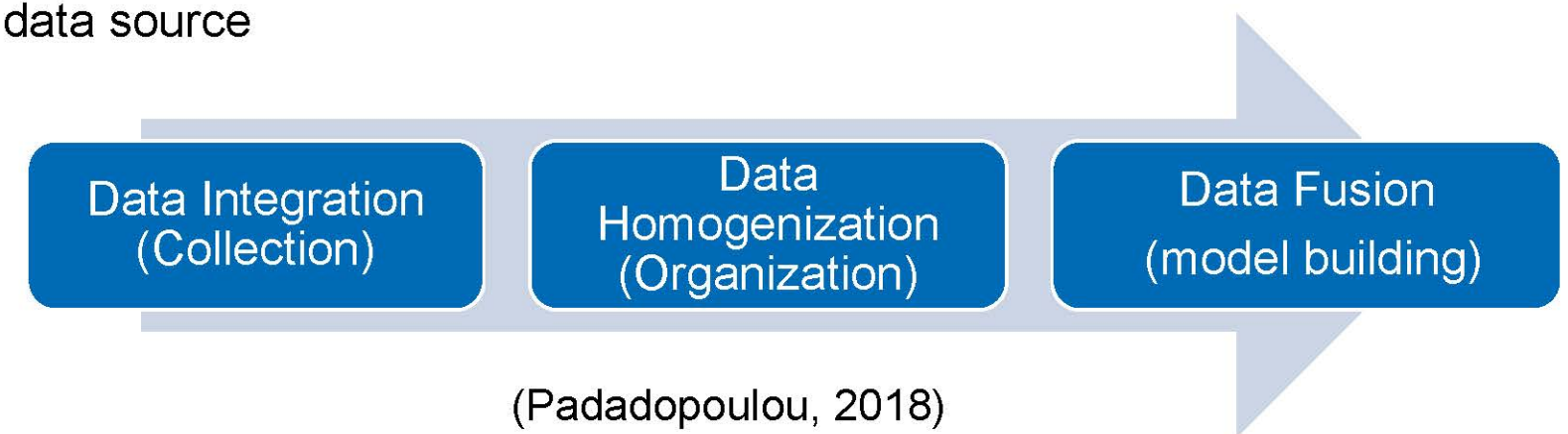
  - **Machine learning model**:
    FER Keras model
  - **Input**: video file
  - **Output**: moment-by-moment facial expression detection with confidence level

PhD student
Guo SU's work



Data Integration and Data Fusion

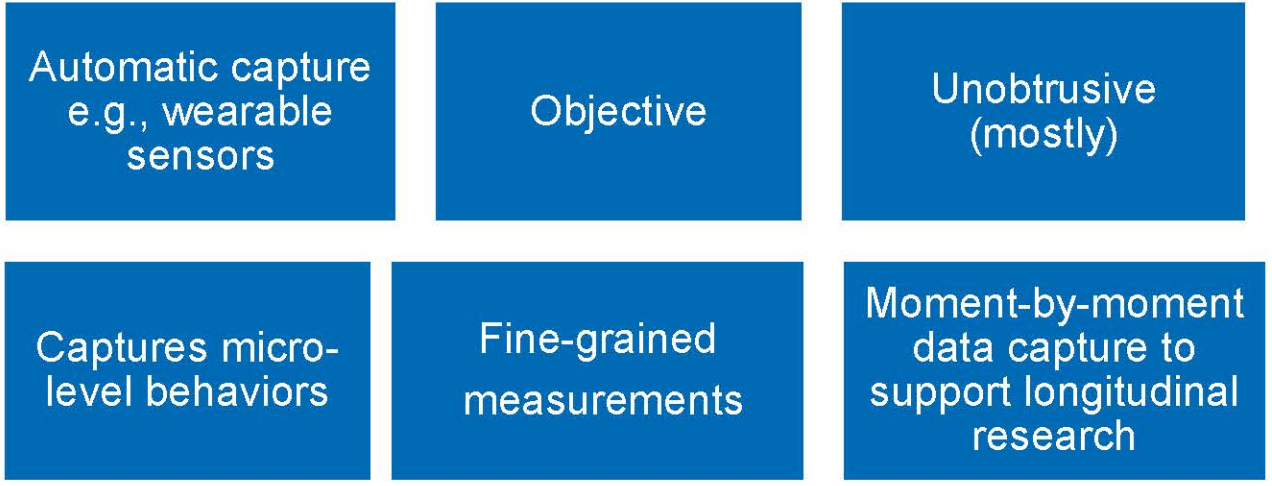
- Multimodal data integration: the “synchronous alignment and combination of data from different modalities (or contexts) in order to get a clearer understanding of the learning cues that students are producing” (Blikstein& Worsley, 2016, p.232)
- Data fusion is the process of integrating multiple data sources to produce more consistent, accurate and useful information than that provided by any individual data source



(Padadopoulou, 2018)

Advantages of MMLA

- Extends conventional LA (e.g., moving beyond self-reported and trace (logfile) data) by integrating learning data from a wide range of modalities towards the goals of understanding and optimizing the **complex, contextualized, and dynamic** learning experiences and environments



Challenges and Issues

- Difficulty in accessing data
- Ethical and privacy issues
- Data Quality
- Finding meaningful indicators and measures
- Challenges in data fusion
- Algorithms and models could be biased
- Findings may not lead to actionable insights for educators and learners

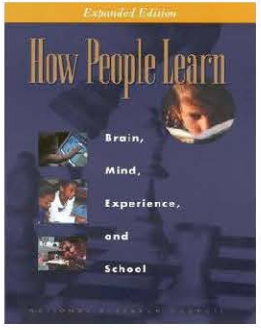
What counts can't always be measured.

