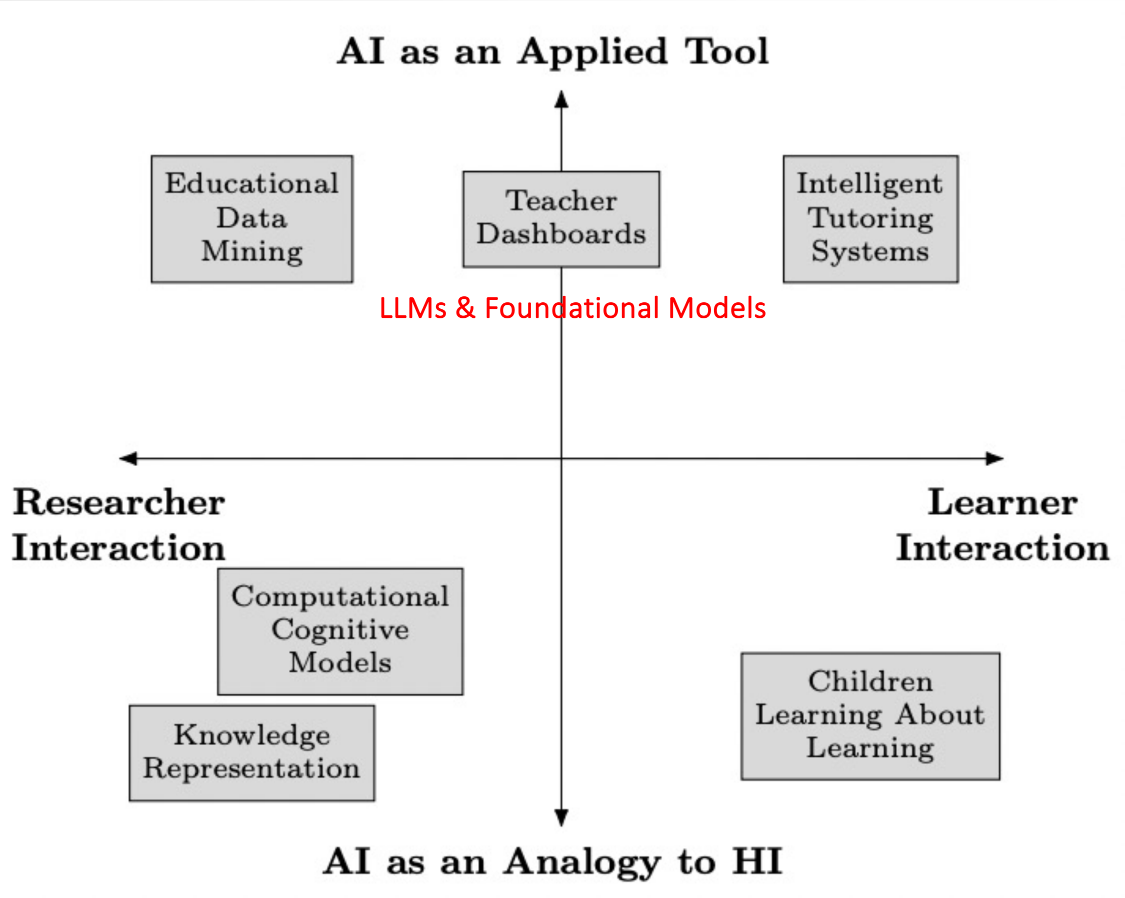
Artificial Intelligence in Education

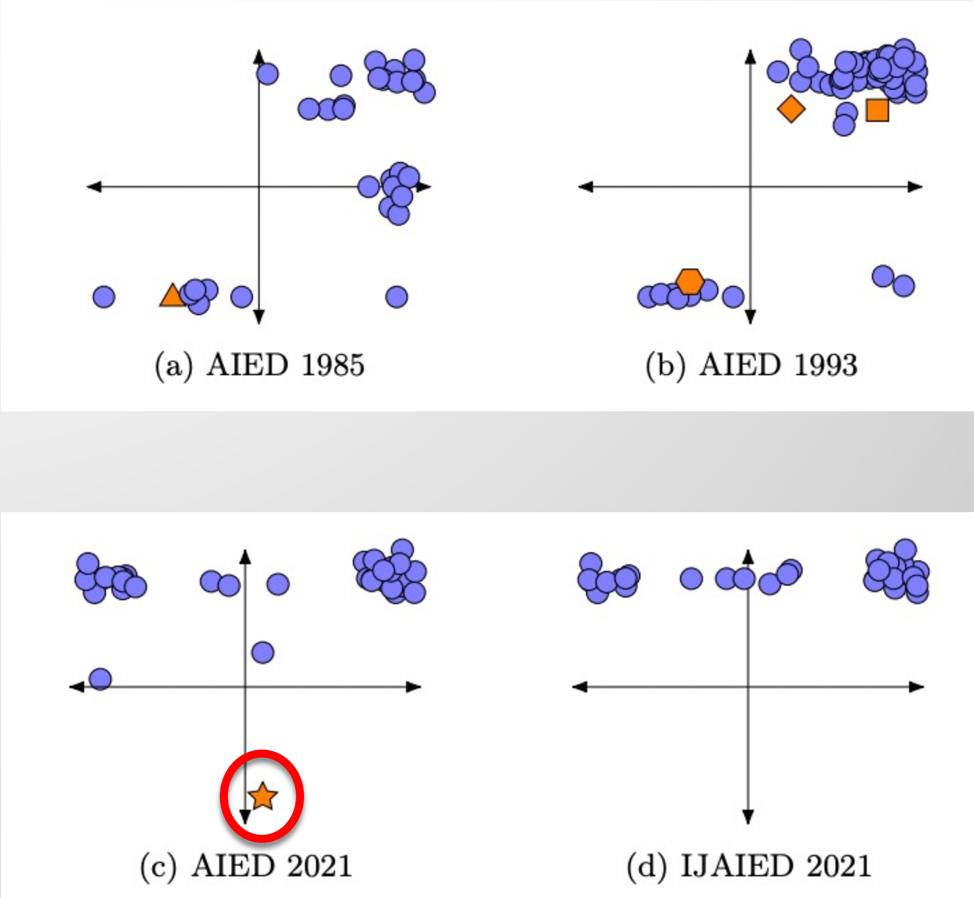
Professor Mutlu Cukurova
University College London
m.cukurova@ucl.ac.uk
@mutlucukurova

Knowledge Lab UCL UCLAIT - Team

UCL

AI is More than Applied Tools





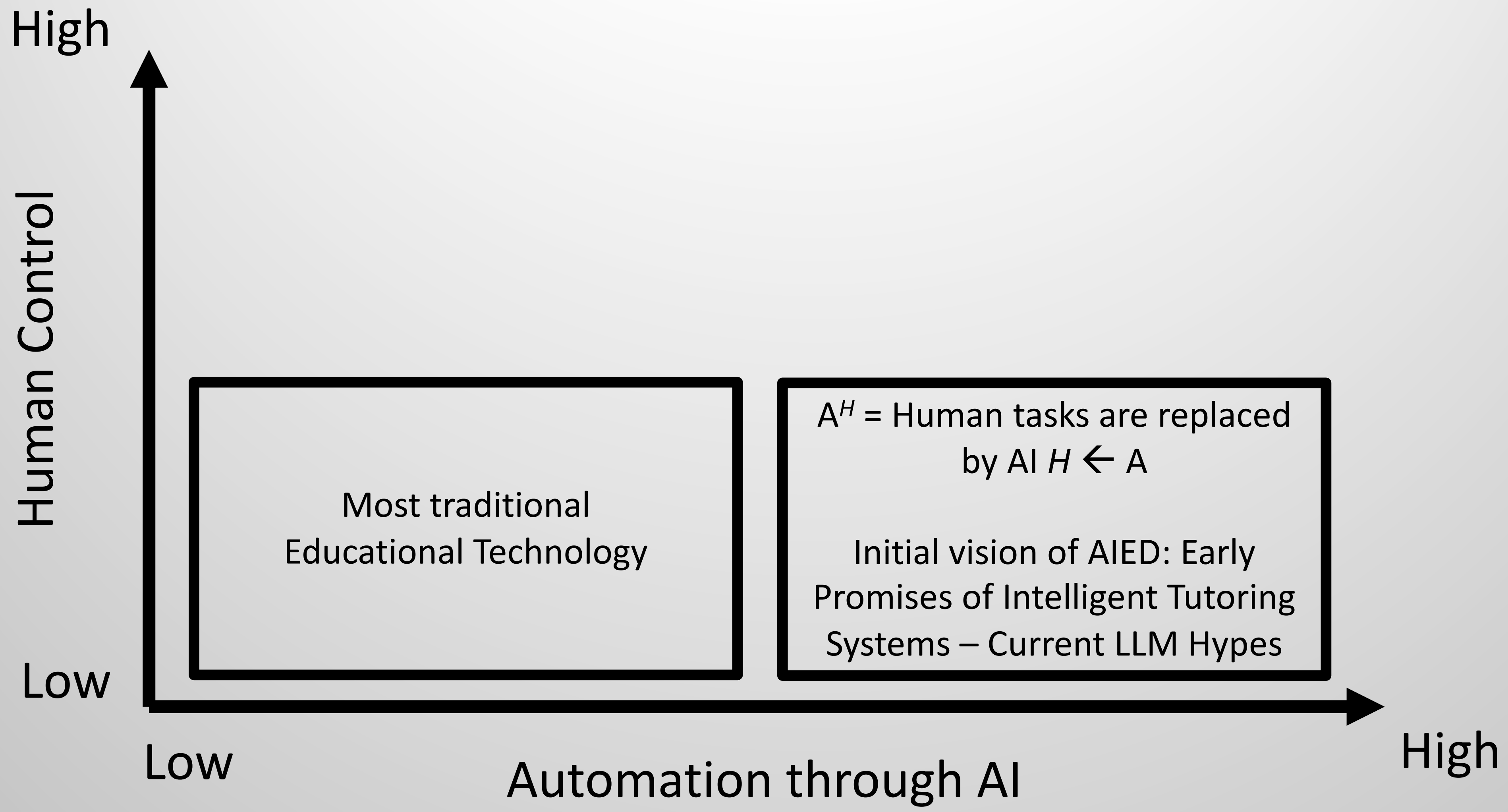
Rismanchina, S., & Doroudi, S. (2023). Four interactions between AI and education: Broadening our perspective on what AI can offer education, https://edarxiv.org/kps79.

Conceptualisations of AI in Education

- AI can be conceptualised to externalize, be internalized or extend human cognition.
- A^H = Human tasks are replaced by AI H $\leftarrow$ A
- H^A = Humans can internalise AI models H $\rightarrow$ A
    - Changing the operations and representations of thought (GOFAI)
- H[A] = Human (H) extended with an AI (A), **tightly coupled human and artificial systems.**
- H[A] ≠ H + A
    - The whole should be more than the sum of its parts.
    - Change in H, perhaps also in A, is observed.

