

AI and Education: The need for a system change

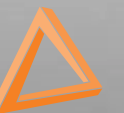
Dr Mutlu Cukurova
University College London

m.cukurova@ucl.ac.uk

@mutlucukurova



Education systems are broader than what current *Artificial Intelligence alone* can provide.



Promise of AI in Education



Access
to Education



Decrease
Teacher Workload



Personalised
Effective Education



Equity
in Education



AI Implications for Education

1.

Design and Use of
AI technologies to
tackle educational
challenges

2.

Educating People
about AI so that
they can use it
effectively and
ethically

3.

Innovation in
Education to prepare
people for an AI-
driven world

Luckin, R., & Cukurova, M. (2019). Designing Educational Technologies in the Age of AI: A Learning Sciences Driven Approach. *British Journal of Educational Technology*, 50(6), 490-504.

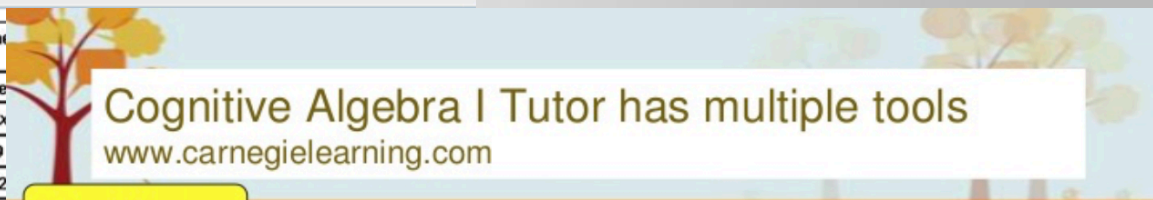
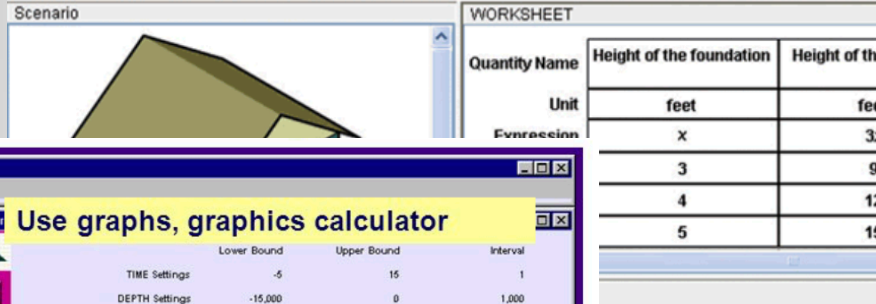
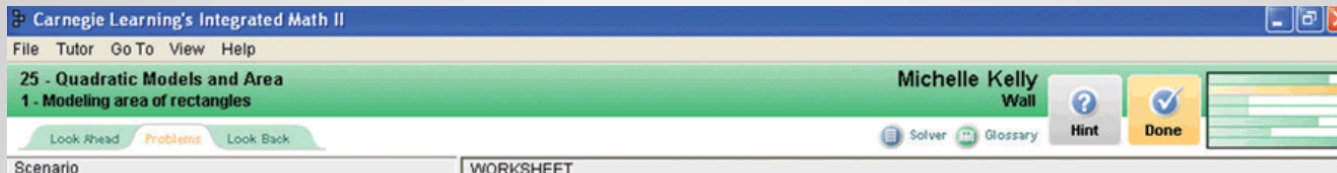


A “perfect intelligence” in Education is not the one that always gets the correct answers.



6

- Initial focus of AIED was on attempts to create systems that are as perceptive as human educators.
- It is possible to create AI in Education that “works”.



Analyze real world problem scenarios

scenario
An experimental aircraft has sunk off the coast of South Africa at a depth of 12,790 feet. The military has located the aircraft and are in the process of raising it to the surface. It is currently 7625 feet below the surface and is being raised at the rate of 185 feet per hour. (Hint: Consider the direction above sea level to be positive)

1. How deep was the aircraft five hours ago?
2. How deep will the aircraft be five hours from now?
3. When did the military start raising the aircraft?
4. When will the aircraft reach the surface?

To write an expression, define a variable for the time from now and use this variable to write a rule for the depth of the aircraft.

Use graphs, graphics calculator



Use table, spreadsheet

Unit	TIME (HOURS)	DEPTH (FEET)
Expression	H	-7625+185H
1	-5	-8,550
2	5	-8,700
3	-27,9189...	-12,790

Use equations, symbolic calculator

solver
-7625+185H = -12790
Add 7625
185H = -5,165
Divide by 185
H = -1,033/37

Tutor learns about each student

- Changing axis bounds
- Changing axis intervals
- Correctly placing points
- Write expression, any form
- Find Y, any form
- Find X, any form
- Identifying units
- Entering a given

Tutor follows along, provides context-sensitive instruction

Messages
You have entered the given 0 in the wrong column of the worksheet.

Problem

A rock climber is currently on the side of a cliff 67 feet off the ground. She can climb an average about two and one-half feet per minute.

- 1 When will she be 92 feet off the ground?
- 2 In twenty minutes, how many feet above the ground will she be?
- 3 In 75 seconds, how far above the ground will she be?
- 4 Ten minutes ago, how far above the ground would she be?

Step: Label a column

Step: Fill in a cell

Step: Divide both sides

Step: Plot a point

Step: Define an axis

Quantity Name	Unit	Expression
CLIMBING TIME	MINUTES	50 - 2.5T
Question 1	10	92
Question 2	20	117
Question 3	1.25	70.125
Question 4	-10	42

