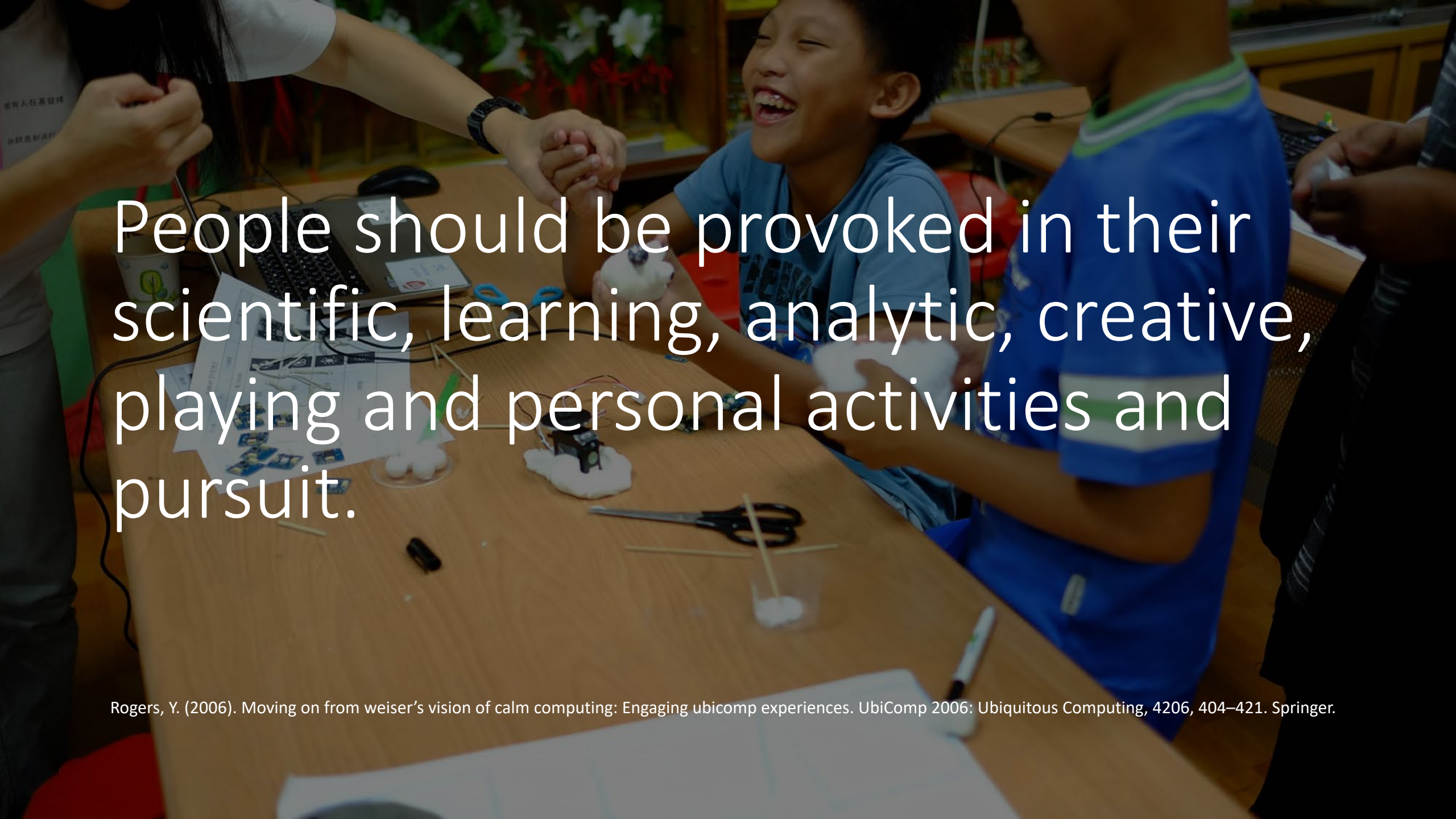
Shadows and Light MMLA: Play and Learning in the Digital Age

Daniel Spikol

UNIVERSITY OF COPENHAGEN

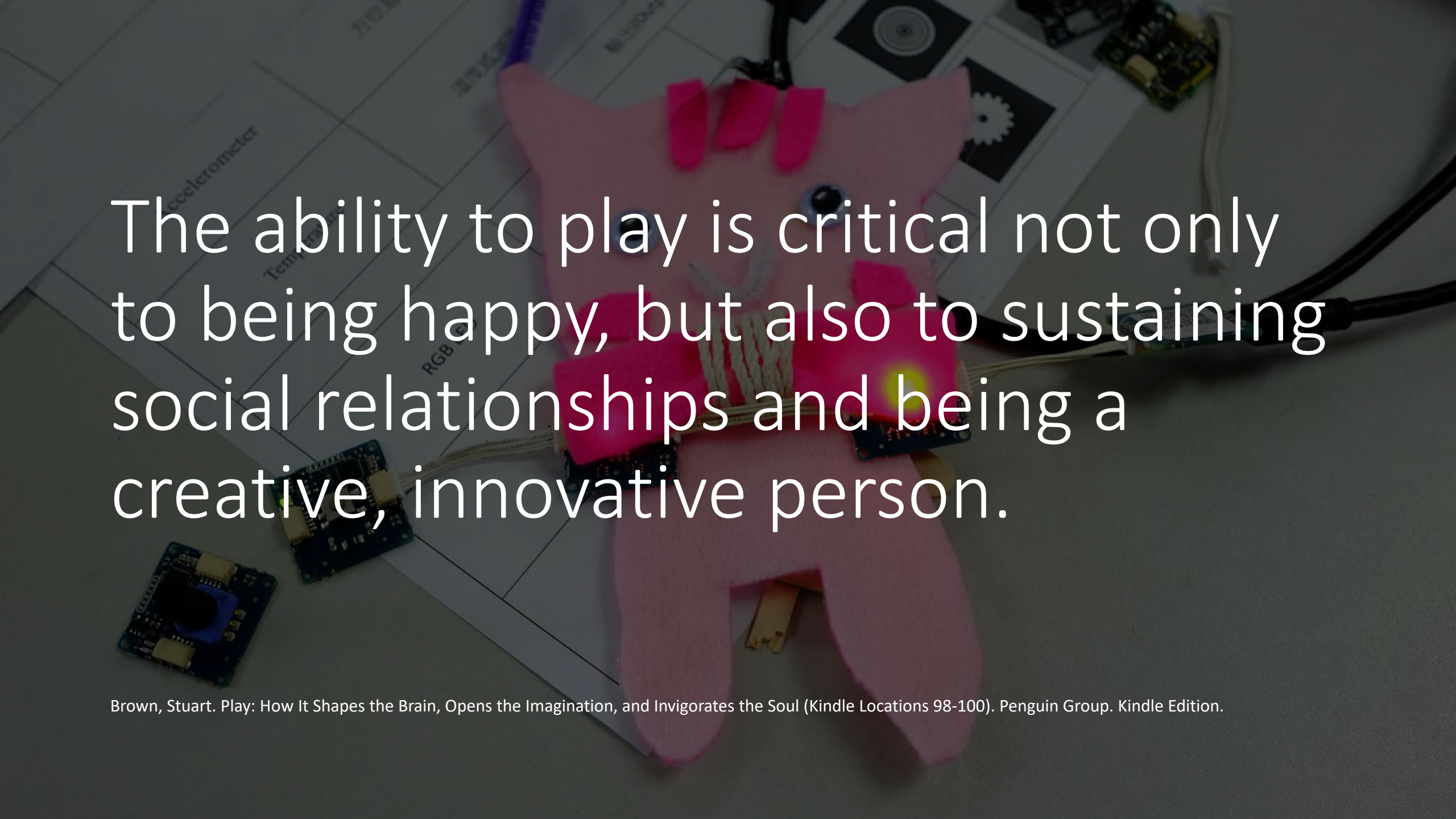
Today's Plan

- Introduction to MMLA
- Exploring Theoretical Foundations for MMLA
- Discussion about Privacy and Ethics



People should be provoked in their scientific, learning, analytic, creative, playing and personal activities and pursuit.

Rogers, Y. (2006). Moving on from weiser's vision of calm computing: Engaging ubicomp experiences. UbiComp 2006: Ubiquitous Computing, 4206, 404–421. Springer.

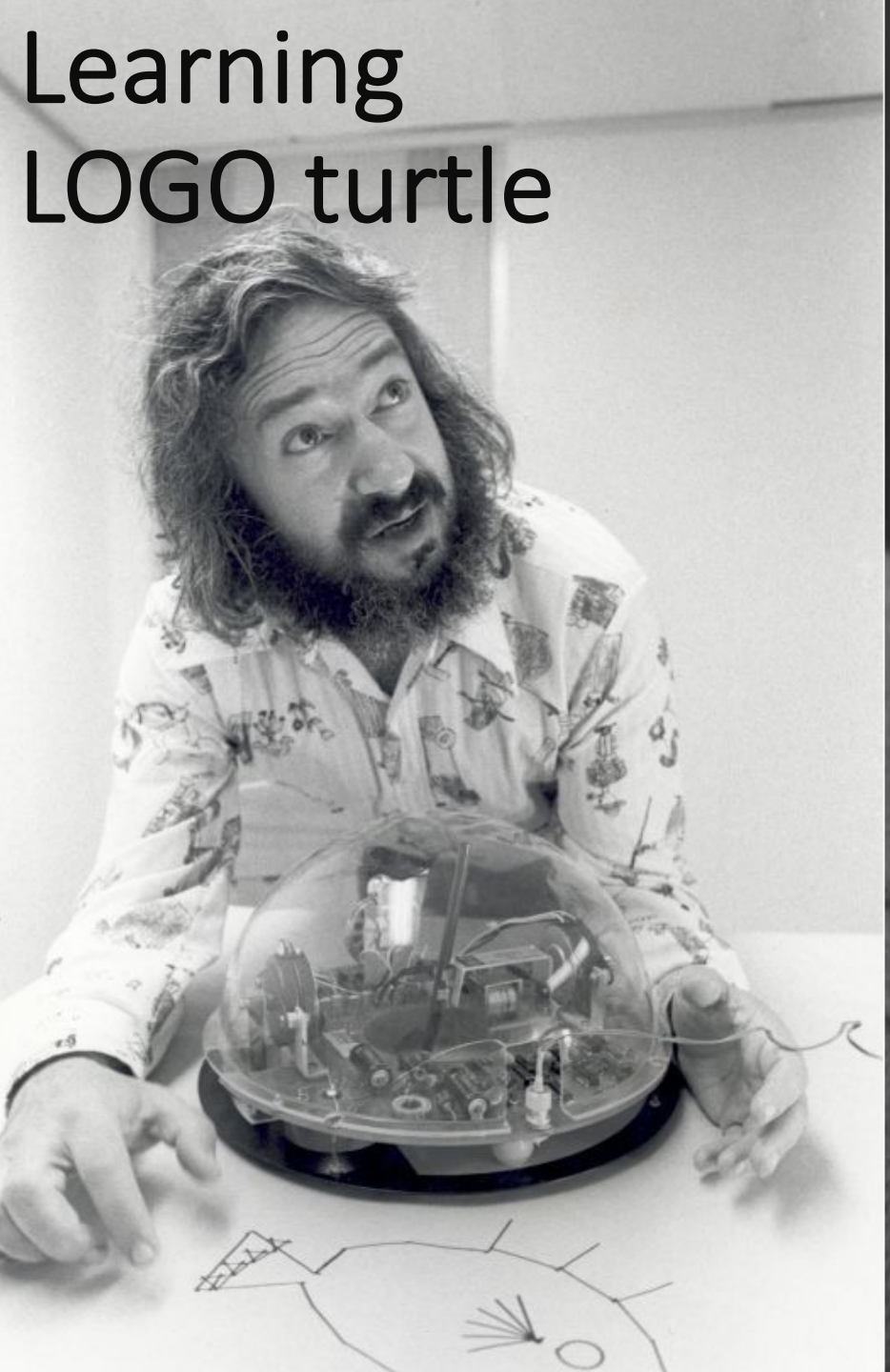


The ability to play is critical not only to being happy, but also to sustaining social relationships and being a creative, innovative person.

