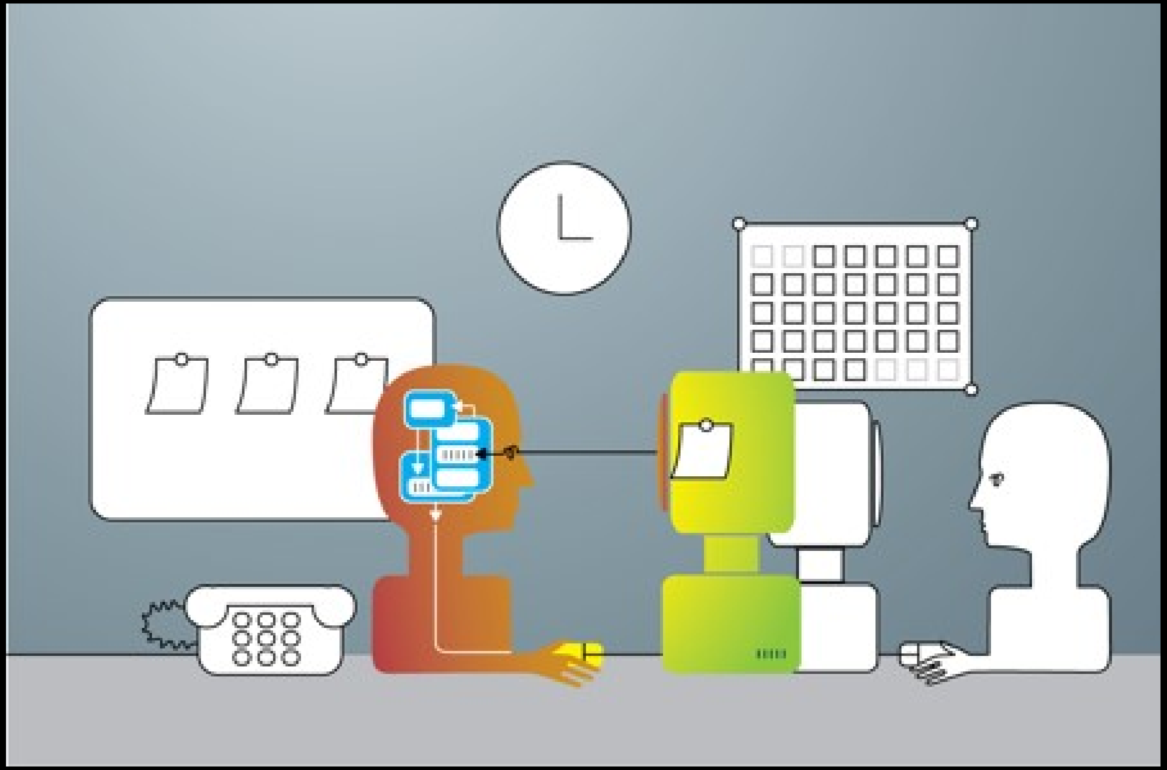
Understanding Human Functioning & Enhancing Human Potential through Computational Methods



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October 8, 2020

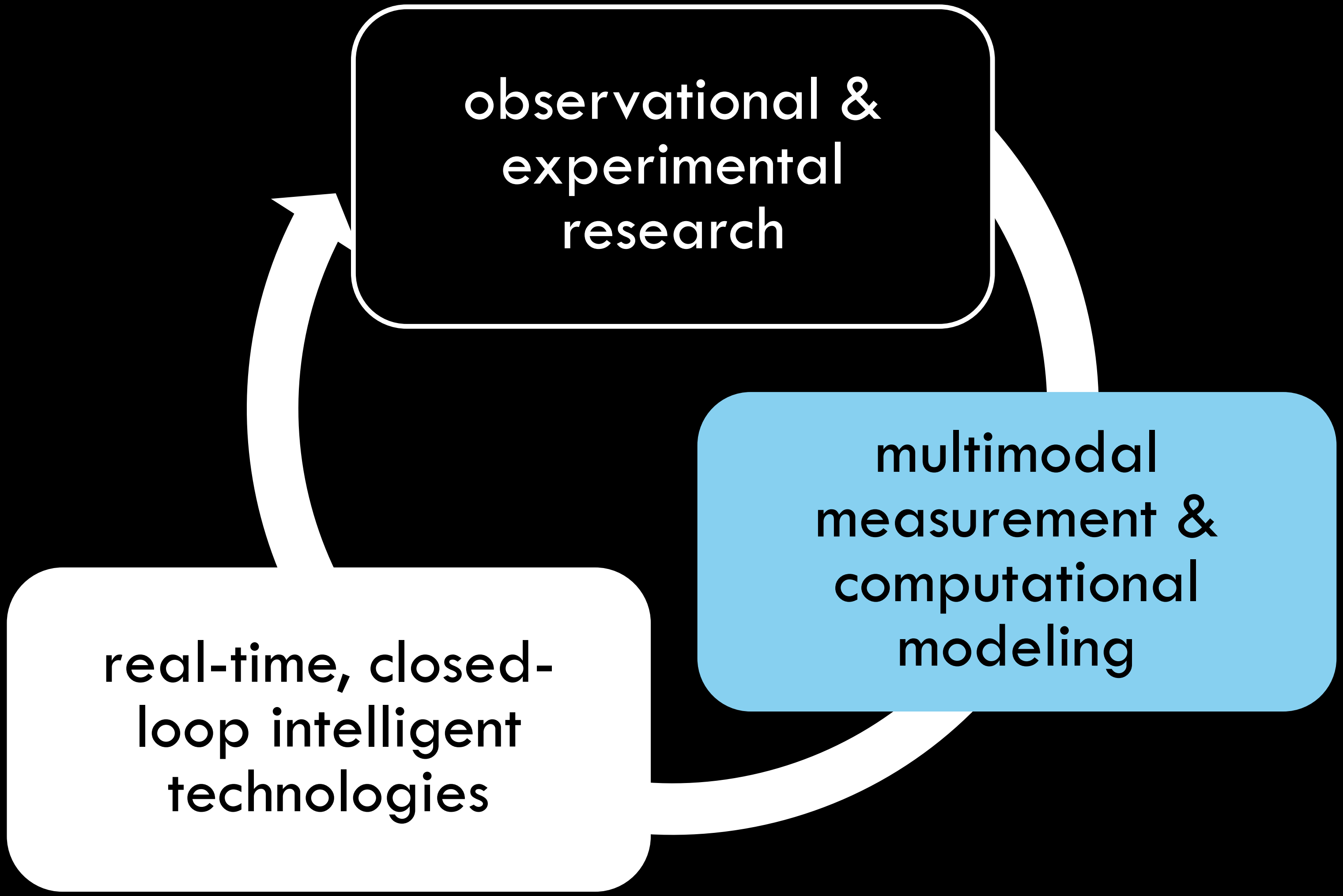
the study of cognition, emotion, & social interaction has greatly benefitted from

- observational & experimental methods
- analytical approaches (e.g., think alouds, code and count)
- instrumentation (e.g., eye tracking, fMRI)
- traditional computational models (e.g. EZ Reader, SWIFT)

(machine-learned) computational models can take us even further

- essential when there are no adequate theoretical or mechanistic accounts
- essential when there is too much data or when data is too complex
- can provide (with caveats) insights into underlying phenomena
- can promote change via dynamic intervention or after-action reflection
- the art lies in how they are constructed
  - phenomenon must be studied in ecologically valid contexts (including lab)
  - grounded in but not overly constrained by theoretical accounts

central claims



research approach – unapologetically pluralistic

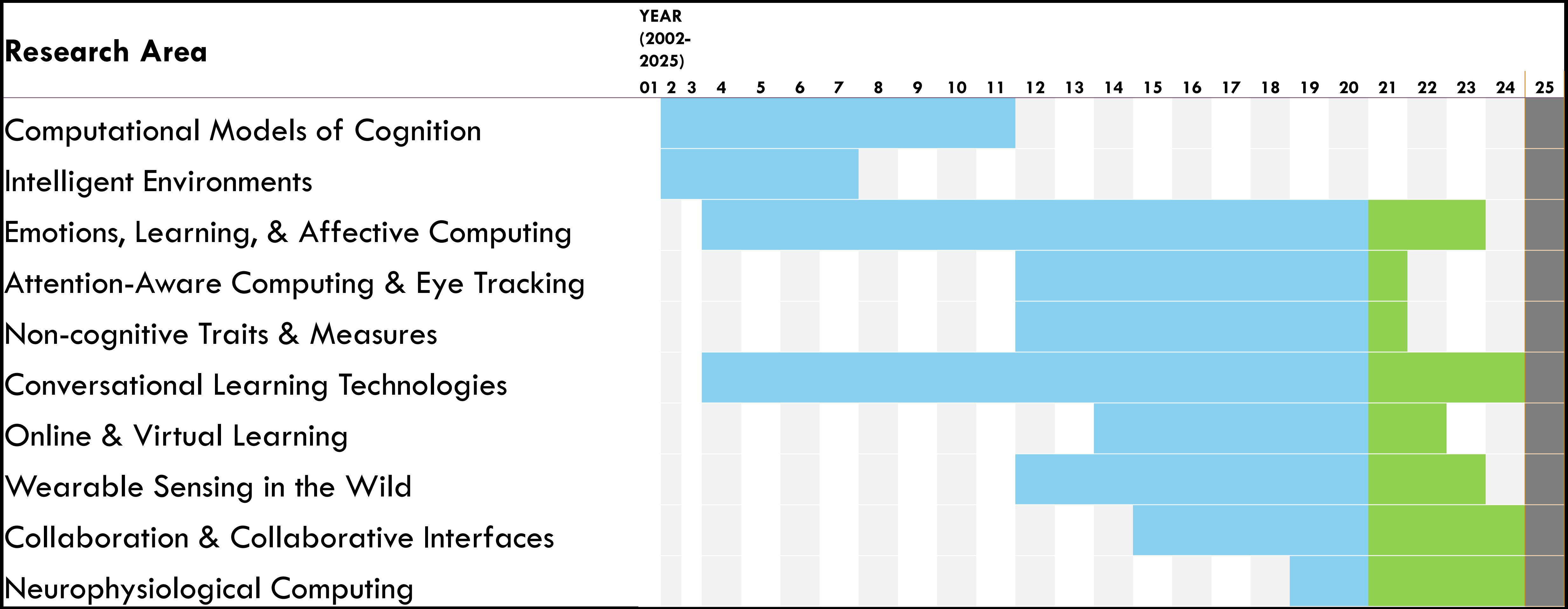
psychological sciences

cognitive psychology
affective science
learning sciences
social psychology
team science
discourse processes