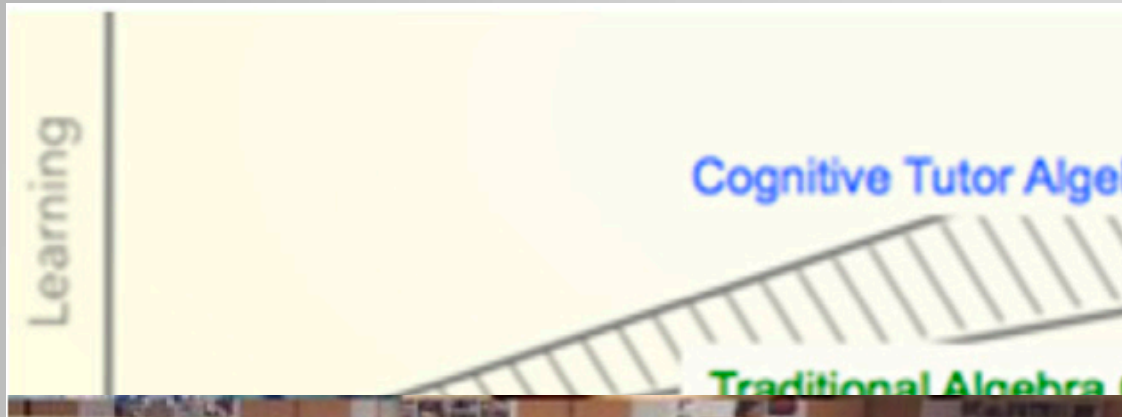
Evidence of Impact

- 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

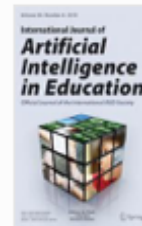
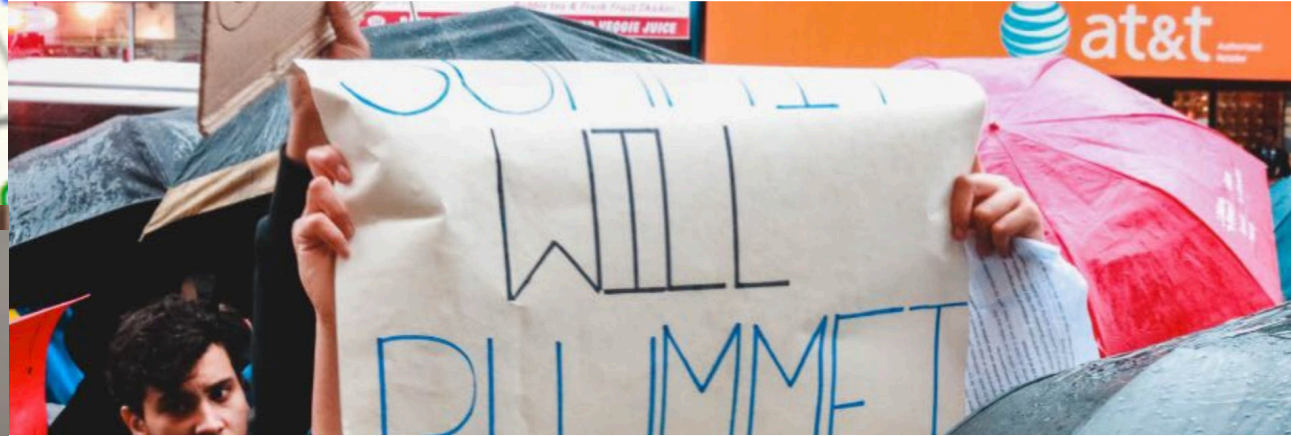
- VanLehn (2011) found that the effectiveness of the intelligent tutoring systems were nearly as effective as average human tutors.
- Ma et al. (2014) found similar results both when compared to a no tutoring or to large group human-tutor instruction.
- Steenbergen-Hu, & Cooper (2014) found more positive effects for ITSs as compared to conventional instruction.
- Similarly, Pane et al. (2014) found evidence of the relative effectiveness of online tutors over conventional teaching.





'Dear Mr. Zuckerberg': Students Take Summit Learning Protests Directly to Facebook Chief

By Emily Tate Nov 15, 2018



[International Journal of Artificial Intelligence in Education](#)

pp 1-31 | [Cite as](#)

Impact of an Artificial Intelligence Research Frame on the Perceived Credibility of Educational Research Evidence

- 1) Lovett, M., Meyer, O., & Thille, C. (2008). The open learning initiative: Measuring the effectiveness of the OLI statistics course in accelerating student learning. *Journal of Interactive Media in Education*. Retrieved from <http://jime.open.ac.uk/2008/14>
- 2) Cukurova, M., Luckin, R., & Kent, C. (2019). Impact of an Artificial Intelligence Research Frame on the Perceived Credibility of Educational Research Evidence. *International Journal of Artificial Intelligence in Education*, 1-31.
- 3) 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.



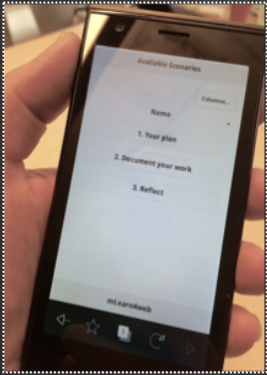
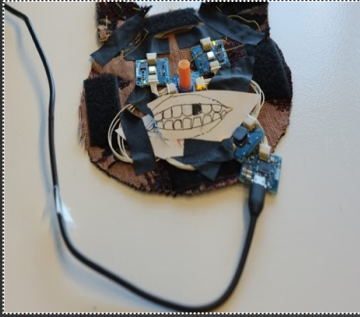
What is an appropriate role for AI in education?

- Adopted systems at scale have high human agency.
- Non-autonomous **human-AI hybrid systems** may be *the state* for education rather than a transition state to full-autonomy.

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., Kent, C., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology, 50(6)*, 3032-3046.