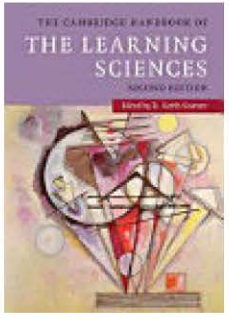
What's measurable doesn't always count.

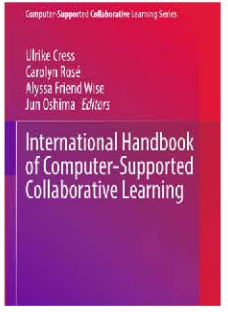
What is available doesn't always count.

Grounding MMLA in Theory

- Why need theory?
  - "Theory helps decide what we're going to do in education; theory helps us **to know what to look for next**. So, I think that without theory, we are in a place where it's a lot of people reinventing wheels and doing things that don't actually make much sense" (Swiecki, Baker, Järvelä, & Shaffer, 2023).
  - "LA needs to build on and better connect with the existing body or research knowledge about learning and teaching" (Gaševic, Dawson & Siemens, 2015)

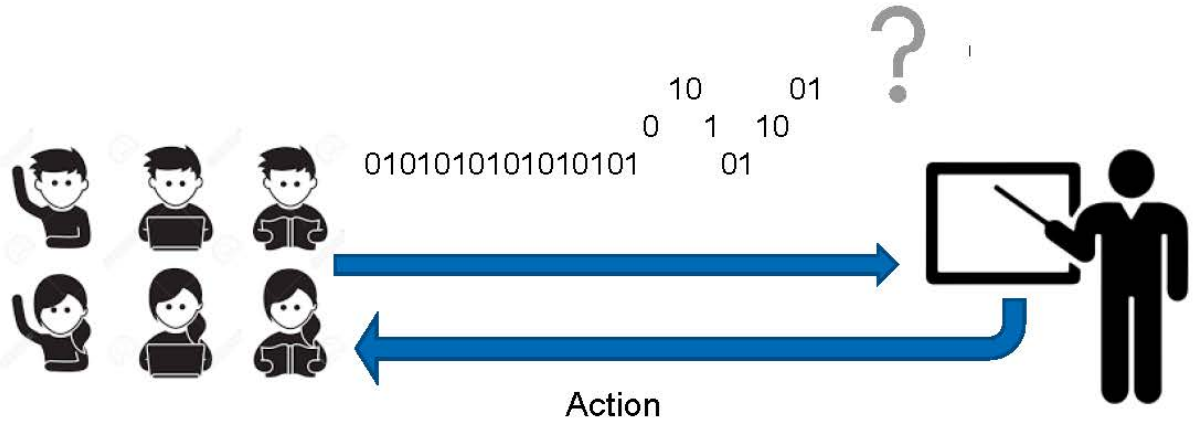






MMLA to Inform Teachers/Learners

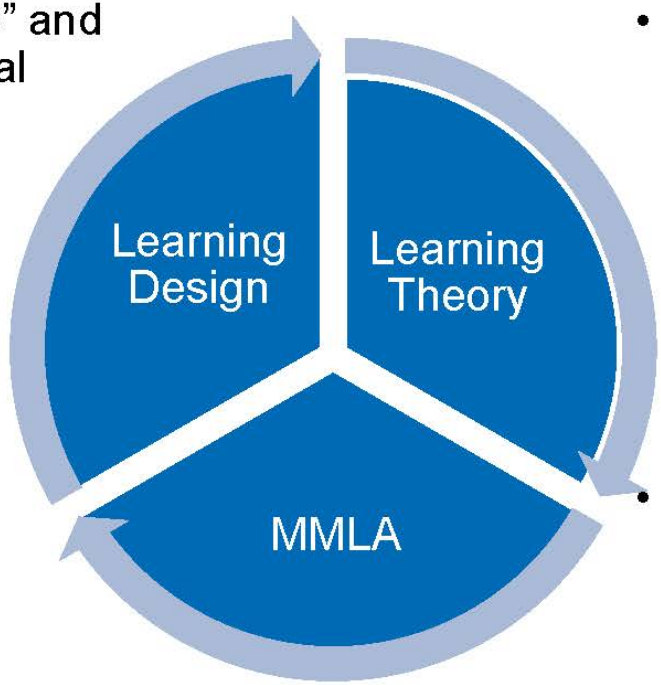
- How MMLA can be interpreted, applied and acted by learners and teachers?



- From researcher facing to teacher/ learner facing
- Need to “complete the loop” by providing actionable insights to learners and teachers

MMLA, Learning Theory, and Learning Design

- MMLA helps "validate" and inform the pedagogical decisions in learning design



- Learning theory helps identify useful MMLA (or gap of MMLA) and guide the interpretation, application and action of MMLA

- Learning design need MMLA for evidence – based design iterations (redesign)

- MMLA can not be used effectively without the understanding of the underlying theory

Thank you

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