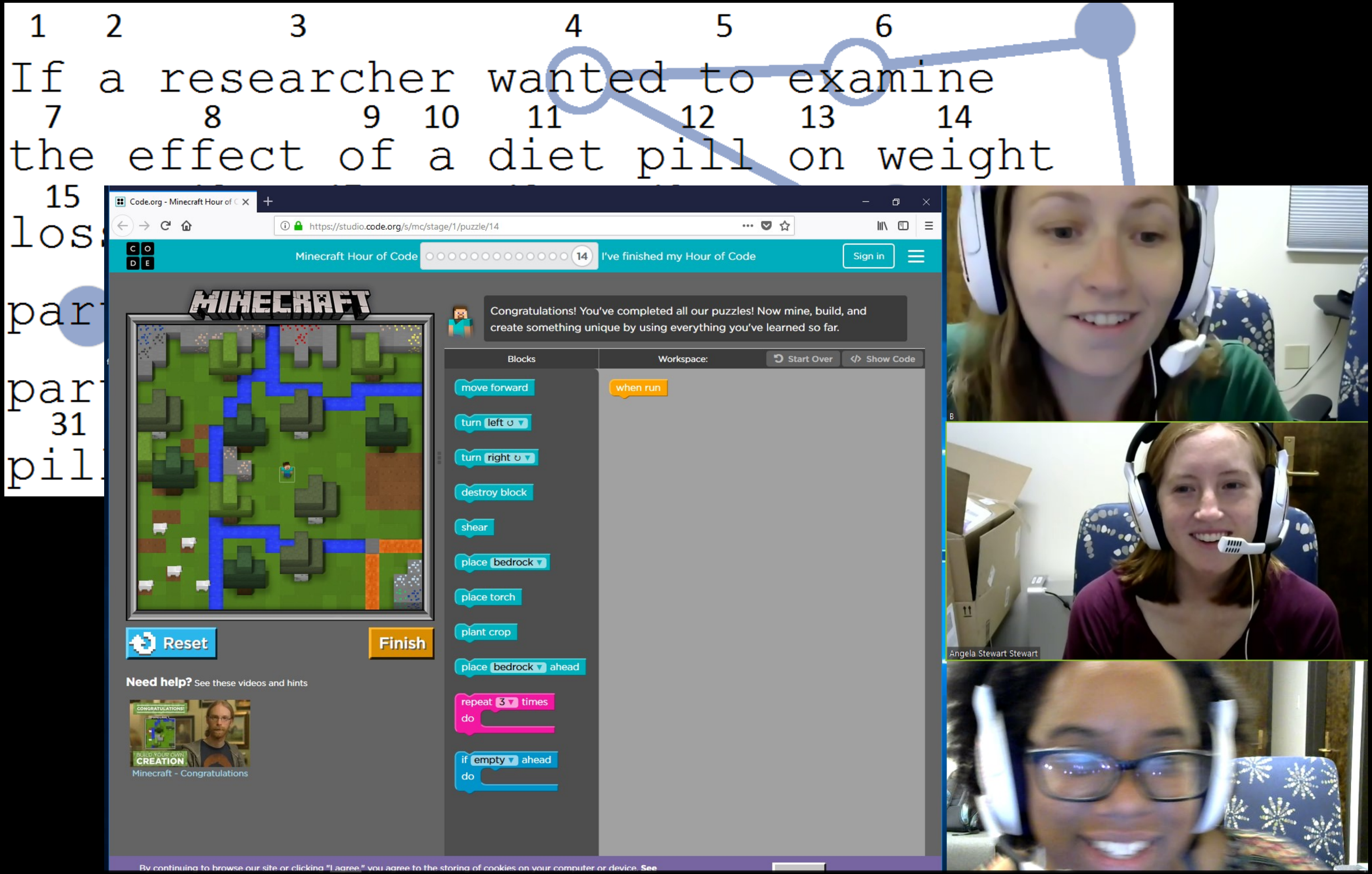
computational sciences

affective computing
attentional computing
multimodal interaction
neurophysiological sensing
human-computer interaction
machine learning