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



Machine Learning Classification of Collaboration Competence

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

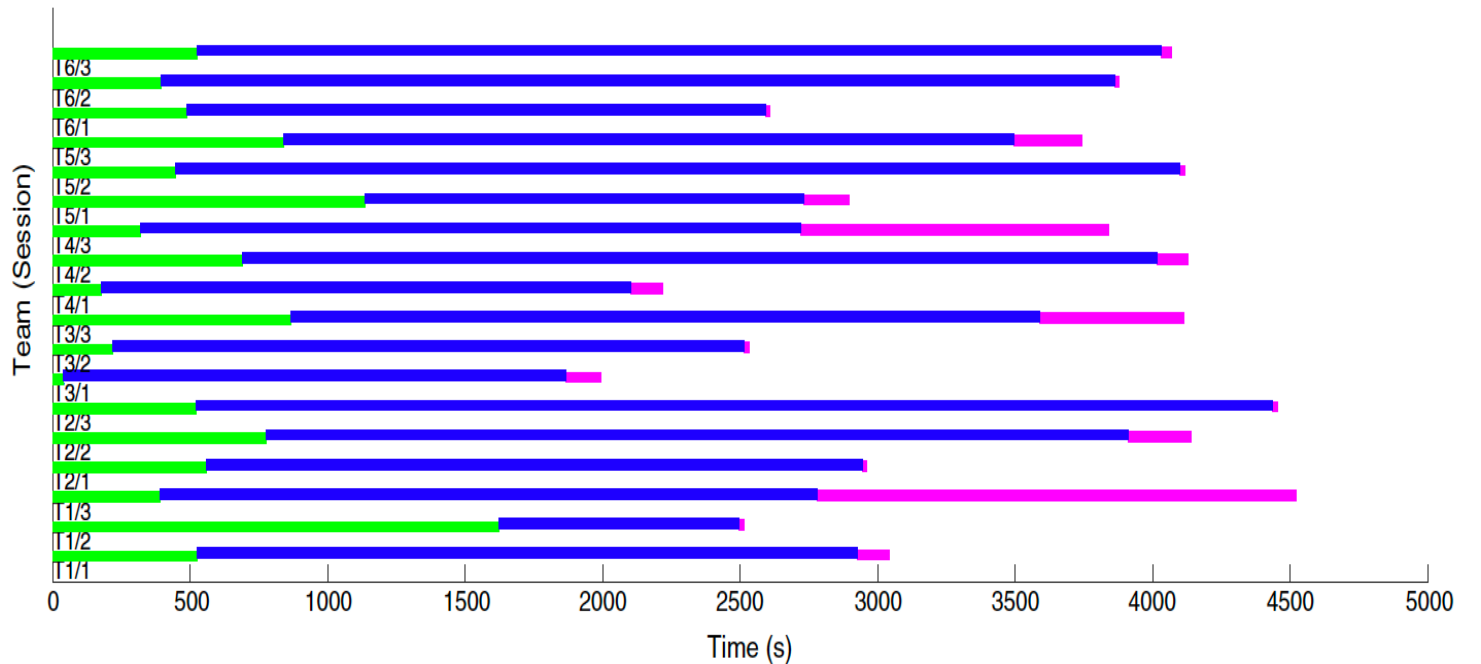
IDEX - Arduino measure of complexity

IDEVHW - Arduino active hardware blocks

IDEVSW - Arduino active software blocks

IDEC - Arduino active blocks

PWR - Student Work Phases



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 Collaboration 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.



Deductive Approach: Nonverbal Indexes of Students' Physical Interactivity (NISPI Framework)

Some important components of collaboration may be interpreted through nonverbal indexes of students physical interactivity:

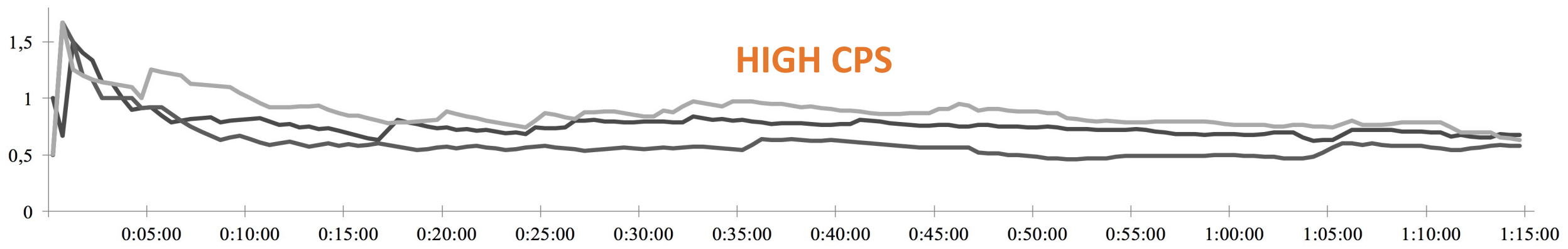
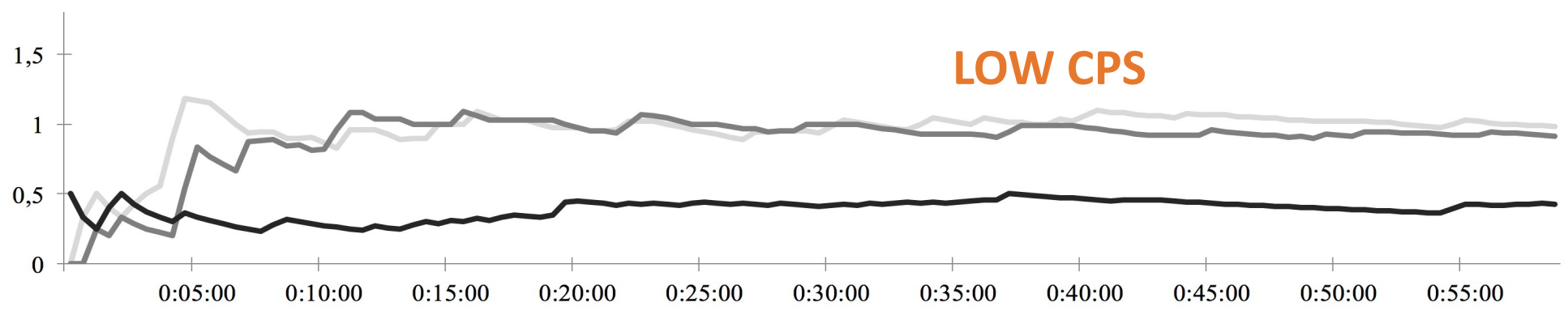
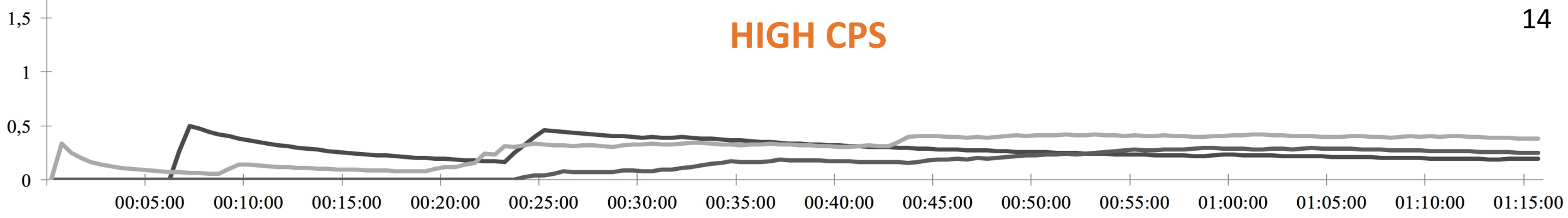
- synchrony,
- individual accountability,
- equality,
- mutuality.