Brown, Stuart. Play: How It Shapes the Brain, Opens the Imagination, and Invigorates the Soul (Kindle Locations 98-100). Penguin Group. Kindle Edition.

How do we design to provoke people to explore, play and learn?

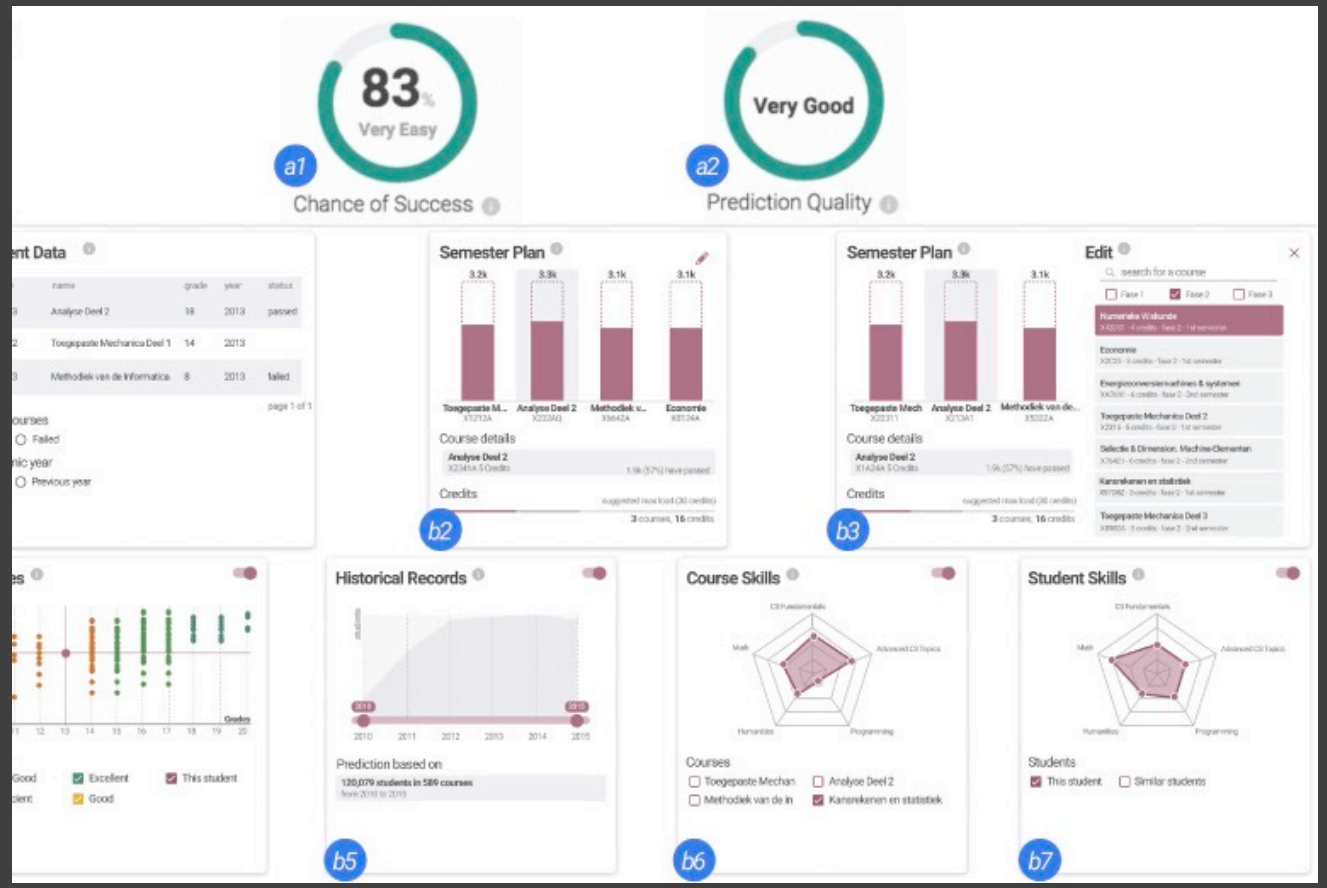
Learning LOGO turtle



Learning analytics is the **measurement**, **collection**, **analysis** and reporting of **data** about learners and their contexts, for purposes of understanding and optimising **learning** and the **environments** in which it occurs.

Society of Learning Analytics Research - https://solaresearch.org/

Problems with Learning Analytics



- Strong focus on online learning
- e.g. Click Stream data
- Learning at Scale (EDM and AIED)
- Generally, at higher education
- Focused less on collaboration

Gutiérrez, F., Seipp, K., Ochoa, X., Chiluiza, K., De Laet, T., & Verbert, K. (2020). LADA: A learning analytics dashboard for academic advising. *Computers in Human Behavior, 107*, 105826. doi:10.1016/j.chb.2018.12.004

Where Learning and Play happen

- How can we approach the human (complex and messy) learning from a Learning Analytics perspective?
- In the real-world humans communicate and leave traces across multiple modalities
- Measure, collect, analyse, and report to understand and improve
- Capture these learning traces from the real world

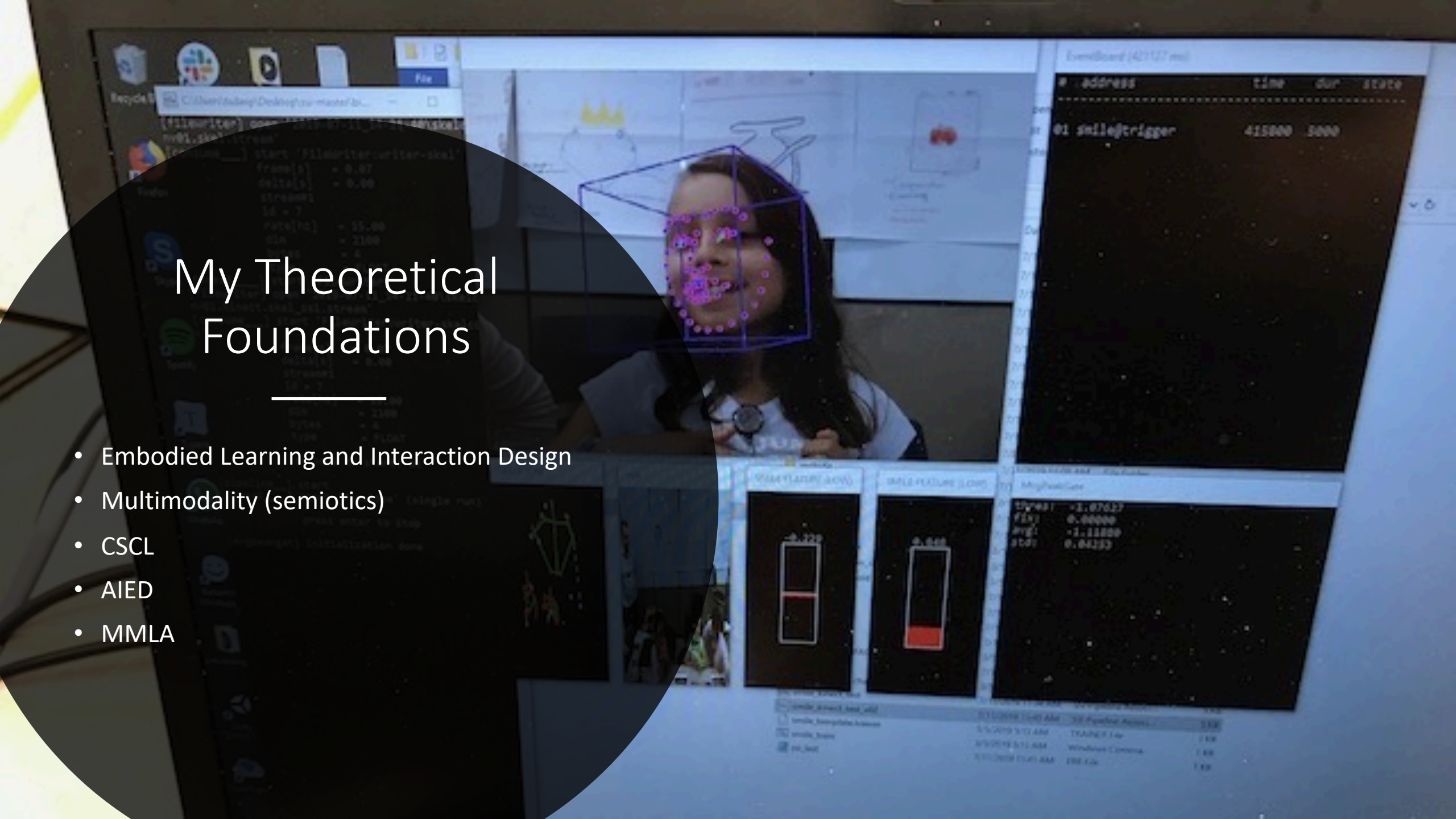
Modalities

- What we see
- What we hear
- How we move
- How we write
- How we blink
- Our pulse
- Brain activity?
- Our hormones?
- Future things?

Boto, E., Holmes, N., Leggett, J., Roberts, G., Shah, V., Meyer, S. S., … Brookes, M. J. (2018). Moving magnetoencephalography towards real-world applications with a wearable system. *Nature*, *555*(7698), 657–661. http://doi.org/10.1038/nature26147

My Theoretical Foundations

- Embodied Learning and Interaction Design
- Multimodality (semiotics)
- CSCL
- AIED
- MMLA



Embodied Learning

- An important consequence of the embodied approach to cognition is that it highlights the importance of “the surroundings/environment” for cognitive work. By using language, representations or other artefacts humans are able to augment their cognitive capabilities, and - in relation to mathematics - shape their potential for mathematical insights.
- Such cognitive tools allow anchoring, generation of overview, conceptual blending and further investigation of mathematical phenomenon (Menary 2015, Johansen & Misfeldt 2020)

Menary, R. (2015). Mathematical Cognition - A Case of Enculturation. In T. Metzinger & J. M. Windt (Eds). Open MIND: 25(T). Frankfurt am Main: MIND Group. doi: 10.15502/9783958570818
Johansen, M. W., & Misfeldt, M. (2020). Material representations in mathematical research practice. Synthese, 197(9), 3721-3741. doi:10.1007/s11229-018-02033-4

Multimodality (semiotics)

- Within the human sciences, multimodality thus implicates both abstract and physical phenomena in its study: the semiotic (e.g., abstract systems and structures of semiotic resources and intersemiotic processes through which semiotic choices combine to create meaning, as well as the actual multimodal artifacts and events); and the physical media through which semiosis takes place.