intersection of psychological & computing sciences

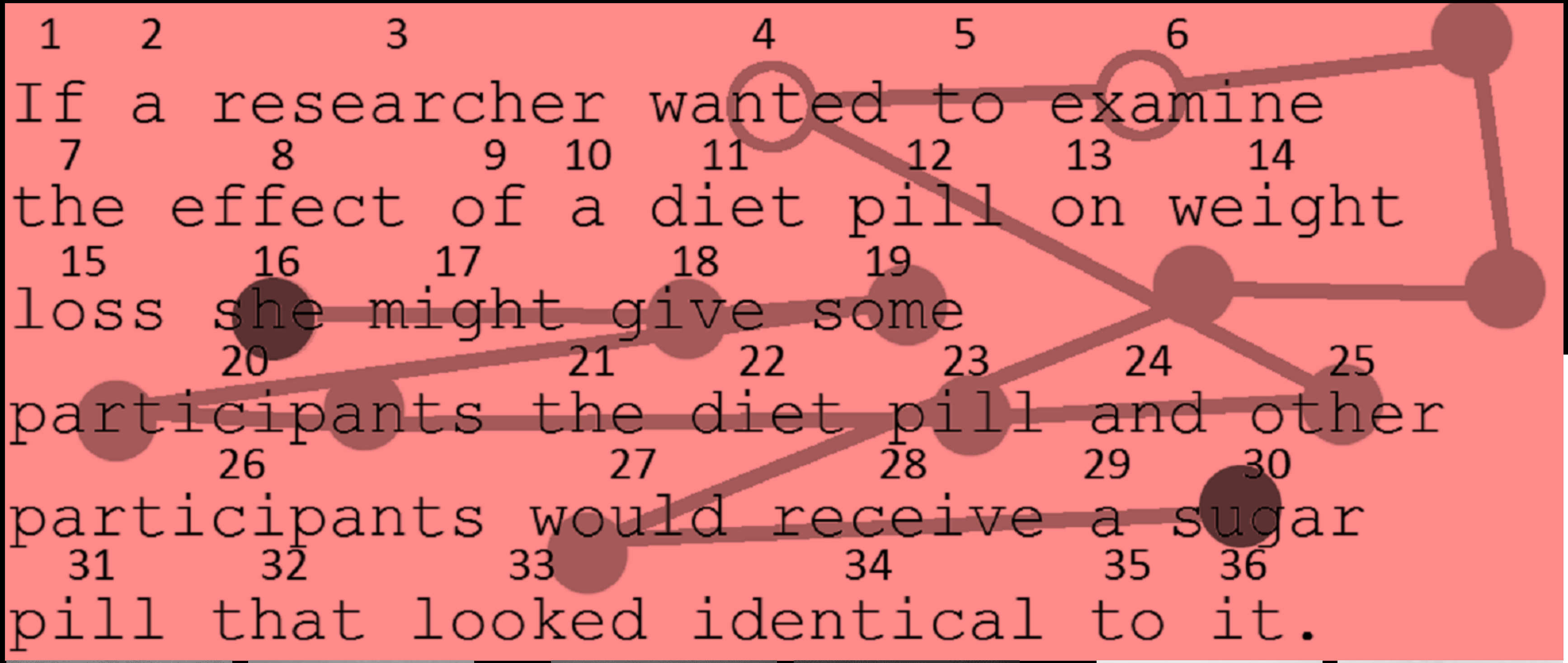


major research areas & timeline



multimodal, multiparty modeling of collaborative discourse

illustrative projects

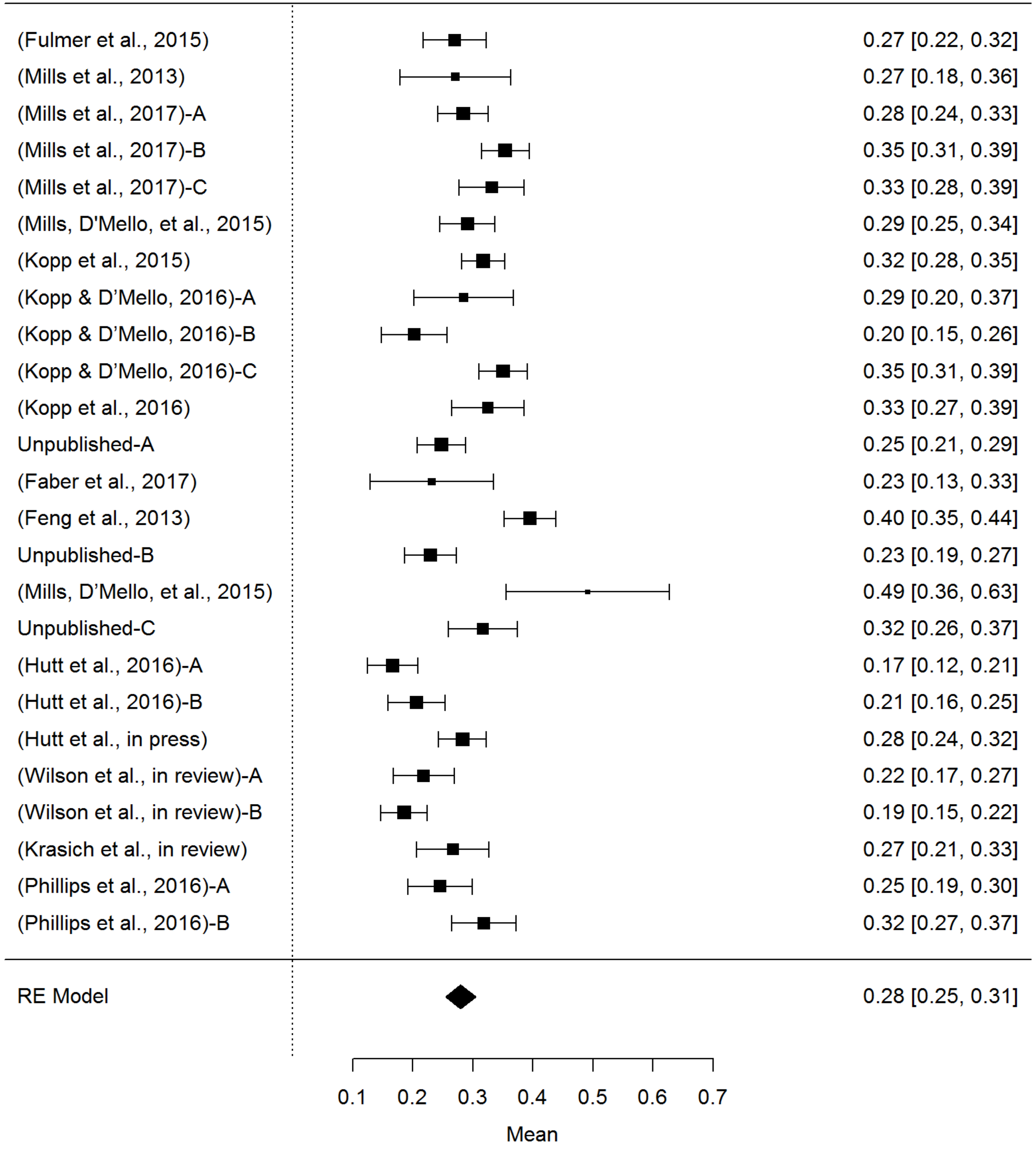


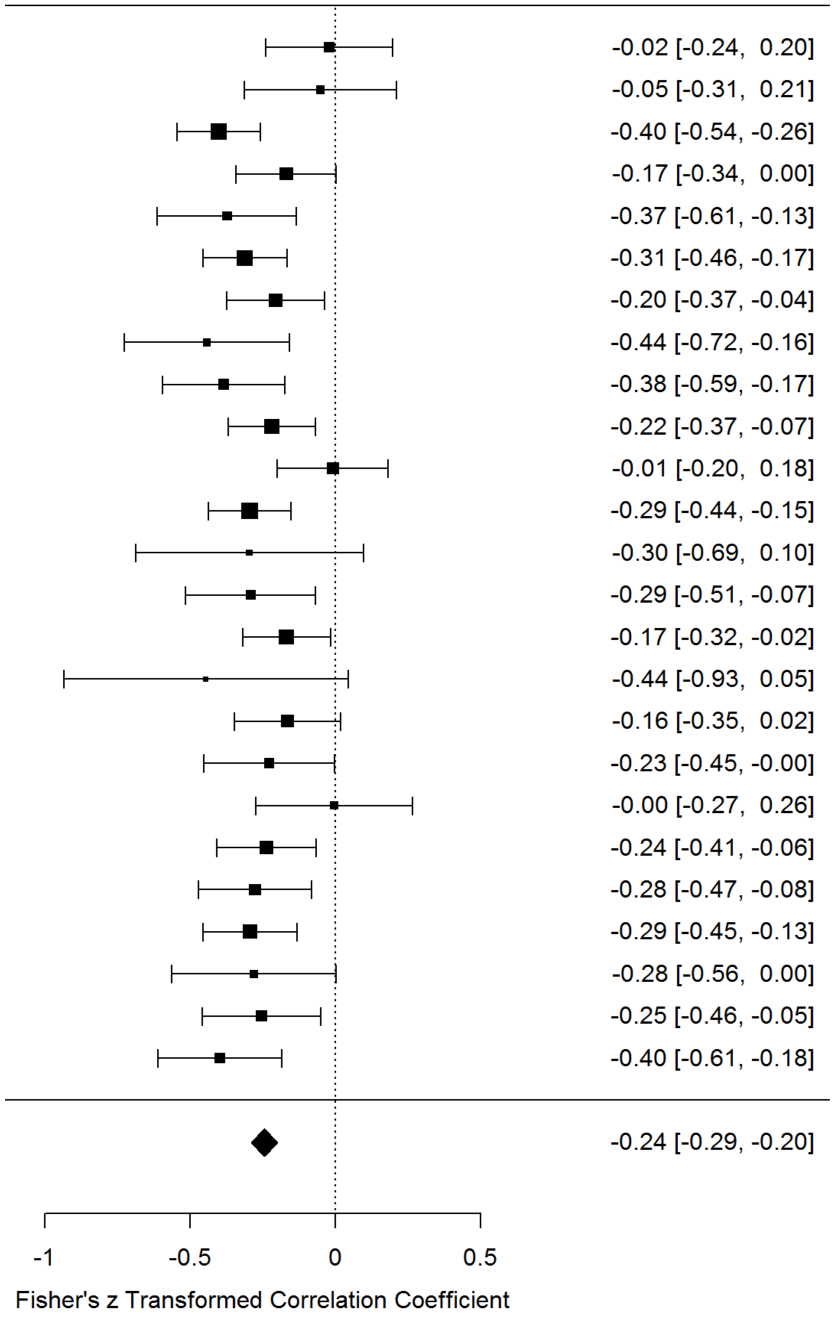
exploring the eye-mind link during reading

	Direction of attention	
Content of thoughts	*Focal activity*	*Elsewhere*
Goal-related	**Overt attention** Focused attention Alternating attention Divided attention	**Covert attention** Help seeking Concentrating (appearing disengaged)
Goal-unrelated	**Covert inattention (mind wandering)** Tune outs Zone outs	**Overt inattention** Off-task Distracted

a multicomponential view of attention

D'Mello, 2016





mind wandering during learning

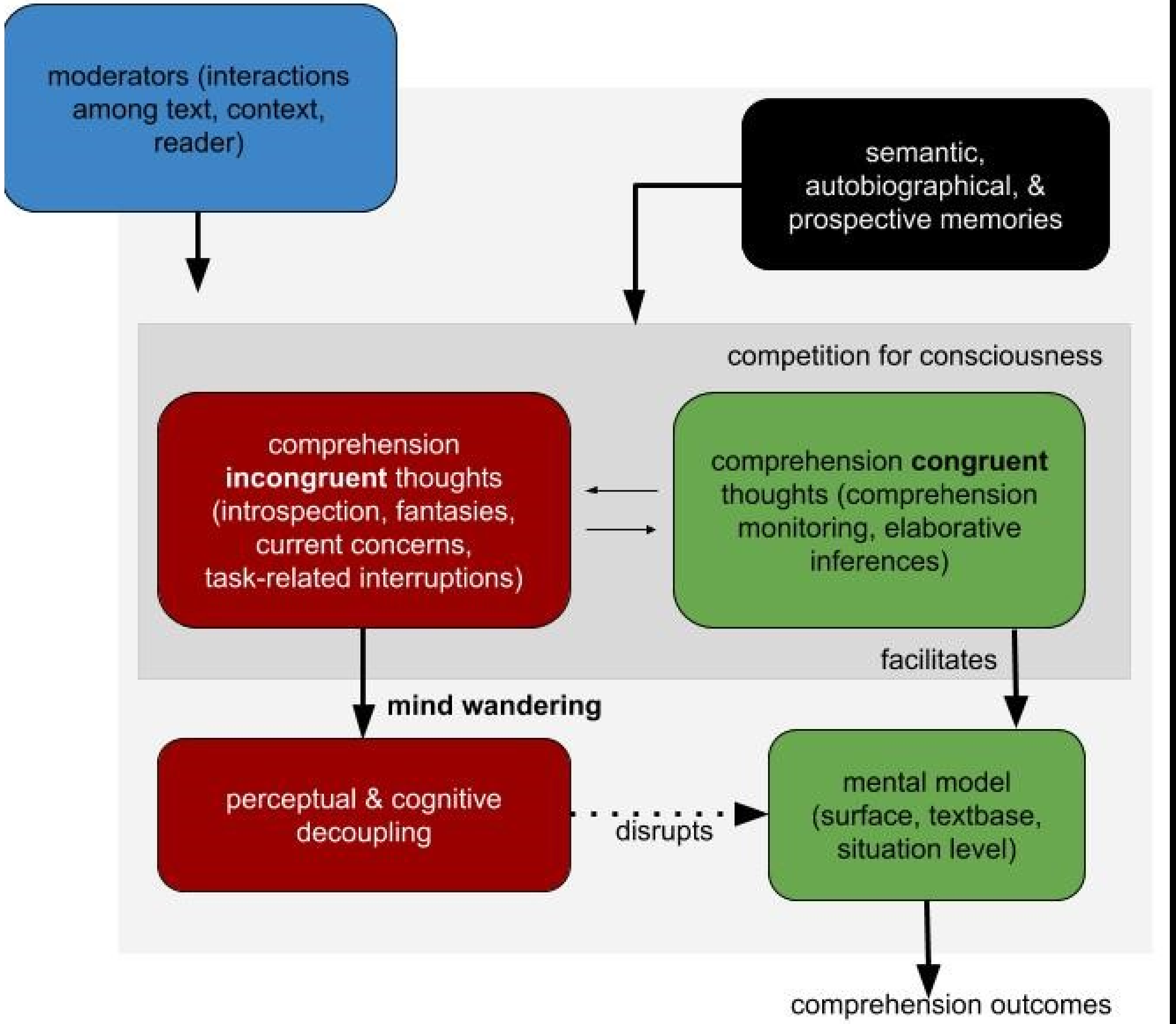
- meta analysis of 25 studies from 2787 learners
- mind wandering is **frequent** (30% of the time)
- & **negatively correlates** (r = -.28) with outcomes

- Text difficulty will increase mind wandering
  (Feng, D'Mello, & Graesser, 2013, *Psych Bull & Review)*
- Perceptual difficulty will decrease mind wandering
  (Faber, Mills, & D'Mello, 2017, *Psych Bull & Review*)

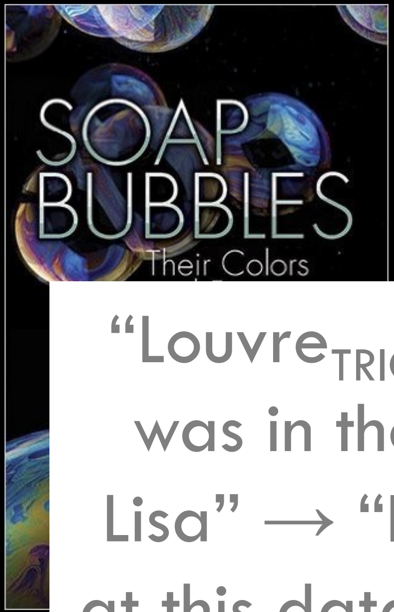
- Providing situational model will suppress MW
  (Kopp, Mills, & D'Mello, 2016, *Psych Bull & Review)*
- Activation of current concerns will increase mind wandering
  (Kopp, Mills, & D'Mello, 2015, *Consciousness & Cognition)*

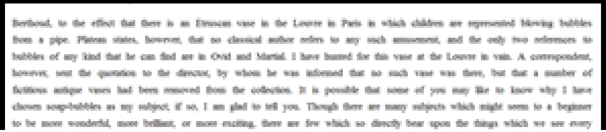
- Mind wandering will engender perceptual decoupling
  (Mills, Graesser, Risko, & D'Mello, *JEP General*)
- Event boundaries should disrupt mind wandering
  (Faber, Radvansky, & D'Mello, Cognition)

- Consumption of modalities will decrease mind wandering
  (Kopp & D'Mello, 2015, Applied Cognitive Psychology)



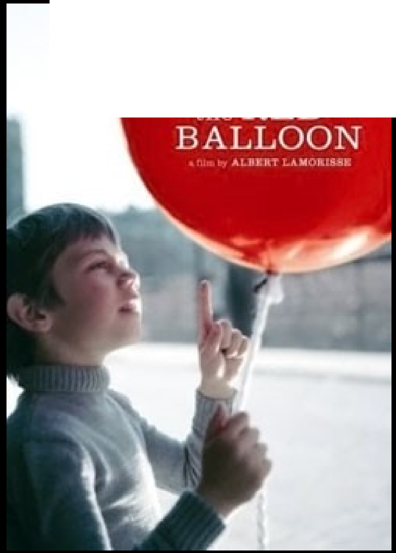
theoretical model & experimental research

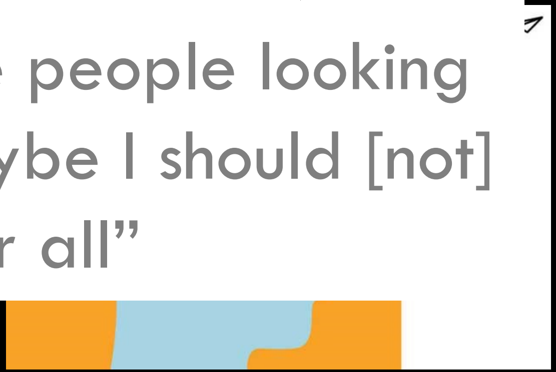



Berthoud, to the effect that there is an Etruscan vase in the Louvre in Paris in which children are represented blowing bubbles from a pipe. Plateau states, however, that no classical author refers to any such amusement, and the only two references to bubbles of any kind that he can find are in Ovid and Martial. I have hunted for this vase at the Louvre in vain. A correspondent, however, sent the quotation to the director, by whom he was informed that no such vase was there, but that a number of fictitious antique vases had been removed from the collection. It is possible that some of you may like to know why I have chosen soap-bubbles as my subject; if so, I am glad to tell you. Though there are many subjects which might seem to a beginner to be more wonderful, more brilliant, or more exciting, there are few which so directly bear upon the things which we see every