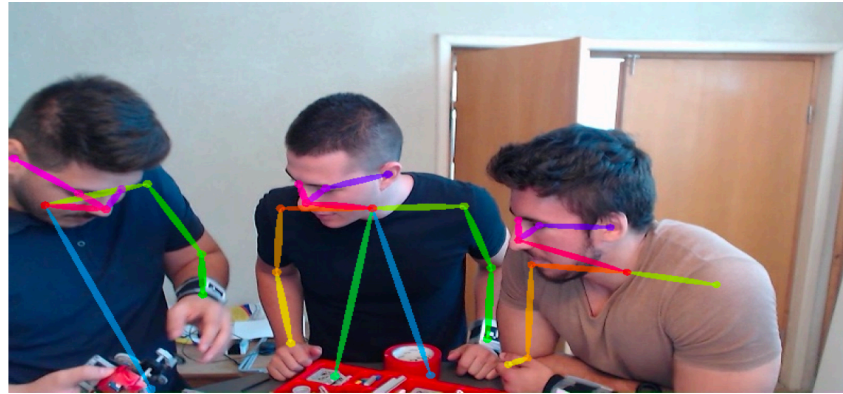


Cukurova, M., Luckin, R., Millán, E., & Mavrikis, M. (2018). The NISPI framework: Analysing collaborative problem-solving from students' physical interactions. *Computers & Education*, 116, 93-109.

Cukurova, M. (2018). A syllogism for designing collaborative learning technologies in the age of AI and multimodal data. In *European Conference on Technology Enhanced Learning* (pp. 291-296). Springer, Cham.





Face patches
(64x64)

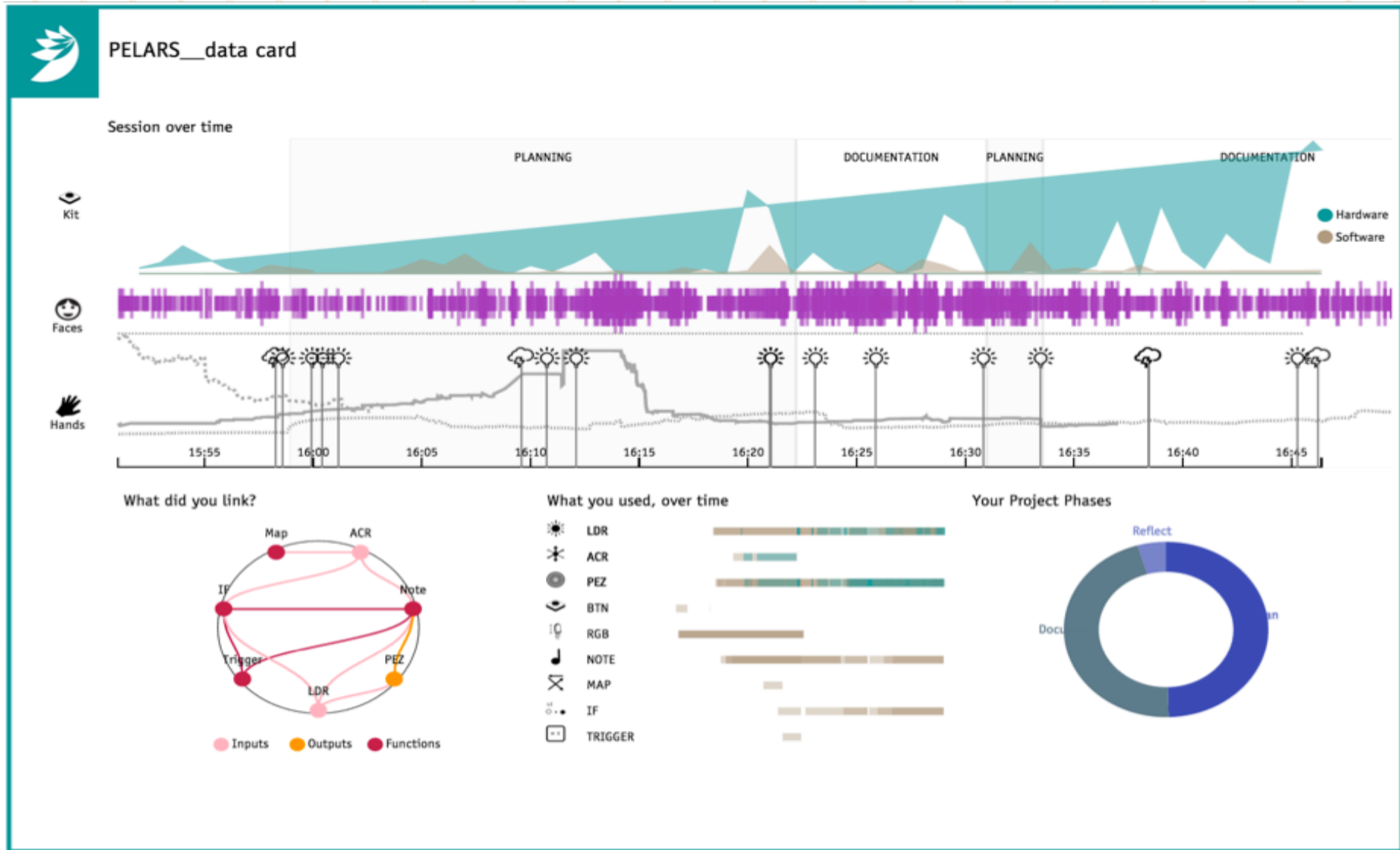
Deep CNN (FaceNET)

