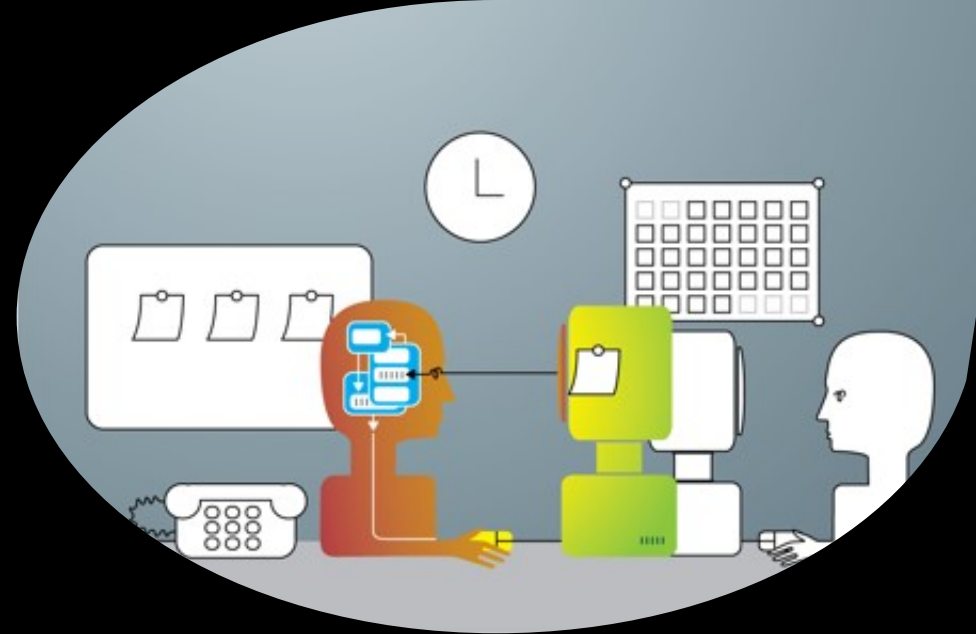


# Machine-learned Computational models to Assess ILL-defined Constructs



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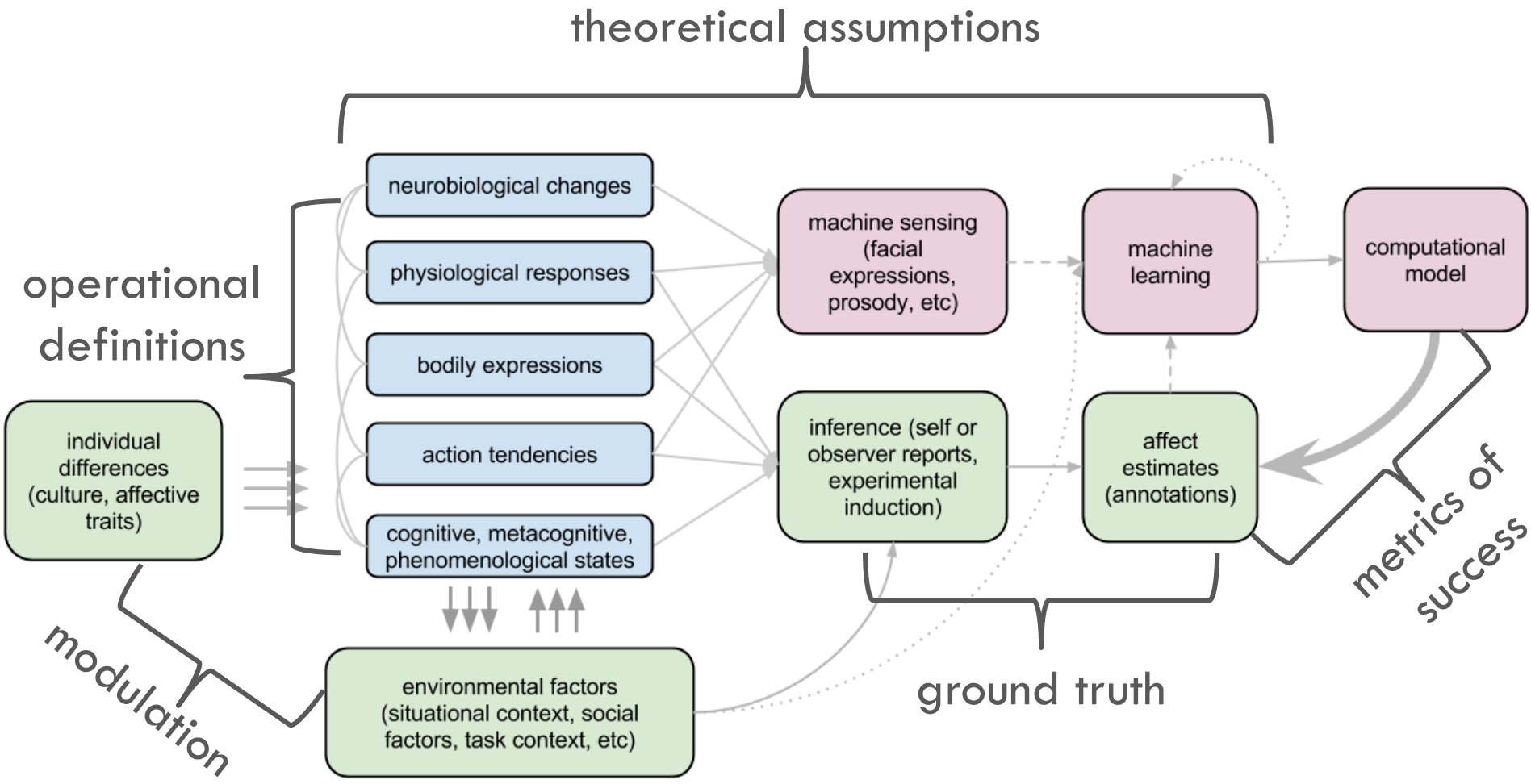
August 23, 2019

- traditional methods (classical test theory, item response theory, evidence centered design) have been invaluable for assessing a range of constructs (e.g., knowledge, skills)
- but what about “ill-defined” constructs that cannot be precisely defined, are ephemeral states, especially in situ?

machine-learned, computational models are essential

- when constructs are “ill-defined” like emotion, collaboration
- when there are no adequate theoretical mechanistic accounts
- when underlying models are “multilevel circular causal”
- models can promote change via intervention or reflection
- the art lies in how they are constructed and evaluated
- and in setting realistic expectations and contexts of use

claims



conceptual model [affect example]

D'Mello, Kappas, & Gratch (2018)

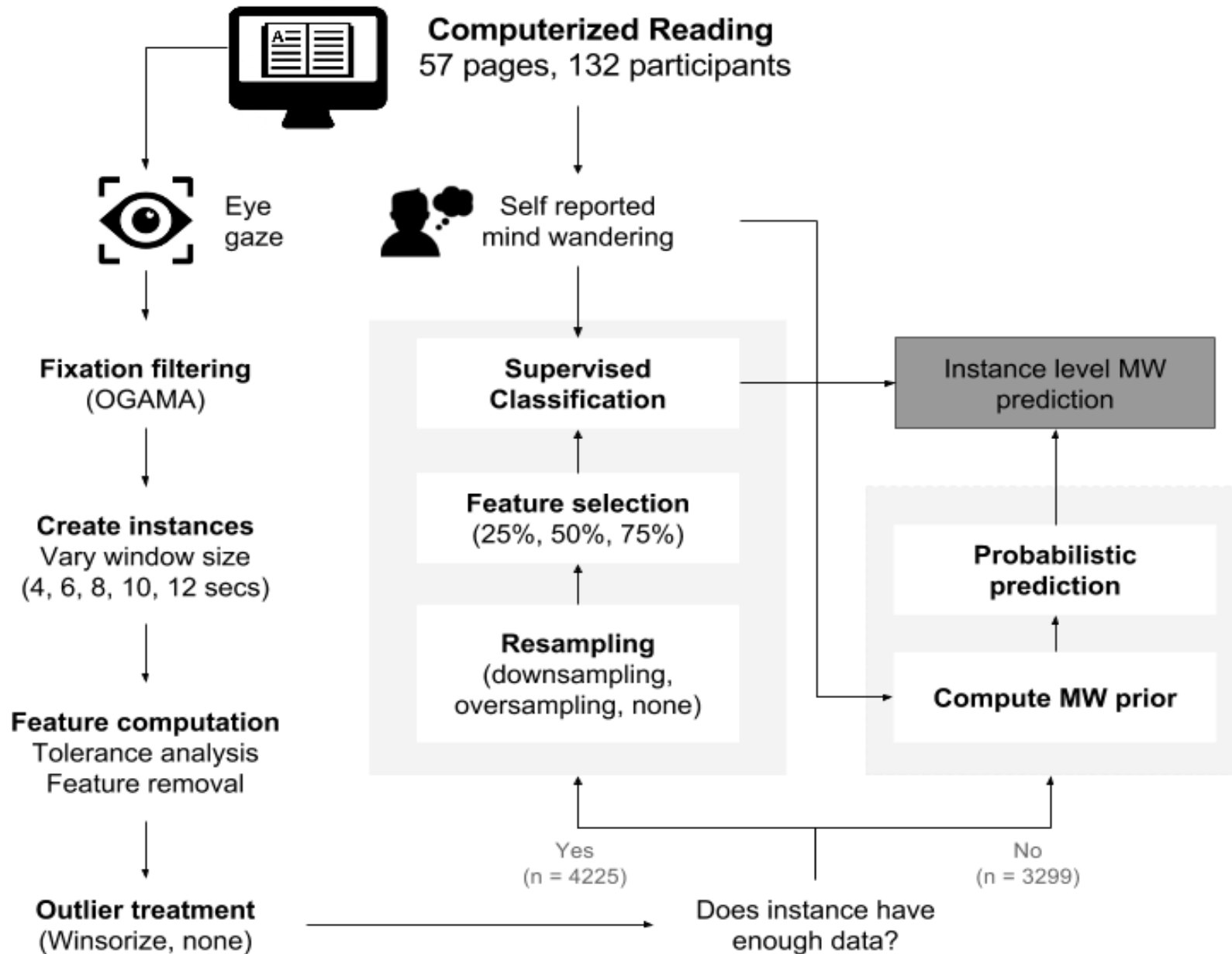
1 2 3 4 5 6  
If a researcher wanted to examine  
7 8 9 10 11 12 13 14  
the effect of a diet pill on weight  
15 16 17 18 19  
loss she might give some  
20 21 22 23 24 25  
participants the diet pill and other  
26 27 28 29 30  
participants would receive a sugar  
31 32 33 34 35 36  
pill that looked identical to it.



