STUDENT LEARNING AND ANALYTICS AT MICHIGAN

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Next-Generation Analytics with the Learning Dashboard

Marsha Lovett, Director of Carnegie Mellon University's Eberly Center for Teaching Excellence and Associate Teaching Professor in the Department of Psychology

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Carnegie Mellon University

Cognitively Informed Analytics to Improve Teaching and Learning

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Teaching Professor, Department of Psychology

"How's your course going?"

Question

How do you know how your course is going?

A. Based on latest quiz/exam scores
B. Comparing to previous students/classes
C. By the “feel” of discussions, participation
D. Other
E. It’s often rather hard to tell

Students spend 100+ hours across the term, and yet show learning gains of only 3%.

(Lovett, Meyer, & Thille, 2008)

3%

We can improve that.

Is learning analytics enough?

Is learning analytics enough?

Prediction  Action

Is learning analytics enough?

Prediction + Understanding ⇨ Targeted Action

Instructors need up-to-date, *actionable* information

- Quick snapshot of how class is doing
- Access to details on areas of strength & difficulty
- Alerts to noteworthy patterns in student learning
- Pointers to opportunities for adapting their teaching

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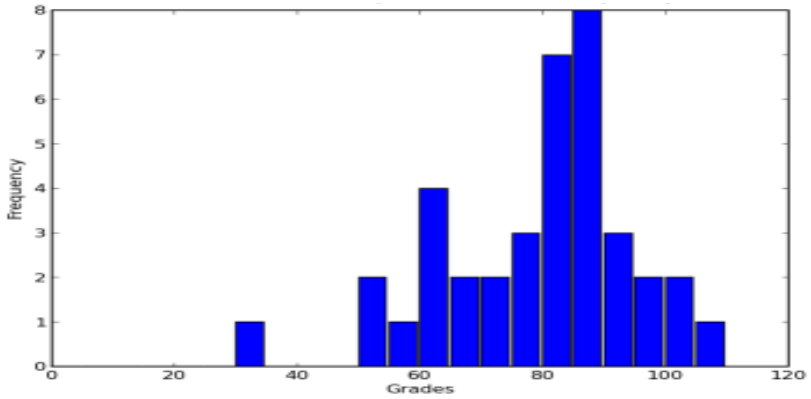
But instructors typically only have access to averages or distributions of student scores on graded activities



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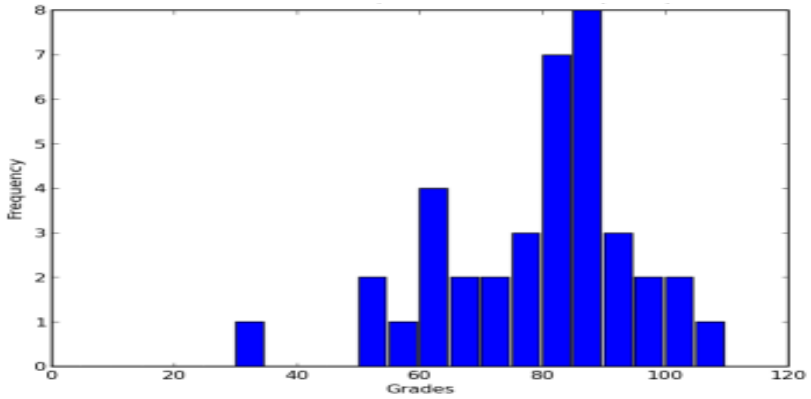

Implications are rather coarse

Results come late, after unit is completed

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Emotional response

No reason/incentive to remediate

Don't know what to do next

We want:

Understanding of students' *learning states*

We need:

Learning analytics *informed by cognitive theory*

The *Learning Dashboard*

Cognitively informed learning analytics system that estimates students' learning skill by skill

Instructors
Students
Designers
Administrators

Deep insights into student learning

When students interact with online learning systems, they produce a rich data stream

Most learning analytic systems barely tap this potential:

Track what students do

Record which questions students get right or wrong

Summarize student progress and performance

Predict some future behavior

The *Learning Dashboard* gets more out of the data:

Reveals what students did/not learn

Quantifies how well students have learned each skill

Identifies consequential patterns in students' learning behaviors

Measures effectiveness of instructional and design choices

Learning Dashboard's Key Ingredients

Cognitive & Learning Theory

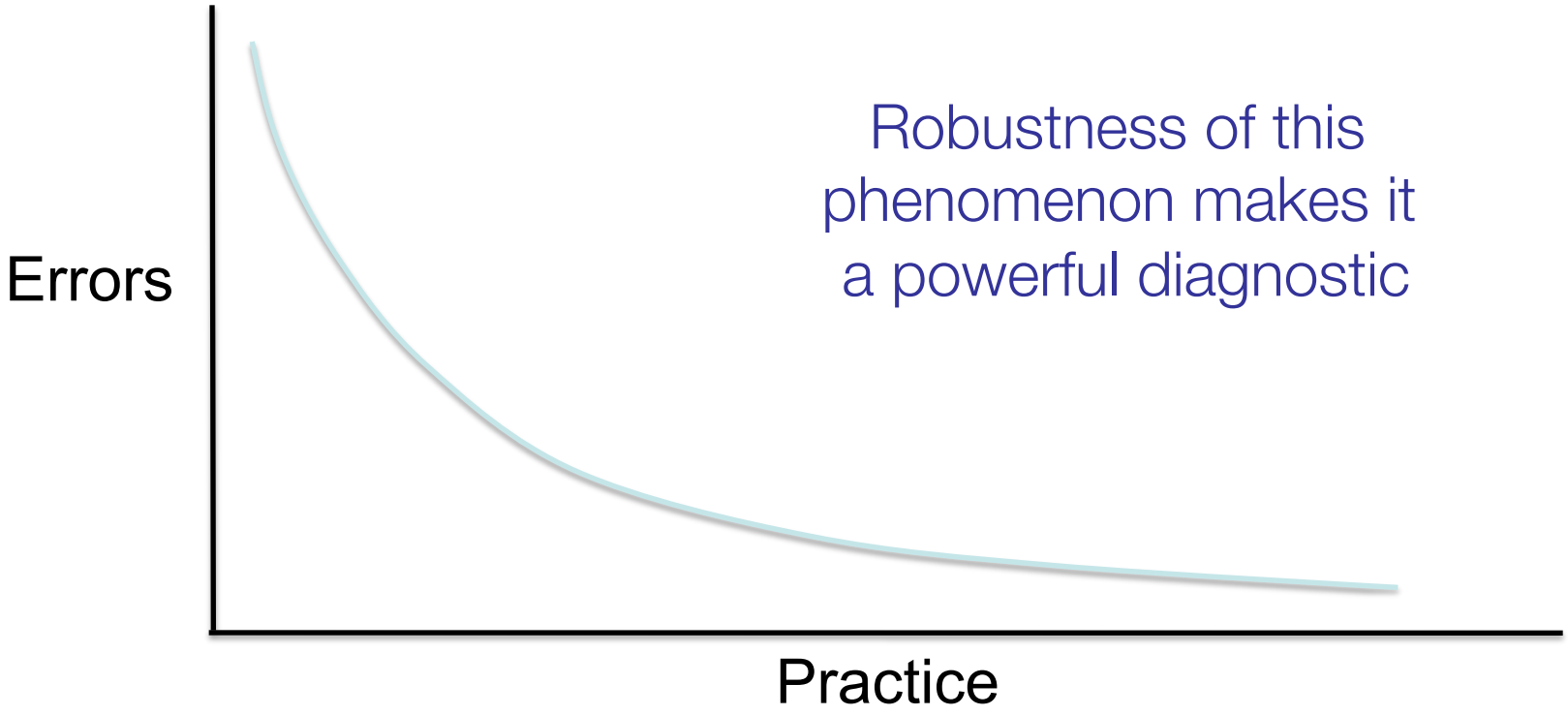
State-of-the-Art Statistical Models

Learning Dashboard's Key Ingredients

Cognitive & Learning Theory

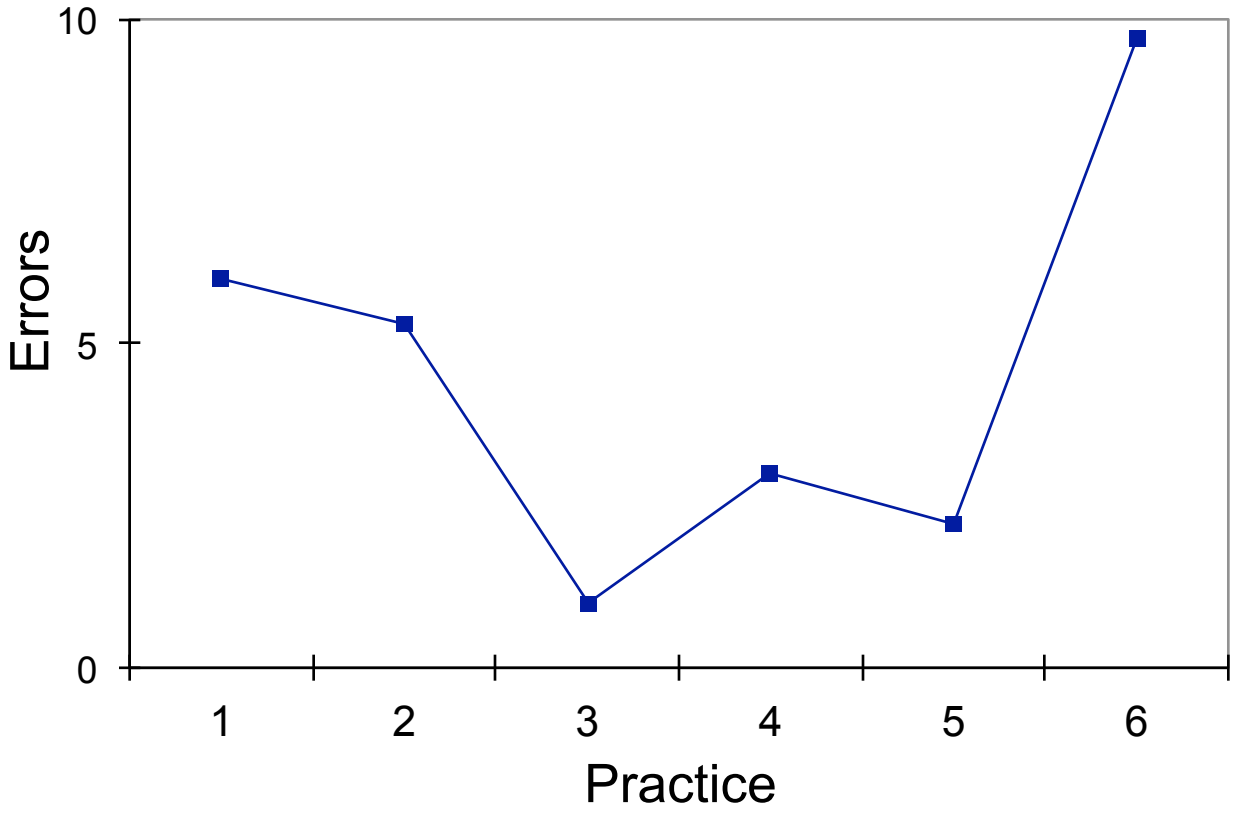
- Decades of research about how people learn
- Starting from a core architecture of cognition, we build a quantitative cognitive model of skill learning
- This exposes deeper features of students' learning than you can get at by looking at just raw performance
- A key idea is that learning is *skill specific:*