O'Halloran, K. L., & Smith, B. A. (2012). Multimodality and technology. The encyclopedia of applied linguistics.
Bezemer, J., & Kress, G. (2015). Multimodality, learning and communication: A social semiotic frame. Routledge.

CSCL

- Computer-Supporter Collaborative Learning (CSCL) aims to understand the diverse interactions in and outside the learning enviroment that exist between people with the understanding that learning is complex and socially constructed.
- Jeong and Hmelo-Silver (2016 p 247) argue for seven core affordances of technology for collaborative learning based on theories of collaborative learning and CSCL practices. Technology affords learner opportunities to (1) engage in a joint task, (2)communicate, (3) share resources, (4) engage in productive collaborative learning processes,(5) engage in co-construction, (6) monitor and regulate collaborative learning, and (7) find, build groups, and communities.

Jeong, H., & Hmelo-Silver, C. E. (2016). Seven Affordances of Computer-Supported Collaborative Learning: How to Support Collaborative Learning? How Can Technologies Help? *Educational Psychologist, 51*(2), 247-265. doi:10.1080/00461520.2016.1158654

AIED & EDM

- The field investigates learning wherever it occurs, in traditional classrooms or in workplaces, in order to support formal education as well as lifelong learning. It brings together AI, which is itself interdisciplinary, and the learning sciences (education, psychology, neuroscience, linguistics, sociology, and anthropology) to promote the development of adaptive learning environments and other AIED tools that are flexible, inclusive, personalised, engaging ,and effective.
- EDM researchers are addressing questions of cognition, metacognition, motivation, affect, language, social discourse, etc. using data from intelligent tutoring systems, massive open online courses, educational games and simulations, and discussion forums. The data include detailed action and timing logs of student interactions in user interfaces such as graded responses to questions or essays, steps in rich problem solving environments, games or simulations, discussion forum posts, or chat dialogs. They might also include external sensors such as eye tracking, facial expression, body movement, etc.

Koedinger, K. R., D'Mello, S., Mclaughlin, E. A., Pardos, Z. A., & Rosé, C. P. (2015). Data mining and education. Wiley Interdisciplinary Reviews: Cognitive Science, 6(4), 333-353. doi:10.1002/wcs.1350

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), 2824-2838. doi:10.1111/bjet.12861

Buckingham Shum, S. J., & Luckin, R. (2019). Learning analytics and AI: Politics, pedagogy and practices. British Journal of Educational Technology, 50(6), 2785-2793. doi:10.1111/bjet.12880

Holstein, K., McLaren, B. M., & Aleven, V. (2018). Student Learning Benefits of a Mixed-Reality Teacher Awareness Tool in AI-Enhanced Classrooms. In (pp. 154-168): Springer International Publishing.

...ile using *Lumilo*. Top row: ...*milo* (taken after the end ...t view of the class thro... ...udent's indicator.

PELARS Project

Practice Based Learning Analytics for Research and Support (PELARS)

- What new types of learning analytics can be derived from the hands-on learning of STEM and STEAM subjects?
- How can we use this data to understanding and provide avenues for formative assessment constructivist and practice-based learning?
- How can we better understand how the design of physical space and furniture influence learning interventions?

Key Collaborators

- Mutlu Cukurova, UCL Knowledge Lab, United Kingdom
- Emanuele Ruffaldi, Giacomo Dabisias & Lorenzo Landolfi, Scuola Superiore Sant'Anna, Italy
- David Cuartielles, Ardunio Verkstad, Sweden
- Bato Vogel, Malmö University, Sweden
- Donal Healion & Sam Russell, National College of Art and Design, Ireland
- Eva-Sophie Katterfedlt, Bremen University, Germany
- Nina Valkanova, Copenhagen Institute for Interaction Design, Denmark
- Simon Denehey and Phil Hamilton, PERCH, Ireland
- European Network of Living Labs

This project has received funding from the European's Seventh Framework Programme for research technological development and demonstrations under grant agreement 619738

Different Approach for Learning Analytics

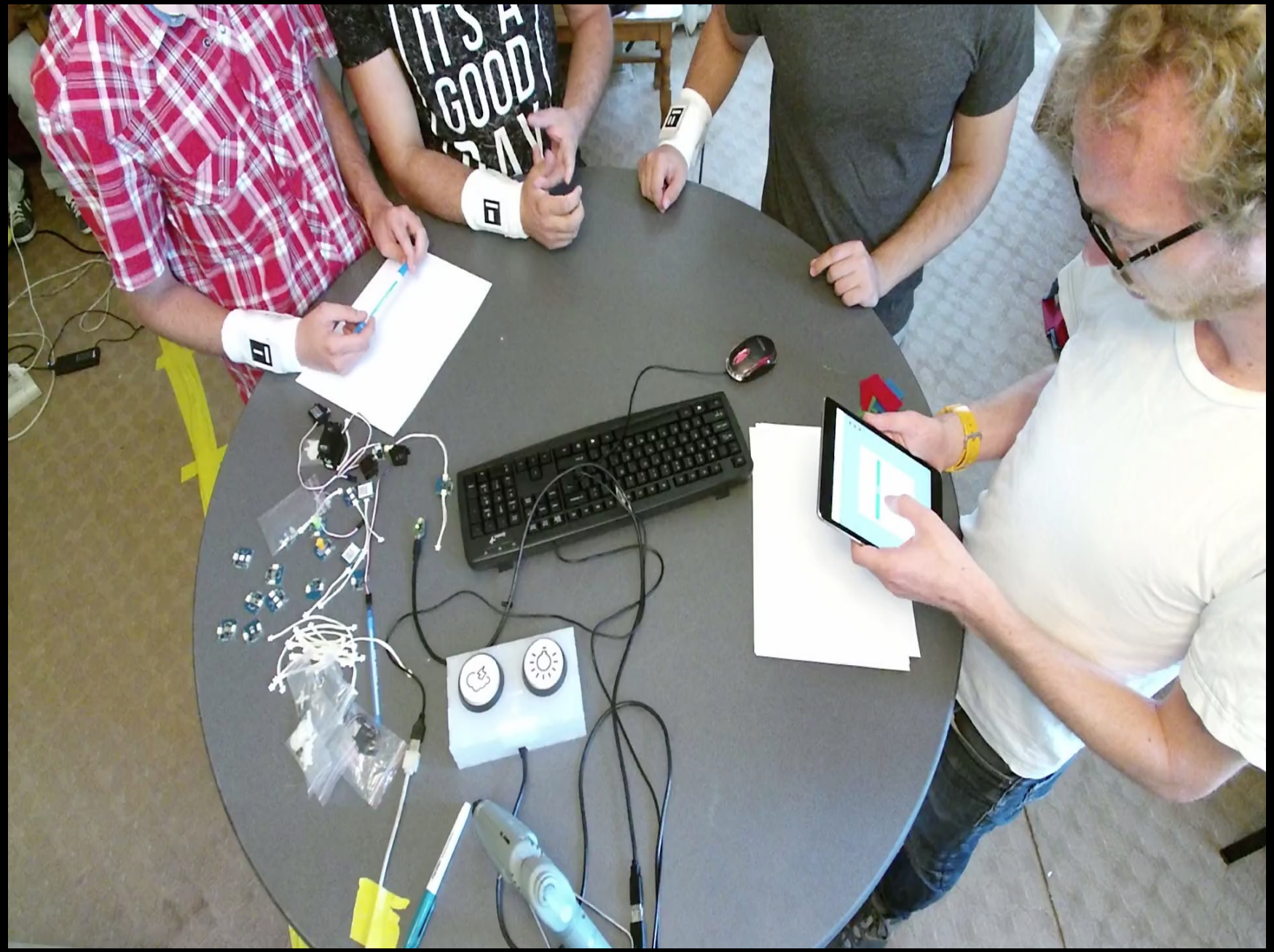
- Less intrusive data collection - Multimodal Learning Analytics (MMLA)
- Focus on non-verbal interactions between people and objects
- Collect data in real-world settings
- Explore different techniques for data analysis
- Explore how to design environments for improved collaboration

What we did…

- LAS system for collecting diverse traces (data):
  - Computer vision systems for capturing and analyzing “collaboration”
  - Mobile and Web-based tools for student self-documentation and research on-the fly coding
  - Visual Programming Platform including sensors and actuators
  - Sentiment feedback devices
- Learning Analytics
  - Logic and Reasoning based on the data collected
  - Visualizations
  - Specially designed furniture

What the groups did – the interventions

- Focus on groups of 3 students
  - open-ended design task
  - 57 minutes (mean of each session)
- Specially developed learning scenarios
  - Interactive toy
  - Color sorter
  - Autonomous vehicle


IT'S A
GOOD

Data Collected

MMLA FEATURES (Independent)

FLS - Number of faces looking at screen
DBF - Mean distance between faces
DBH - Mean distance between hands
HMS - Mean hand movement speed
AUD - Mean audio level
HP - Mean hand positions
ACA - Mean Arduino components activity
DEC - Number of connected Arduino components
SB - Sentiment Buttons
PWR - Student Work Phases

Approach

1. Data Processing
2. Clustering
3. Regression
4. Variable refinement
5. Regression
6. Deep Learning

How do these features affect the student out-puts of collaboration patterns(Dependent)