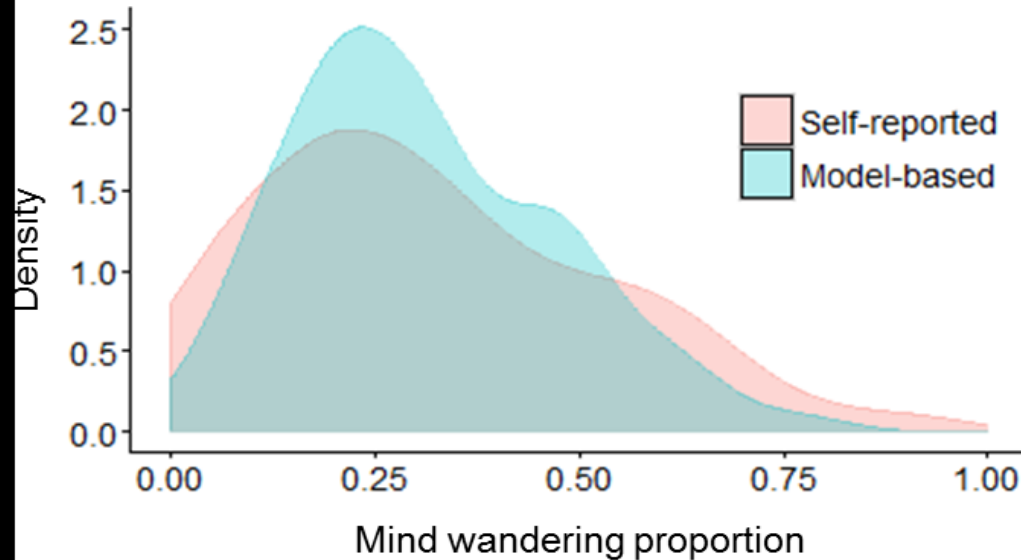
exploring the  
eye-mind link  
during reading



ubiquity of mind wandering

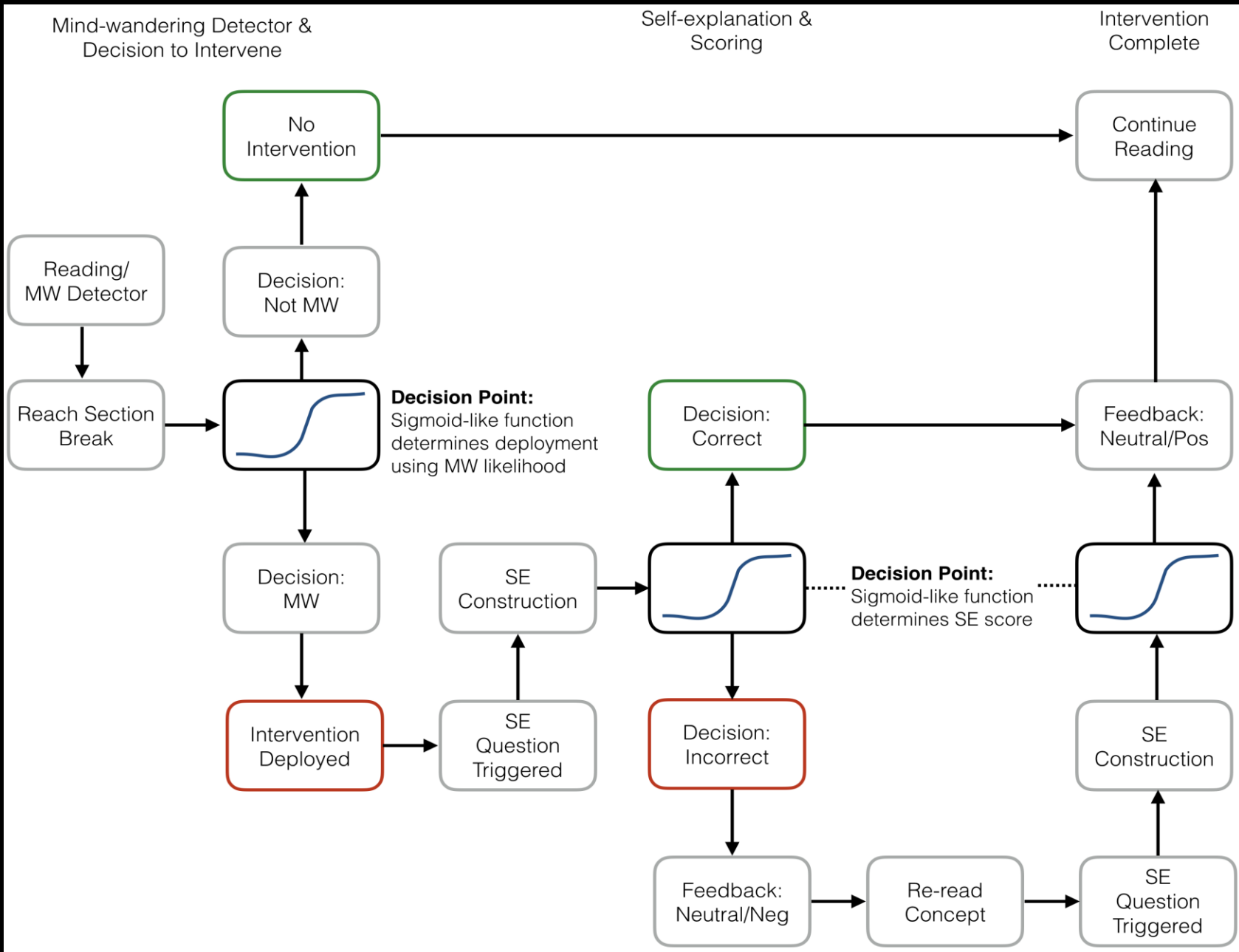


**method** (Faber, Bixler, & D'Mello, 2018)



- model estimates correlated with self-reported mind wandering ( $r = .400$ )
- correlated with comprehension ( $r = -.374$ ) stronger than self-reports ( $r = -.208$ )
- models robust to missing data and internally consistent ( $r = .751$ )
- page-level predictions moderate – precision of 72.2%; recall of 67.4%
- fewer but longer fixations and fewer horizontal saccades related to mind wandering

key results

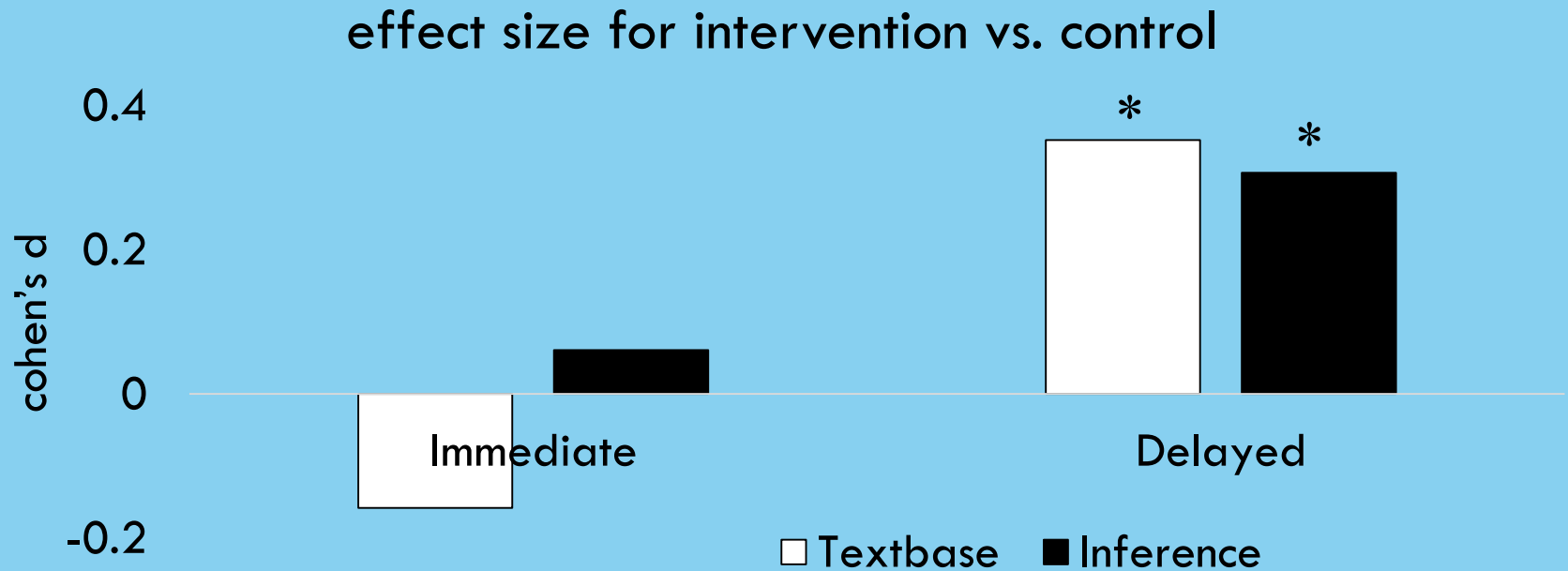


real-time intervention (Mills, et al., in review)