The Power Law of Learning

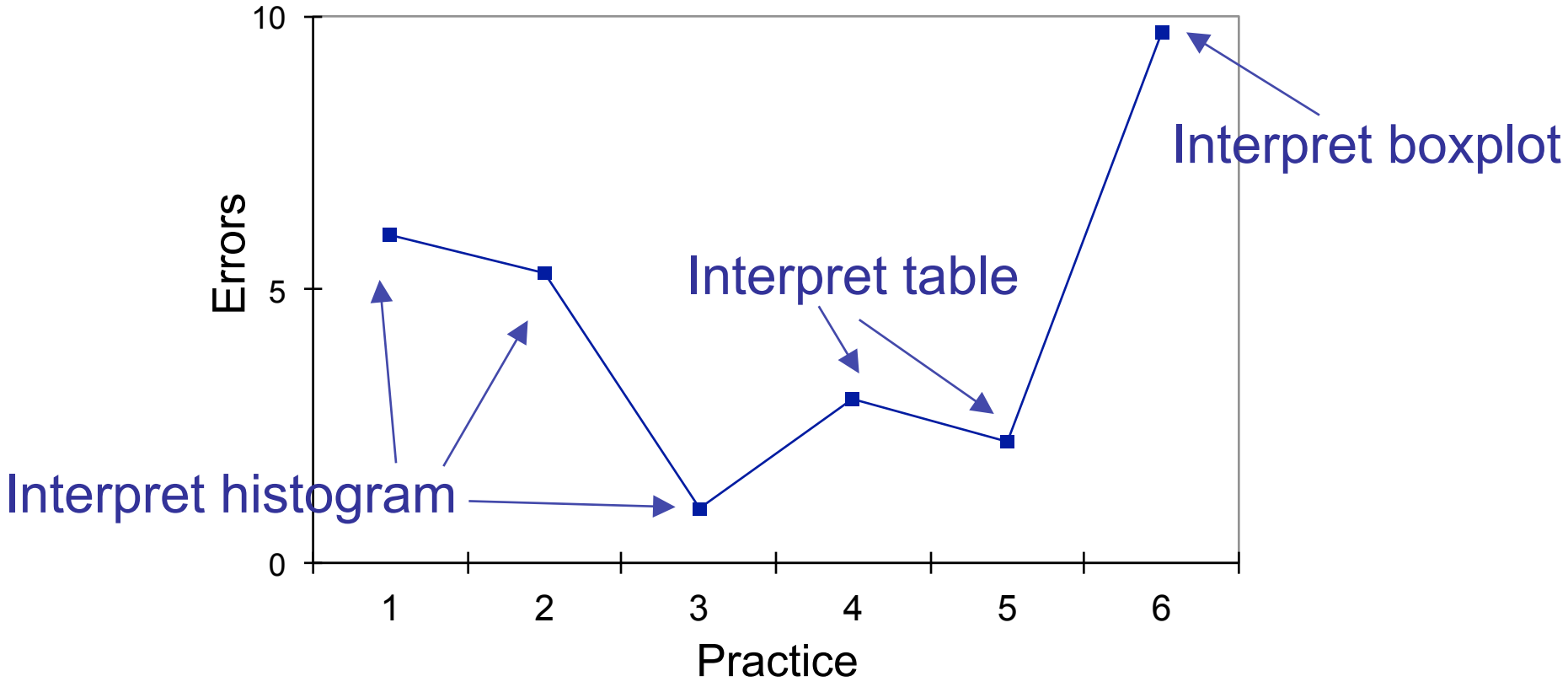


As students practice, performance improves with marginally decreasing returns

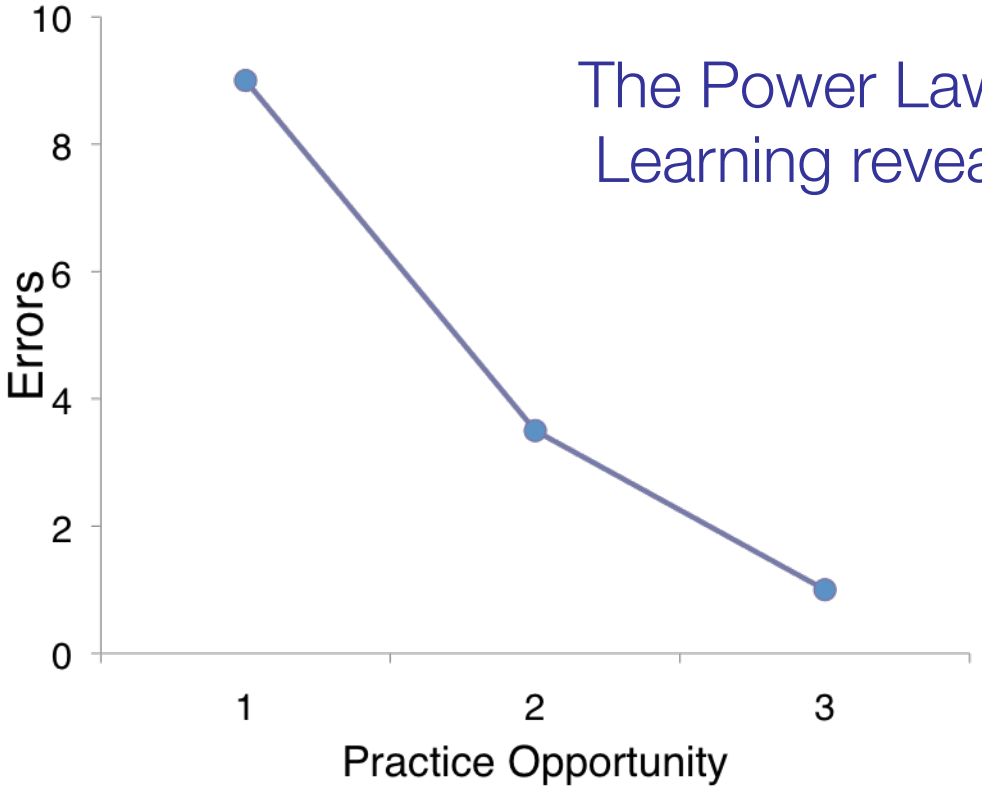
The Performance We Observe



The Underlying Skills

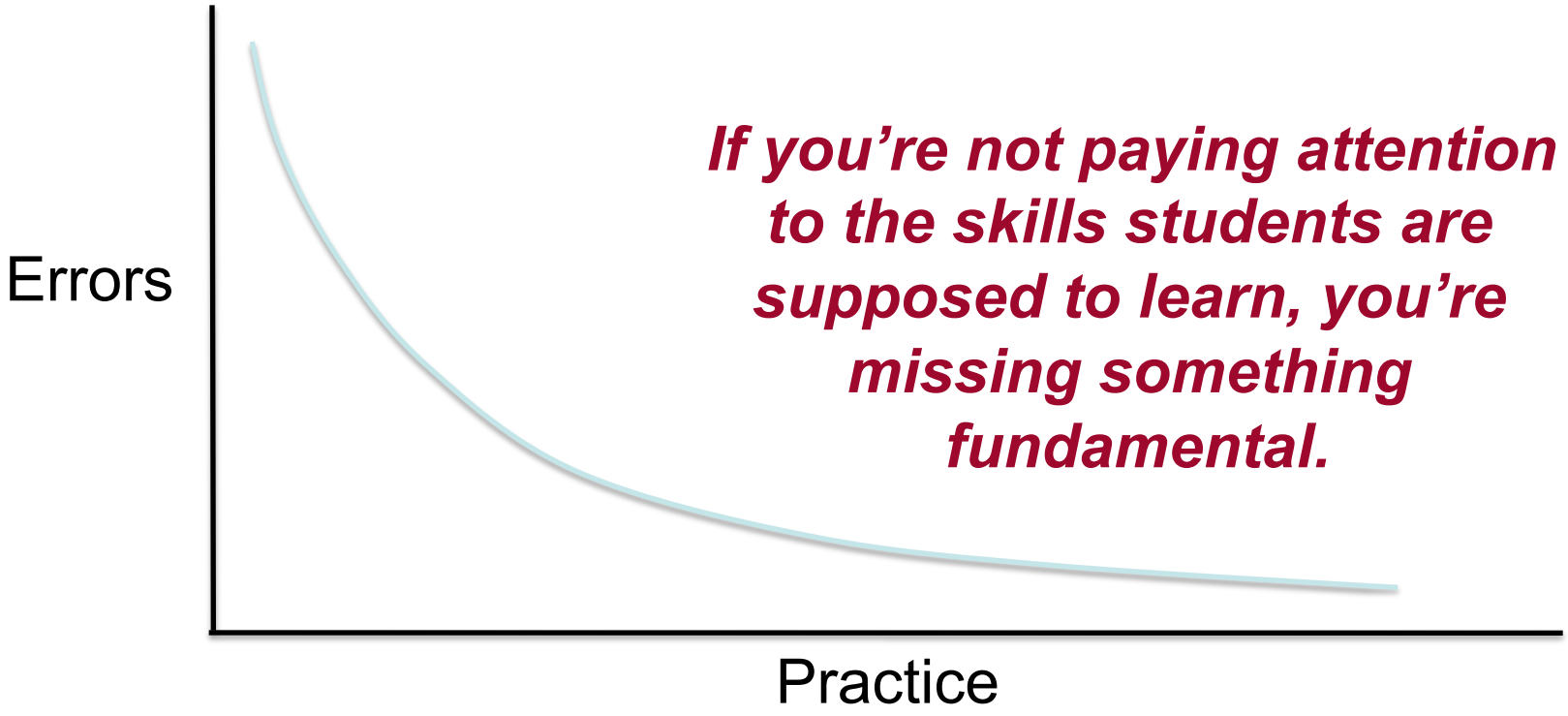


Performance Re-indexed



The Power Law of Learning revealed

The Power Law of Learning



If you're not paying attention to the skills students are supposed to learn, you're missing something fundamental.

As students practice *a given skill*, their performance *at that skill* improves; Other skills are not affected.