ASQ- Artefact grade
CPS - Score IA, PE & IPV

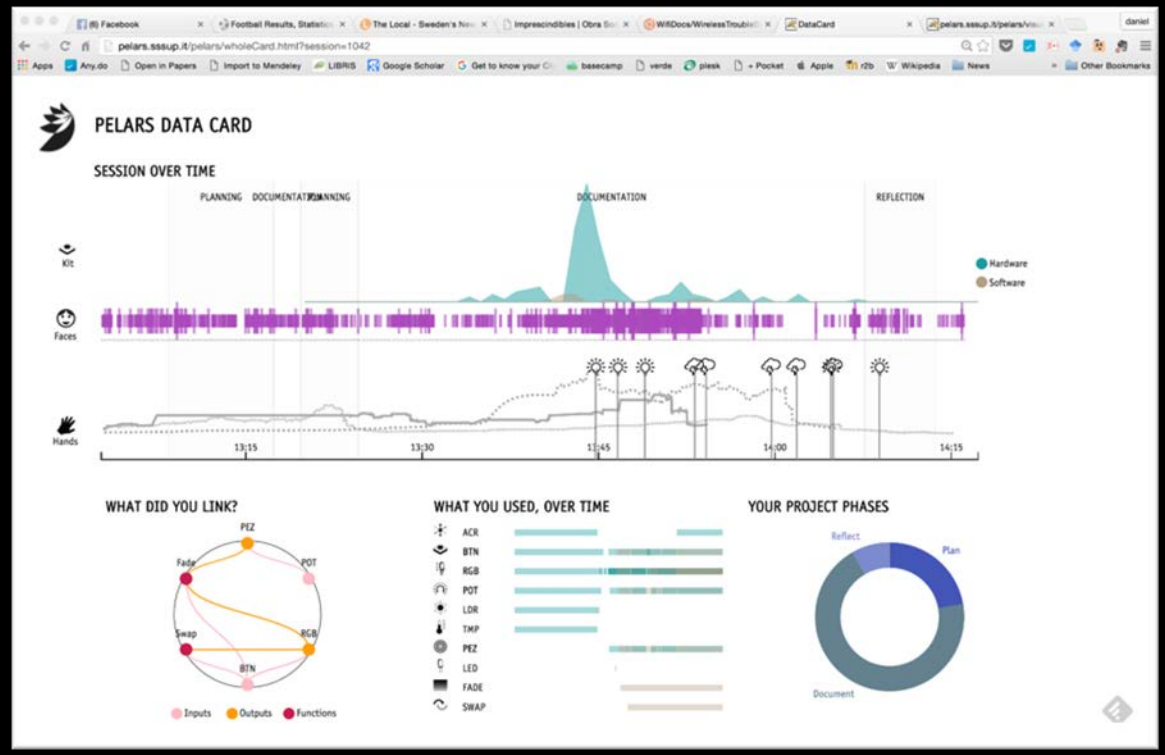
Briefly the Results

- Artefact solution (What the groups created)
  - Dependent variables – score of the solution
    - Features Distance between Hands, (DBH), Distance between Learners (DBL), and Audio (AUD) can predict after 30 minutes

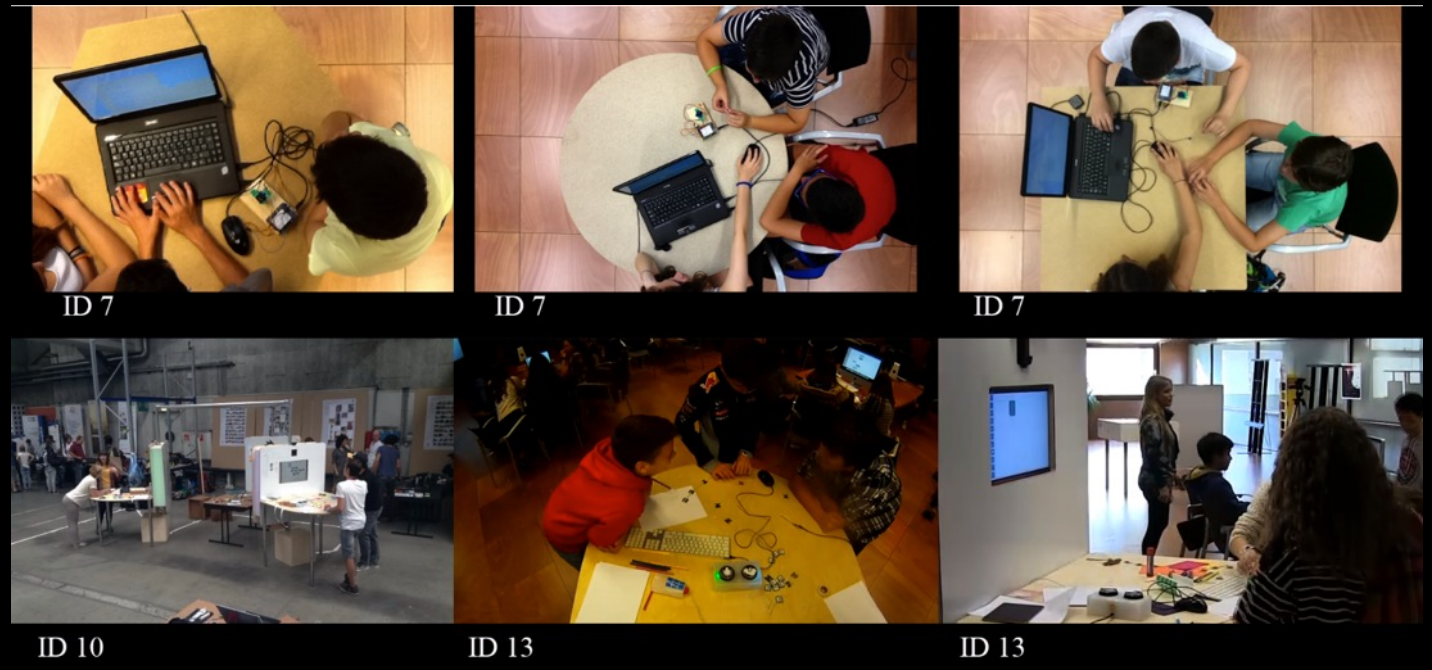
- Collaborative Problem Solving Framework (How the groups worked together)
  - Dependent variables - Individual Accountability, Physical Engagement, and Synchronicity
    - Individual Accountability (IA) and Synchrony (SYN) are strong features for prediction with Distance between hands (DBH)
    - Synchronicity - DBH is an important feature with Faces Looking at Screen (FLS)
    - Physical Engagement (PE) is a strong feature for Hand Distance (DBH)

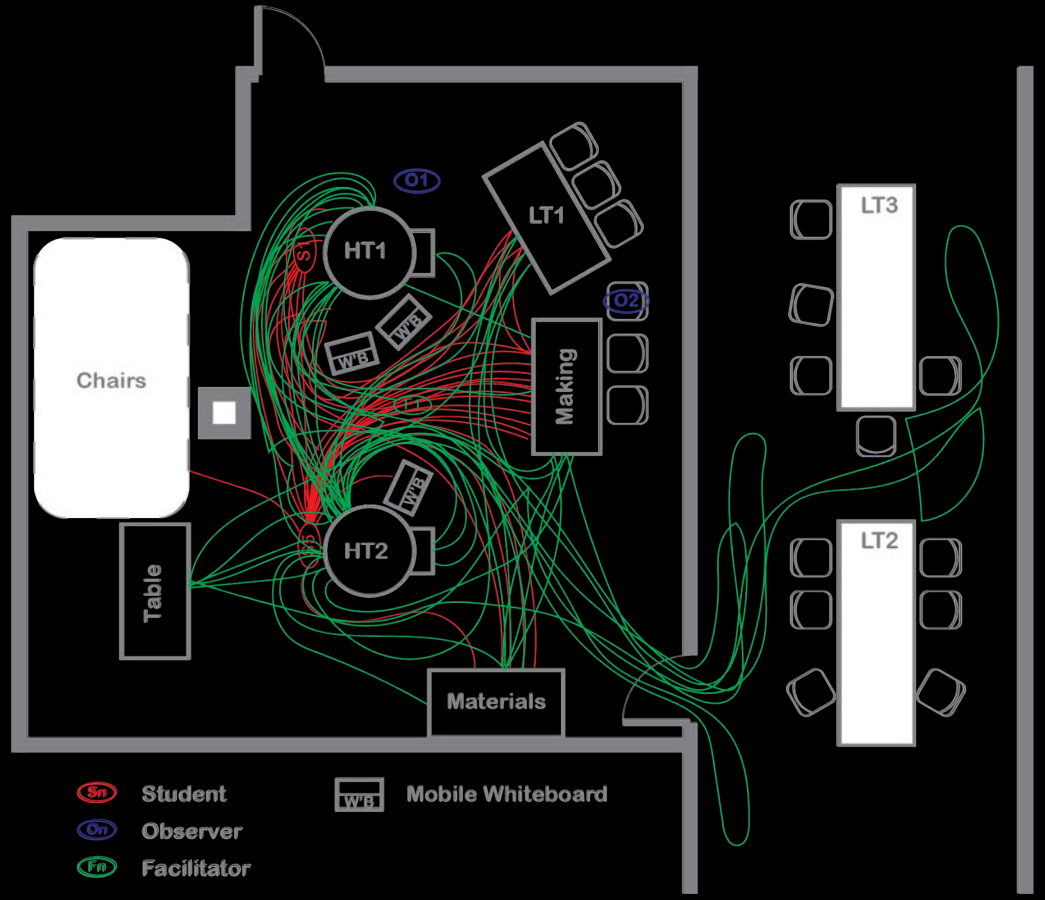
Spikol, D., Ruffaldi, E., Dabisias, G., & Cukurova, M. (2018). Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. *Journal of Computer Assisted Learning, 34*(4), 366-377. doi:10.1111/jcal.12263
Vujovic, M., Hernández-Leo, D., Tassani, S., & Spikol, D. (2020). Round or rectangular tables for collaborative problem solving? A multimodal learning analytics study. *British Journal of Educational Technology, 51*(5), 1597-1614. doi:10.1111/bjet.12988
Spikol, D, Ruffaldi, E, Dabisias, G, Cukurova, M. Supervised machine learning in multimodal learning analytics for estimating success in project-based learning. Journal of Computer Assisted Learning. 2018; 34: 366– 377. https://doi.org/10.1111/jcal.12263
D. Spikol, E. Ruffaldi, L. Landolfi and M. Cukurova, "Estimation of Success in Collaborative Learning Based on Multimodal Learning Analytics Features," 2017 IEEE 17th International Conference on Advanced Learning Technologies (ICALT), Timisoara, Romania, 2017, pp. 269-273, doi: 10.1109/ICALT.2017.122.