## method

- 70 participants read book on surface tension in liquids
- randomly assigned to intervention or yoked-control
- tested for text- AND inference- level comprehension after reading AND one week later (parallel forms)

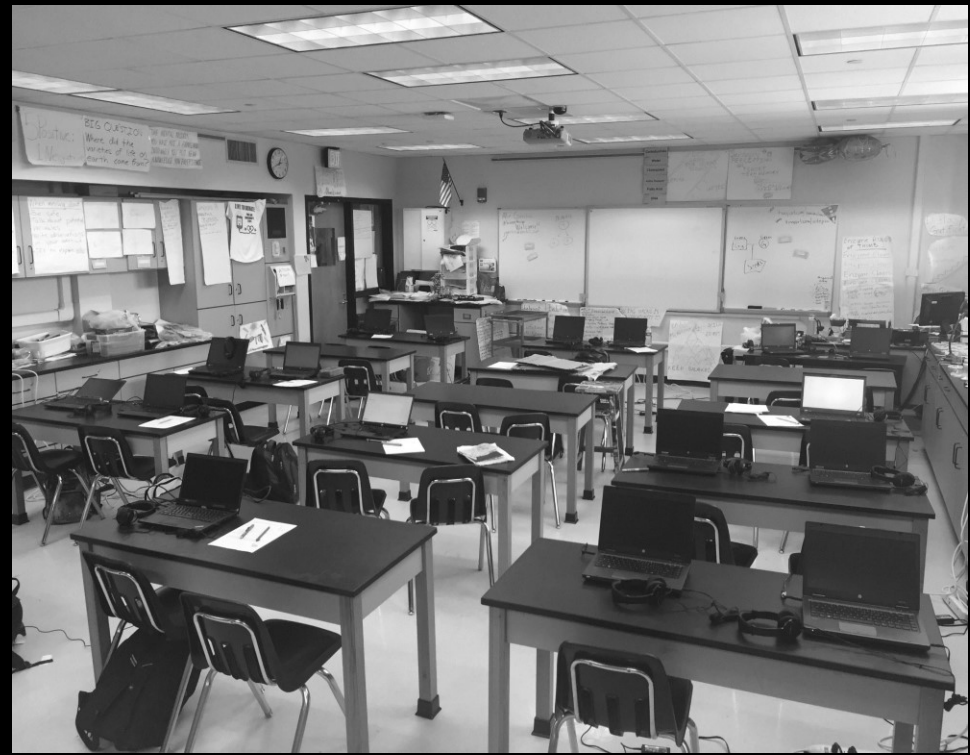


experimental validation

**Tobii EyeX**  
(consumer-grade)



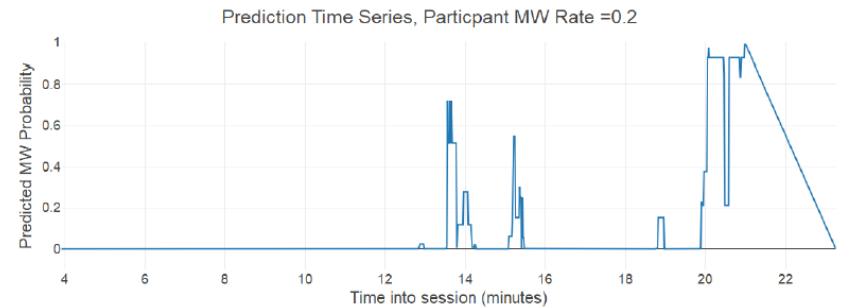
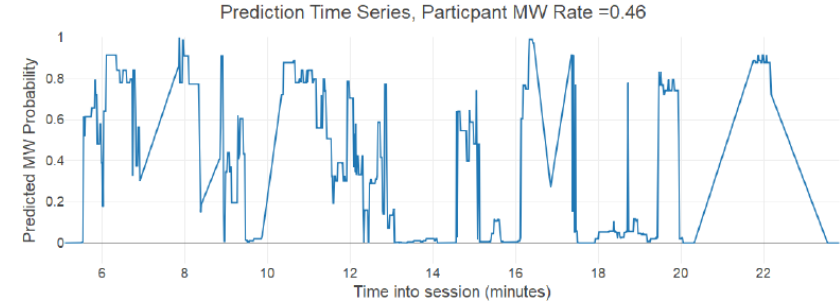
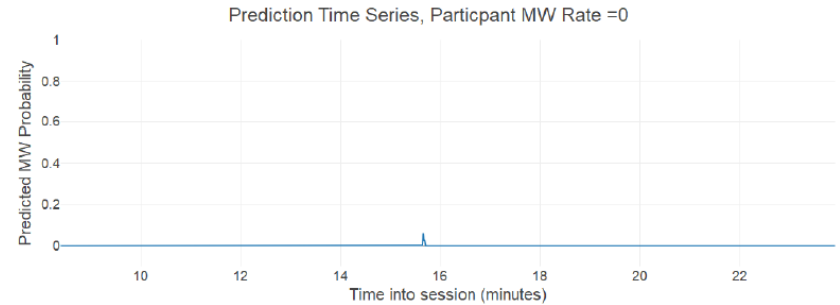
**EyeTribe**  
(consumer grade)



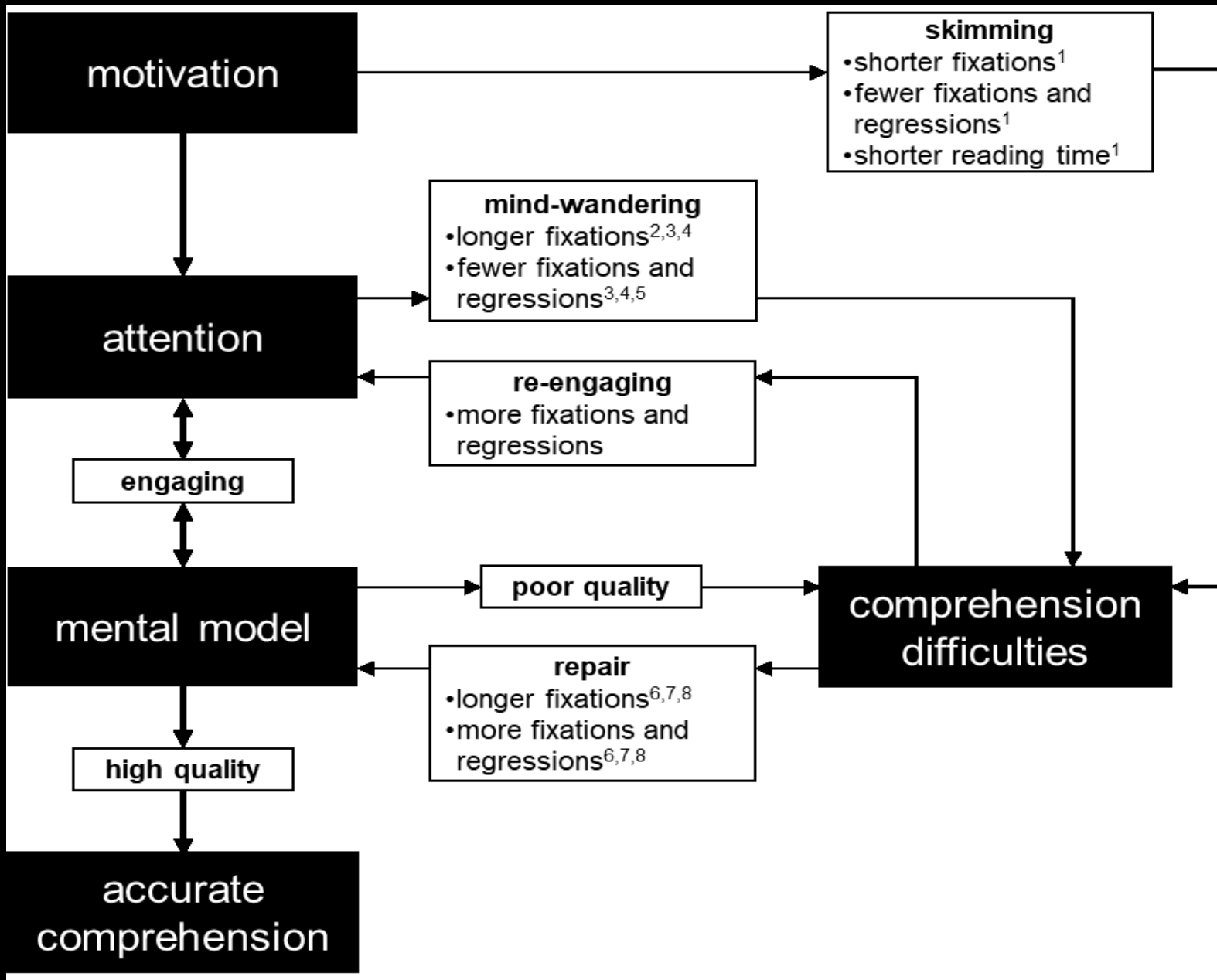
out of the lab and into the wild (Hutt et al., 2019)

- tracking validity between 75% (both eyes) and 95% (one eye)
- moderately accurate at mind wandering detection (precision .55; recall .65)
- model predictions correlated with learning ( $r = -.20$ )