Cukurova, M. (2019). Learning Analytics as AI Extenders in Education: Multimodal Machine Learning versus Multimodal Learning Analytics. *Proceedings of the Artificial Intelligence and Adaptive Education Conference, xx1-xx3.*
Cukurova, M. (2024). The Interplay of Learning, Analytics, and Artificial Intelligence in Education. arXiv preprint arXiv:2403.16081. https://doi.org/10.48550/arXiv.2403.16081

AI in Education: A vision for the future



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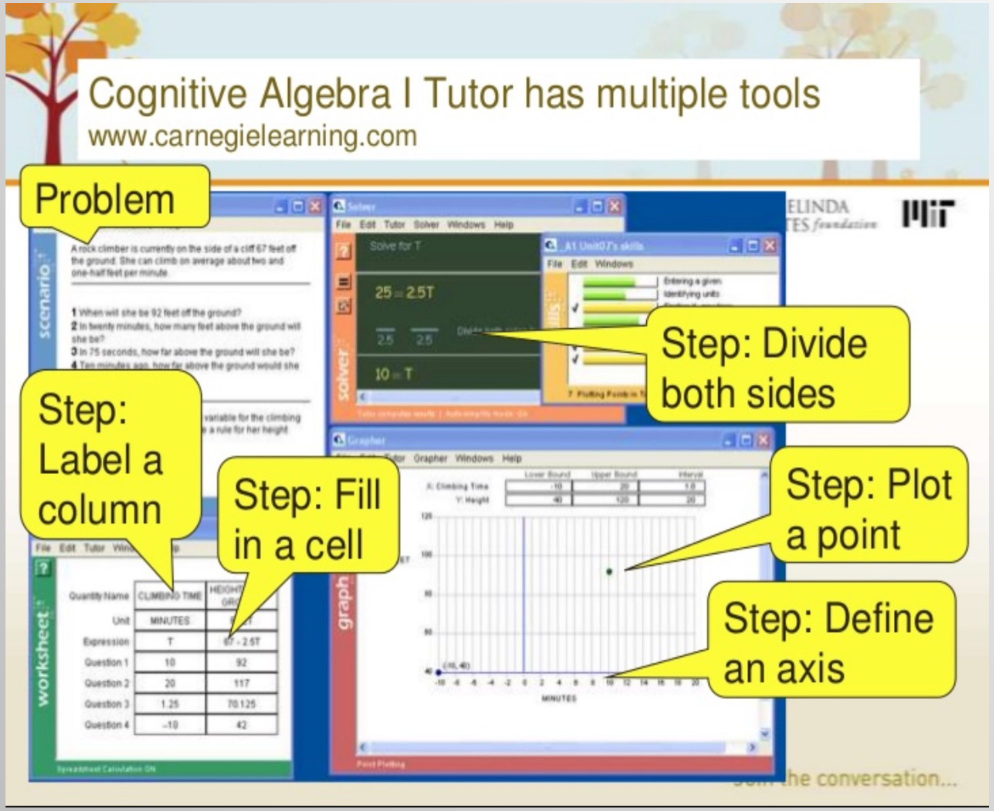
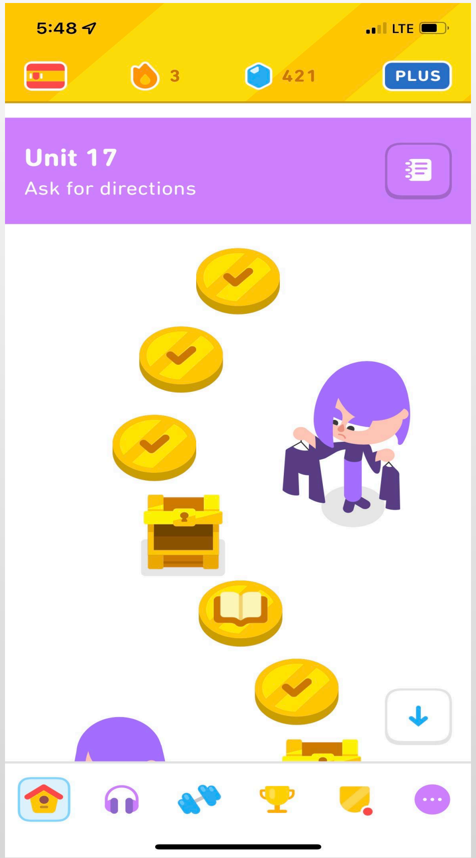
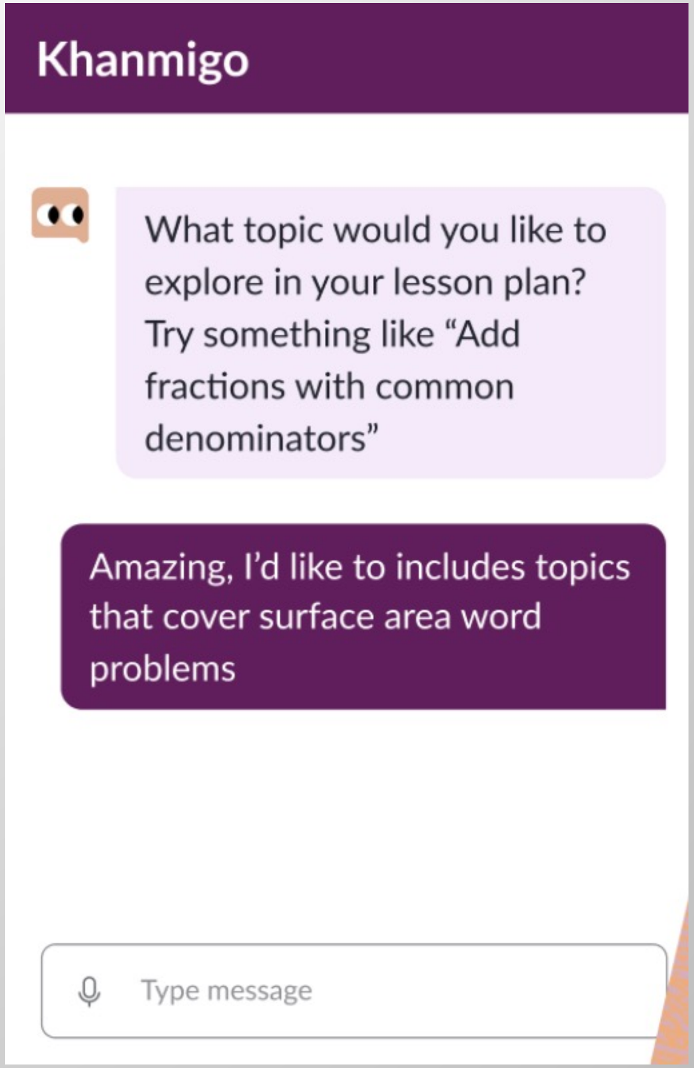
The most common applications of AI in Education were focusing on pedagogical task automation with ITSs

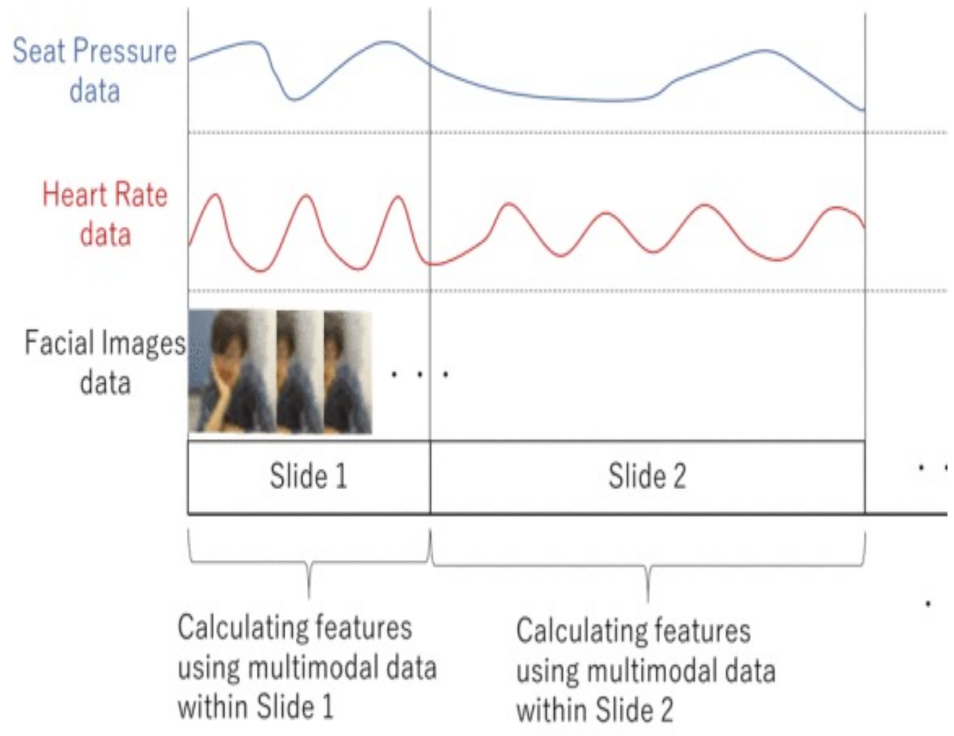




duolingo



Detecting Drowsy Learners at the Wheel of e-Learning Platforms With Multimodal Learning Analytics

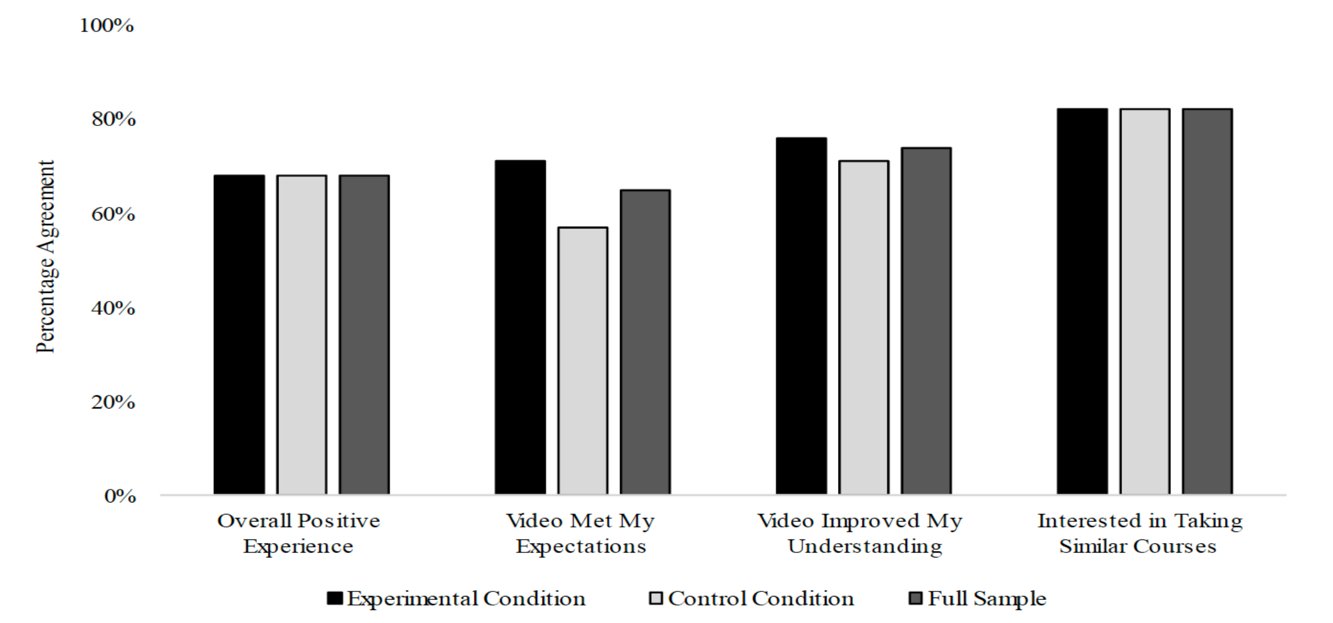


Features	Metrics	Constructs Represented
Heart rate (HR)	Mean/ standard deviation of RRI, HR, LF/HF, Body surface temperature	Heart rate in general represents the activity of the autonomic nervous system. RRI is an index of heart rate variability. HR is the heart rate. Low frequency (LF) power and high frequency (HF) power represent stress and rest states. Body surface temperature is environmental temperature in clothing.
Seat Pressure (SP)	Mean pressure	Mean of each frame's total pressure and mean of pressure per second. They are used to estimate a learner's motions.
	Mean time of MS (moving state) and SS (static state)	Represents how long a learner moves or stays still.
	Ratio of MS (moving state)	Represents how often a learner changes posture.
	Mean of absolute pressure difference between pressure current and previous frame.	Represents how large and how often a learner changes posture along vertical axis.
Facial Expression (Face)	Mean/ standard deviation of AU 2, 15, 26, 45 (occurrence and intensity)	AU2: Outer Brow Raiser, AU15: Lip Corner Depressor, AU26: Jaw drop, AU45: Blink.
	Mean/ standard deviation of head rotation (yaw, pitch, roll)	Represents how large a learner's head rotation is.
	Mean/ standard deviation of head transition along x, y, z	Represents how large a learner's head transition is.

R. Kawamura et al., Detecting Drowsy Learners at the Wheel of e-Learning Platforms With Multimodal Learning Analytics, *IEEE Access*, vol. 9, pp. 115165-115174, 2021, doi: 10.1109/ACCESS.2021.3104805

Investigating the potential of AI-generated synthetic learning videos

	Pre-Learning M (*SD*)	Post-Learning M (*SD*)	Knowledge Gains M (*SD*)	p (*d*)
Experimental	0.45 (*0.61*)	1.45 (*0.95*)	1.00 (*1.04*)	< .001 (*0.96*)
Control	0.66 (*0.70*)	1.16 (*0.94*)	0.94 (*1.13*)	< .001 (*0.83*)
Full Sample	**0.59 (*0.66*)**	**1.55 (*1.03*)**	**0.96 (*1.11*)**	**< .001 (*0.91*)**



- Condition (experimental vs. control) was not a significant predictor of knowledge gains (β = .03, *p* = .80, *r* = .03).
- Even when controlled for participants' pre-learning performance (β = - .03, *p* = .79, *r* = .03) or their self-reported prior knowledge (β = .01, *p* = .92, *r* = .01).