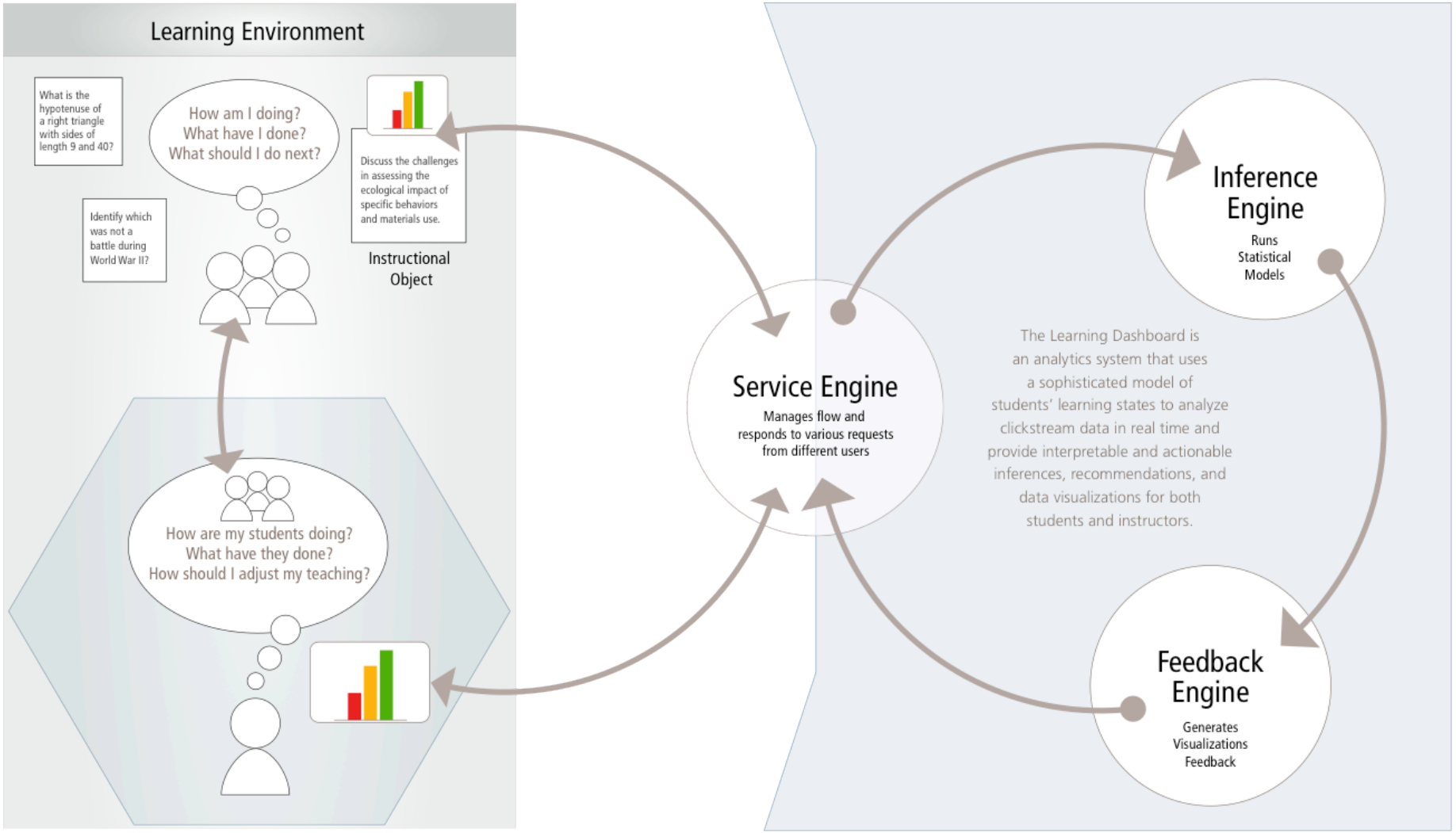
Learning Dashboard's Key Ingredients

State-of-the-Art Statistical Models

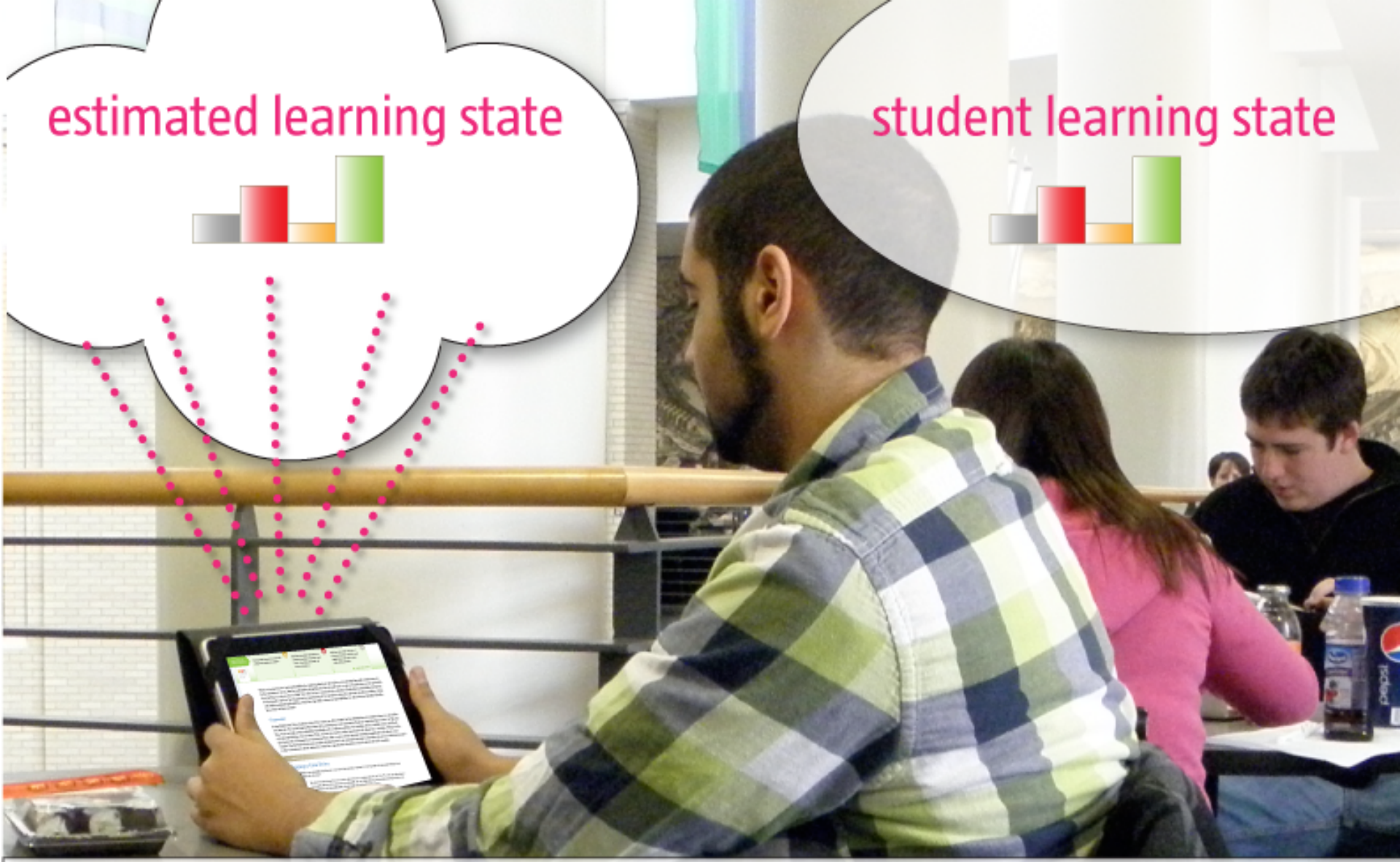
- Bayesian hierarchical models capture multiple components of variation in the data to make sharp inferences
  - The latent variables of interest – *students' learning states* - become more accurate as data accrues
  - "Borrowing strength" across students, classes, and populations improves precision and generalizability
- Sophisticated algorithms enable efficient computation