Embeddings



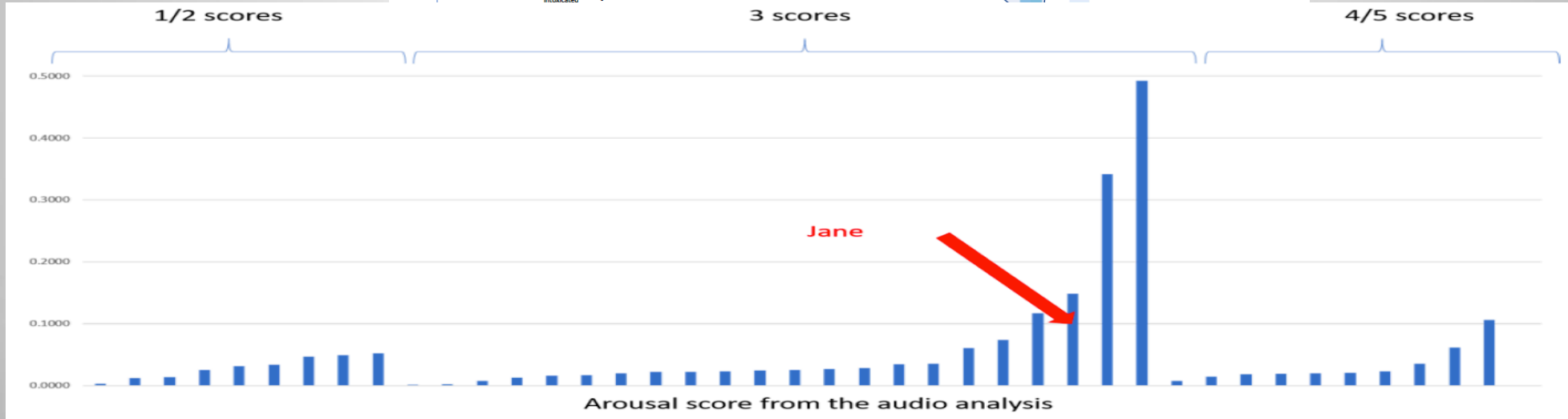
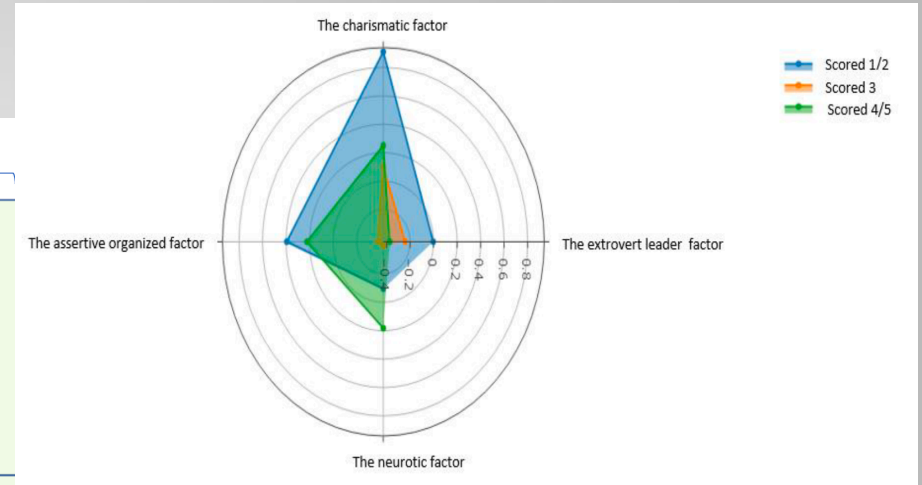
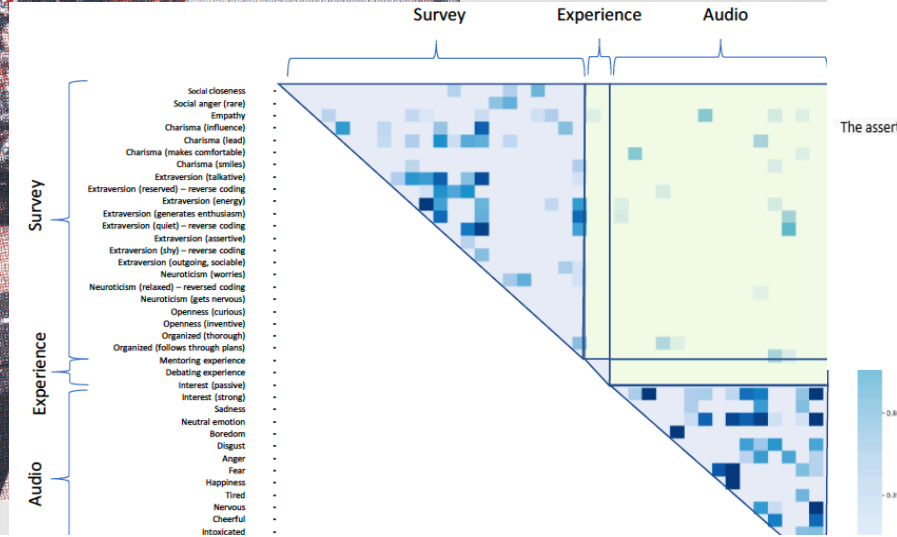
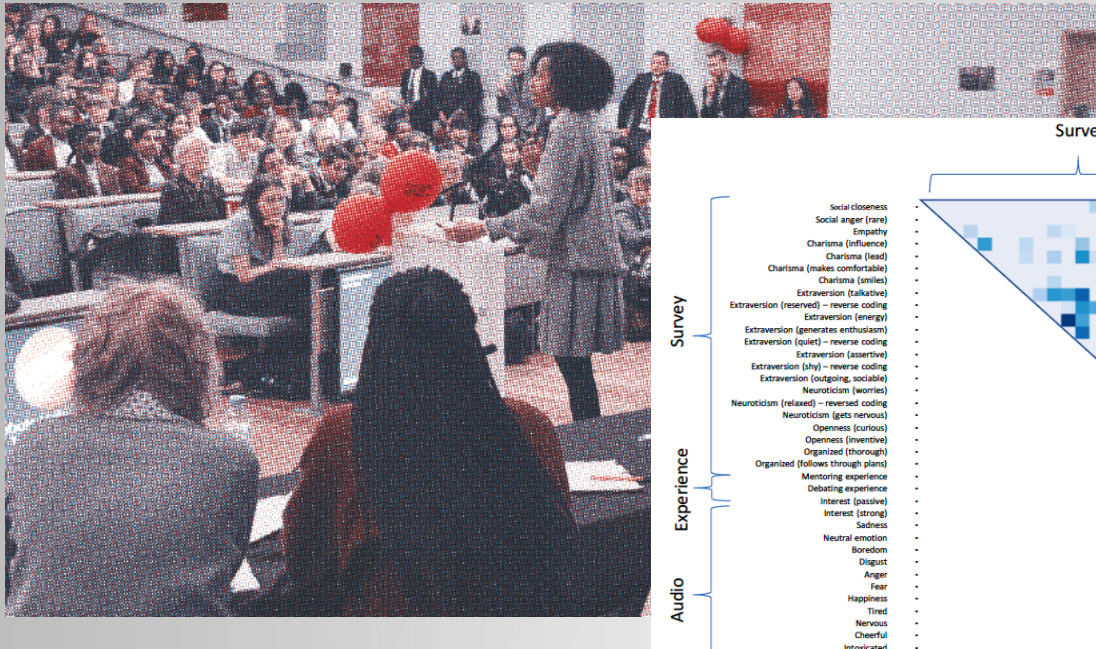
- 1) Apply openPose to videos to get skeleton data
- 2) Used facial recognition from dlib and FaceNET to identify students
- 3) Utilised Hungarian algorithm for assigning faces to names
- 4) LSTM to detect Active, Semi-active, Inactive
- 5) Exploring Social LSTM to train classifier on 3 students jointly.