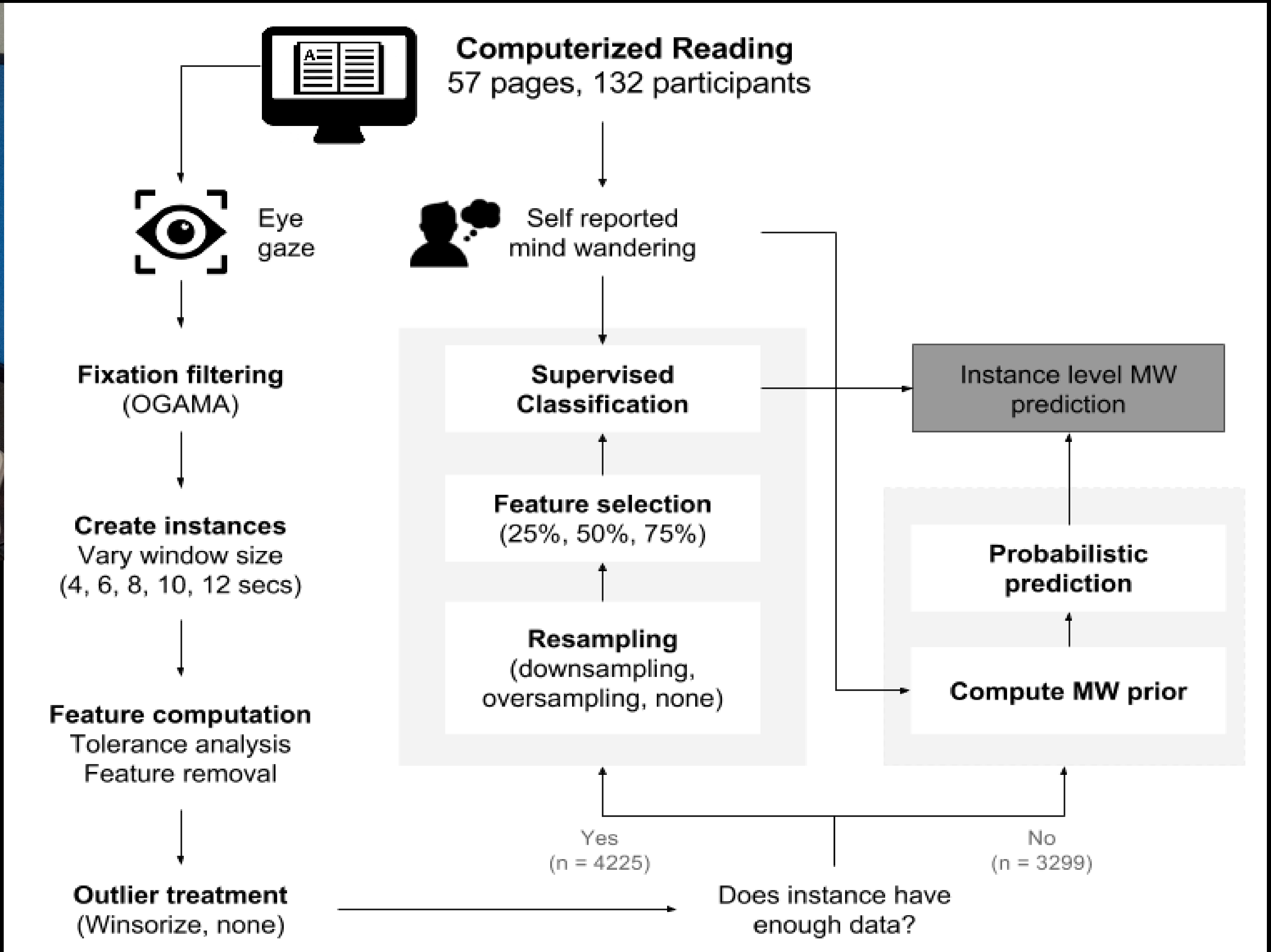
content of thought &

"Louvre$_{\text{TRIGGER}}$" → "the Louvre" →"haha last time I was in the Louvre I threw up in front of the Mona Lisa" → "I wonder how strange the people looking at this data will think I am" → "Maybe I should [not] have admitted this after all"