Leiker, D., Gyllen, A.R., Eidesouky, I., & Cukurova, M. (2023). Generative AI for learning: Investigating the potential of synthetic learning videos. AIED2023, Springer, Cham.

Evidence of Impact of Intelligent Tutoring Systems

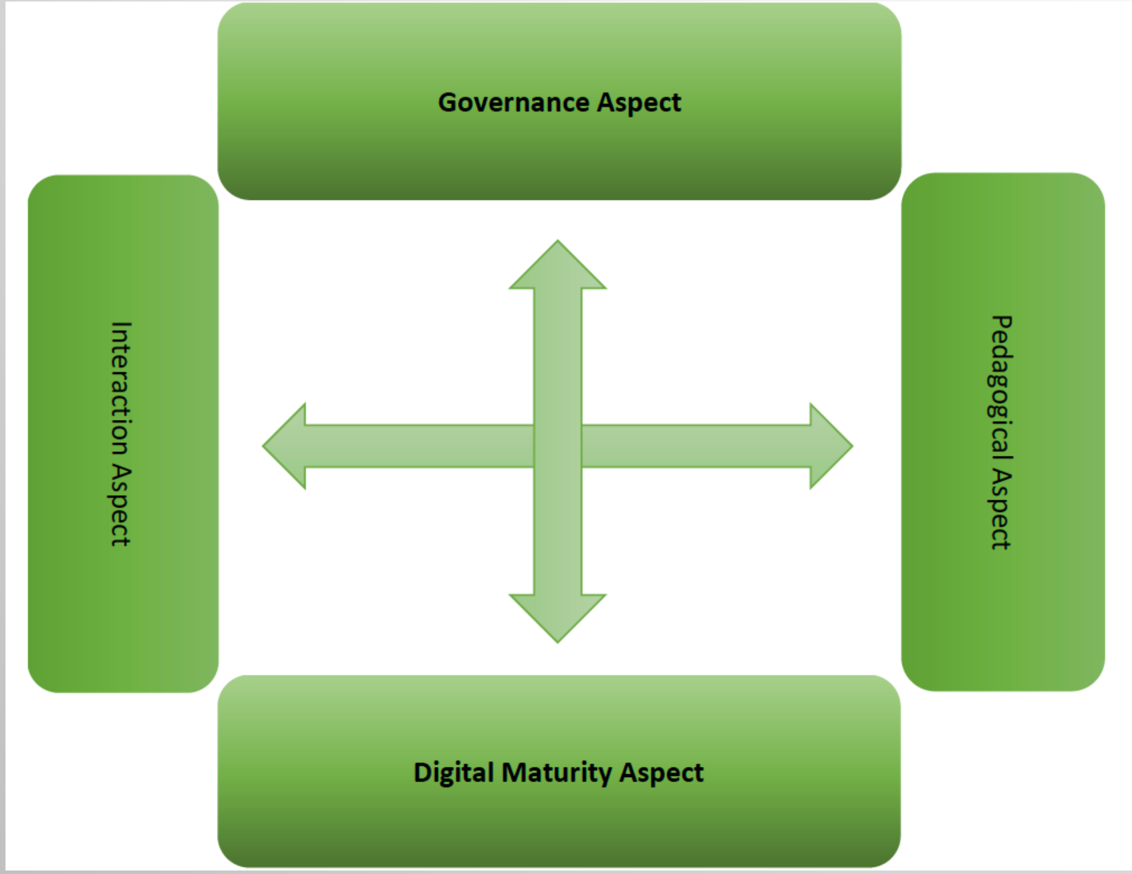
- ITSs can have positive impact on student learning : OLI learning course (Lovett et al., 2008), SQL-Tutor (Mitrovic, & Ohlsson 1999), ALEKS (Craig et al. 2013), Cognitive Tutor (Pane et al. 2014), ASSISTments (Koedinger et al. 2010).

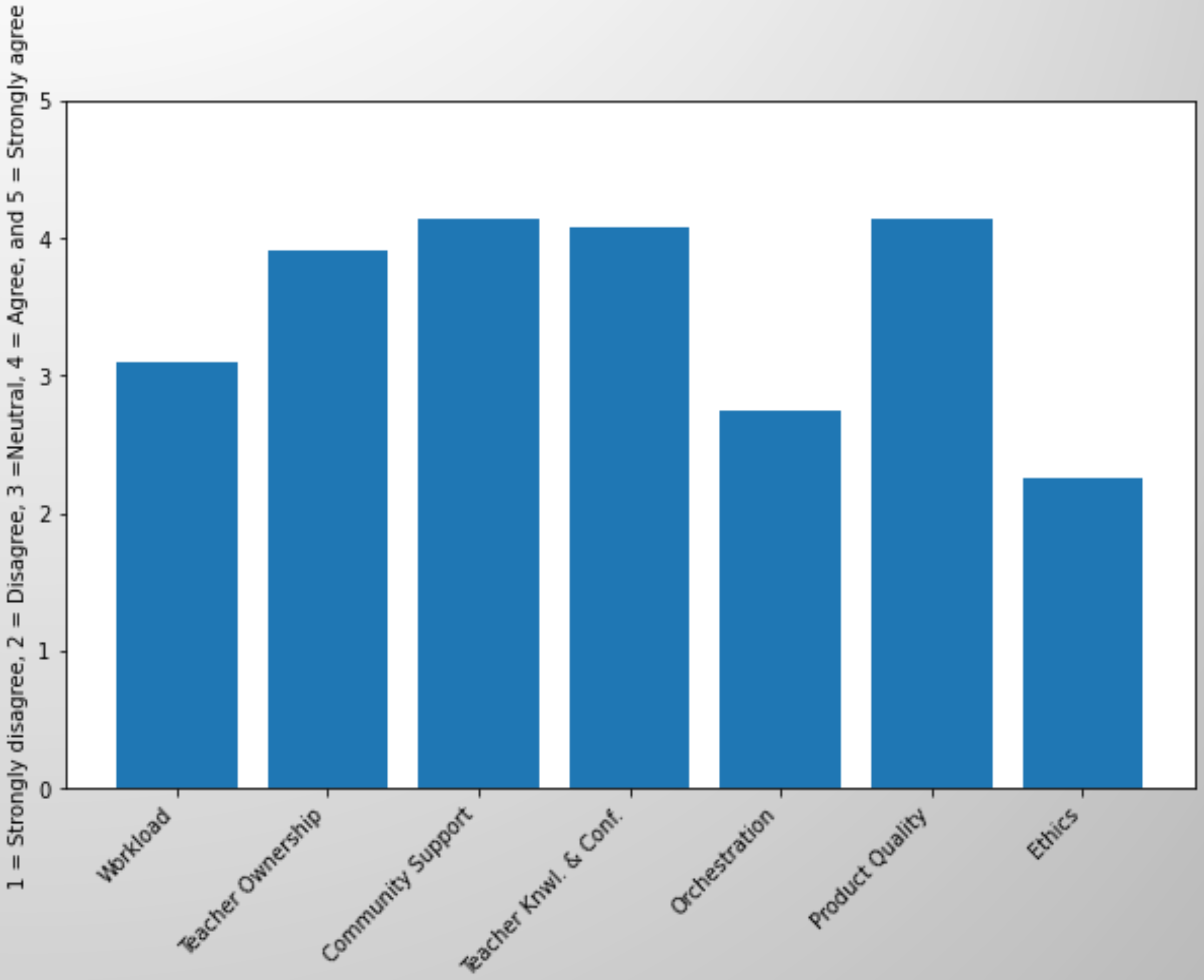
Meta-reviews

- VanLehn (2011) found that the effectiveness of the intelligent tutoring systems were nearly as effective as average human tutors.
- Ma et al. (2014) found similar results both when compared to a no tutoring or to large group human-tutor instruction.
- Pane et al. (2014) found evidence of the relative effectiveness of online tutors over conventional teaching.
- Kulik & Fletcher (2016) median effect was to raise test scores 0.66 standard deviations over conventional levels, or from the 50th to the 75th percentile.
- du Boulay, B. (2016) summary of the metareviews in “Artificial Intelligence As An Effective Classroom Assistant”.

Despite significant advancements in AI and evidence supporting its effectiveness as ITSs, why AI is not prevalent in mainstream education?

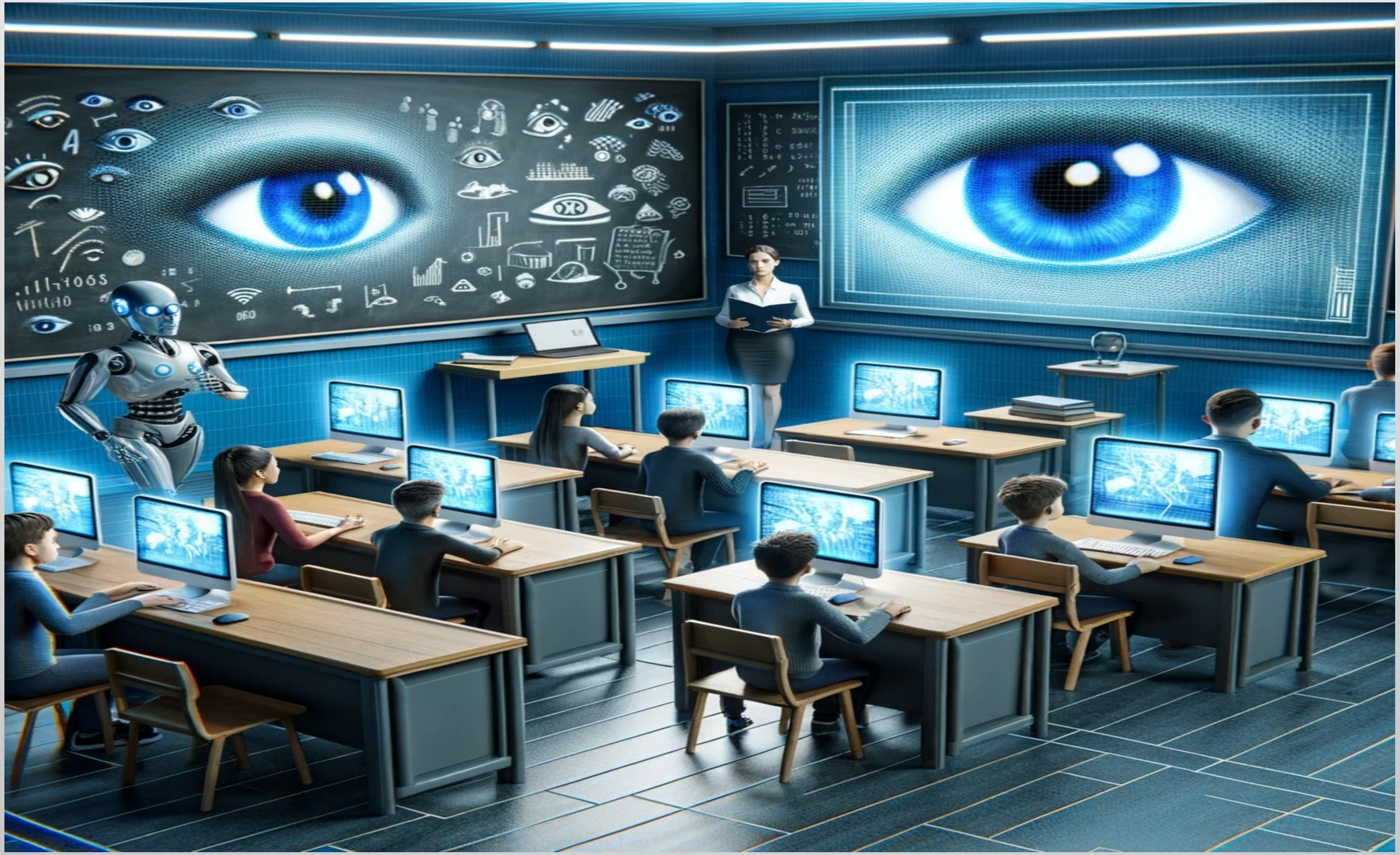
Adoption of AI in Education is an Ecosystem Issue





Cukurova, M., Miao, X., & Brooker, R. (2023). Adoption of Adaptive Learning Platforms in Schools: Unveiling Factors Influencing Teachers Engagement. *Artificial Intelligence in Education, Springer.* https://doi.org/10.1007/978-3-031-36272-9_13