Visualizations

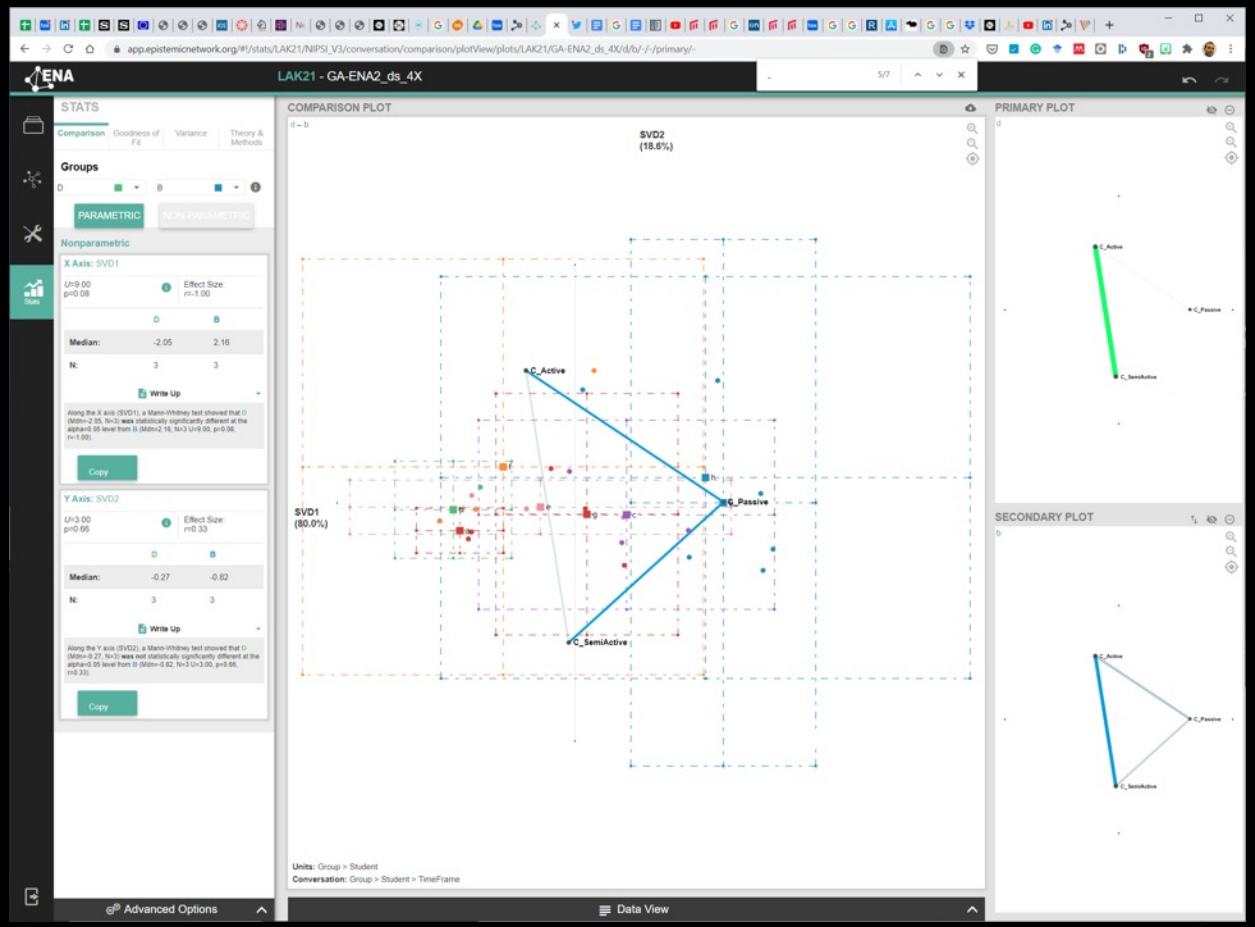


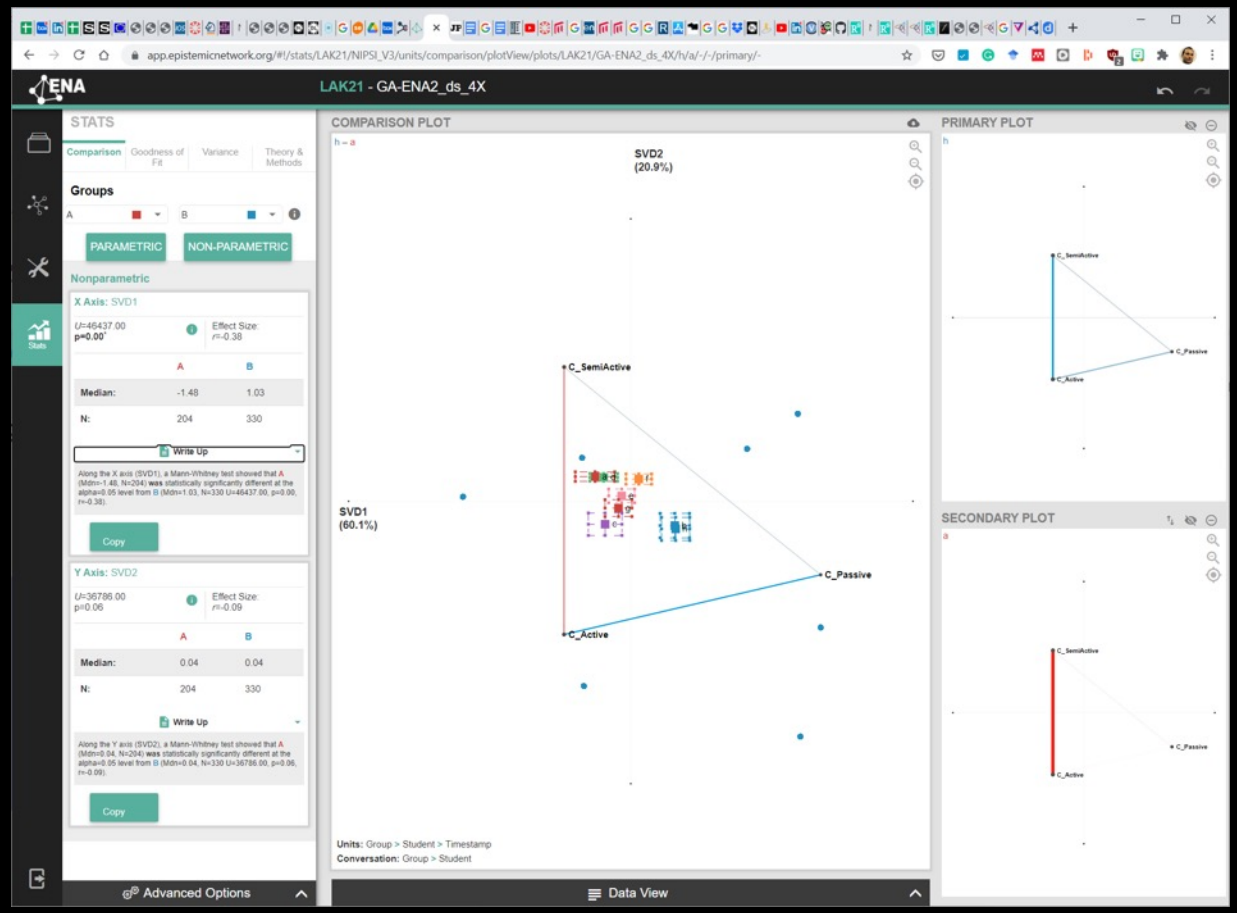
Designing Spaces



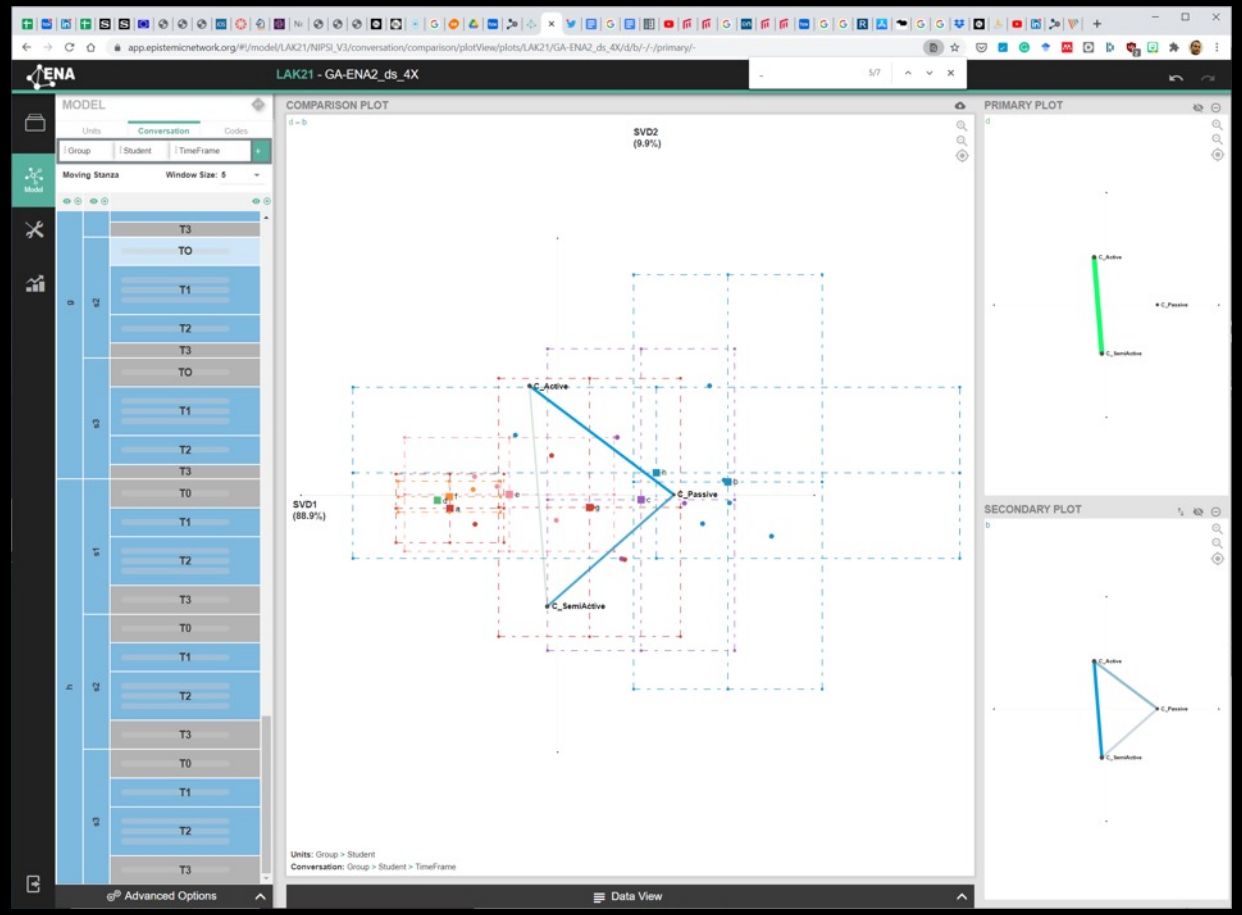


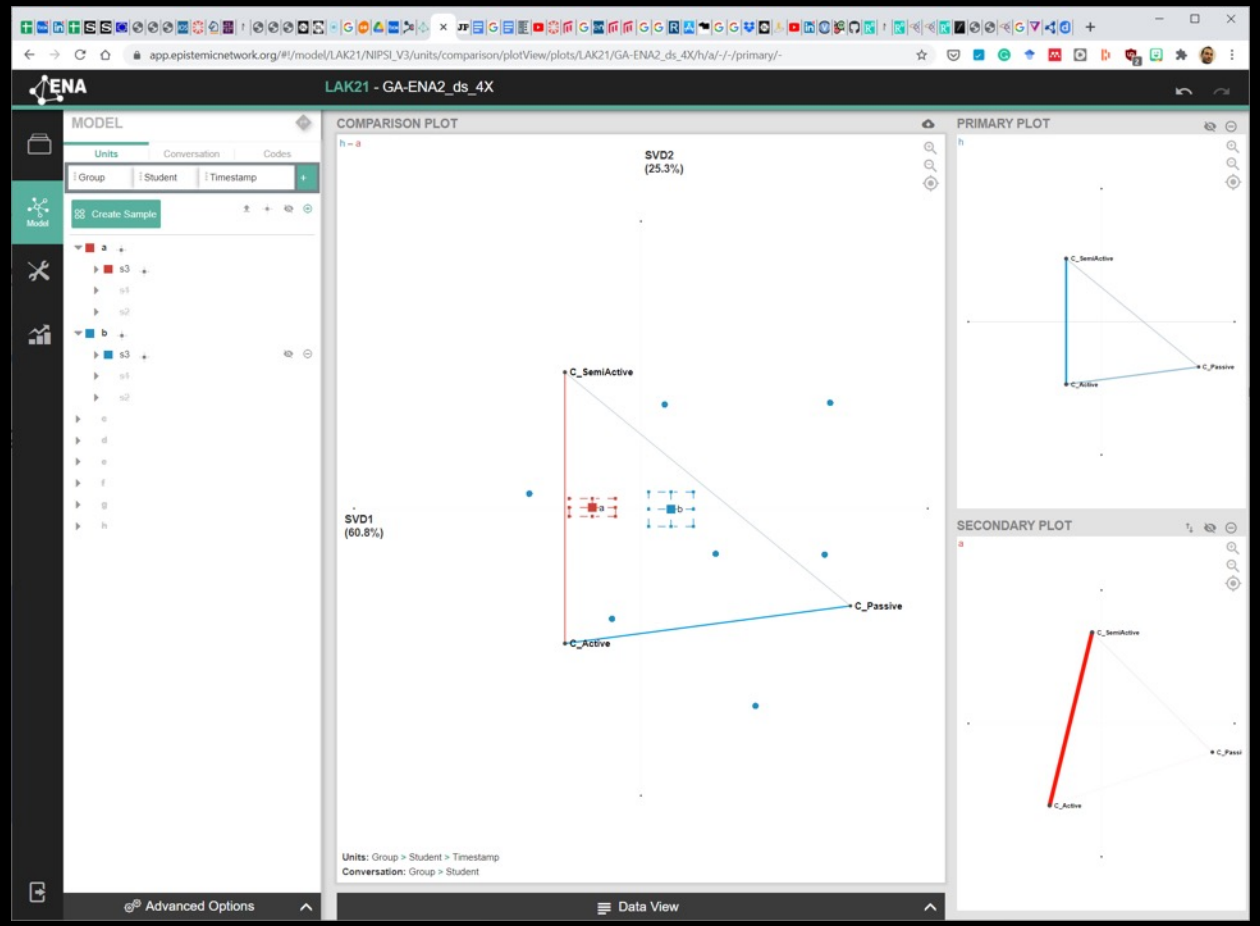
Exploring ENA to set System Requirements





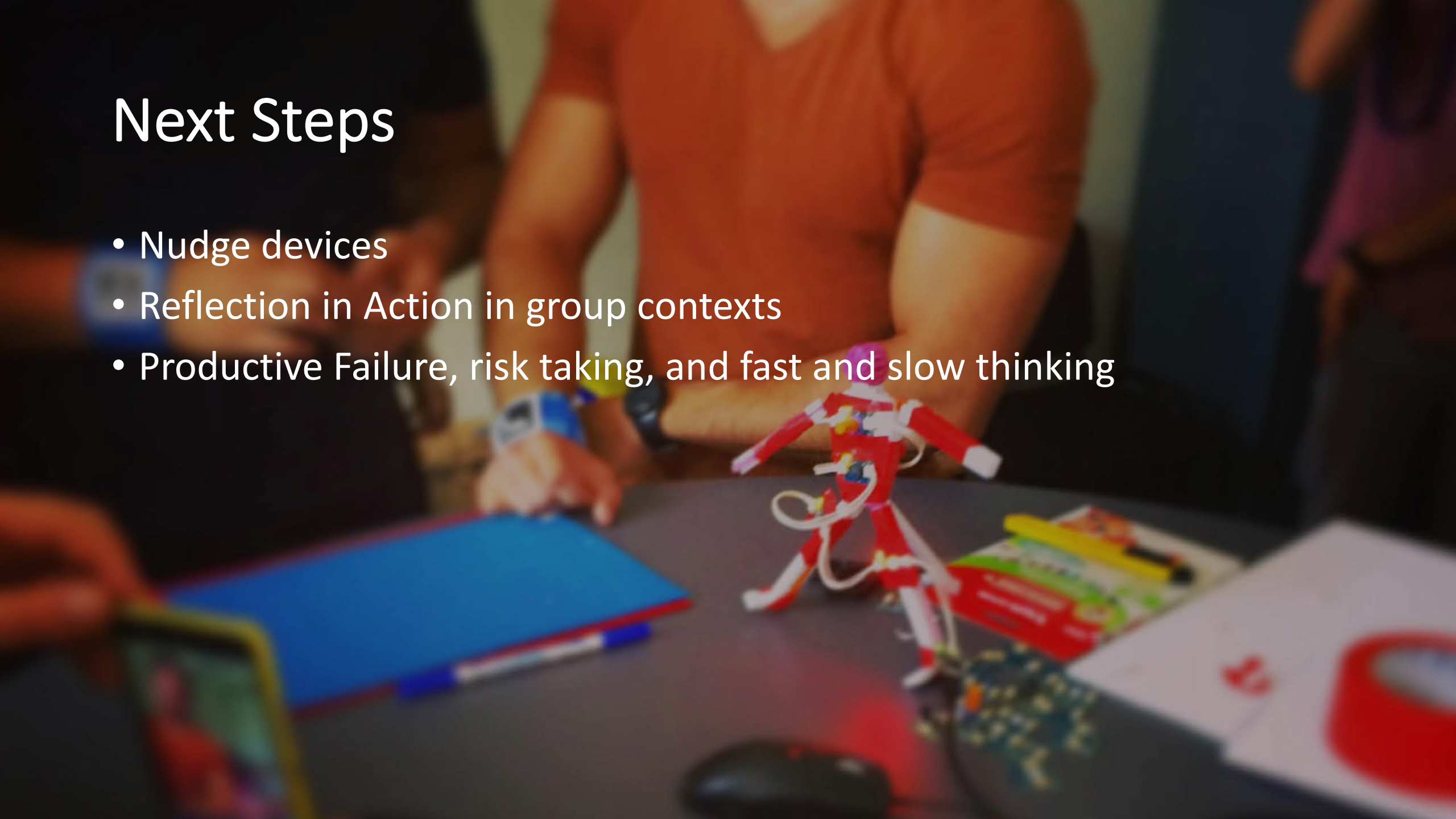
Individual Students