Cukurova, M., Mavrikis, M., & Luckin, R. (2017). Evidence-Centered Design and Its Application to Collaborative Problem Solving in Practice-based Learning Environments. *Analytics4Learning*. Stanford Research Institute, Menlo Park, USA.

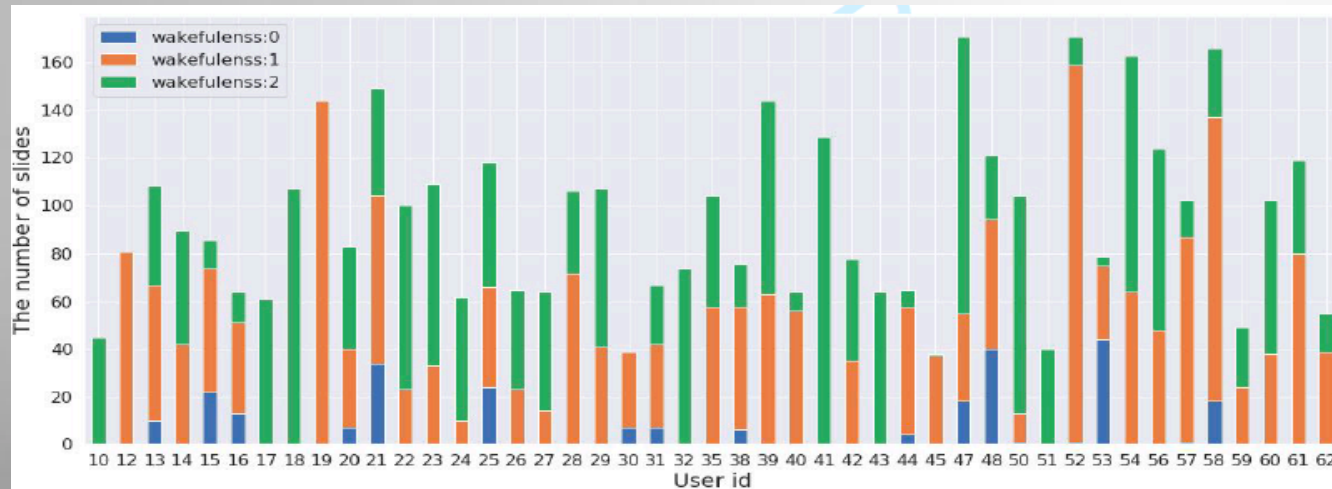
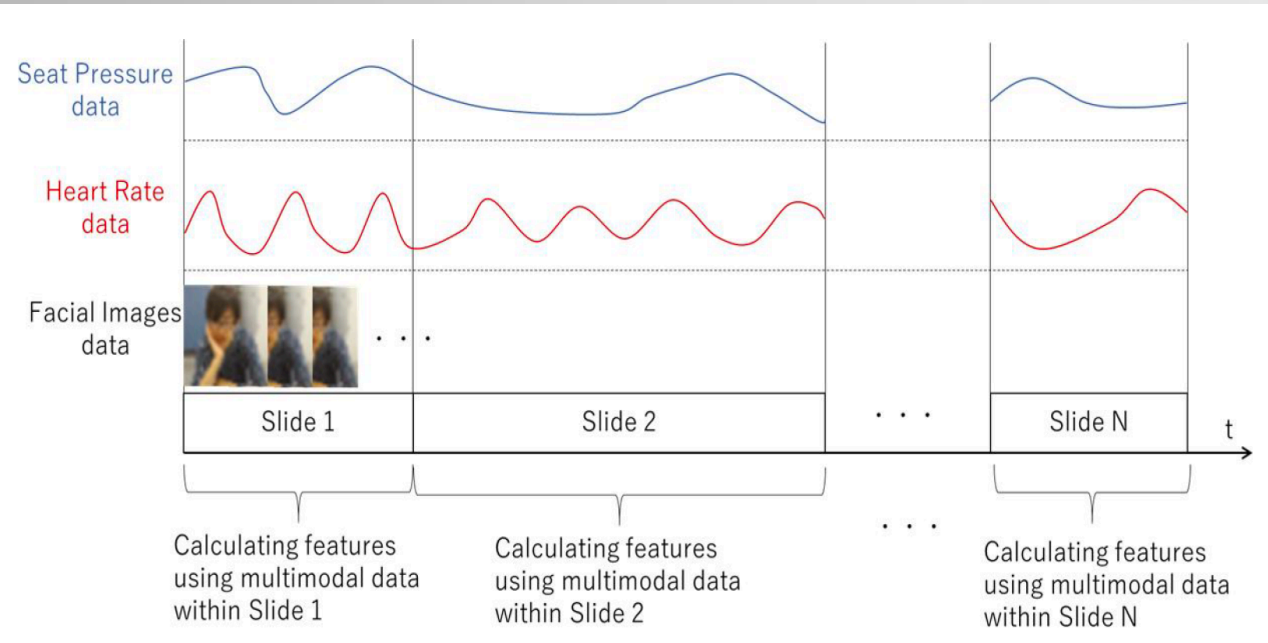