LEARNING DASHBOARD

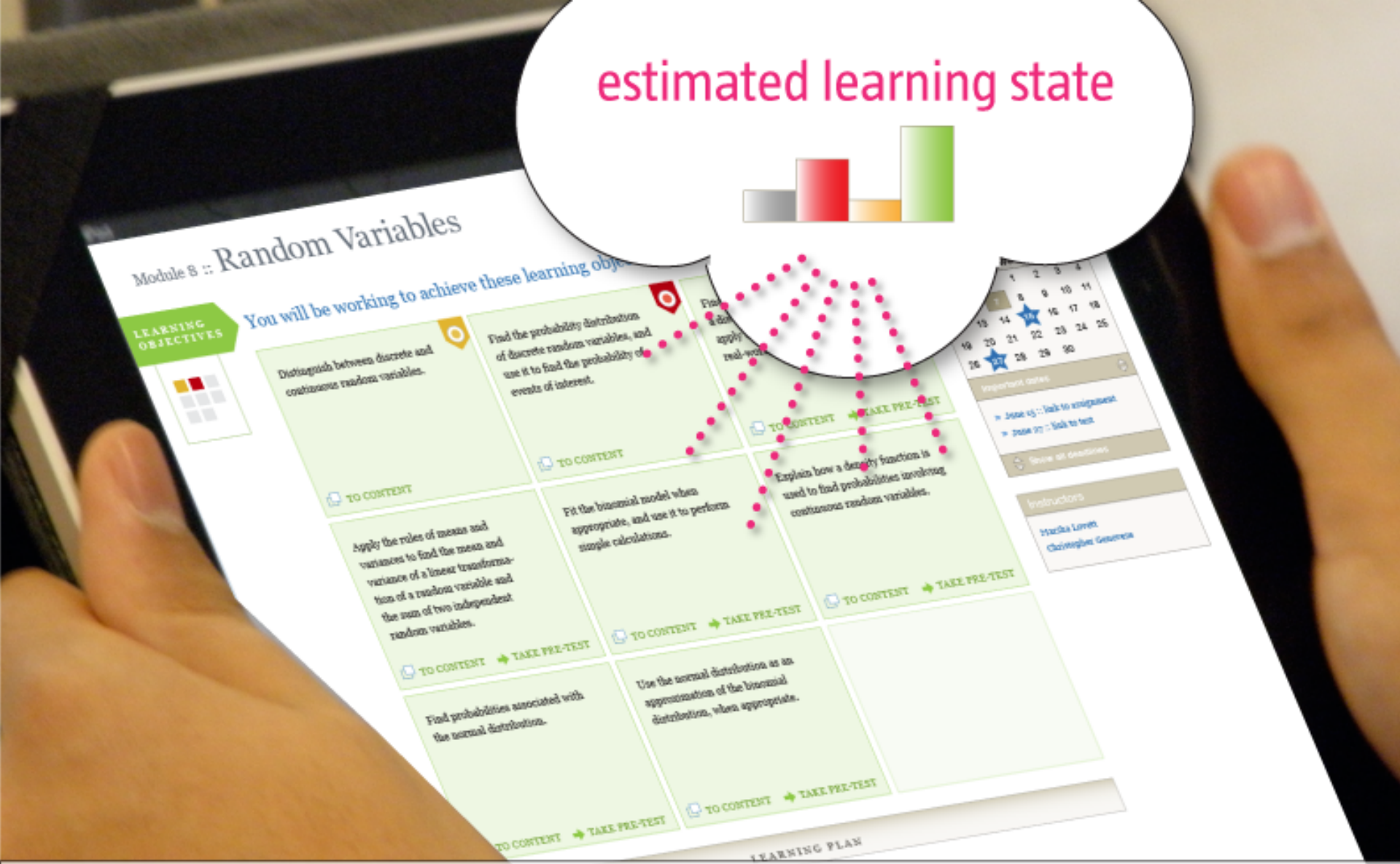
Instrumenting for the Learning Dashboard is simple and easily automated