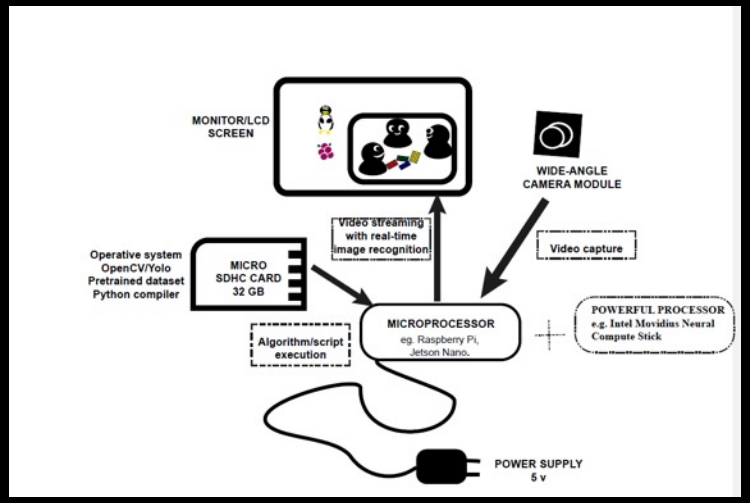


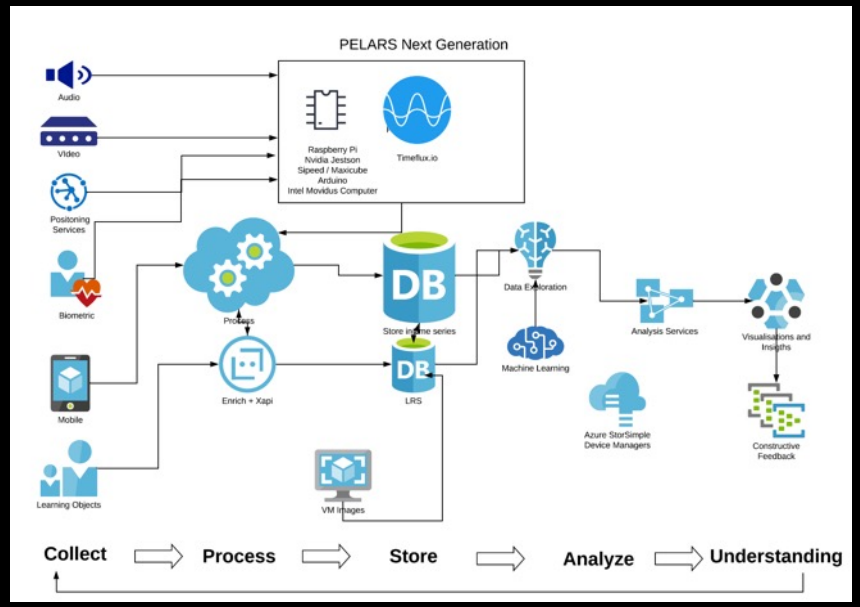


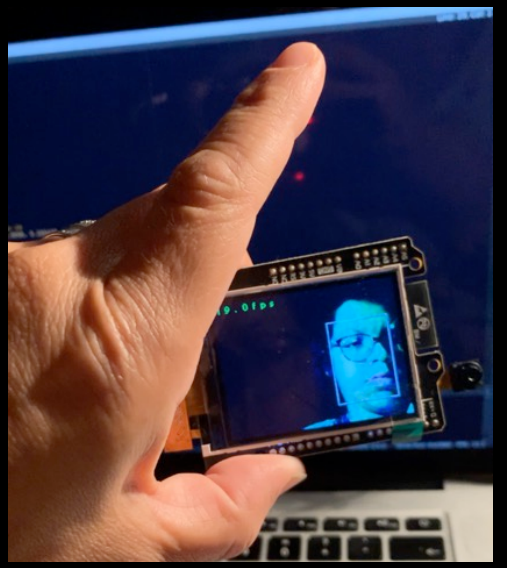
Next Steps

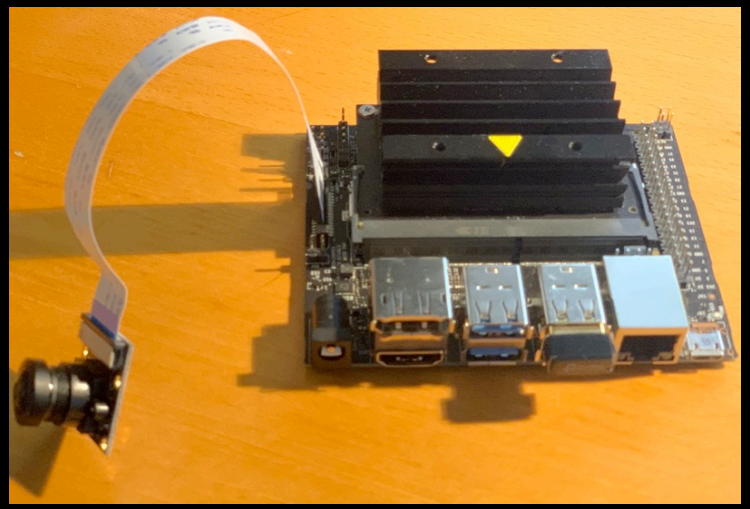
- Nudge devices
- Reflection in Action in group contexts
- Productive Failure, risk taking, and fast and slow thinking