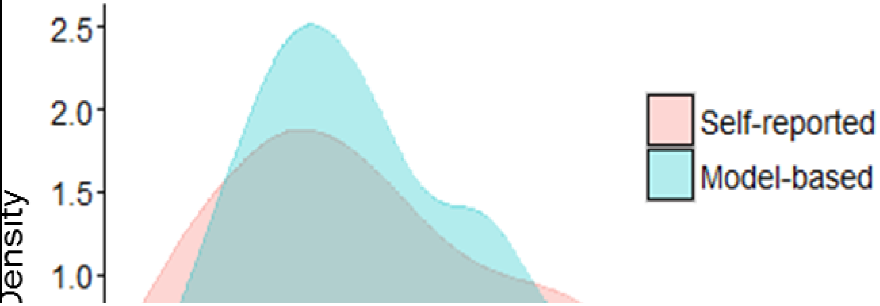




sample study: content of mind wandering

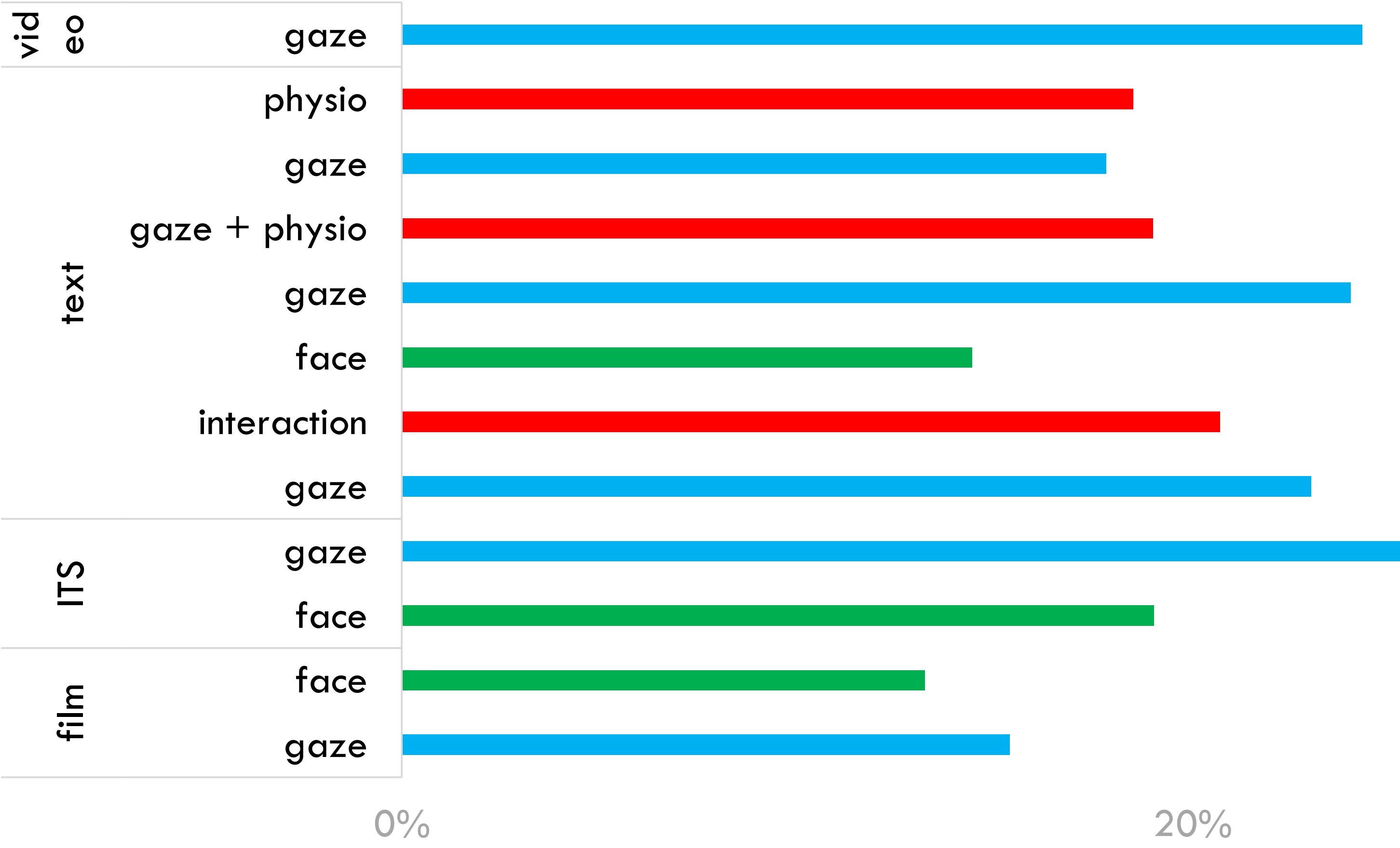


eye tracking as a window into the mind



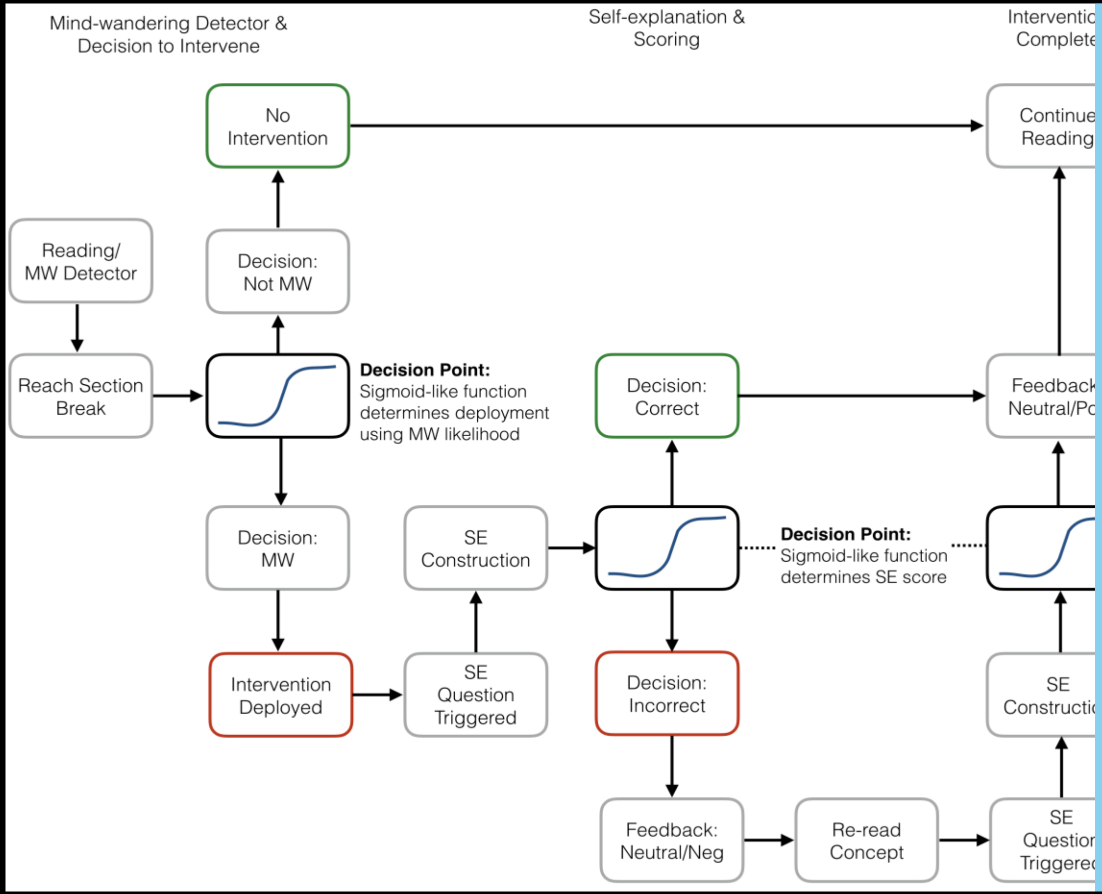
main findings

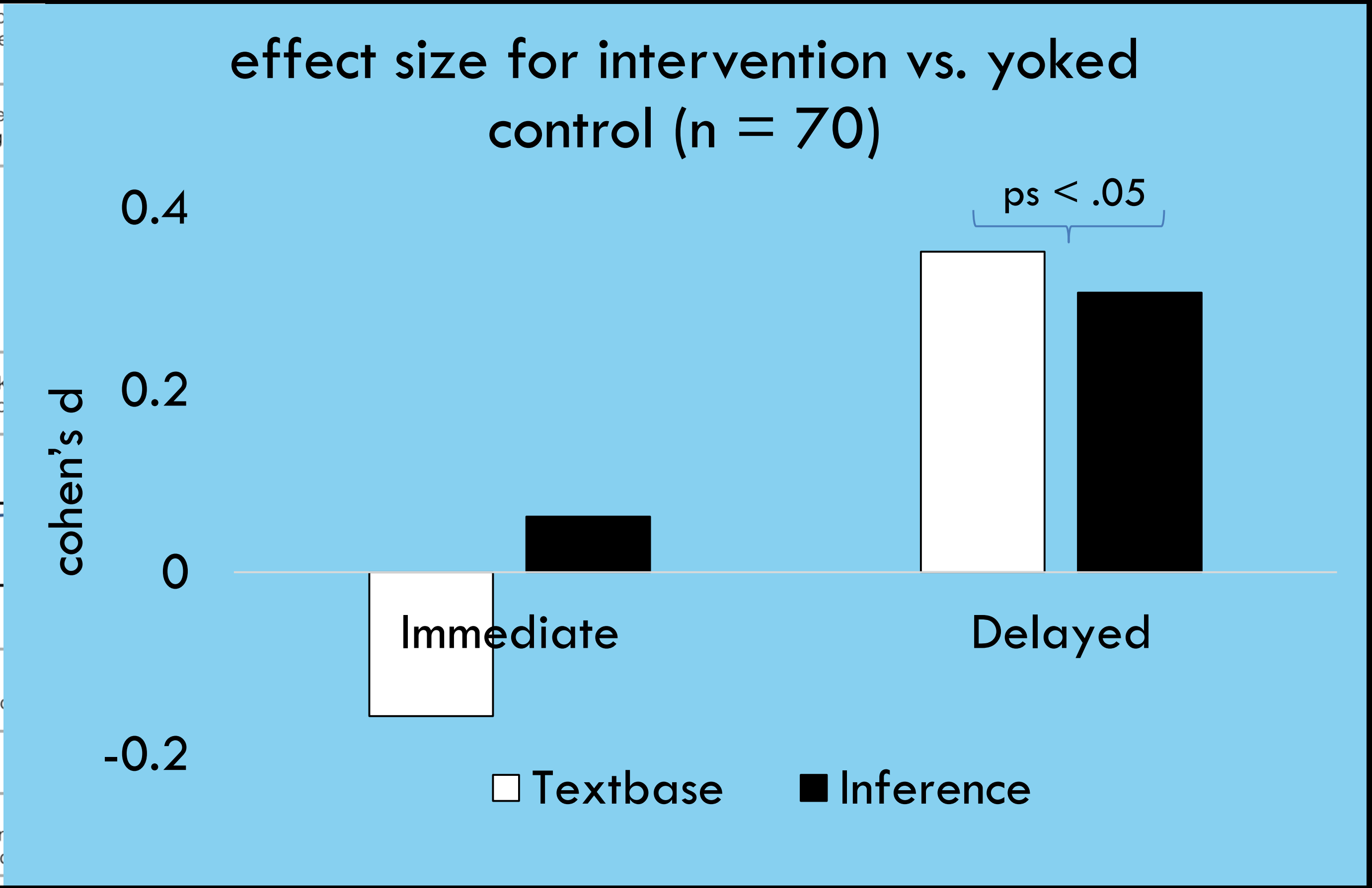
- model is moderately accurate (r = .400 with respect to self-reports)
- precision (72.2%); recall (67.4%)



mind wandering detectors across domains and sensors (about 20% above chance accuracy)

automated mind wandering detection

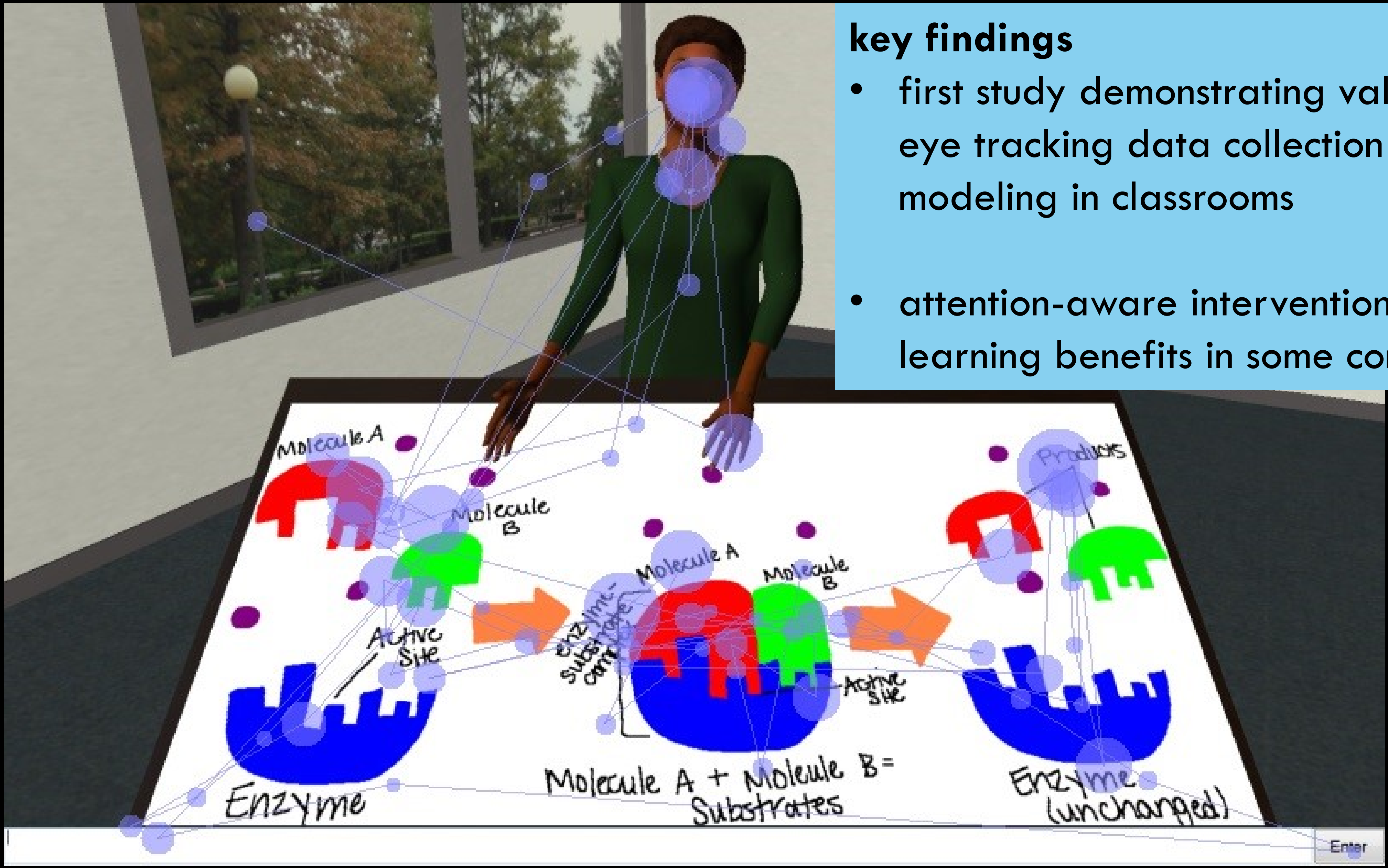




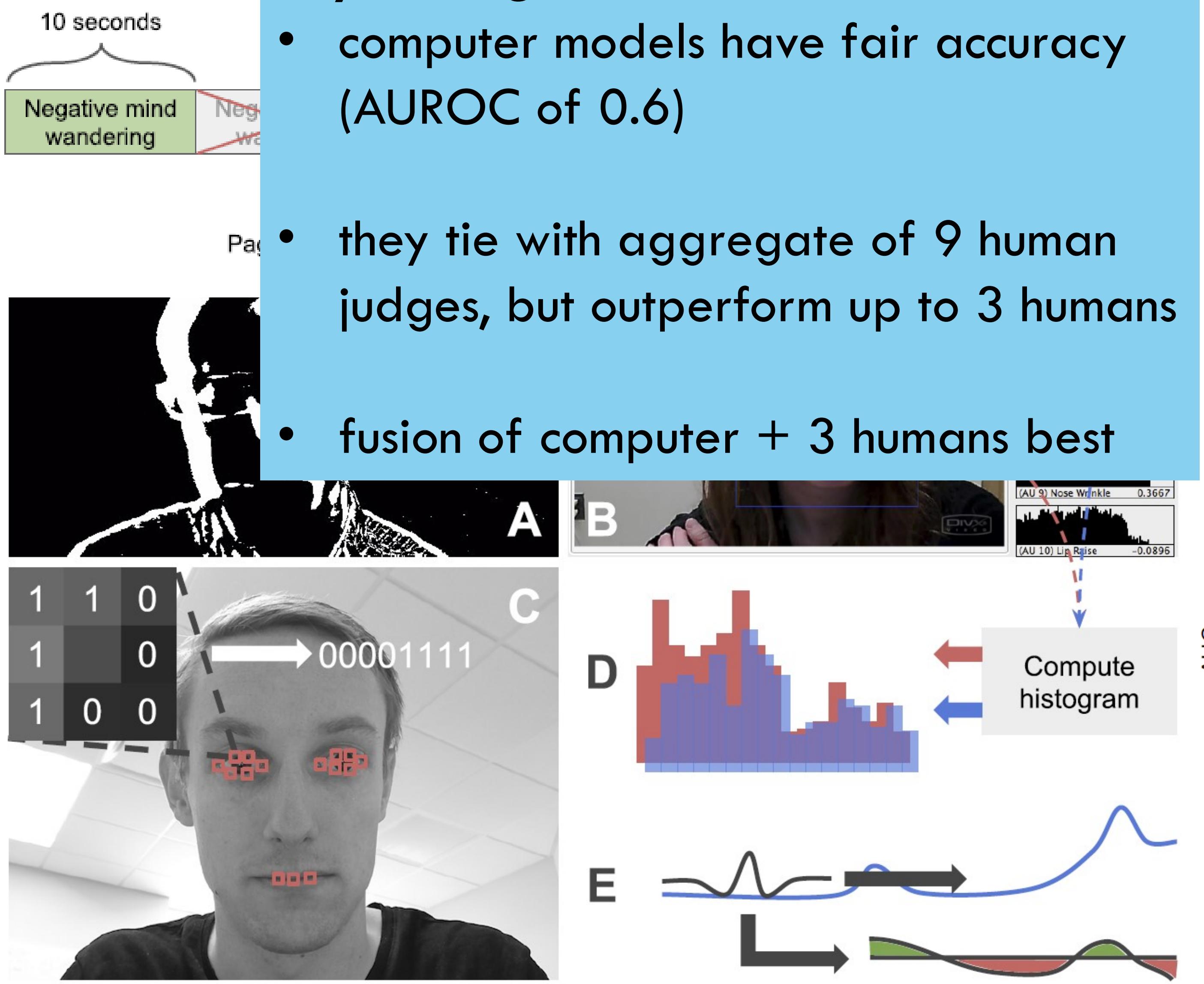
real-time intervention (D'Mello et al., 2017; Mills, et al., 2020)

key findings

- first study demonstrating valid eye tracking data collection & modeling in classrooms
- attention-aware intervention show learning benefits in some contexts