AI might be Considered to Dehumanise Learning and Education

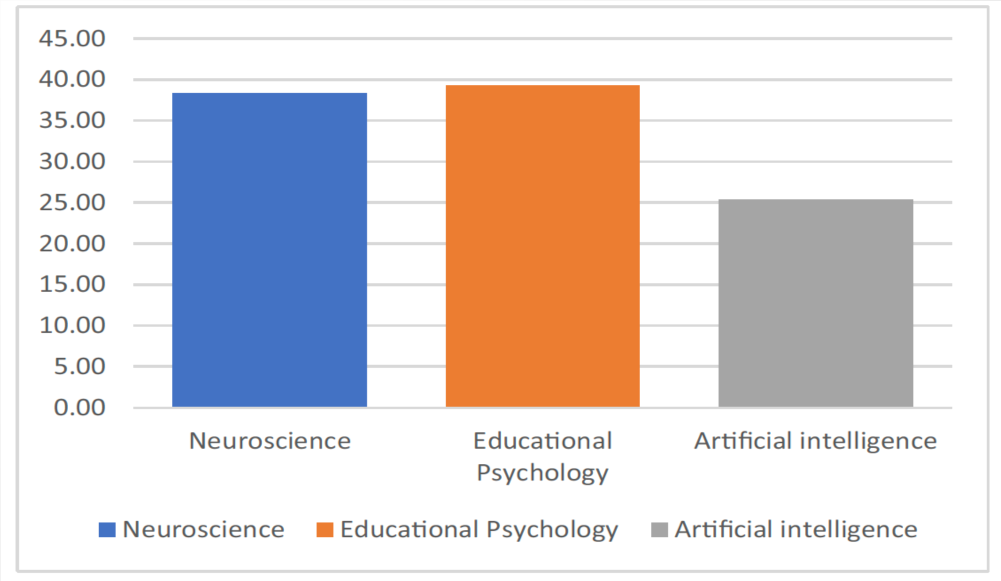


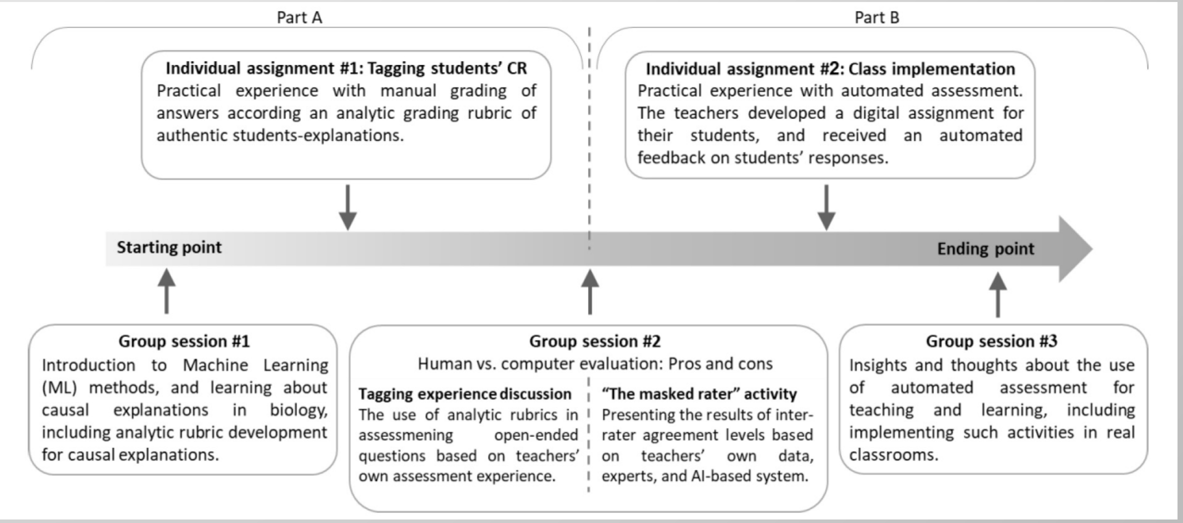
Trust in AI-EdTech is a Significant Concern

Teachers and learners have confirmation biases and unrealistic expectations from AI-EdTech.

"AI framing effect": when people are presented with content framed as coming from AI, they tend to judge it as less credible compared to educational psychology and neuroscience.

Considerable research is needed to gain end users' critical trust in AI-EdTech.





Cukurova, M., Luckin, R., & Kent, C. (2020). Impact of an Artificial Intelligence Research Frame on the Perceived Credibility of Educational Research Evidence. *International Journal of Artificial Intelligence in Education*, 1-31.

Nazaretsky, T., Ariely, M., Cukurova, M., Alexandron, G. (2022). Teachers' Trust in AI-powered Educational Technology and a Professional Development Program to Improve It, *British Journal of Educational Technology*, DOI: 10.1111/bjet.13232

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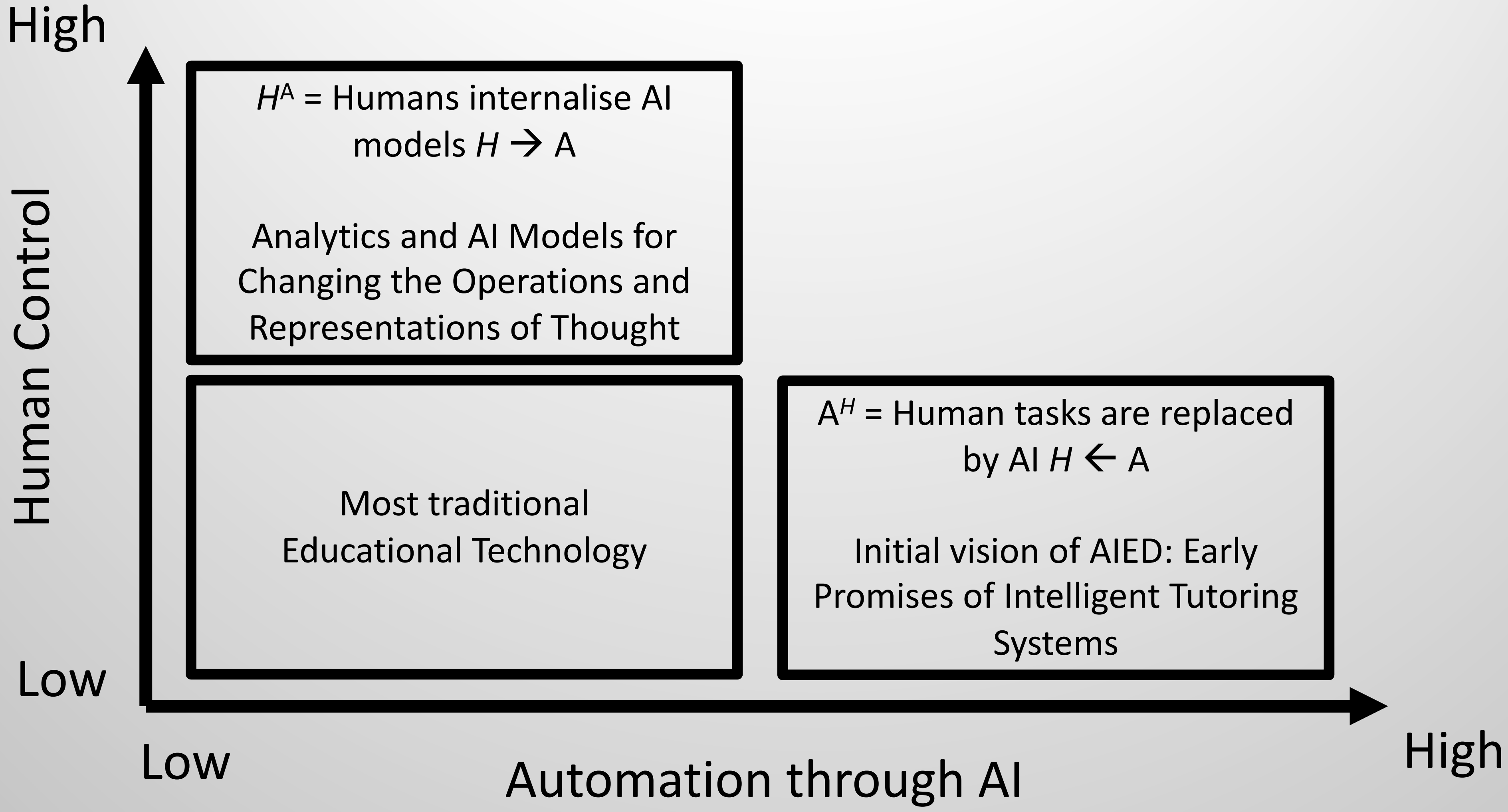

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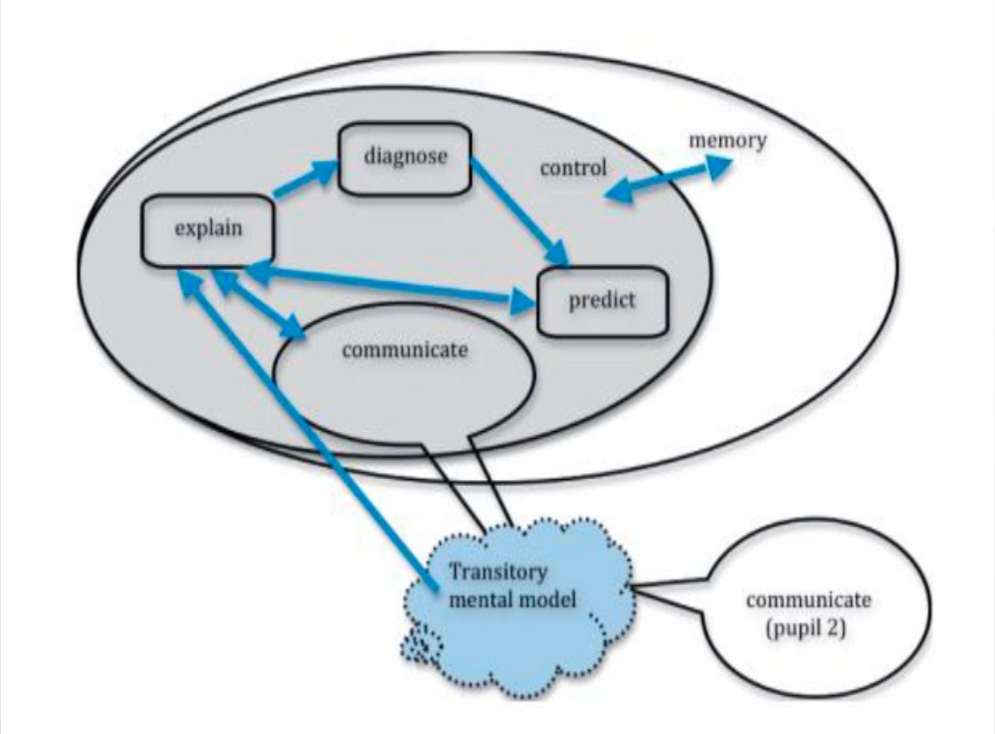
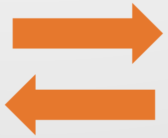
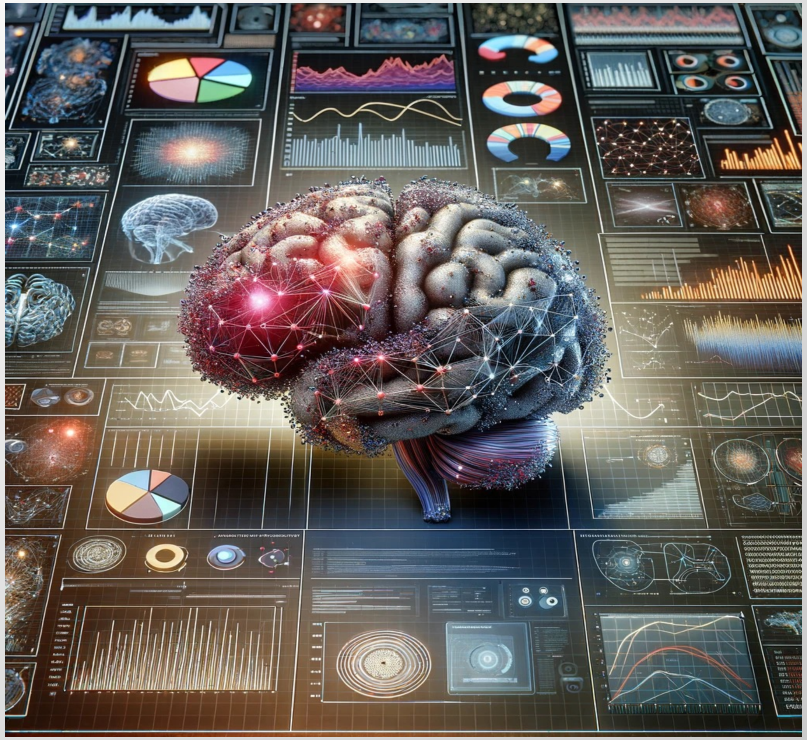
AI Models as Learning Affordances for Humans



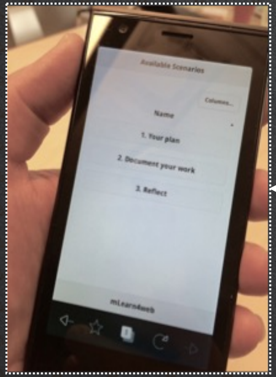
Mental model mode: diagram of functionality

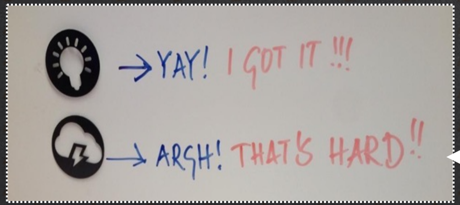




Computational and Statistical Models of Learners and Learning Processes

Kent, C., Chaudhry, M., Cukurova, M. Bashir, I., Pickard, H., Jenkins, C., du Boulay, B., Luckin, R., (2021). Machine learning models and their development process as learning affordances for humans. *International Conference of Artificial Intelligence in Education*, Springer, Cham.