## using models for interventions

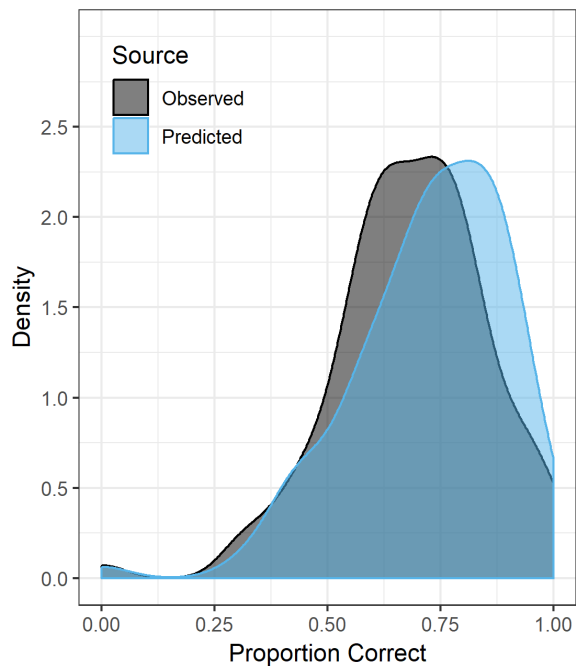


key results

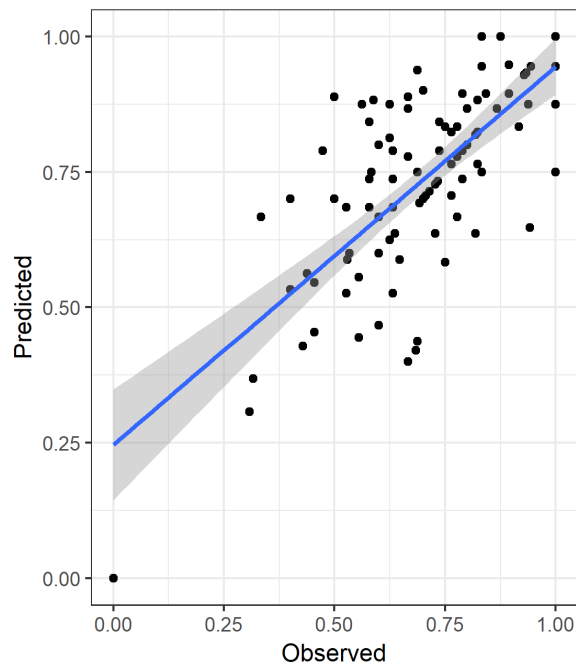


can eye movements predict comprehension?

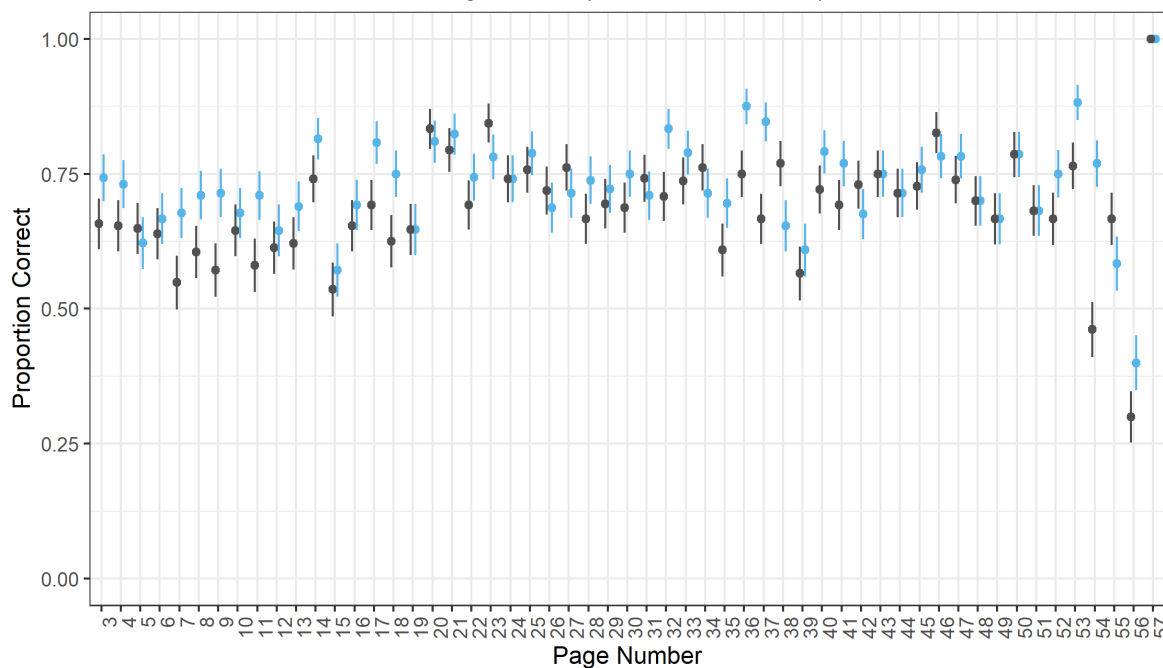
Eye Movements + Reading Time



Participant-Level (  $r = 0.687$  )



Page-Level ( AUROC = 0.907 )



very accurate for  
textbase-level  
comprehension  
assessed during  
reading  
(AUROC = 0.9;  
 $r = 0.68$ )  
Gregg & D'Mello (in  
review)

## motivation

- surprising lack of consistency in literature
- very little research on long connected texts, especially after reading
- tested weak vs. strong association hypotheses ( $R_{sq.}$  of 1% vs. 10%)

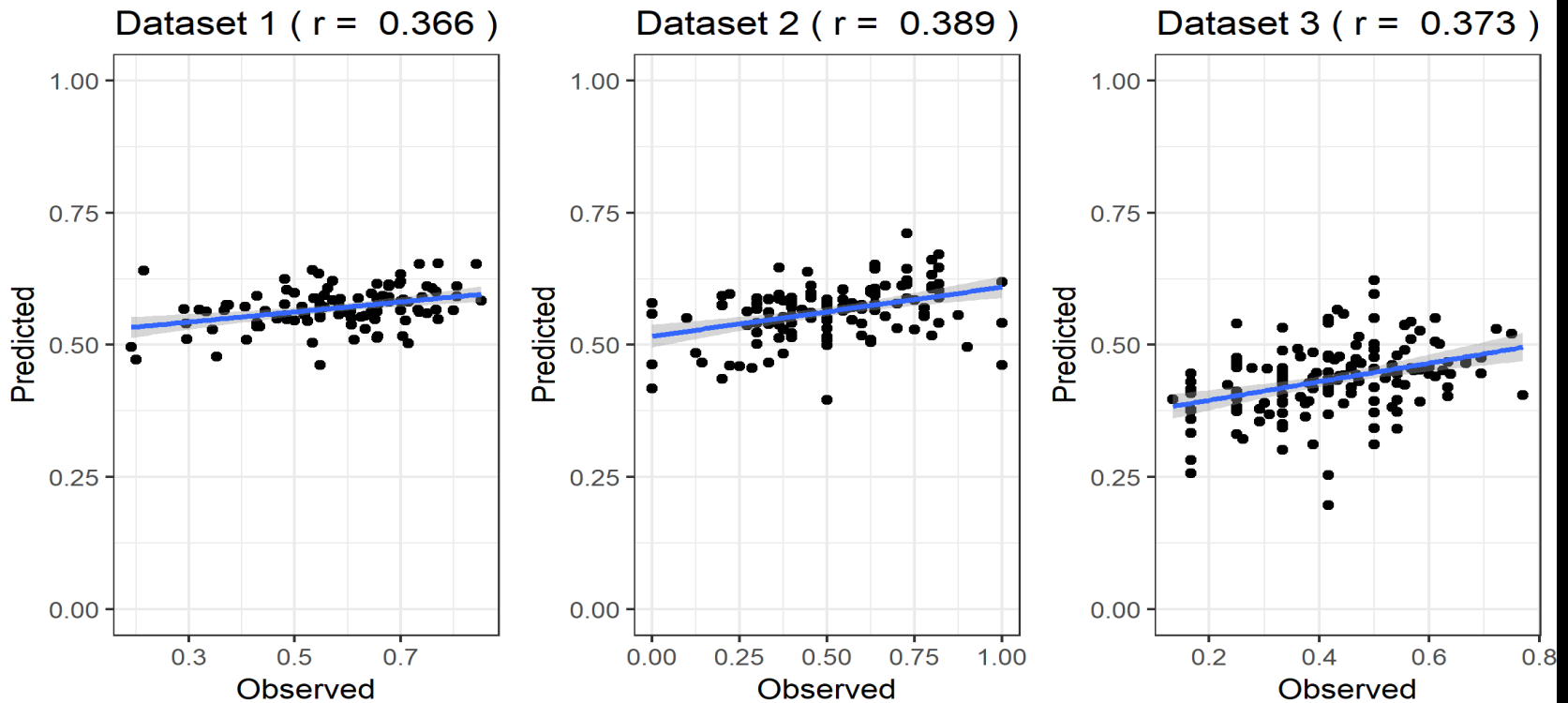
## methods

- datasets 1 and 2: predict textbase-level comprehension 30-mins after reading one long connected text
- dataset 3: predict textbase- and inference-level comprehension after reading upto 8 short texts
- focused on seven eye gaze features and reading times
- simple cross-validated regression models

what about comprehension *after* reading?