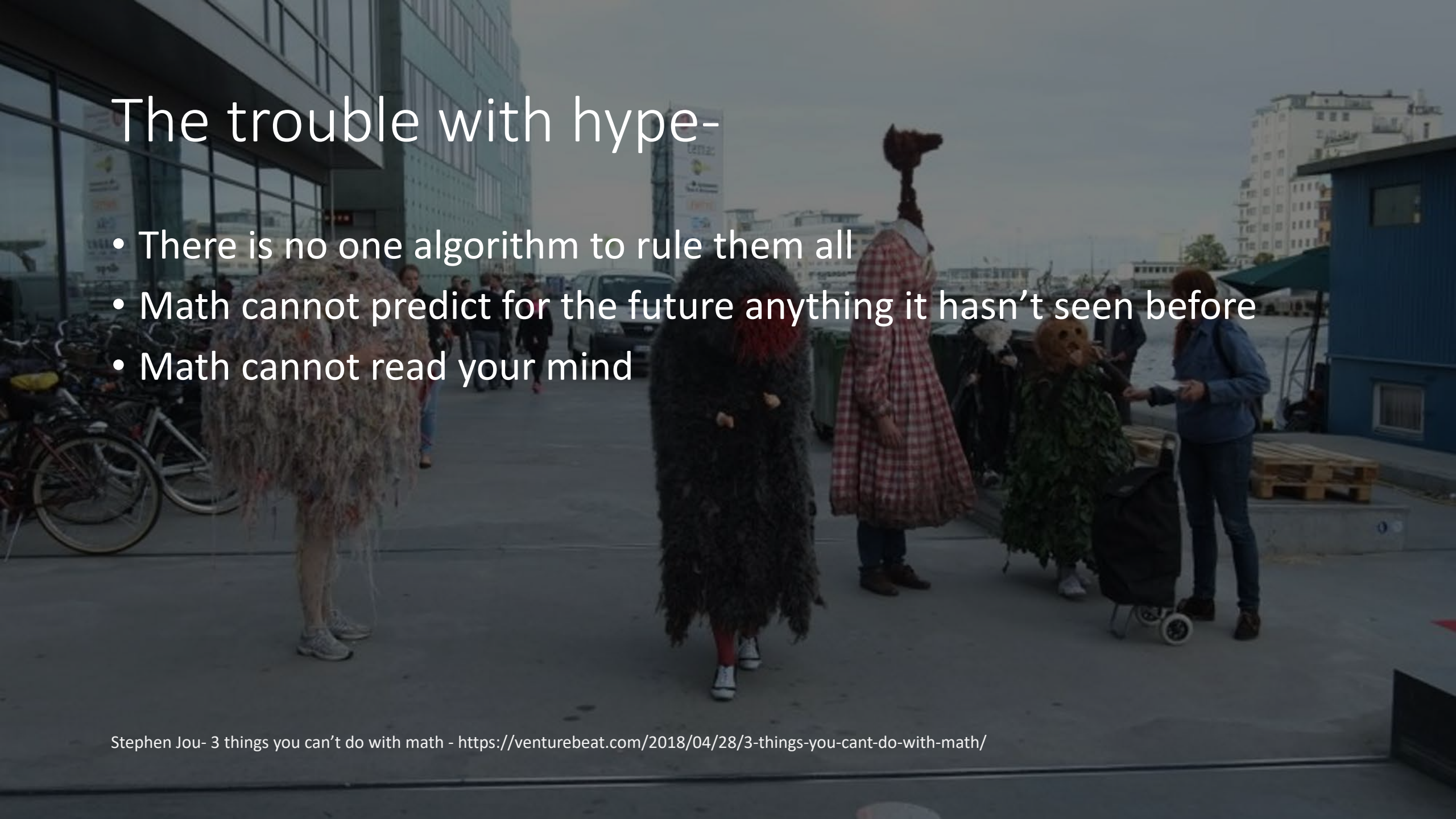
Hardware Setups

Shadows and Light

Bush, V. (1945). As we may think. *The atlantic monthly*, *176*(1), 101-108.

The trouble with hype-

- There is no one algorithm to rule them all
- Math cannot predict for the future anything it hasn’t seen before
- Math cannot read your mind



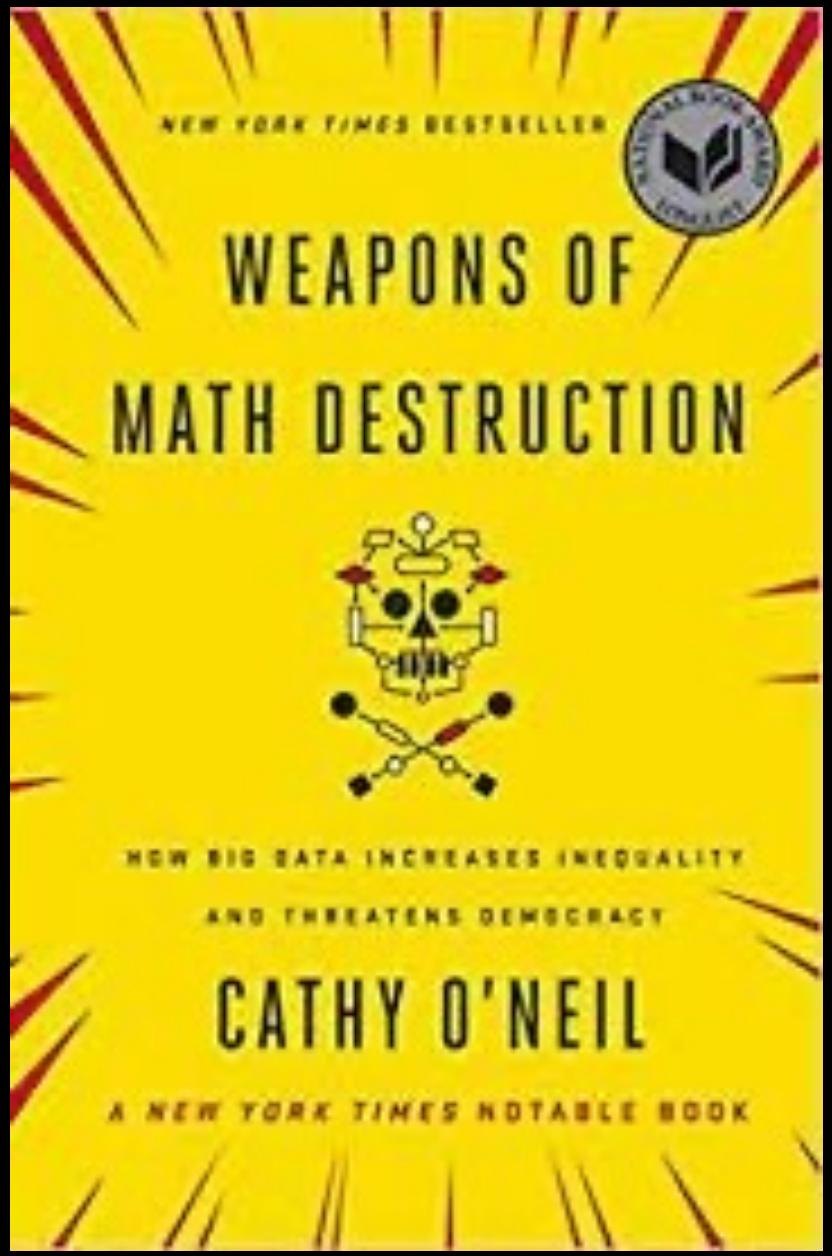
Stephen Jou- 3 things you can’t do with math - https://venturebeat.com/2018/04/28/3-things-you-cant-do-with-math/

Light

- Predictive understanding in specific contexts
- Personalization – adaptive feedback
- Social Recommendation systems
- Larger tools for societal reflection

Shadows

- Performance only learning
- Panopticon Environment
- lockdown of learning (lack of creativity)
- lack of socio-cultural aspects of education
- role of teacher
- manipulation (priming and bias)



Most troubling, they reinforce discrimination: If a poor student can't get a loan because a lending model deems him too risky (by virtue of his zip code), he's then cut off from the kind of education that could pull him out of poverty, and a vicious spiral ensues. Models are propping up the lucky and punishing the downtrodden, creating a "toxic cocktail for democracy."

Cathy O'Neil - https://www.ted.com/talks/cathy_o_neil_the_era_of_blind_faith_in_big_data_must_end

Privacy and Algorithmic Challenges

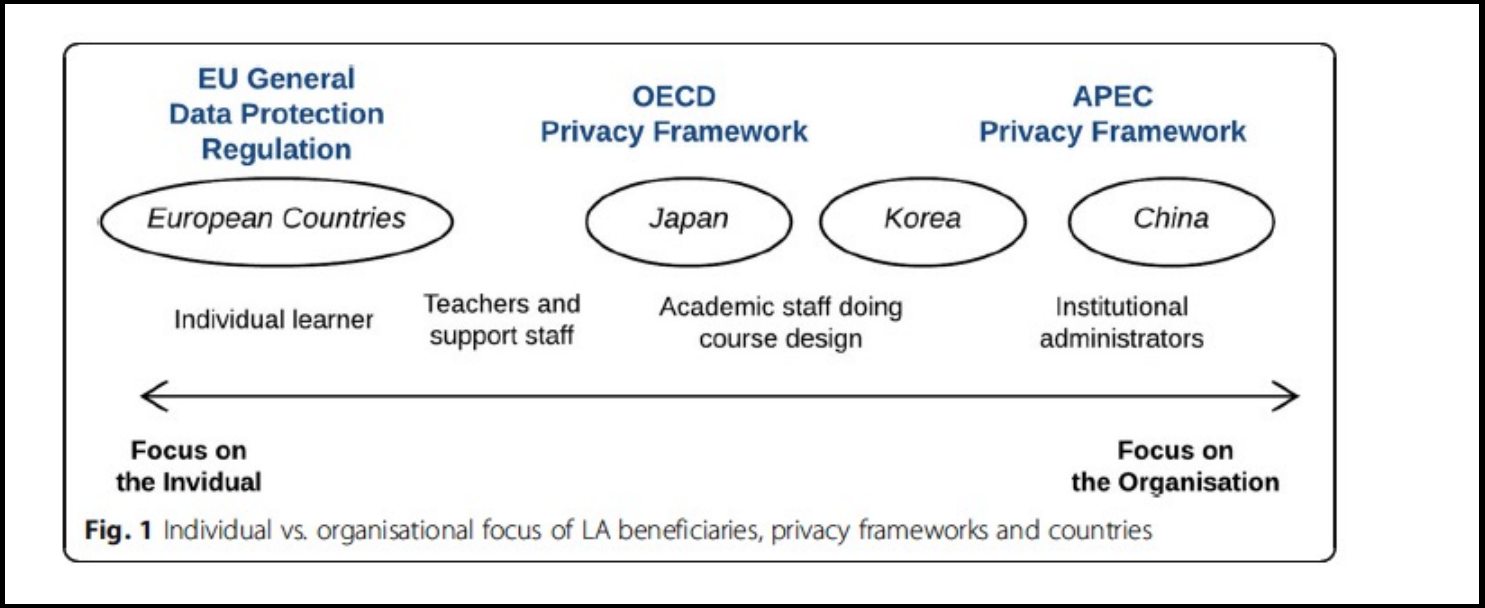


Fig. 1 Individual vs. organisational focus of LA beneficiaries, privacy frameworks and countries