Available Scenarios
Columns...
Name
1. Your plan
2. Document your work
3. Reflect
mLearn4web


→ YAY! I GOT IT !!!
→ ARGH! THAT'S HARD!!

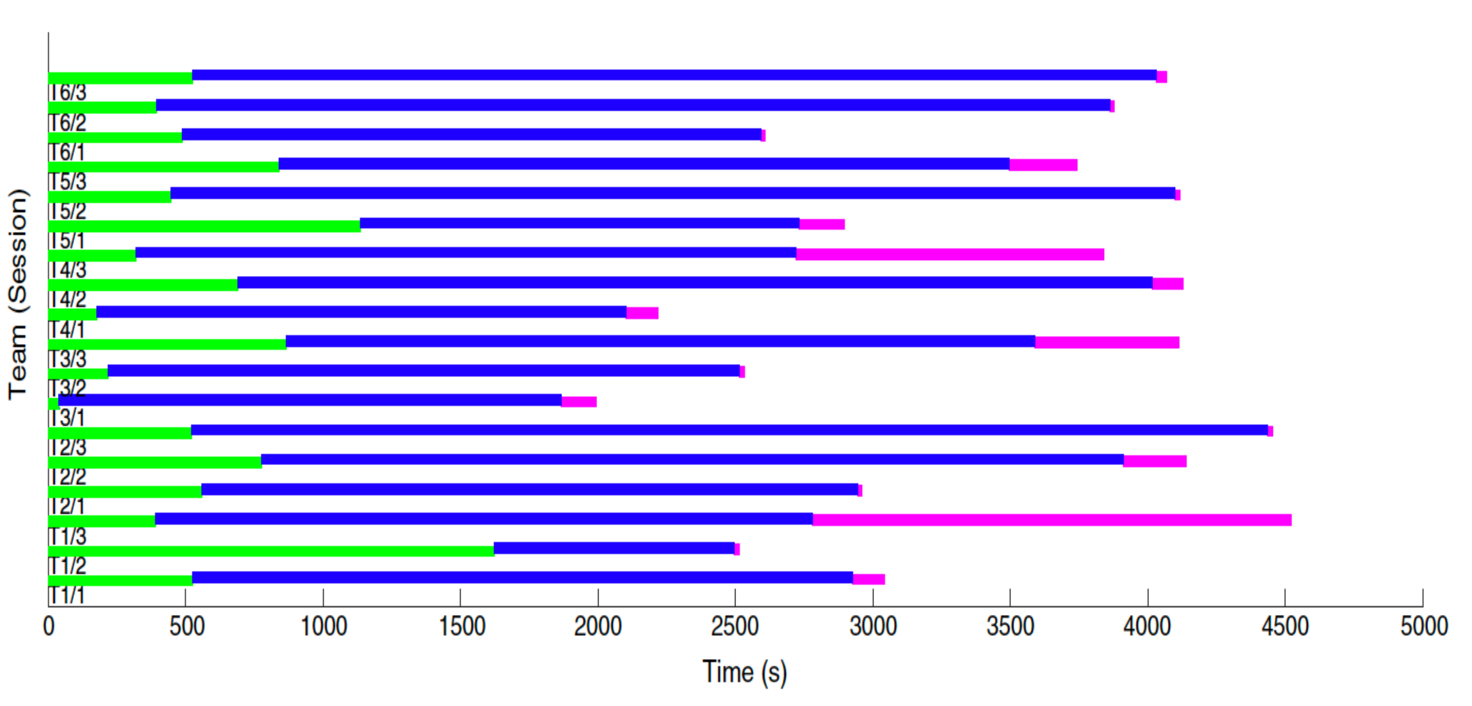
A^H = Human tasks are replaced by AI $H \leftarrow A$

Independent Variables (MMLA Features)

FLS - Number of faces looking at screen
DBL - Mean distance between learners
DBH - Mean distance between hands
HMS - Mean hand movement speed
AUD - Mean audio level

IDEX - Arduino measure of complexity
IDEVHW - Arduino active hardware blocks
IDEVSW - Arduino active software blocks
IDEC - Arduino active blocks

PWR - Student Work Phases



Ground Truth: Expert labelling of video data using CPS frameworks

Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*, *34*(4), 366-377.

Machine Learning Classification of CPS Competence

Method	Deep learning	Traditional
Task	Regression	Classification
Input	18 variables	9 variables per window
Output	6 scores over 5 levels	1 score with 3 levels
Metrics	Regression score	Classifier accuracy
Windowing	120,240 and 360 s	10,20,30,90 min
Phase exclusion	Reflection	Reflection
Method	Multiple layers	NB, LR, SVML, and SVMR

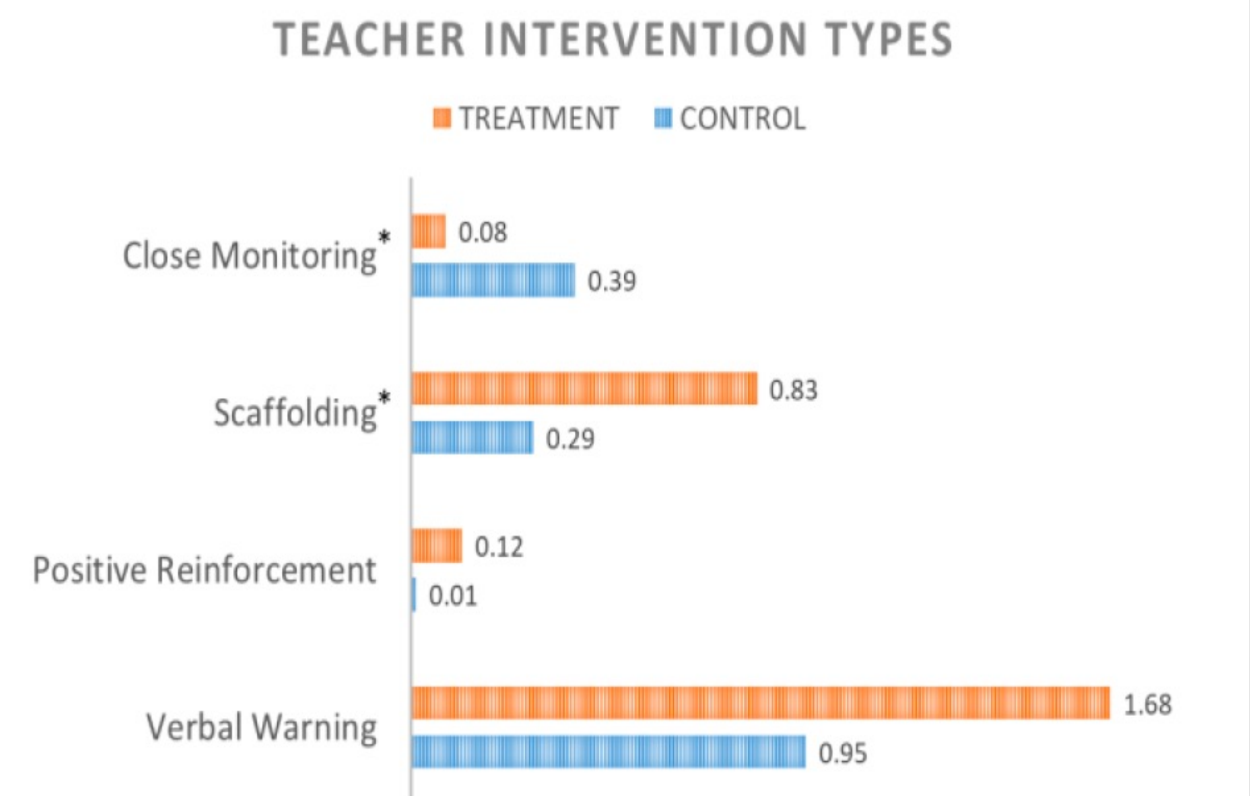
Note. NB = naive Bayesian; LR = logistic regression; SVML = support vector machines with linear kernel; SVMR = support vector machines for regression.

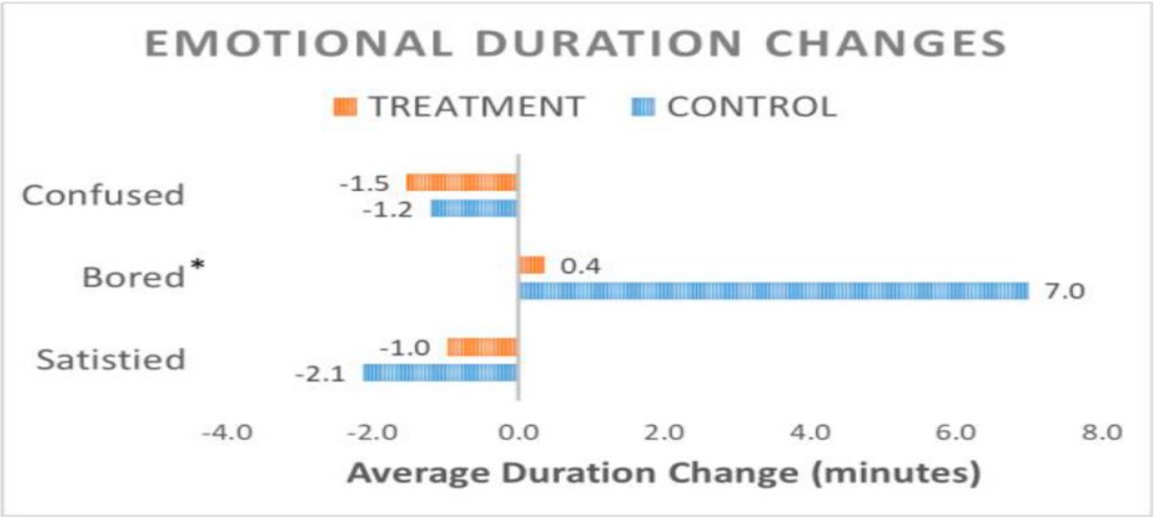
	PWR	PW	W	WR
NB	0.8	0.8	0.6	0.75
SVML	0.6	0.75	0.75	0.8
SVMR	0.75	0.75	0.75	0.75
LR	0.6	0.75	0.5	0.6

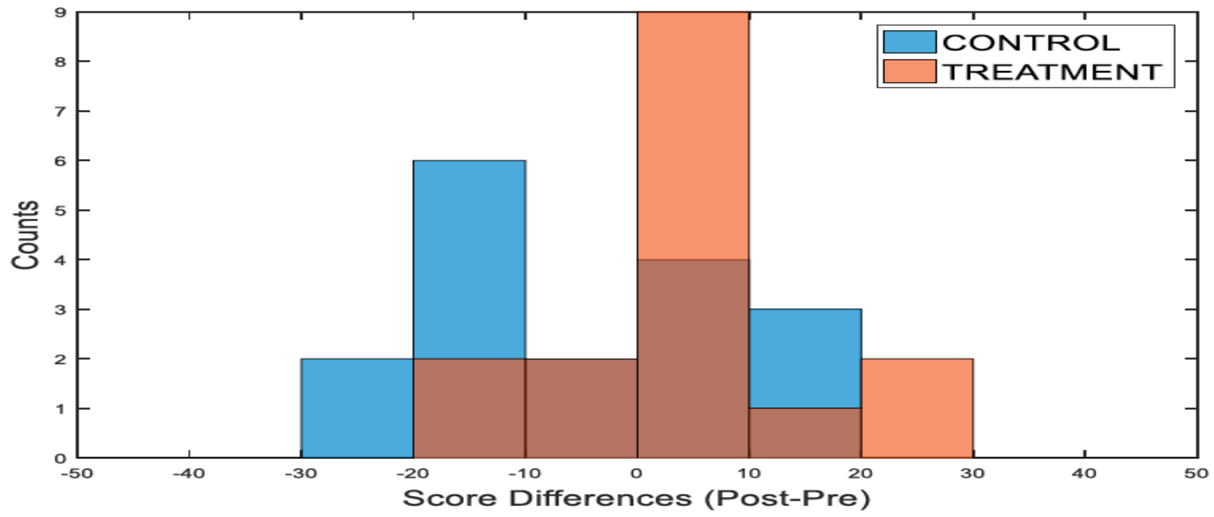
Note. NB = naive Bayesian; LR = logistic regression; SVML = support vector machines with linear kernel; SVMR = support vector machines for regression.