(Gregg, Bixler, & D'Mello, in review)

- moderate cross-validated correlations between observed and predicted comprehension
- models from one study generalized to another
- more, but shorter, fixations predicted comprehension
- results hold after accounting for mind wandering and exposure to print (author recognition test)



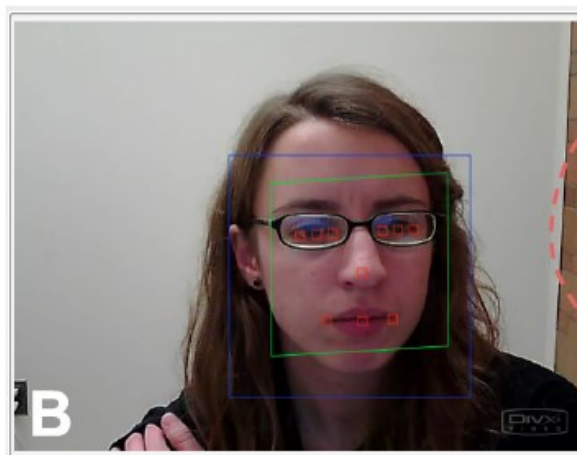
data support the strong association hypothesis

machine-learned computational models of eye movements can assess reading processes and outcomes & can drive intervention

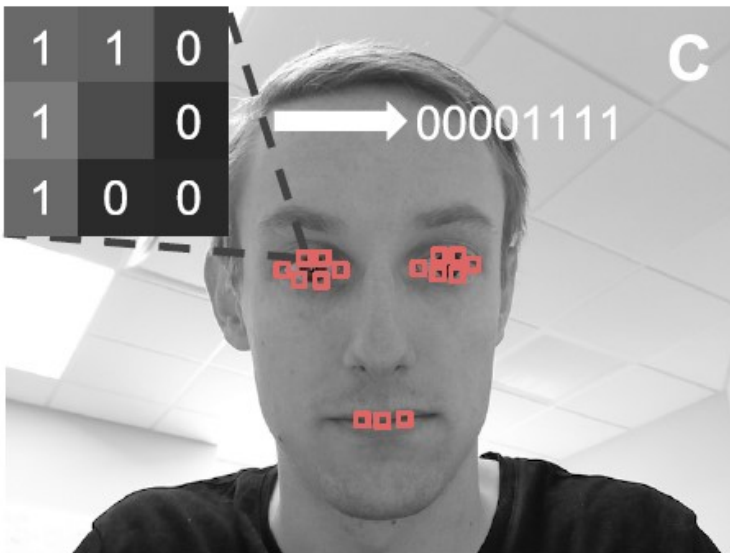
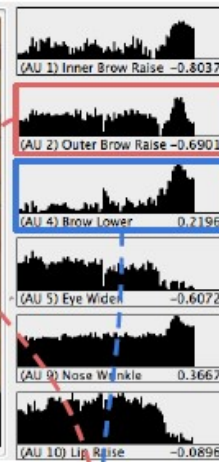




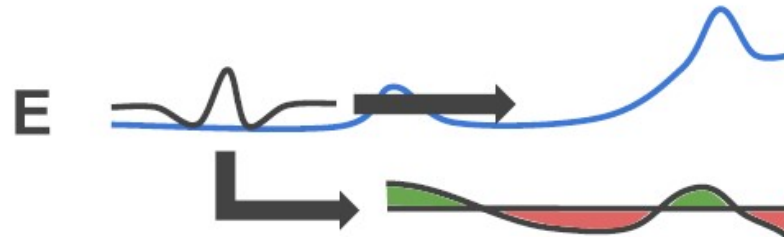
**A**



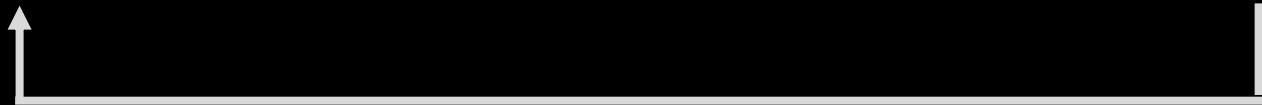
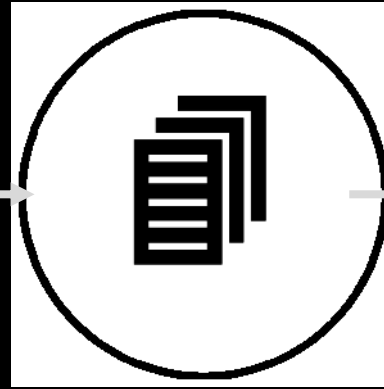
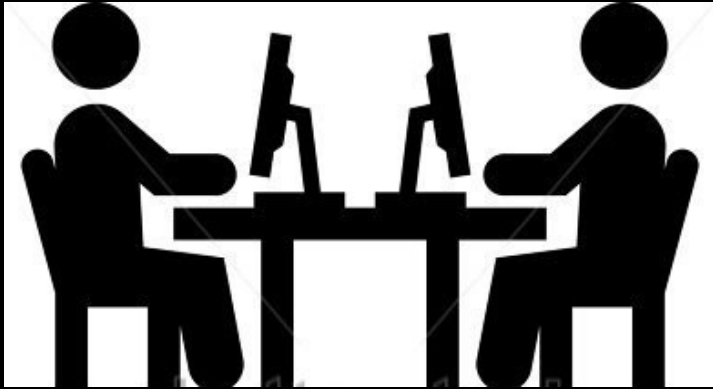
**B**



**C**



video-based modeling of affect and attention



\* 9 iterations

does frame-of-reference coding help

D'Mello (2016)



it depends...

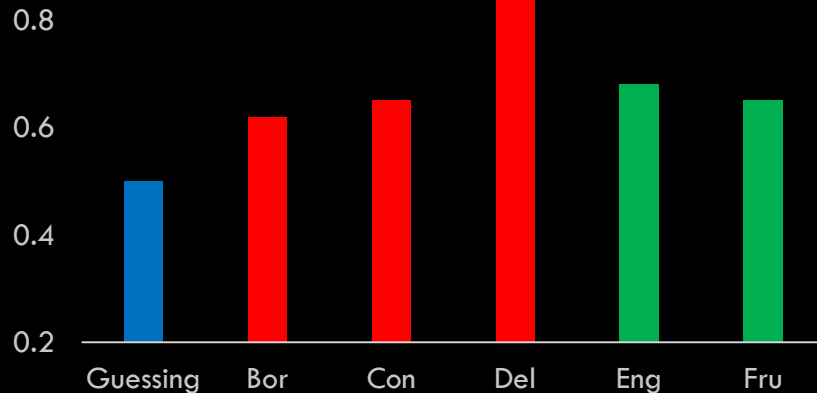
# Physics Playground



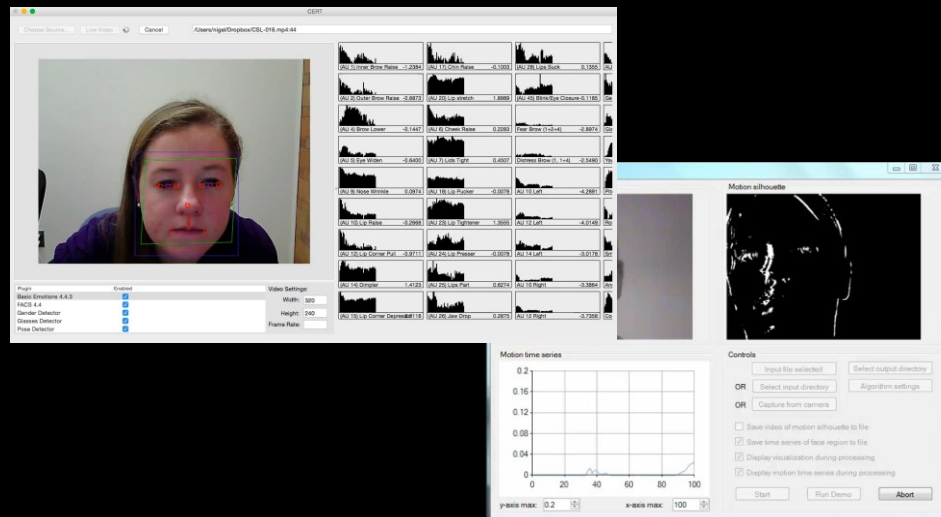
# online observations



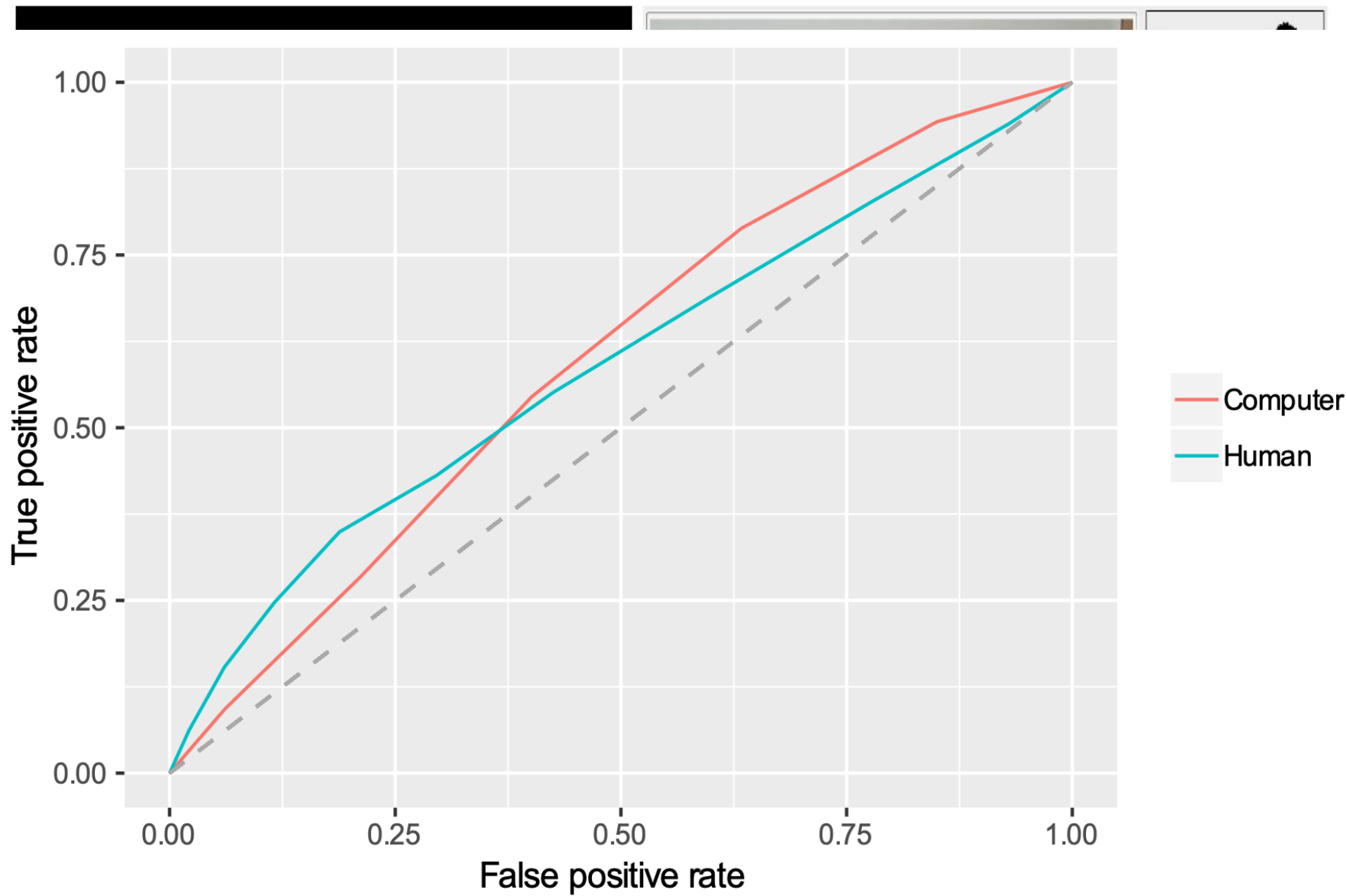
## results (AUC)