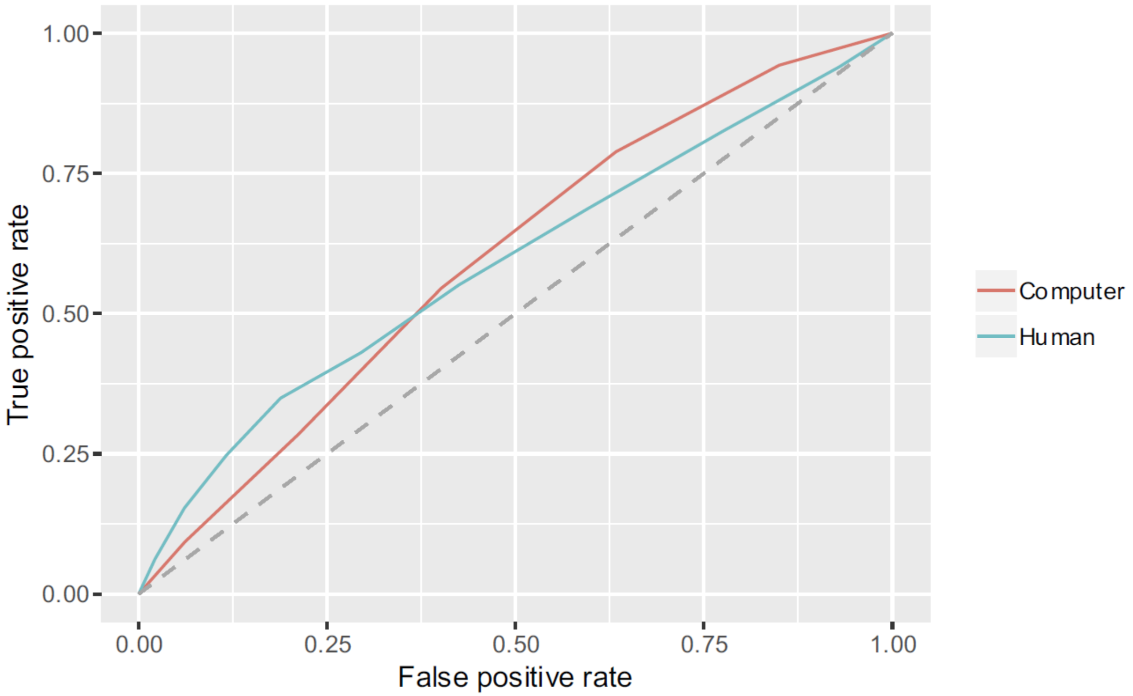


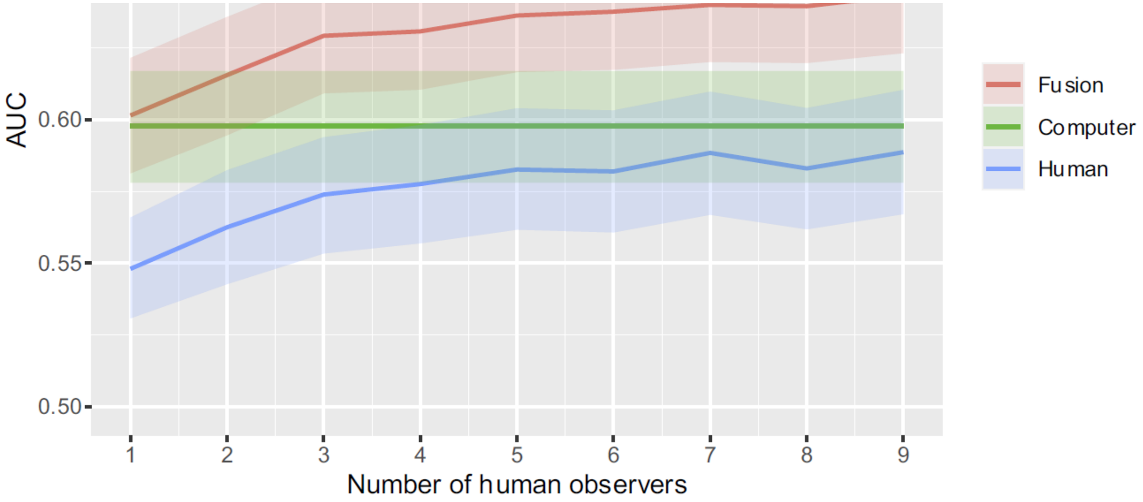
out of the lab and into the wild (Hutt et al., 2019; in press)



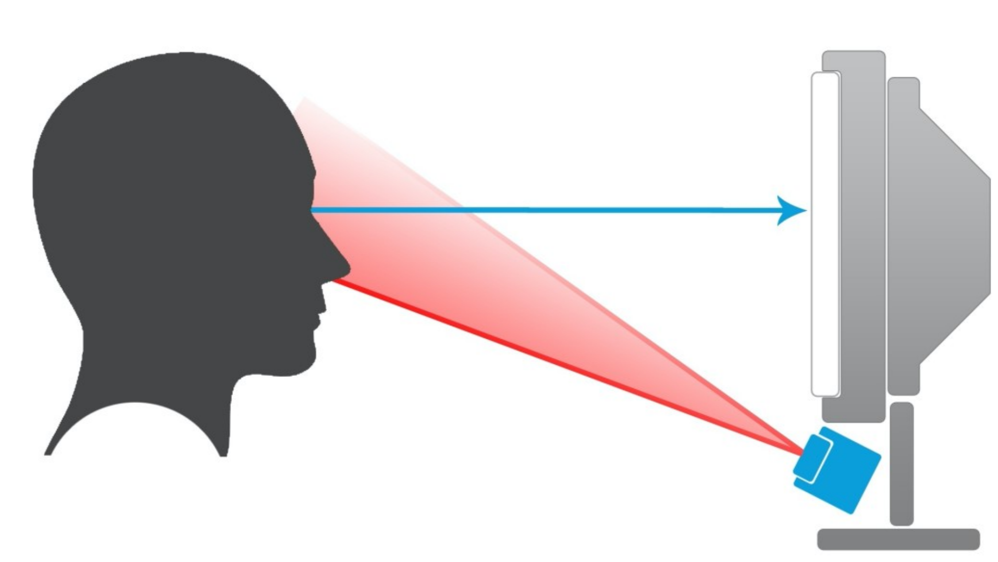
key findings

- computer models have fair accuracy (AUROC of 0.6)
- they tie with aggregate of 9 human judges, but outperform up to 3 humans
- fusion of computer + 3 humans best





video-based detection (Bosch & D'Mello, 2020; in review)

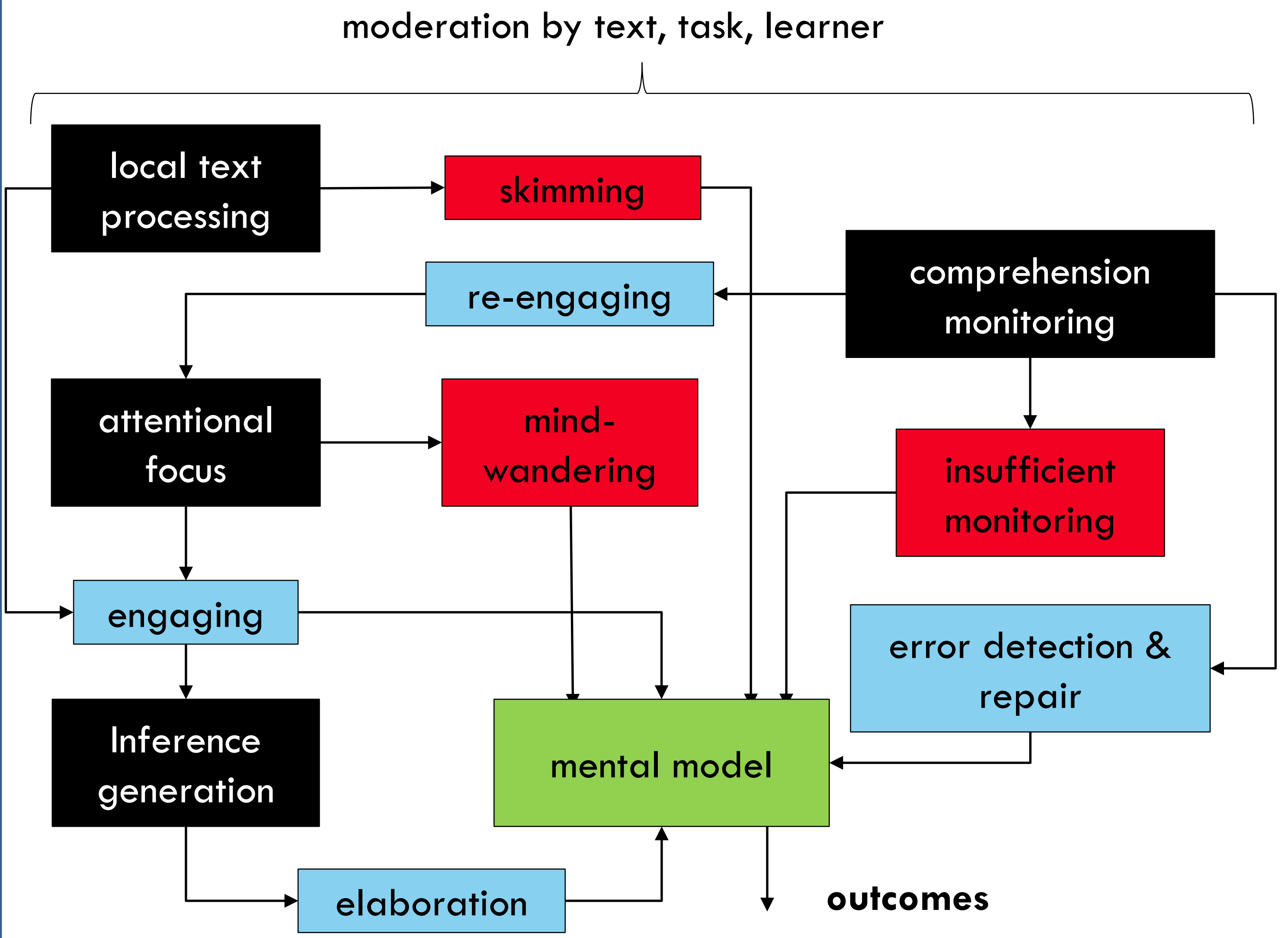


```
Function CalculateFixations(Samples, SpatialThreshold, TemporalThreshold, MinimumSamples)
  for P in Samples do
    if P is visited then
      Continue
    end
    Mark P as visited
    neighbours ← getNeighbours(P, SpatialThreshold, TemporalThreshold)
    if neighbours.length < MinimumSamples then
      //Ignore P as Noise
    else
      C = newFixation
      expandCluster(P,C,neighbours SpatialThreshold, TemporalThreshold, MinimumSamples)
    end
  end
  Clean Fixations()
```

key findings

- video- and eye-tracker features correlate (*rs* .41-75 for lab; .21-.23 for classroom)
- both yield similar accuracies for restricted features but not full feature set
- results can be improved with some training data containing eye gaze and video