Cukurova, M., Kent, C., & Luckin, R. (2019). Artificial Intelligence and Multimodal Data in the Service of Human Decision-making: A case Study in Debate Tutoring, *British Journal of Educational Technology*, 50 (6), 3032-3046.



Detecting Asleep Learners at the Wheel of e-Learning Platforms



	Features Generated	Constructs Represented
Heart rate	Mean/ standard deviation/ min/ max of RRI, HR, LF/HF, 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. Temperature is partially related to drowsiness.
Seat pressure	Total/ mean pressure	Mean of each frame's total pressure and mean of pressure per second. They are used to estimate a learner's motions.
	Total moving distance	Represents how large a learner's posture change is.
	Total /mean/ max/ min 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	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/ min/ max of head rotation (yaw, pitch, roll)	Represents how large a learner's head rotation is.
	Mean/ standard deviation/ min/ max of head transition along x, y, z	Represents how large a learner's head transition is.

Confusion matrix of SVM and RF using personalised model

		Predicted					
		SVM			RF		
		Asleep	Drowsy	Awake	Asleep	Drowsy	Awake
True label	Asleep	398	152	70	495	100	25
	Drowsy	205	964	311	187	1064	229
	Awake	27	207	726	12	165	783

Confusion matrix of SVM and RF using general model

		Predicted					
		SVM			RF		
		Asleep	Drowsy	Awake	Asleep	Drowsy	Awake
True label	Asleep	35	131	44	81	82	45
	Drowsy	76	368	131	118	248	111
	Awake	41	141	240	25	136	155

1) Split data into train and test dataset:
Cross validation of personalised model and general model.

2) Over/under sampling to deal with imbalanced label distribution of wakefulness states (SMOTE and random sampling)

3) Standardised train and test datasets: to have zero mean and unit variance.

4) SVM and RF are used to build model.

F1-macro scores of cross validation

General model: SVM: 0.46; **RF: 0.47**

Personalised model: SVM:0.76; **RF:0.77**



Results of ANOVA for three groups of behaviours to establish explainable characteristics of them with multimodal data

	0: Asleep	1: Drowsy	2: Awake
Facial images	AU02_c_mean	(0 > 1 > 2)	
	AU02_r_std	(0 > 1 > 2)	
	AU26_r_mean	(0 < 1 < 2)	
	AU45_r_mean	(0 > 1 > 2)	
	AU45_r_std	(0 > 1 > 2)	
	pose_Rx_mean	(0 > 1 > 2)	
	AU45_c_mean (+)	pose_Tx_max (+)	AU02_c_std (+)
	AU26_c_std (-)	pose_Tx_mean (+)	AU15_r_std (-)
	AU26_r_std (-)	pose_Tx_std (+)	AU26_c_mean (+)
	pose_Rx_min (+)	pose_Ty_max (+)	pose_Ty_mean (-)
	pose_Rx_max (+)	pose_Ty_std (+)	pose_Ry_mean (-)
	pose_Rx_std (+)	pose_Tz_max (+)	
	pose_Ty_min (+)	pose_Tz_std (+)	
	pose_Rz_std (+)		
Heart rate	HR_mean	(0 < 1 < 2)	
	HR_min	(0 < 1 < 2)	
	RRI_max	(0 > 1 > 2)	
	RRI_mean	(0 > 1 > 2)	
	RRI_std	(0 > 1 > 2)	
	HR_max (-)		HR_std (-)
	RRI_min (+)		LF/HF_std (-)
	LF/HF_min (+)		temperature_min (-)
	LF/HF_max (+)		temperature_max (-)
	LF/HF_mean (+)		temperature_mean (-)
Seat Pressure			mean_prs (+)

(+) Significantly higher than other groups
 (-) Significantly lower than other groups