## facial features + body movements



modeling affect from video  
(Bosch, et al., 2016)



# video-based mind wandering detection

Bosch & D'Mello (2019)

video-based models can provide human-comparable results for  
affect and attention



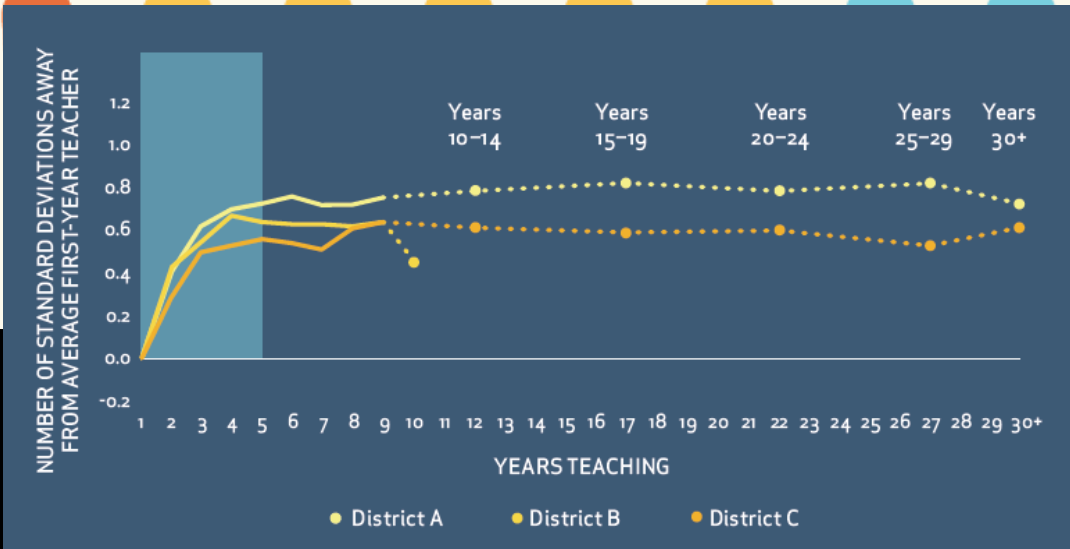
speech and language  
processing for discourse  
analysis

# TUE

The districts we studied spend an average of nearly \$18,000 per teacher, per year on

Give teachers a clear, deep understanding of their own performance and progress.

Confronti



Teachers  
substantial  
t.



# Which of these would you consider authentic?

Teacher: *“How does a person become a noble?”*

Student: *“They’re born into it”*

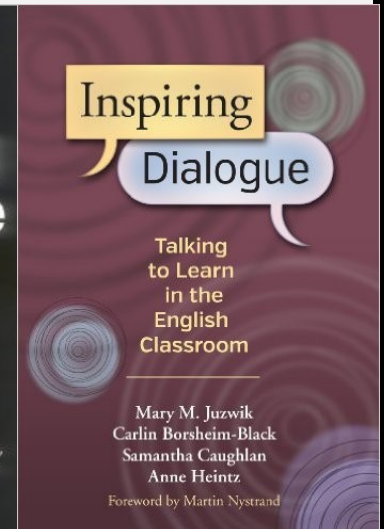
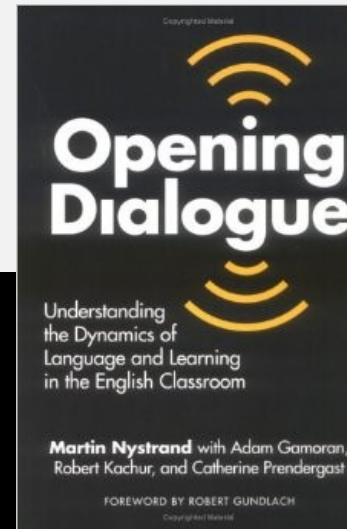
Teacher: *“They’re born into it, right? It’s by family. It gets passed down*

....

Teacher: *“How did that make you guys feel, I mean what was your gut reaction to all that?”* authentic

Student: *“Ashamed”*

Teacher: *“Ashamed in what way?”*



# authentic questions

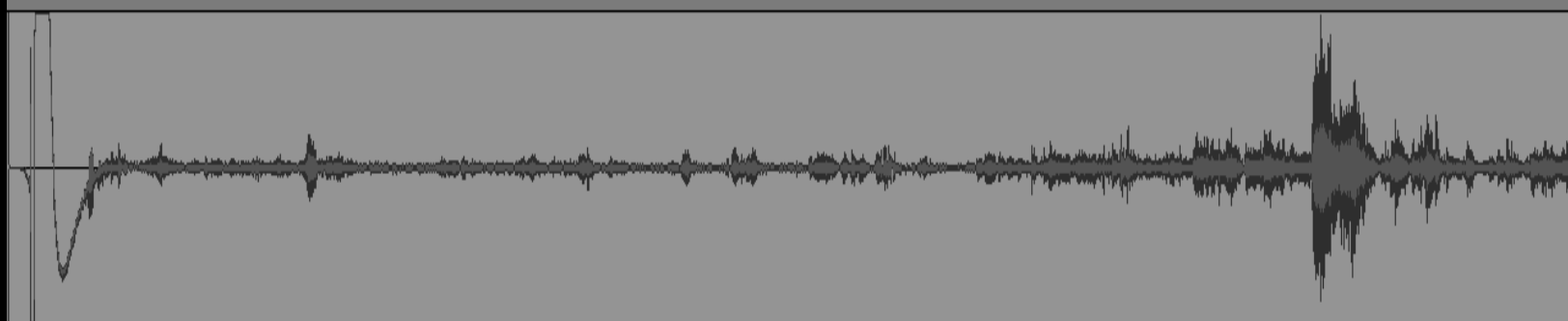


teacher mic  
(Samson  
Airline 300)



Classroom mic

mixer  
(M-Audio M-Track)



1

## Speech and Language Processing

Data collection  
(132 observations  
from 27 classes  
by 14 teachers in  
7 schools)



Teacher mic  
(Samson  
Airline 77)



Live coding + offline  
refinement of codes

Teacher audio  
(7,663 mins  
total)



Gold-standard  
authentic  
question codes

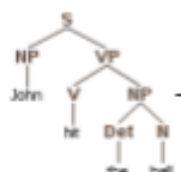


Automatic speech  
segmentation  
(45k utterances)



0 | 0 0  
0 0 0 0  
| 0 | |  
Data for  
machine  
learning

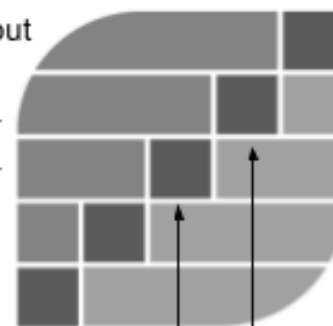
Bing speech  
recognition  
(text transcript)



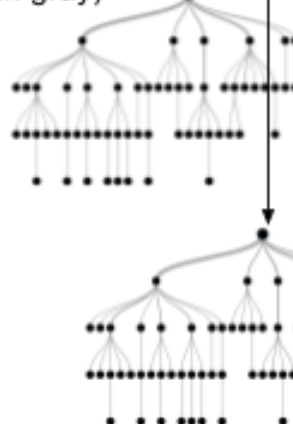
Natural language processing  
(word, sentence, and discourse  
level features)

## Machine Learning & Validation

Leave-one-teacher-out  
cross validation

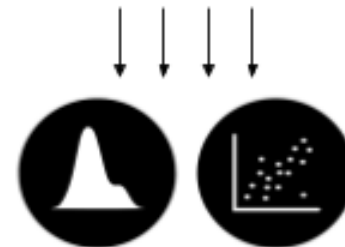


Learn M5P  
regression  
trees for k-1  
teachers  
(in gray)