Removed feature	Best result
No features removed	0.129
All faces data	0.21
All Arduino data	0.21
DBF	0.15
DBH	0.21
HMS	0.19
AUD	0.18
Hand pos	0.21
Arduino comp	0.19

Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning*, *34*(4), 366-377.



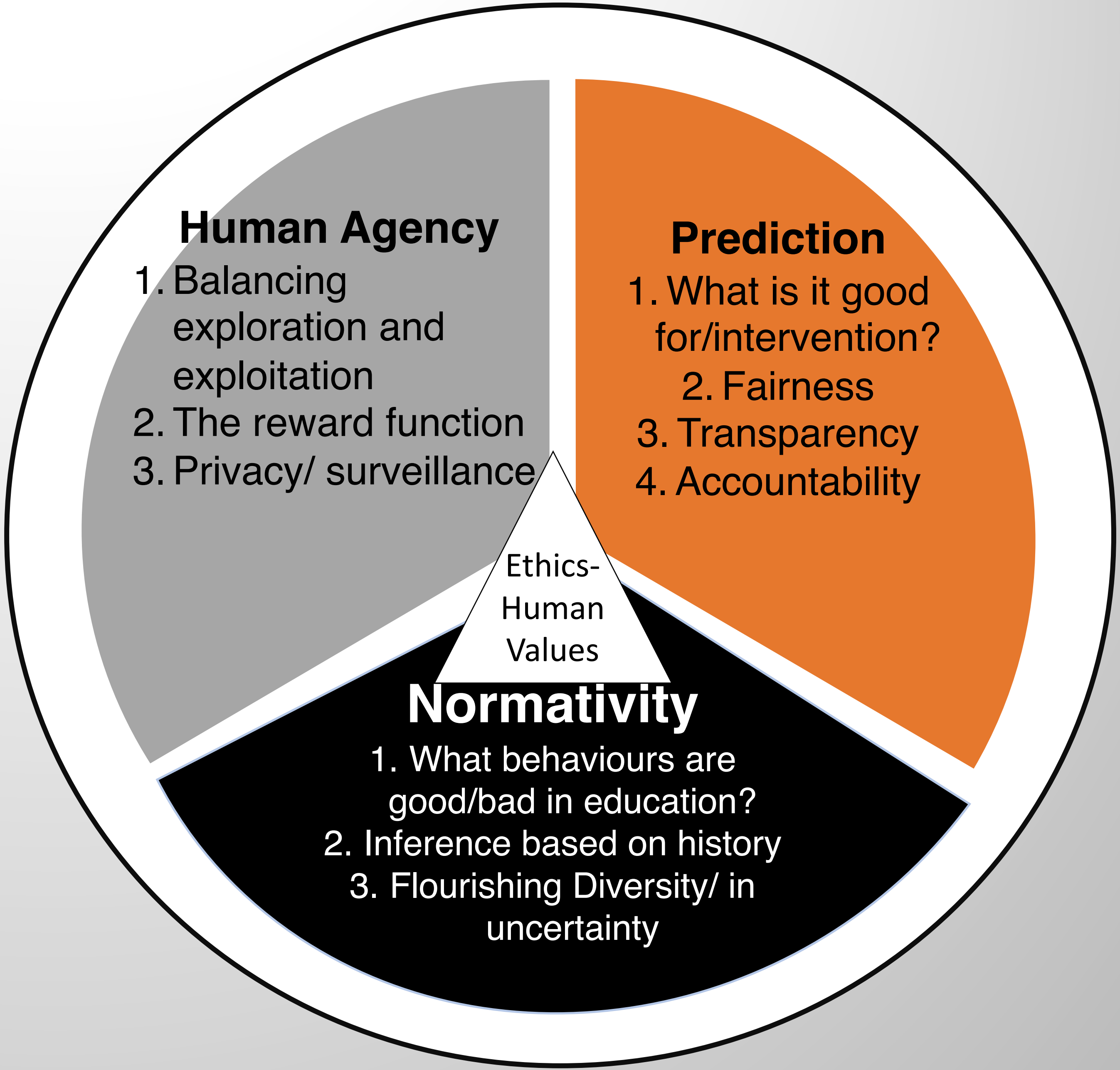




Aslan, S., Alyuz, N., Tanriover, C., Mete, S. E., Okur, E., D'Mello, S. K., & Arslan Esme, A. (2019). Investigating the impact of a real-time, multimodal student engagement analytics technology in authentic classrooms. In *Proceedings of the 2019 chi conference on human factors in computing systems* (pp. 1-12).

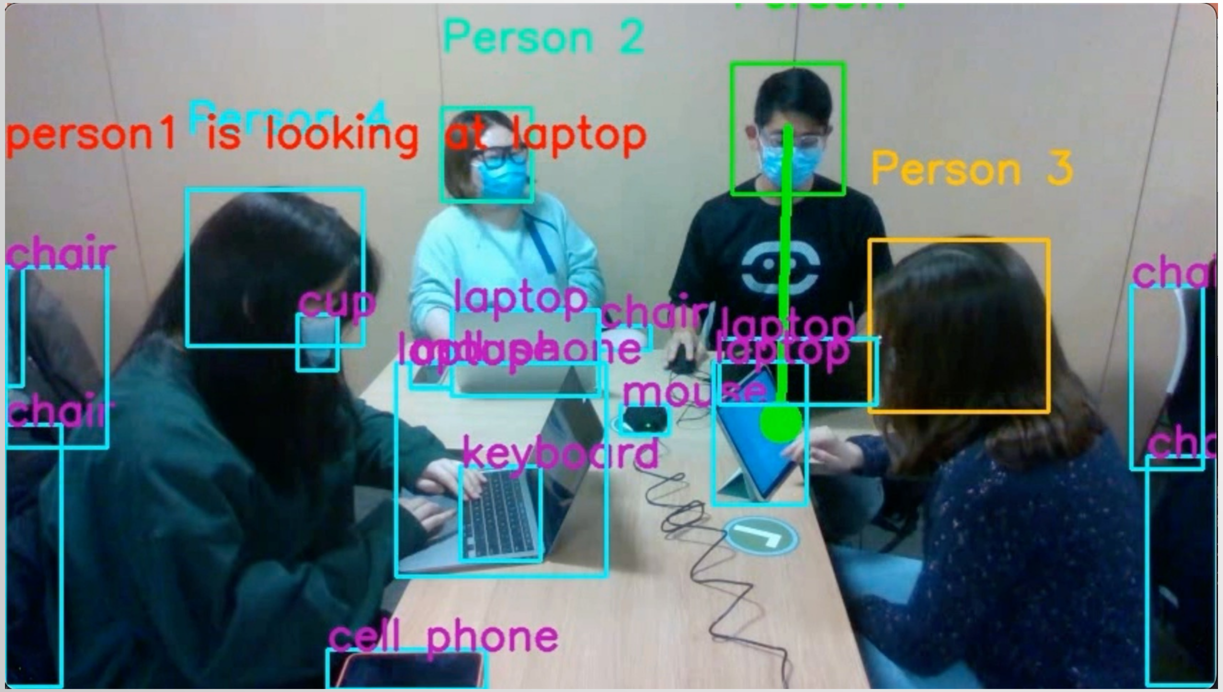
The use of AI as tools to directly intervene on the practice of teaching and learning has significant challenges.

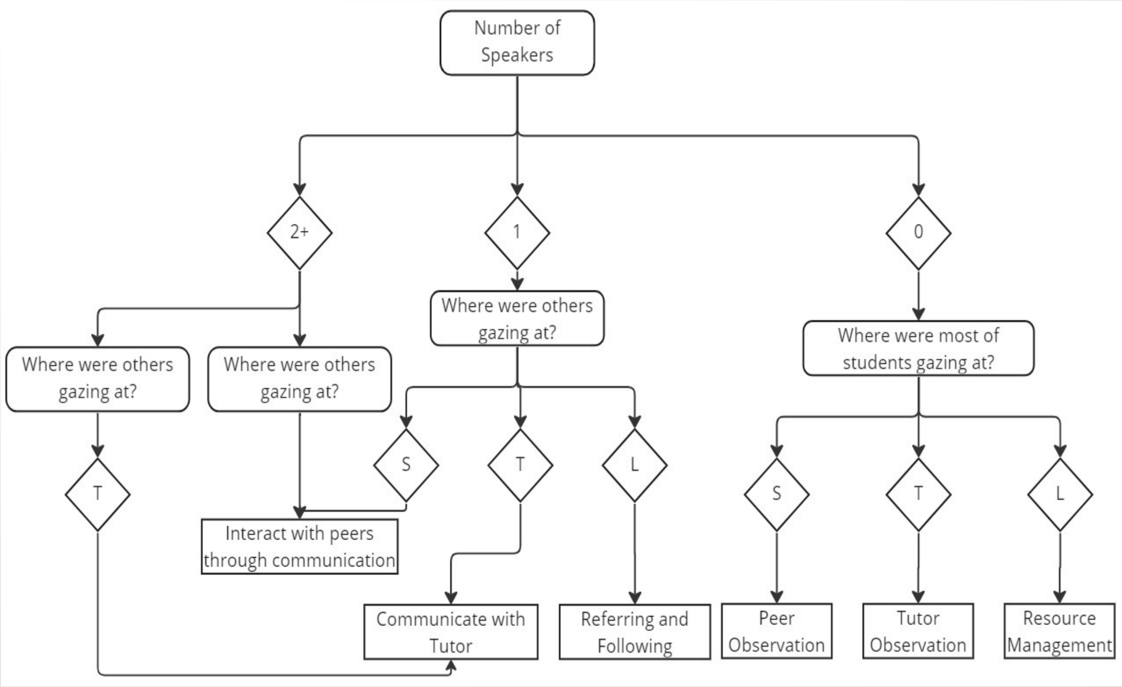
Maybe some aspects of learning just come through the slow experience of living those learning experiences, in the sense that we can't just jump ahead to get the answer!