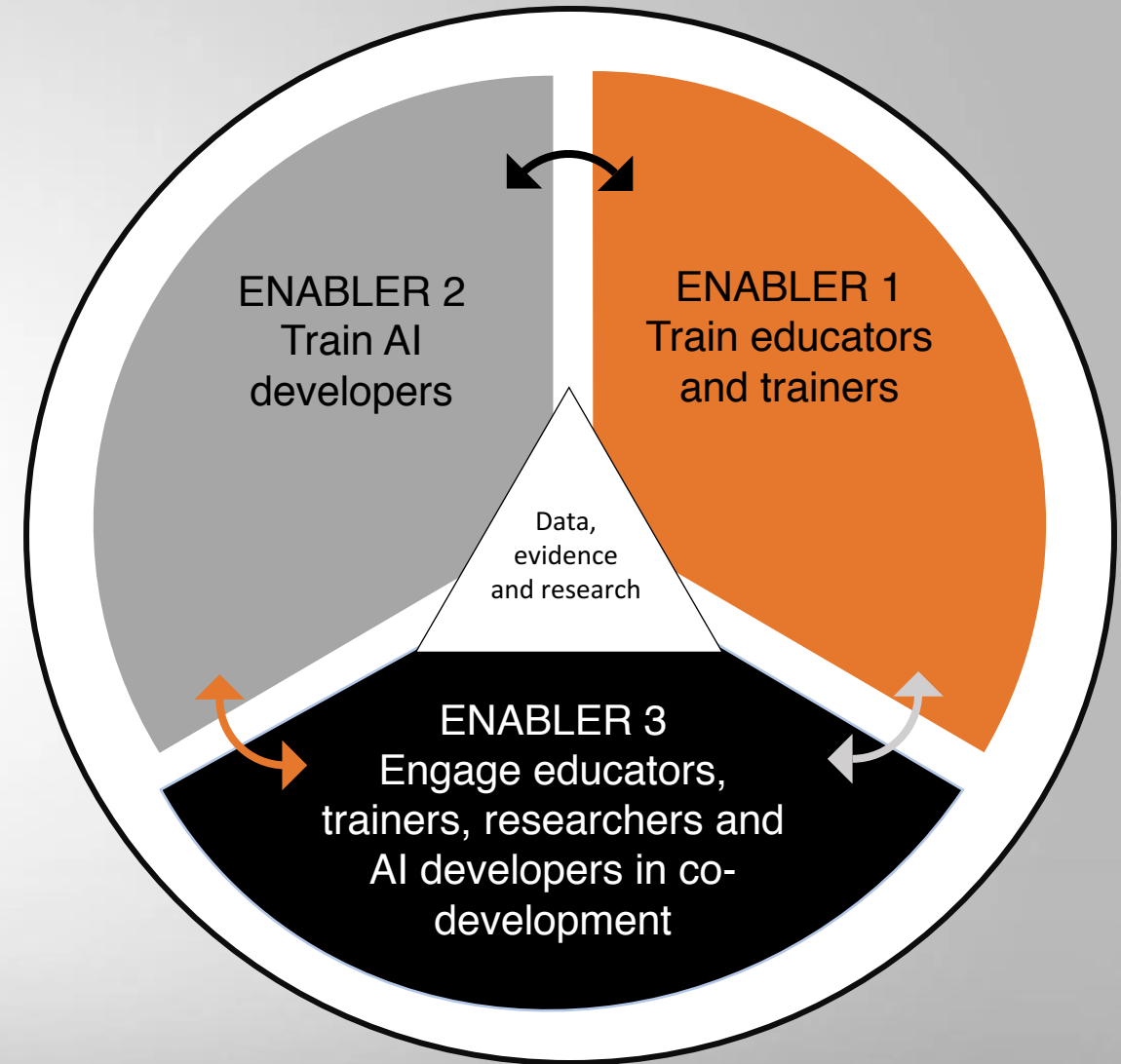
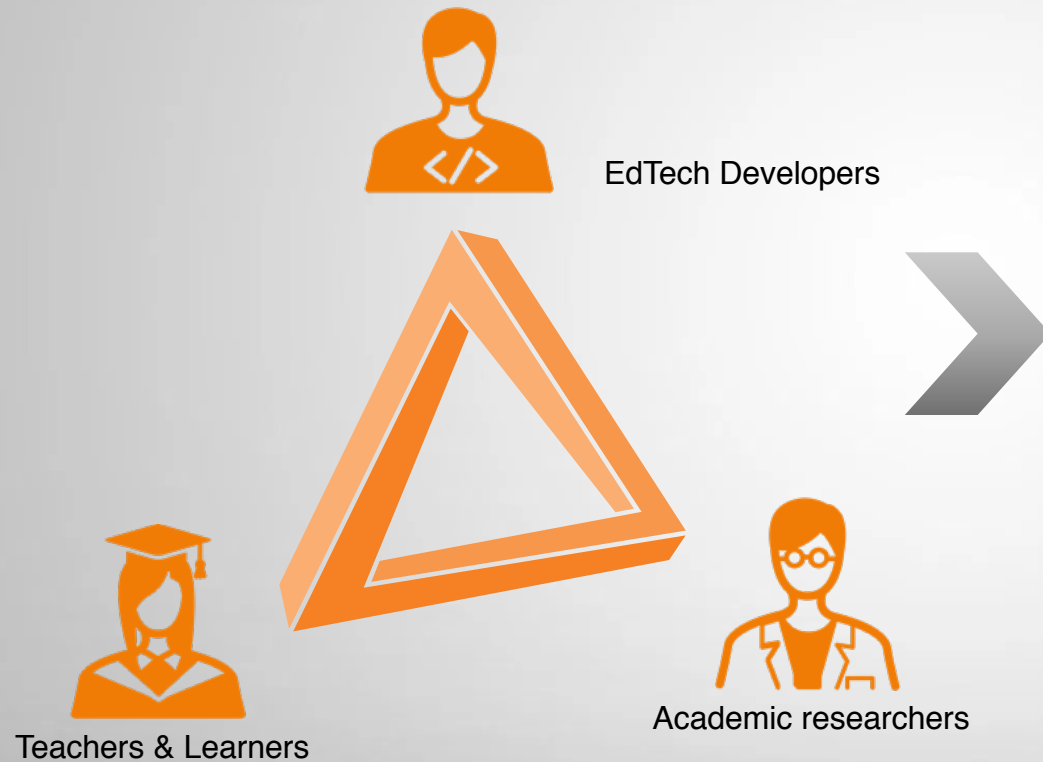
Confusion matrix of personalised and general model

		Predicted					
		Personalised model			General model		
		Asleep	Drowsy	Awake	Asleep	Drowsy	Awake
True label	Asleep	484	104	32	99	63	46
	Drowsy	186	1075	219	115	237	125
	Awake	15	177	768	25	94	197

F1-macro score of cross validation
 Final General Model; **RF: 0.52**
 Final Personalised Model; **RF:0.77**



The Golden Triangle



Cukurova, M., Luckin, R., & Clark-Wilson, A. (2019). Creating the golden triangle of evidence-informed education technology with EDUCATE. *British Journal of Educational Technology*, 50(2), 490-504.

<https://www.ucl educate.com>



To Sum-up

- AI is likely to significantly impact education and there is a need for a system change: design and use AI, educate people about AI, innovate education systems for an AI-driven world.
- With current definitions of AI, I am not convinced that the more intelligent is better for teaching and learning. Tightly coupled human-AI systems, that are not like human but human-centred, can be more appropriate for teaching and learning.
- Better inter-stakeholder collaborations are needed to make progress in AI in Education.



Thank you

Dr Mutlu Cukurova

m.cukurova@ucl.ac.uk

@mutlucukurova