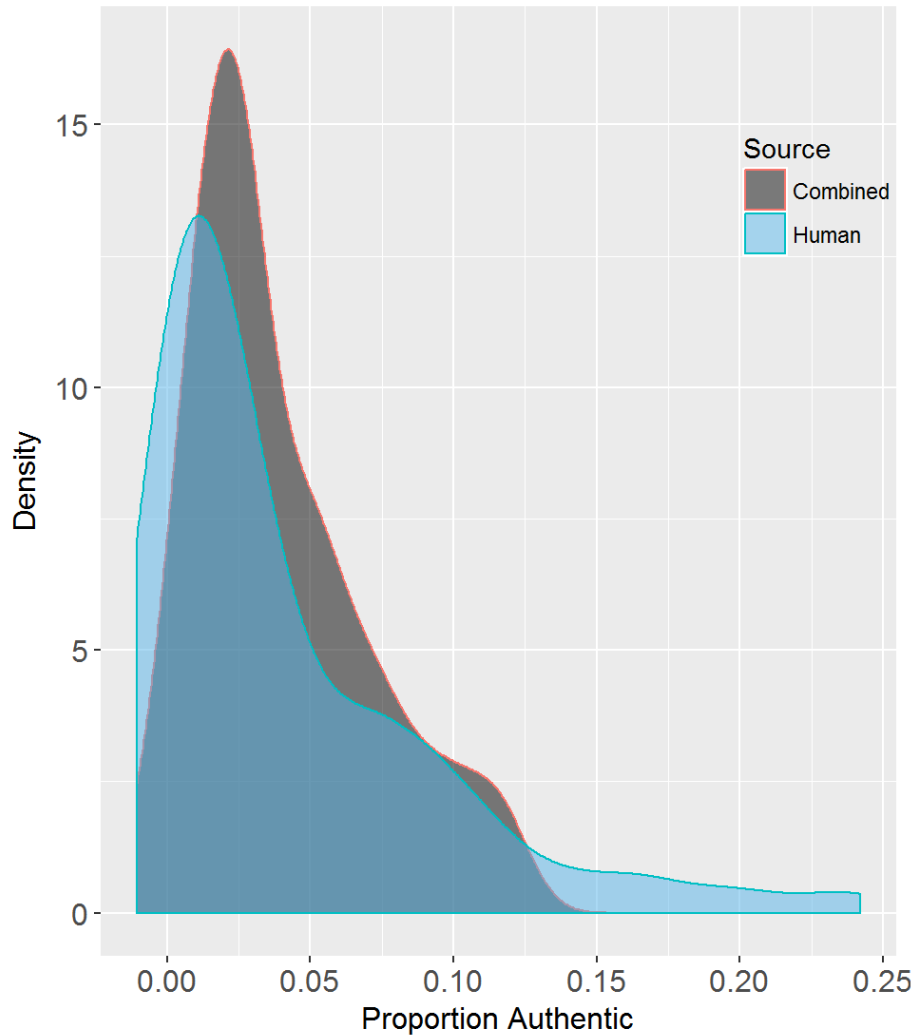
Apply model to  
generate  
estimates for  
held-out teacher  
(in black)