Hoel, T., & Chen, W. (2018). Privacy and data protection in learning analytics should be motivated by an educational maxim—towards a proposal. *Research and Practice in Technology Enhanced Learning, 13*(1). doi:10.1186/s41039-018-0086-8

Algorithmic Bias in Education

- Race/Ethnicity
- Nationality (current national location)
- Gender
- Native language and dialect
- Disabilities
- Urbanicity
- Parental educational background
- Socioeconomic status
- International students
- Military-connected status

Baker, R. S., & Hawn, A. (2021, March 1). Algorithmic Bias in Education. https://doi.org/10.35542/osf.io/pbmvz

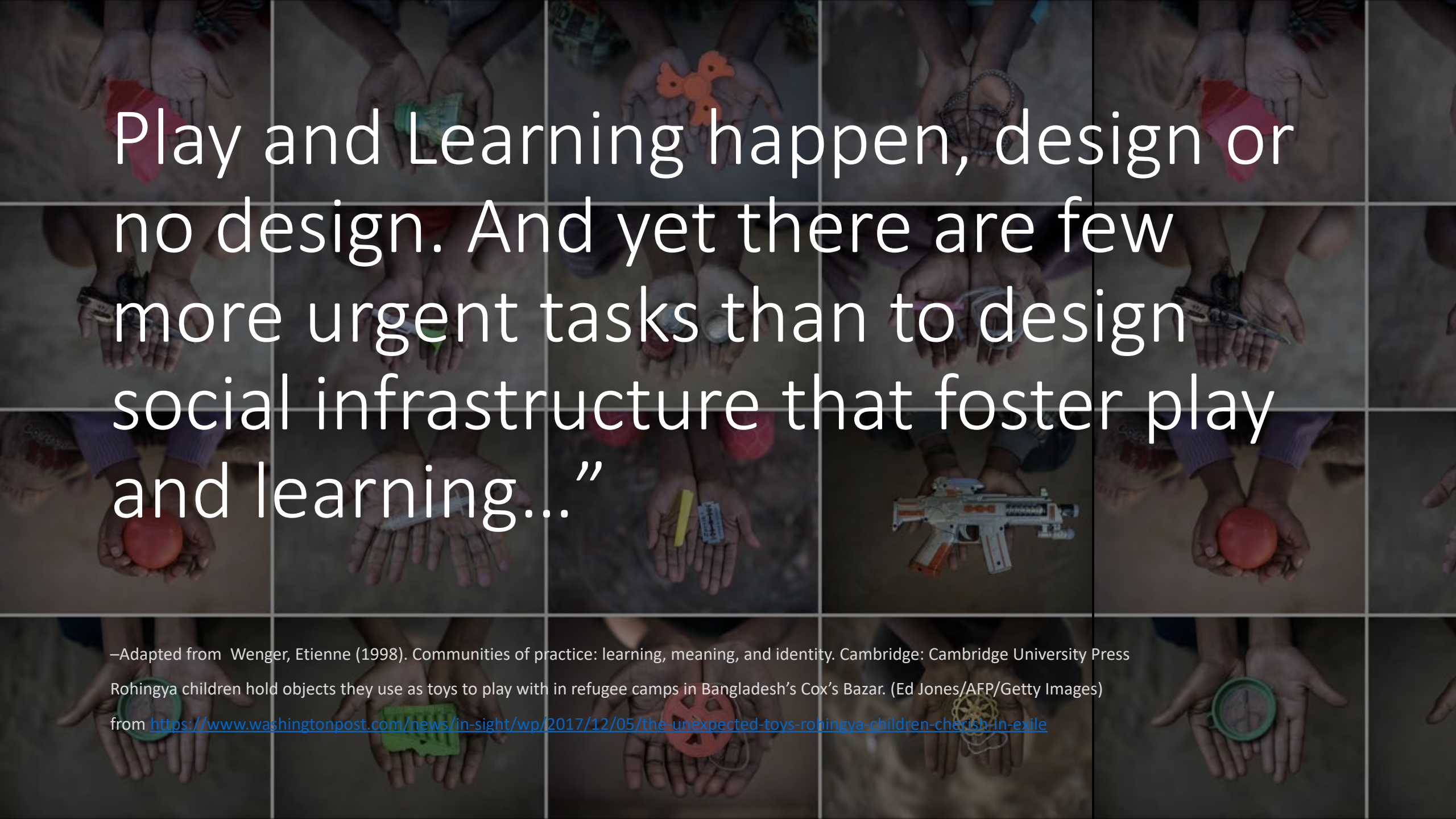
The value of play in learning the digital age

- Technology should be used to augment social interaction and collaboration to provoke people into playing and learning together.
- The moral of this story is to make technology stupid (less smart) which allows us to inspire the future.
- Provides us to make mistakes, learn, and develop resilience

- *“When I let go, I become what I might be” – Lao Tzu*

Play and Learning happen, design or no design. And yet there are few more urgent tasks than to design social infrastructure that foster play and learning…”

–Adapted from Wenger, Etienne (1998). Communities of practice: learning, meaning, and identity. Cambridge: Cambridge University Press



Rohingya children hold objects they use as toys to play with in refugee camps in Bangladesh’s Cox’s Bazar. (Ed Jones/AFP/Getty Images) from https://www.washingtonpost.com/news/in-sight/wp/2017/12/05/the-unexpected-toys-rohingya-children-cherish-in-exile

THE COPENHAGEN LETTER

https://www.techpledge.org/

Copenhagen, 2017

To everyone
who shapes tech

We live in a wor

It is time to take
replace the emp
organize, and to

Tech is not ab
the rules of our

Progress is m
open and nouris
societies. We wi

Let us build fi
We all depend o
access to it. Treating each other as commodities from which to extract maximum economic value is bad, not only for society as a complex, interconnected whole but for each and every one of us.

Design open to scrutiny. We must encourage a continuous, public, and critical reflection on our definition of success as it defines how we build and design for others. We must seek to design with those for whom we are designing. We will not tolerate design for addiction, deception, or control. We must design tools that we would love our loved ones to use. We must question our intent and listen to our hearts.

Let us move from human-centered design to humanity-centered design.
We are a community that exerts great influence. We must protect and nurture the potential to do good with it. We must do this with attention to inequality, with humility, and with love. In the end, our reward will be to know that we have done everything in our power to leave our garden patch a little greener than we found it.

We who have signed this letter will hold ourselves and each other accountable for putting these ideas into practice. That is our commitment.

The Tech Pledge

Tech has fundamentally changed our world. Where we go from here is up to us. I understand that for my good intentions to actually matter, I must make myself accountable to my community.

I commit...

- to take responsibility for what I create.
- to only help create things I would want my loved ones to use.
- to pause to consider all consequences of my work, intended as well as unintended.
- to invite and act on criticism, even when it is painful.
- to ask for help when I am uncertain if my work serves my community.

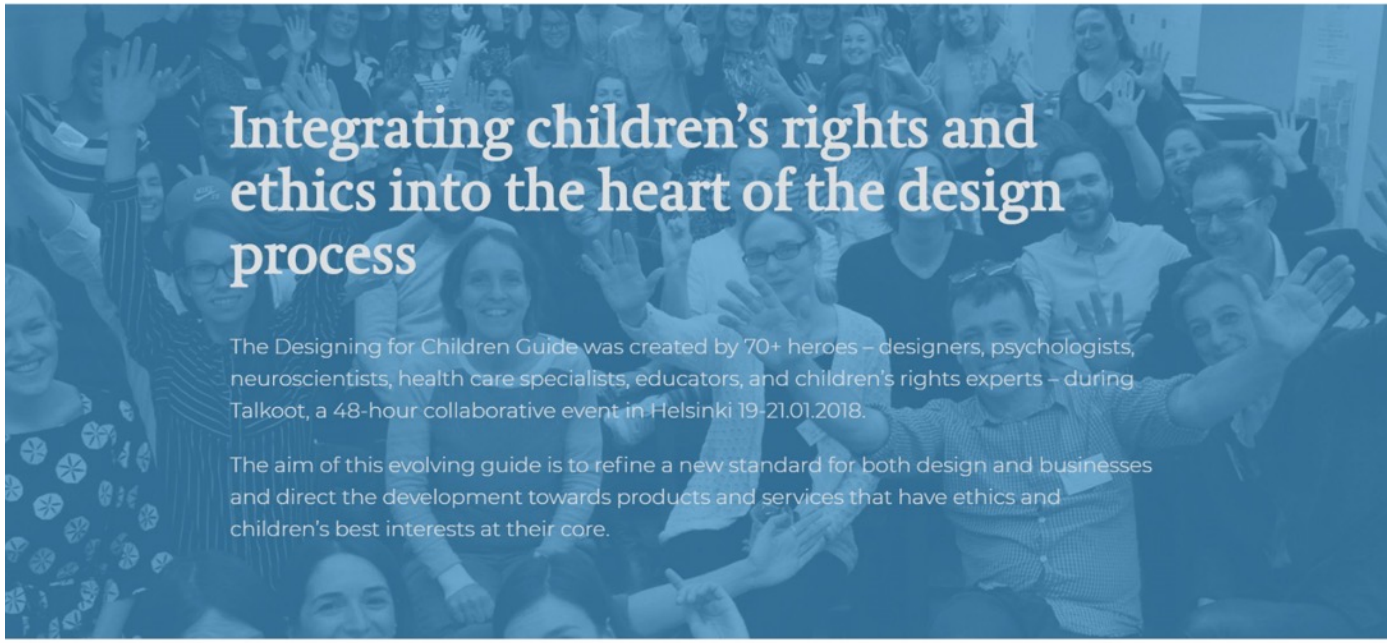
HOME PRINCIPLES METHODS & PRACTICES OUR STORY FE

DESIGNING *for* CHILDREN GUIDE

Integrating children's rights & ethics into the design process

LEARN MORE

http://designingforchildrensrights.org/



Intro

What impact are designers, businesses and technologists creating in the world of children today?

Principles

The 10+ commandments of designing for children. The principles are guiding to design more ethically and

Methods

Hands-on methods and practices on the good-old double diamond with ethics and children's rights

Thanks!

Center for Digital Education
University of Copenhagen, DIKU
daniel.spikol@di.ku.dk

Additional References

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