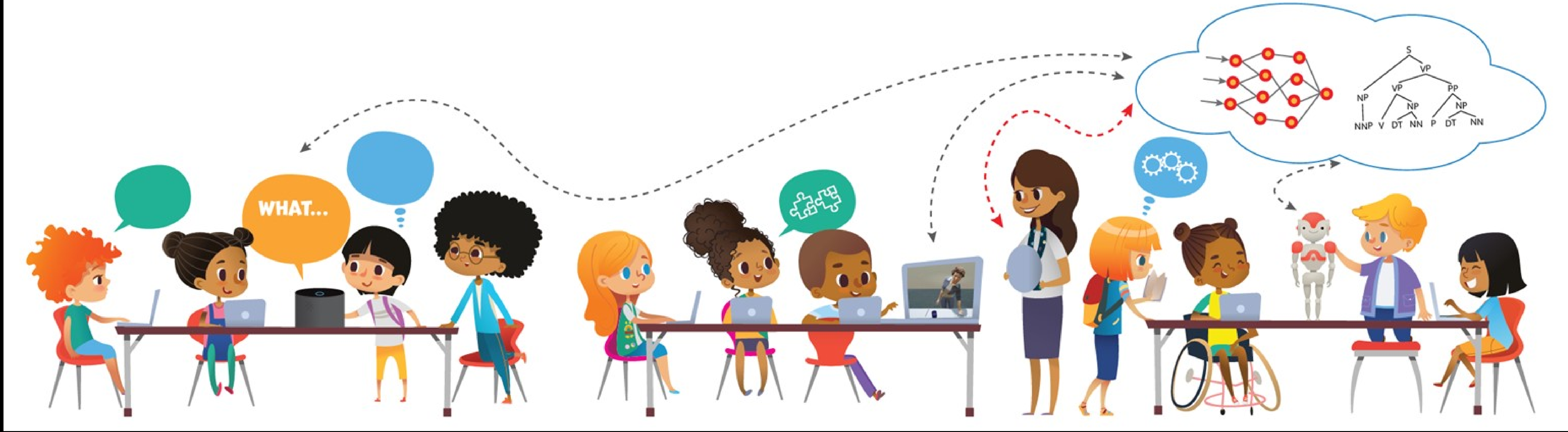
estimating gaze features from video (Hutt & D'Mello in prep)



exploring the eye-**brain**-mind link during reading

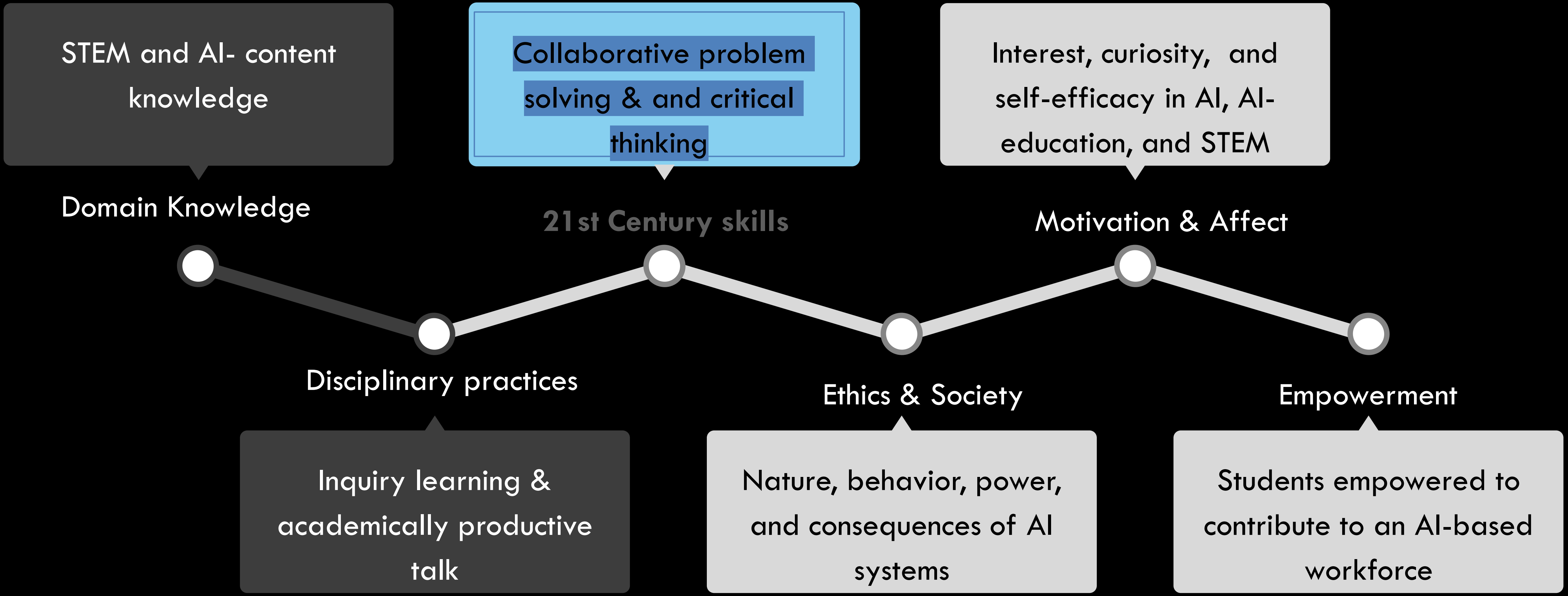
how to promote deep conceptual learning via rich socio-collaborative learning experiences for all students?

in our vision, AI is viewed as a **social, collaborative partner** that helps both students and teachers work and learn more effectively, engagingly, and equitably



Principle 1	Principle 2	Principle 3	Conjecture 1	Conjecture 2	Conjecture 3
Deep conceptual learning is constructive, interactive and situated in authentic, collaborative activities	Developing collaborative problem solving and critical thinking skills will broaden participation in the STEM workforce	Students' voice, inclusion, equity, and social justice are central aspects of meaningful learning experiences	There is a need to fundamentally rethink the role of technology to support collaborative learning in classrooms	Collaborative problem-solving and critical thinking are ripe for AI-based facilitation and support	Natural social interaction (e.g., language, gestures,) will deepen engagement with AI partners

theoretical framework - principles & conjectures



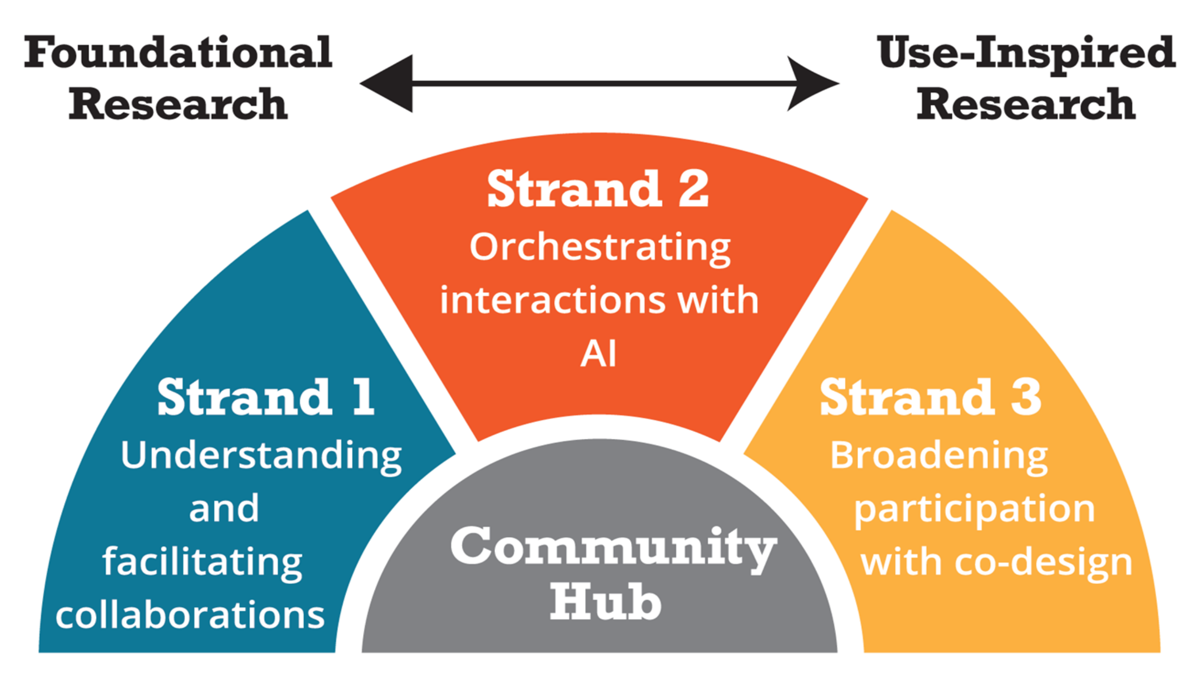
we will integrate *AI-education* in science & tech courses to provide measurable learning outcomes

iSAT blends foundational and use-inspired research with broadening participation, workforce development, & community engagement (led by Sidney D'Mello PI)

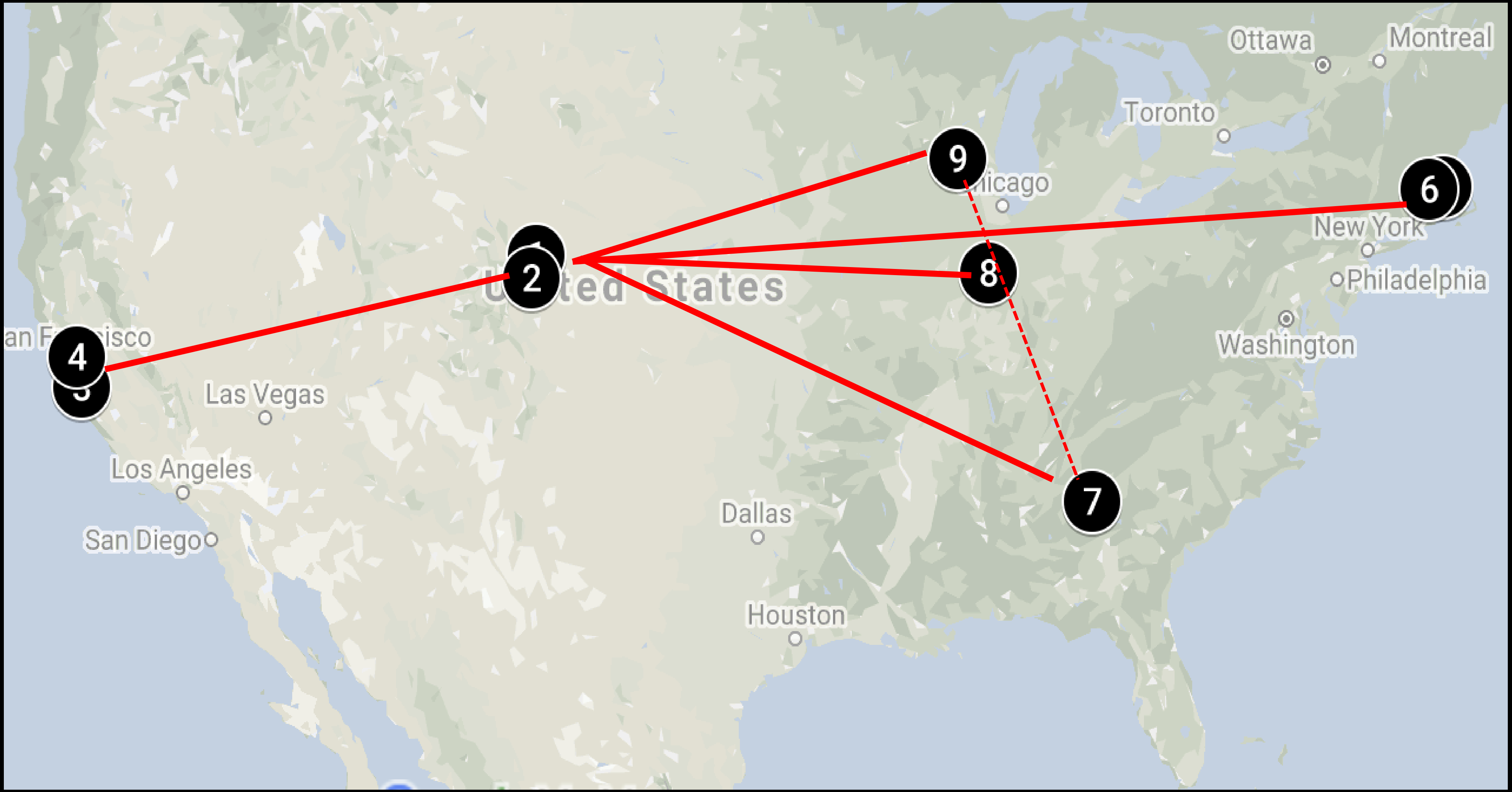
Strand 1: Advances in multimodal machine learning, natural language processing, and knowledge representation **(co-led by Martha Palmer & Ross Beveridge)**