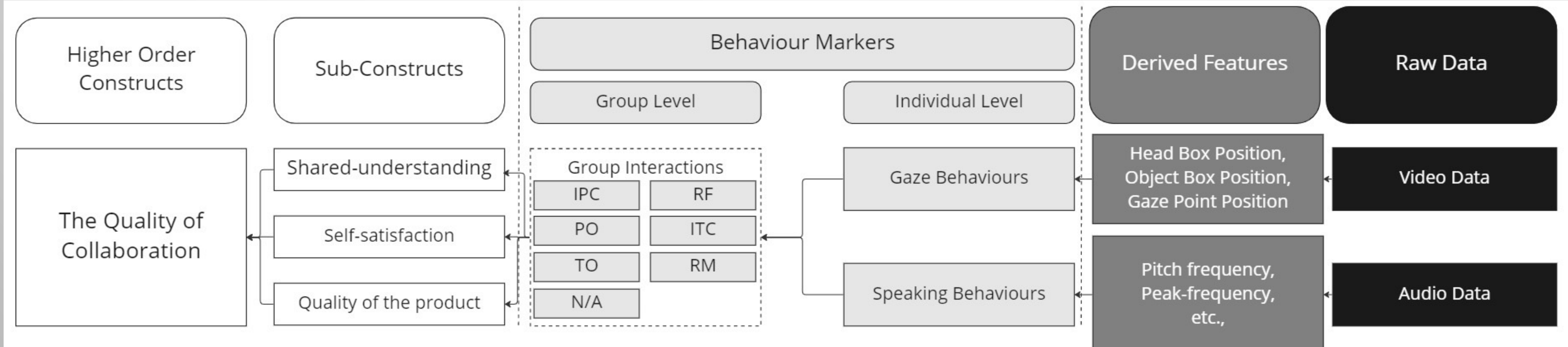


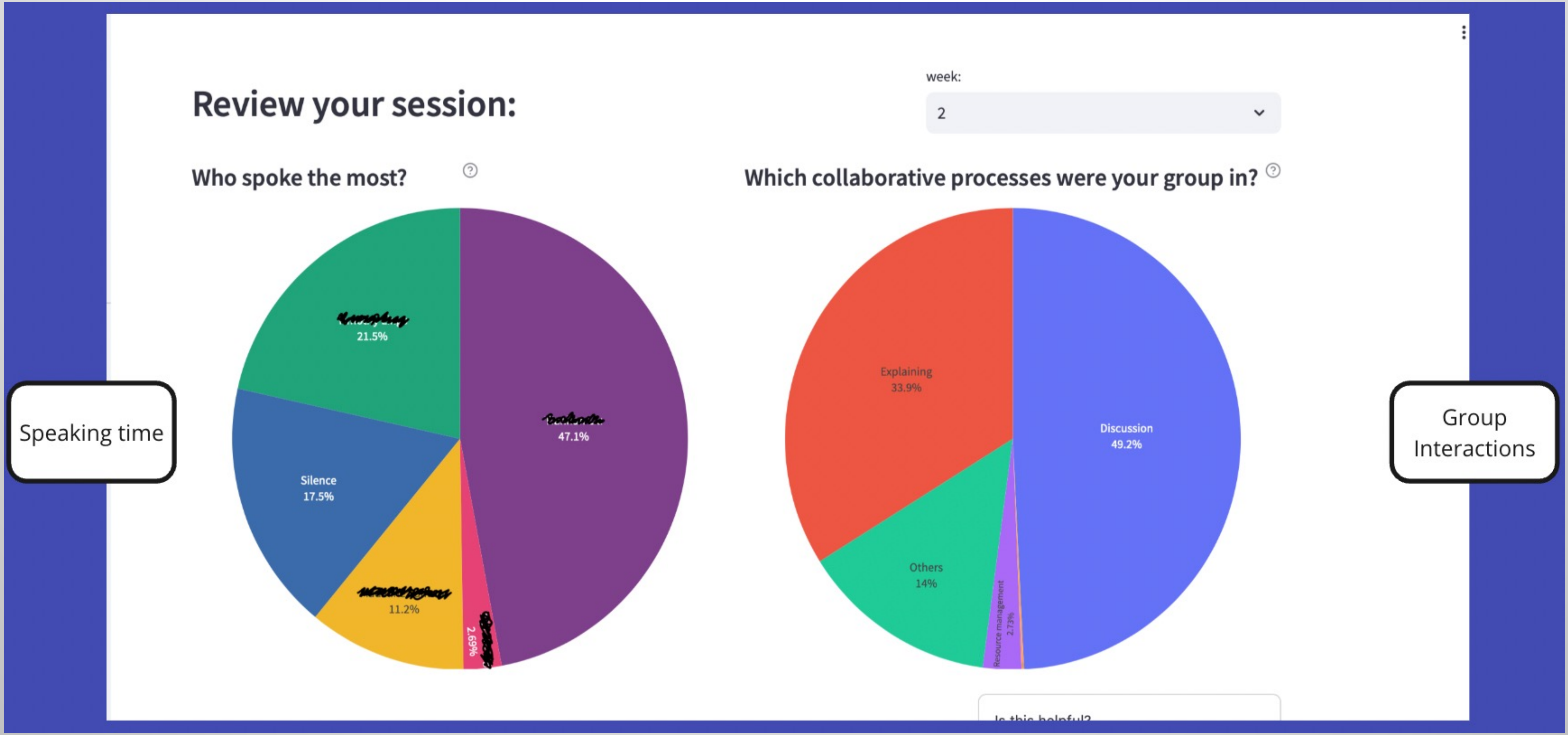
Alwahaby, H., Cukurova, M., Papamitsiou, Z., & Giannakos, M. (2022). The Evidence of Impact and Ethical Considerations of Multimodal Learning Analytics: A Systematic Literature Review. In The Multimodal Learning Analytics Handbook (pp. 289-325). Springer International Publishing. doi:10.1007/978-3-031-08076-0_12

AI Models as Objects to Think about Learning

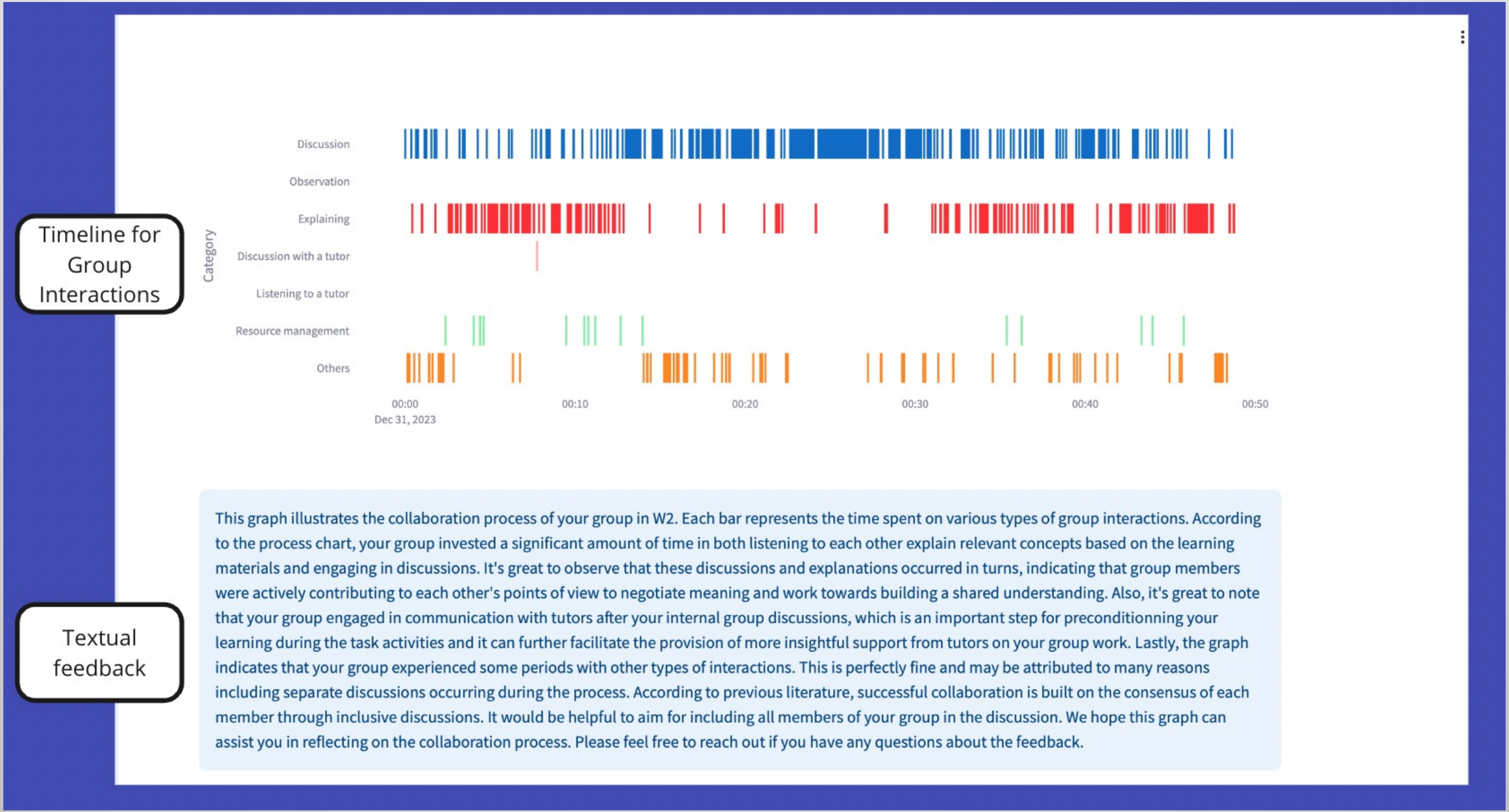








Zhou, Q., Suraworachet, W., & Cukurova, M. (2024). Detecting non-verbal speech and gaze behaviours with multimodal data and computer vision to interpret effective collaborative learning interactions. *Education and Information Technologies*, *29*(1), 1071-1098.



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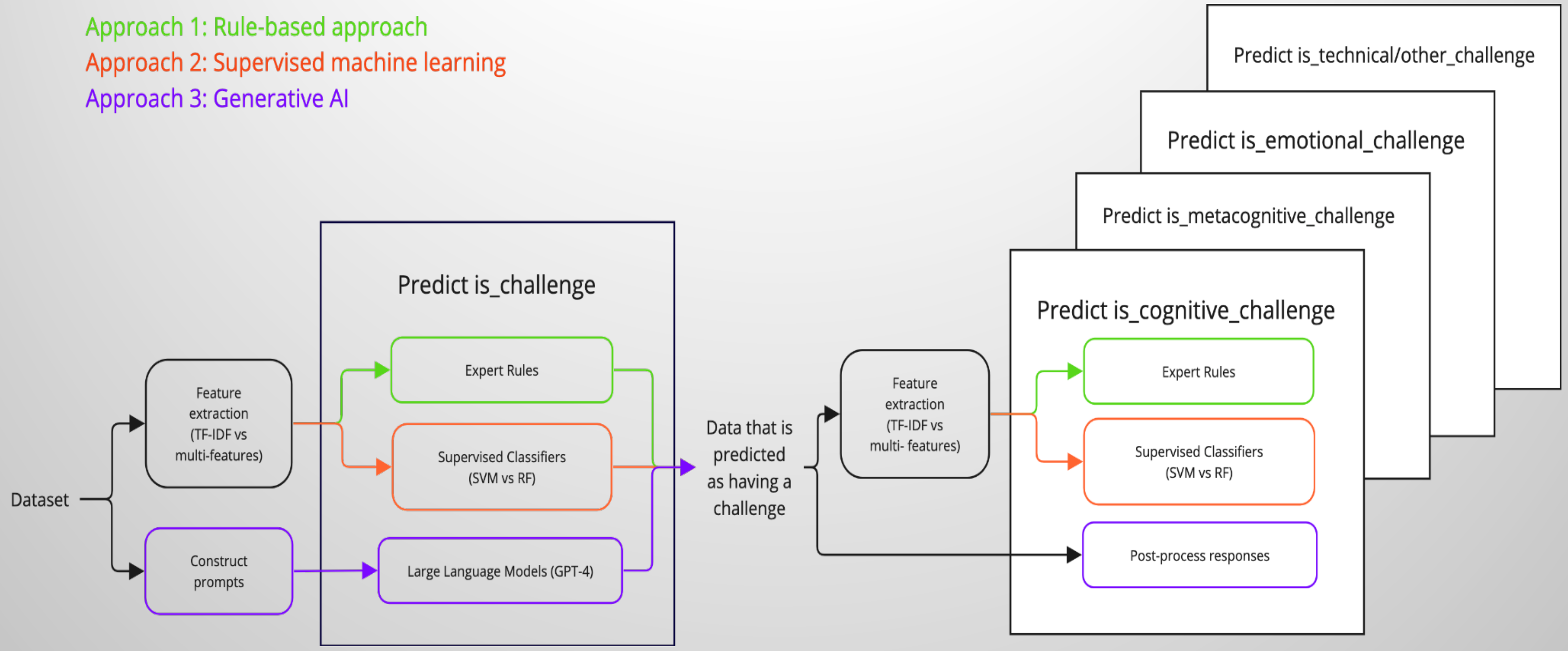

https://duteapp-feedback-test.streamlit.app/

Suraworachet, W., Seon, J., & Cukurova, M. (2024). Predicting challenge moments from students' discourse: A comparison of GPT-4 to two traditional natural language processing approaches. *Learning Analytics & Knowledge, ACM: New York.*