Repeat until each teacher is held  
out once

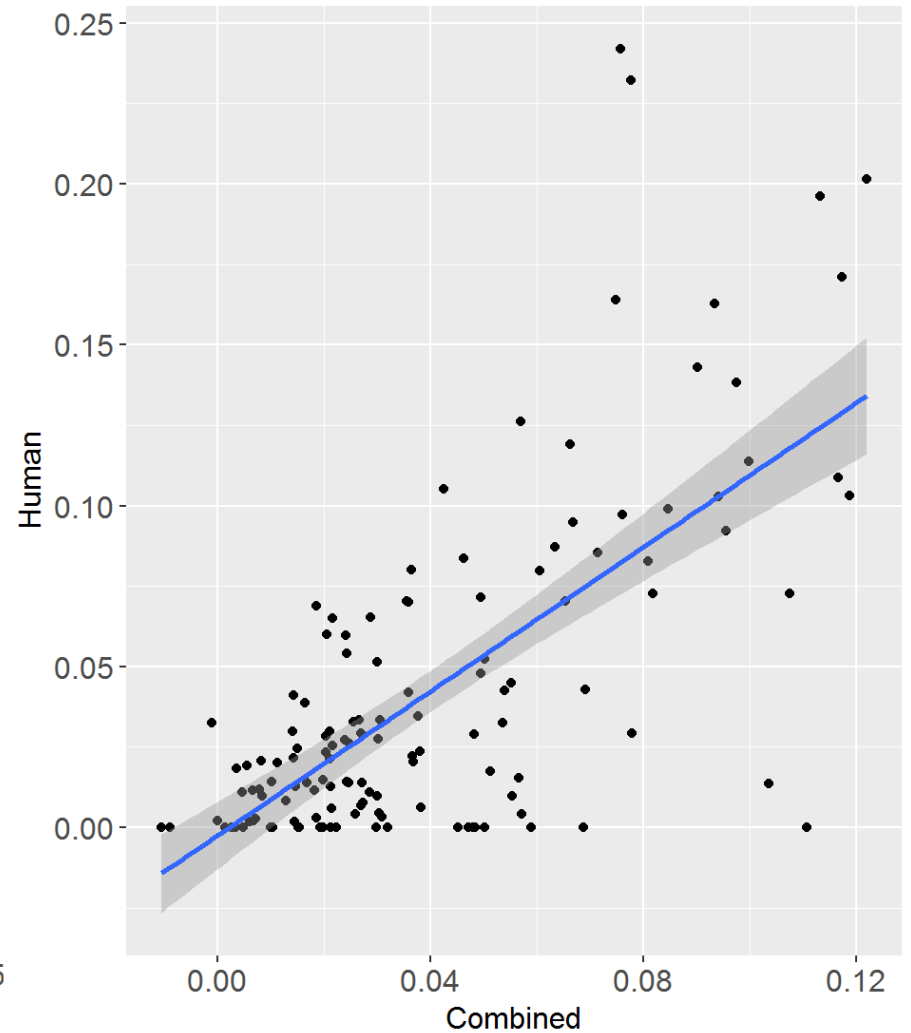


Pool computer-estimates and  
compare with gold-standard codes

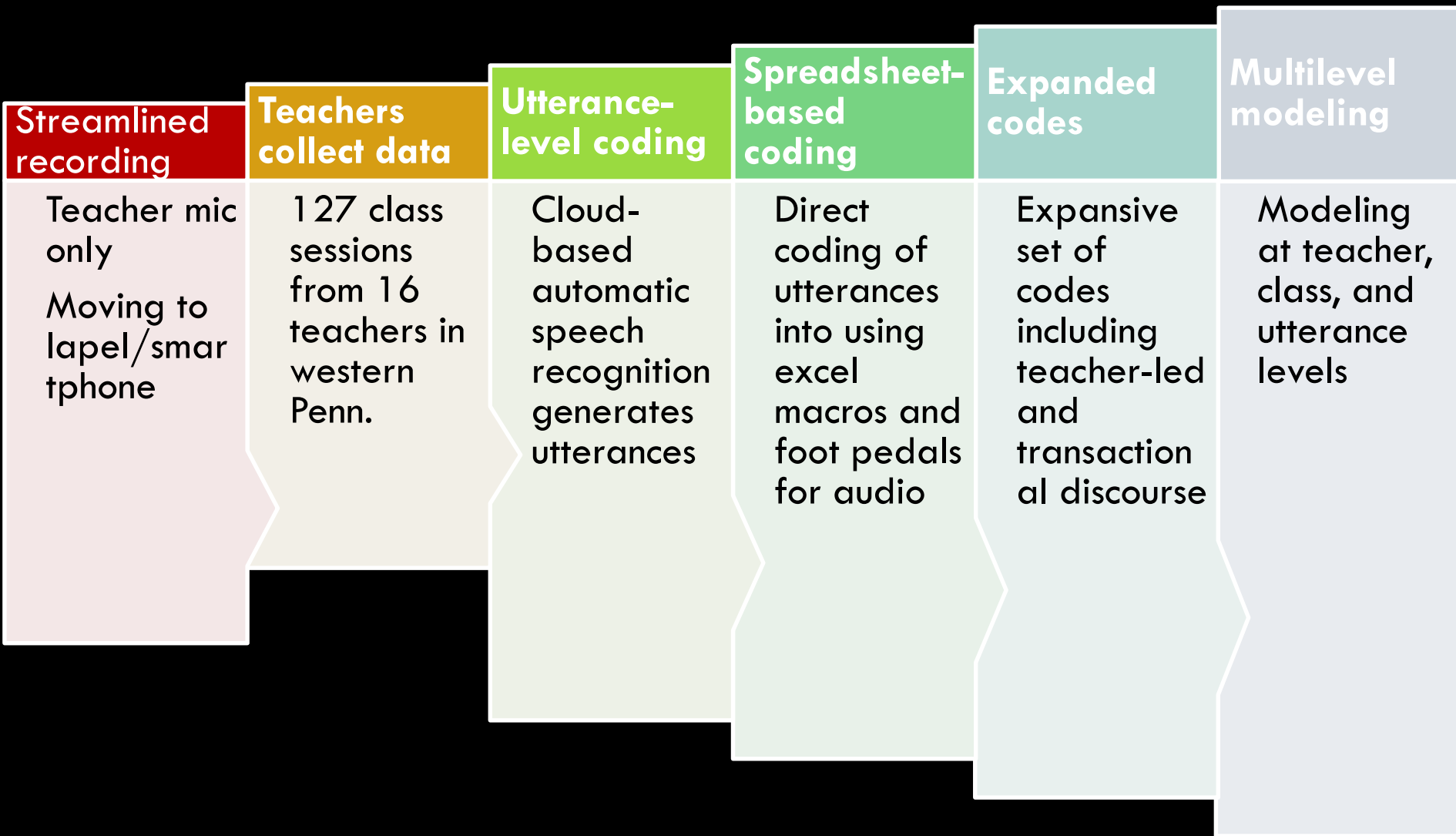
Combined Model



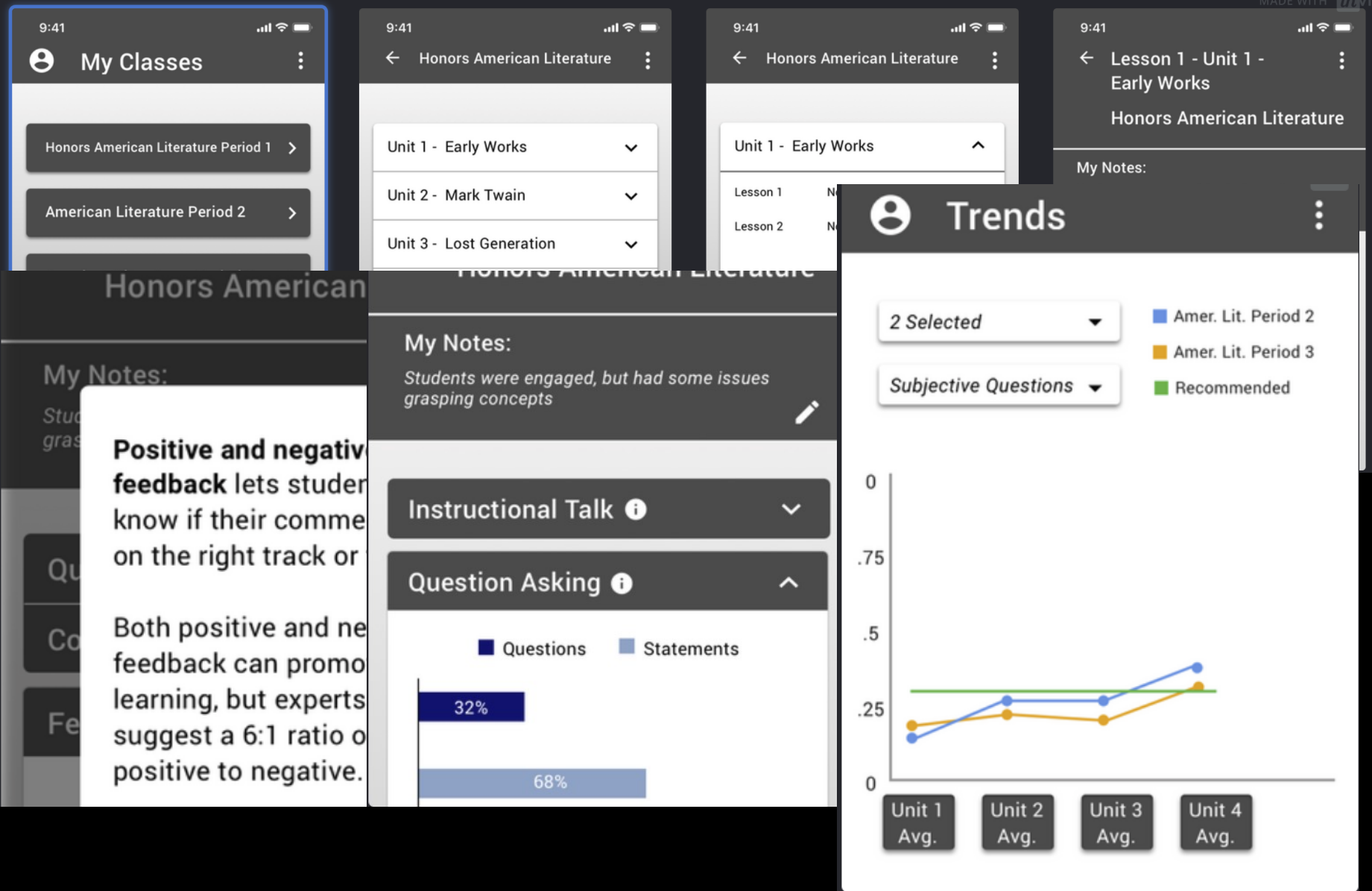
Combined Model (  $r = 0.686$  )



computer scores of authenticity  
correlated with human codes ( $r = .686$ )



new approach



design of feedback app

models of spoken language can capture complex aspects of  
discourse in noisy environments

## **description**

- funded by Intelligence Advanced Research Projects Activity (IARPA)
- challenge was to robustly predict psychological traits, health/well being, and job performance in the real-world from sensors alone?
- target correlation of 0.5 on a blinded sample
- do it all in 16 months

## **our approach**

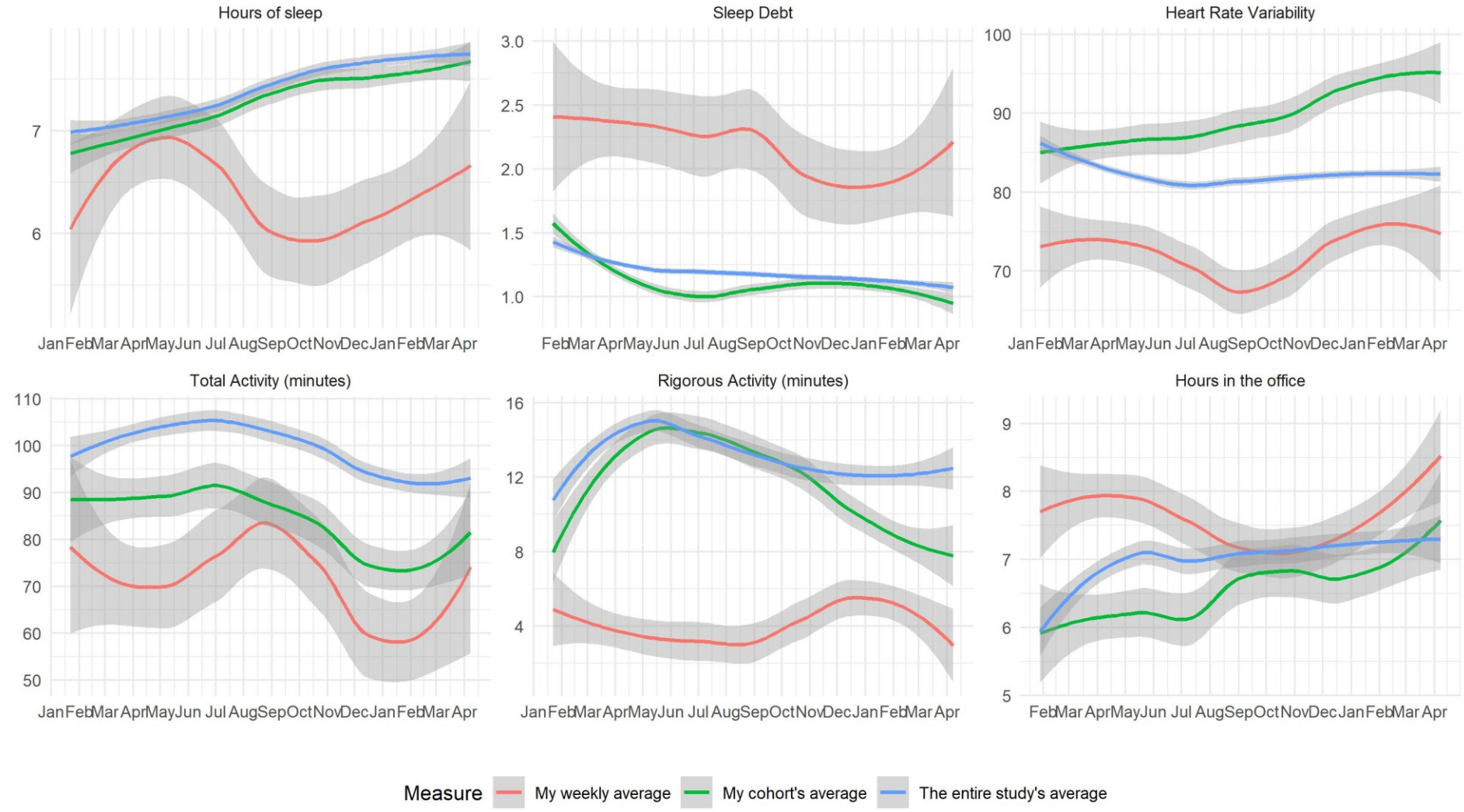
- Project Tessarae - 10 PIs from 8 universities
- collected data from 757 US information workers for 1-year
- four sensors (wearable, Beacons, phone agent, social media)

## **results**

- modeling social, lifestyle, tech use, physiology/behavior, & context
- ensemble-based machine learning approach for robustness
- average correlation of 0.21 [0.08 to 0.41] on 14 constructs

# The MOSAIC Program





These results are based on an average of 63 weeks of data

# patterns of life

## **machine-learned, computational models can enhance assessment**

- machine-learning when theory/mechanisms are sparse
- data is abundant and sufficiently complex (nonlinearities)
- models can promote change with intervention and/or reflection

## **tips on constructing models**

- reliance on theory without being overly constrained by it
- striving for parsimony rather than chasing fads (deep learning)
- important to go beyond minimizing validation loss
- explainability, real-time applicability, fairness, & generalizability

**summary**

## **things to consider when assessing ill-defined constructs**

- defining constructs – *don't really need precise definitions*
- reliability concerns – *reliability important but not a show stopper*
- quantify performance – *external sources critical*
- what is good performance? – *beyond chance probabilistic*
- how good is good enough? – *good for what purpose?*

## **looking into the future**

- standardized testing
- game-based assessments & performance tasks
- machine-learned computational models for specific tasks
  
- is the future robust multimodal sensing in context?

**concluding thoughts**

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