Strand 2: Advances in theories, interaction-paradigms, and orchestration frameworks for student-AI teaming **(co-led by Sadhana Puntambekar & Leanne Hirshfield)**

Strand 3: Advances in inclusive co-design to empower diverse stakeholders to envision, co-create, critique, and apply AI technologies **(co-led by William Penuel & Tamara Sumner)**



Community Hub provides services to integrate participants and partner organizations and is led by a full-time coordinator



1. Colorado State U.
2. U. of Colorado Boulder
3. U. of California, Santa Cruz
4. U. of California, Berkeley
5. Brandeis U.
6. Worcester Polytechnic Institute
7. Georgia Tech
8. U. of Illinois at Urbana Champaign
9. U. of Wisconsin-Madison

Denver Public Schools

St. Vrain Valley Schools

we unite 29 researchers from 14 research areas with partners from academia, K-12, and industry network affiliates

postdocs, graduate, & undergrad students

industry network affiliates

70 teachers

parents & community stakeholders

5,000 diverse K12 students from two school districts (>60% underrepresented groups)

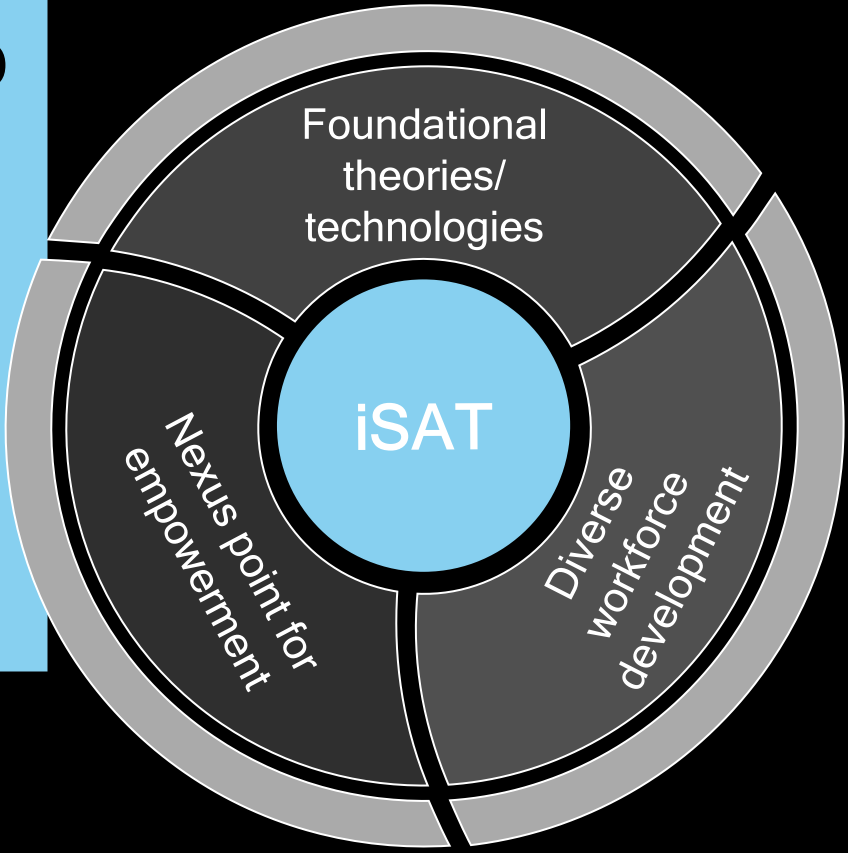
29 researchers from 9 partner research universities

750 undergraduates from nine universities

K12 & development partners

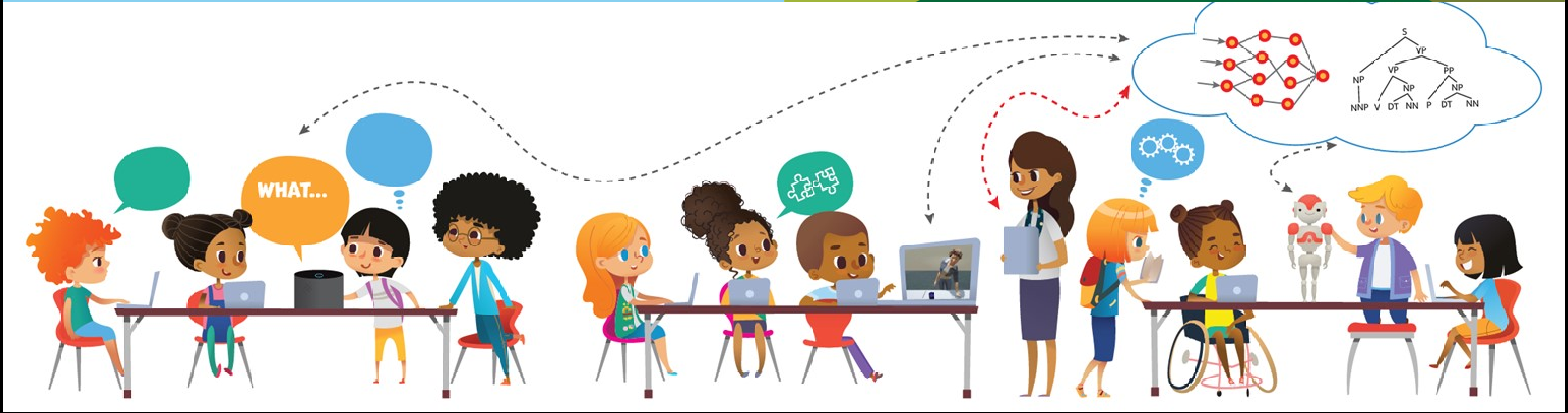
we will engage a large and diverse community

- Develop **foundational theories & AI technologies** for creating next-generation collaborative learning environments composed of diverse student-AI teams.
- **Grow a diverse workforce** of the future by engaging 5,000 middle/high school students in innovative AI education through AI-enabled pedagogies.
- Serve as a **national nexus point for empowering** diverse stakeholders to envision, co-create, critique, and apply student-AI teaming in their communities.

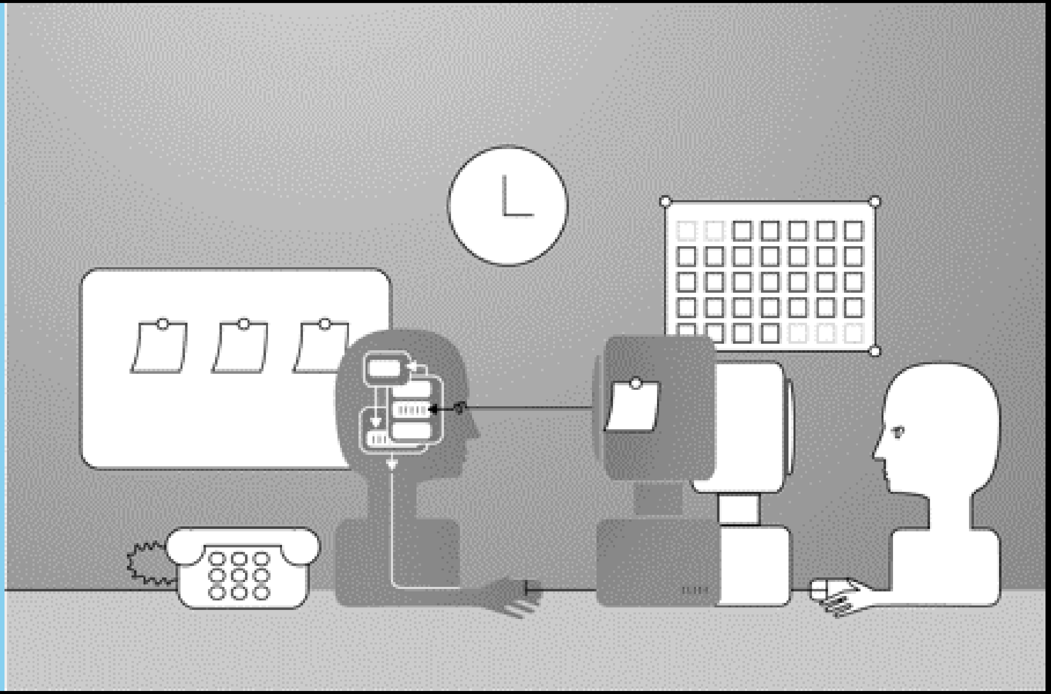


our mission

The Institute will promote deep conceptual learning via rich socio-collaborative learning experiences for all students (both in-person & remotely)



computational methods provide a unique opportunity to advance basic understanding of human functioning and enhance human potential



summary

team

postdocs: Kaitlin Bainbridge, Rosy Southwell, Brandon Booth, Guojing Zhou

phd students: Robert Bixler, Emily Jensen, Nicholas Hunkins Megan Caruso, Samuel Pugh

masters students: Tellie Umada, Arjun Rao, Shree Krishna Subburaj

undergraduate students: Cooper Steputis, Sierra Rose, Anissa Becerra, Julianna Harris

funding

Thanks to the NSF, IES, DoD (IARPA, ARO, AFSOR), Intel, ETS, Gates, Templeton, Walton Foundation, & Mindset Scholars Network for funding this work in 30 grants.

past members

Stan Franklin, Barry Gholson, Scotty Craig, Max Louwerse, Jeremiah Sullins, Rana el Kaliouby, Barry Kort, Rob Reilly, Ashish Kapoor, Holly White, Tanner Jackson, Brent Morgan, Bethany McDaniel, Kristy Tapp, Evie Johnson, Brandon King, Patrick Chipman, Natasha Velaga, Karl Fike, Kimberly Vogt, Lydia Perkins, Rosaire Daigle, Rebekah Combs, A K M Mahbubur Rahman, Ally Dobbins, Nia Dowell, Melissa Gross, Jacqueline Kory, Matthew Hunter, Shi Feng, Hallie Burgess, Eric Roth, Jonathan Cobian, Jennifer Neale, Amber Strain, Blair Lehman, Jon Savakus, Casey Hall, Tera Joyce, Yuxuan (Ethan) Chen, Melissa Rogers, Jennifer Wu, Thomas Behrens, Timothy Pusateri, Catherine Carothers, Luke Garrison, Kristopher Kopp, Abigail Walsh, Rosalyn Tan, Xinyi (Cindy) Wang, Grace Hills, Huili Chen, Shelby White, Disha Waghray, Connor Sullivan, Nathan Blanchard, Caitlin Mills, Nigel Bosch, Jianjan (Ivy) Wang, Mae Raeb, Eugene Choi, Jessica Hardey, Jacob Beiter, Kendyll Kraus, Samantha Scaglione, Taylor Kovacs, Patrick Donnelly, Myrthe Faber, Joseph Grafsgaard, Connor Cook, Catherine Spann, Aruna Gunda, Mary Jean Amon, Zachary Keirn, Julie Gregg, Lucca Eloy, David Blair, Kristina Krasich, Cathyln Stone, Conner Sinjem, Hana Vrzakova, Margo Gardner, Caroline Reinhardt, Erin Clarke, Angela Stewart, Stephen Hutt

thank you

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