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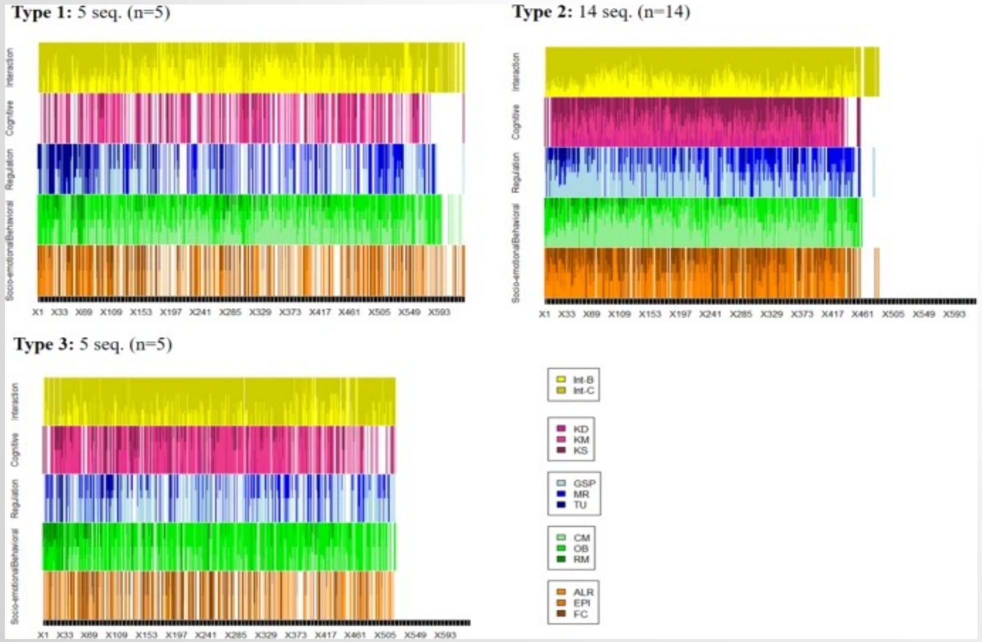
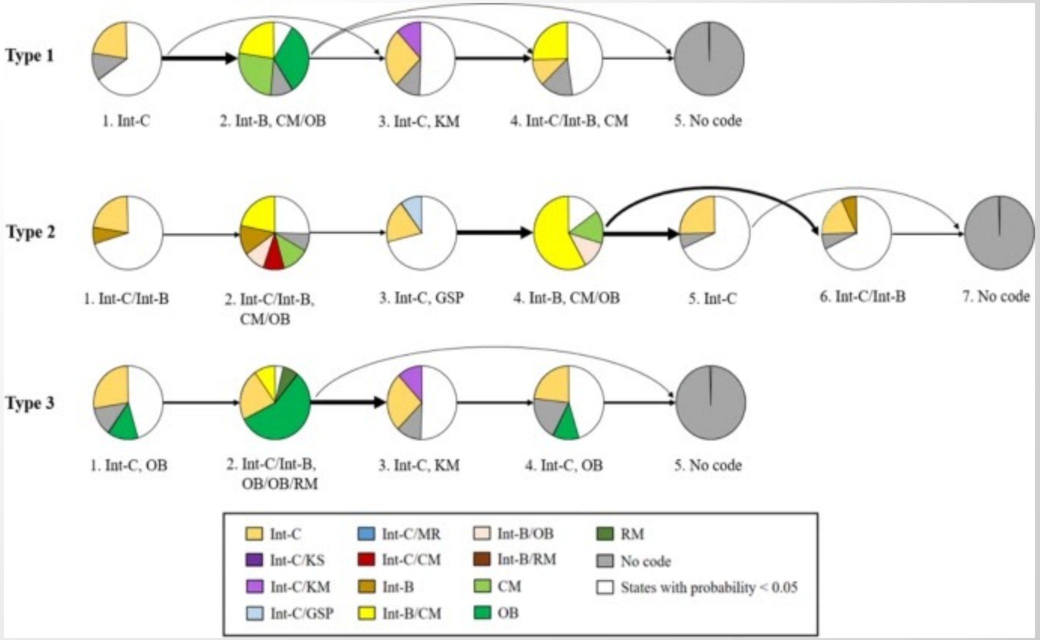
Value of Making Lived Experiences Visible to End Users

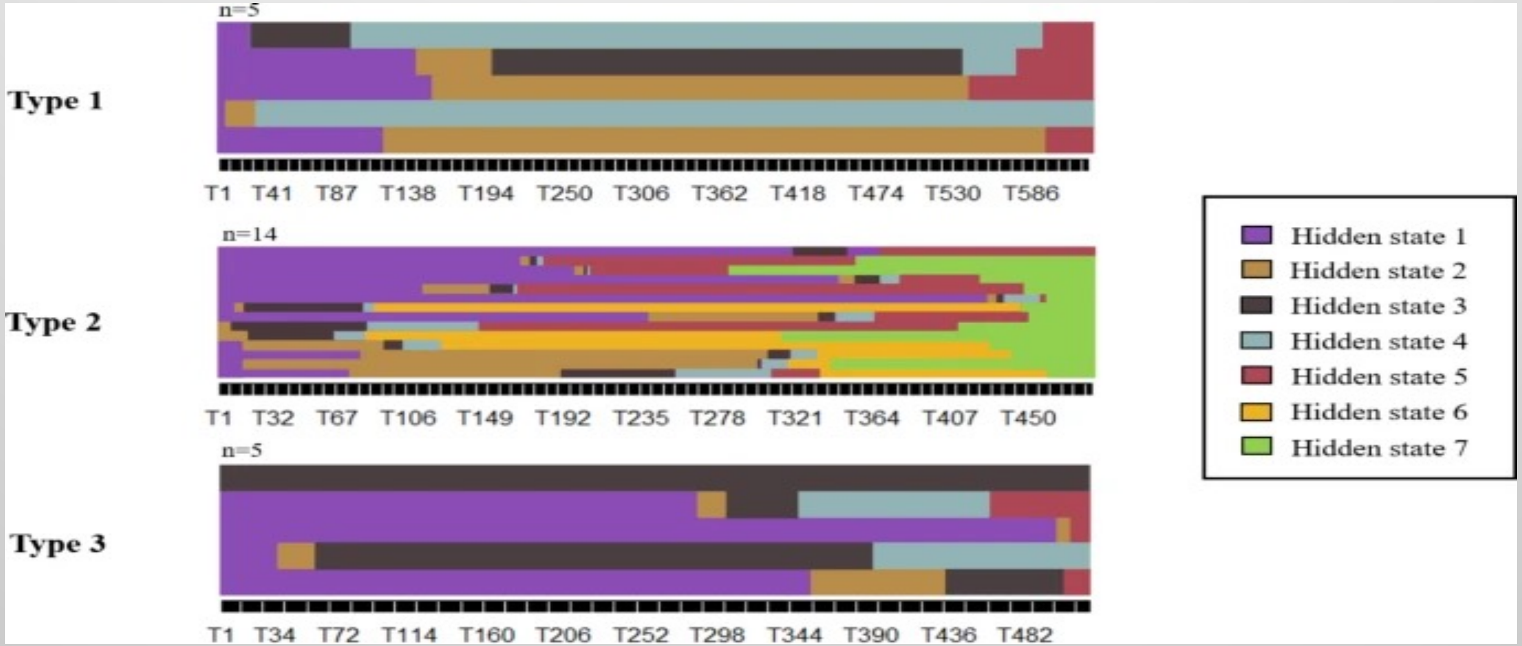
Visibility	•**Comprehensibility** of the collaboration analytics *(easy to understand/interpret)* •**Accuracy/Inaccuracy** of the analytics information *('Similar to their findings', different from lived experiences)* •**Lack of qualitative feedback** and partially represented contribution *(contribution is more than observed, speak more doesn't mean more contribution)*
Awareness	•The value of **seeing one's own performance** *(as external reflective tool that cannot be distorted by observers/post-experienced effects)* •The value of **seeing others' performance** *(determine who's struggling)*
Accountability	•Collaboration analytics to **foster group discussions** *(discuss why contribute less)* •**Self-regulation** *(adjust level/prepare more/seek for help)* and **socially shared regulation** of behaviours *(encourage the least speaker, offer helps, develop group strategies e.g. host)* •**Gaming the system** *(particularly for speech time data – is it bad?)* •**Swinging back** to "normal" behaviours *(lack of monitoring/assessment)*
Privacy	•**Concerns over being monitored** - *Were not concerned or faded due to: the module domain, invisibility, not parts of sum assessment* - *More concerning for low contributors* - *Positive motives to show for the tutors for high contributors*

Zhou,Q., Suraworachet, W., Pozdniakov, S., Martinez-Maldonado, R., Bartindale, T., Chen, P. Richardson, D., & Cukurova M. (2021). Investigating Students' Experiences with Collaboration Analytics for Remote Group Meetings. *International Conference of Artificial Intelligence in Education*, Springer, Cham.

Pozdniakov, S., Martinez-Maldonado, R., Shan-Tsai, Y., Cukurova, M., Bartindale, T., Chen, P., Harrison, M., Richardson, D., & Gasevic, D. (2022). The Question-driven Dashboard: How Can We Design Analytics Interfaces Aligned to Teachers' Inquiry?. *Learning Analytics & Knowledge, ACM.*







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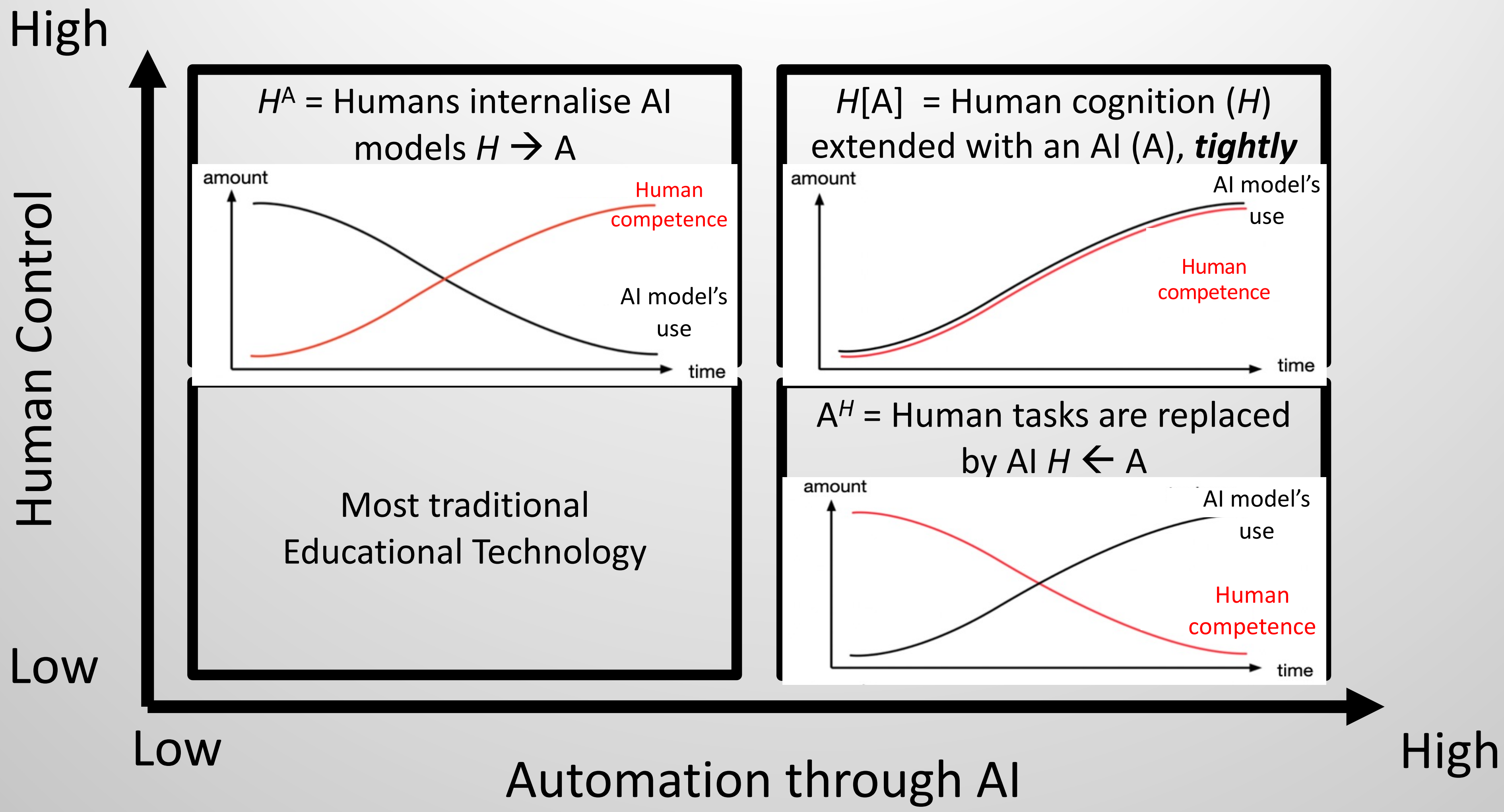

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Thank you

Mutlu Cukurova
m.cukurova@ucl.ac.uk
@mutlucukurova

Knowledge Lab UCL UCLAIT - Team