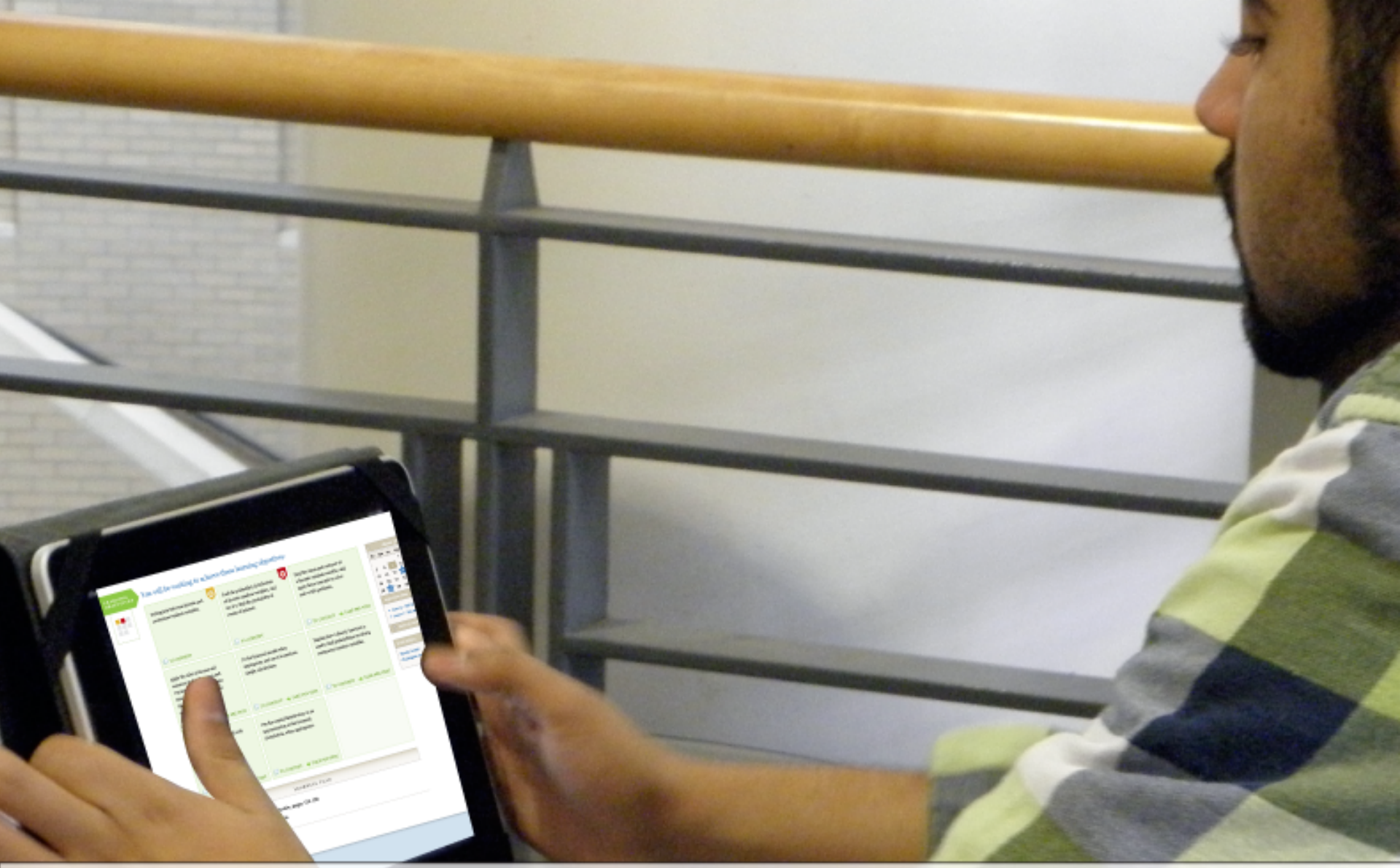
When working on an instructional activity, a student is drawing on particular knowledge and skills, some of which may be correct or incorrect, some of which may be strong or weak.



The student's interactions are transmitted to the *Learning Dashboard* where state-of-the-art statistical and cognitive models make inferences about the student's current learning state.



The *Learning Dashboard* creates interactive displays to communicate key aspects of the learning state to the **student**, instructor, and administrator.



Student clicks on a recommendation from the *Learning Dashboard* and goes back into content.

The *Learning Dashboard* creates interactive displays to communicate key aspects of the learning state to the student, **instructor**, and administrator.

Accelerated Learning Hypothesis

Hypothesis: With this kind of adaptive teaching and learning, students can learn the **same material** as they would in a traditional course in **shorter time** and still show **equal or better learning**.

(Lovett, Meyer, & Thille, 2008)

Three Accelerated Learning Studies

Within the Open Learning Initiative's Statistics course:

#1 Small class, expert instructor

Collect baseline data on standard measures

Test new dependent measures

#2 Replication with larger class

With retention & transfer follow-up 4+ months later

#3 Replication and extension to a new instructor

Adaptive/Accelerated vs. Traditional

Two 50-minute classes/wk	**Four** 50-minute classes/wk
Eight weeks of instruction	**Fifteen** weeks of instruction
Homework: complete OLI activities on a schedule	Homework: read textbook & complete problem sets
Tests: Three in-class exams, final exam, and CAOS test	Tests: Three in-class exams, final exam, and CAOS test

Same content but different *kind* of instruction

Adaptive/Accelerated vs. Traditional

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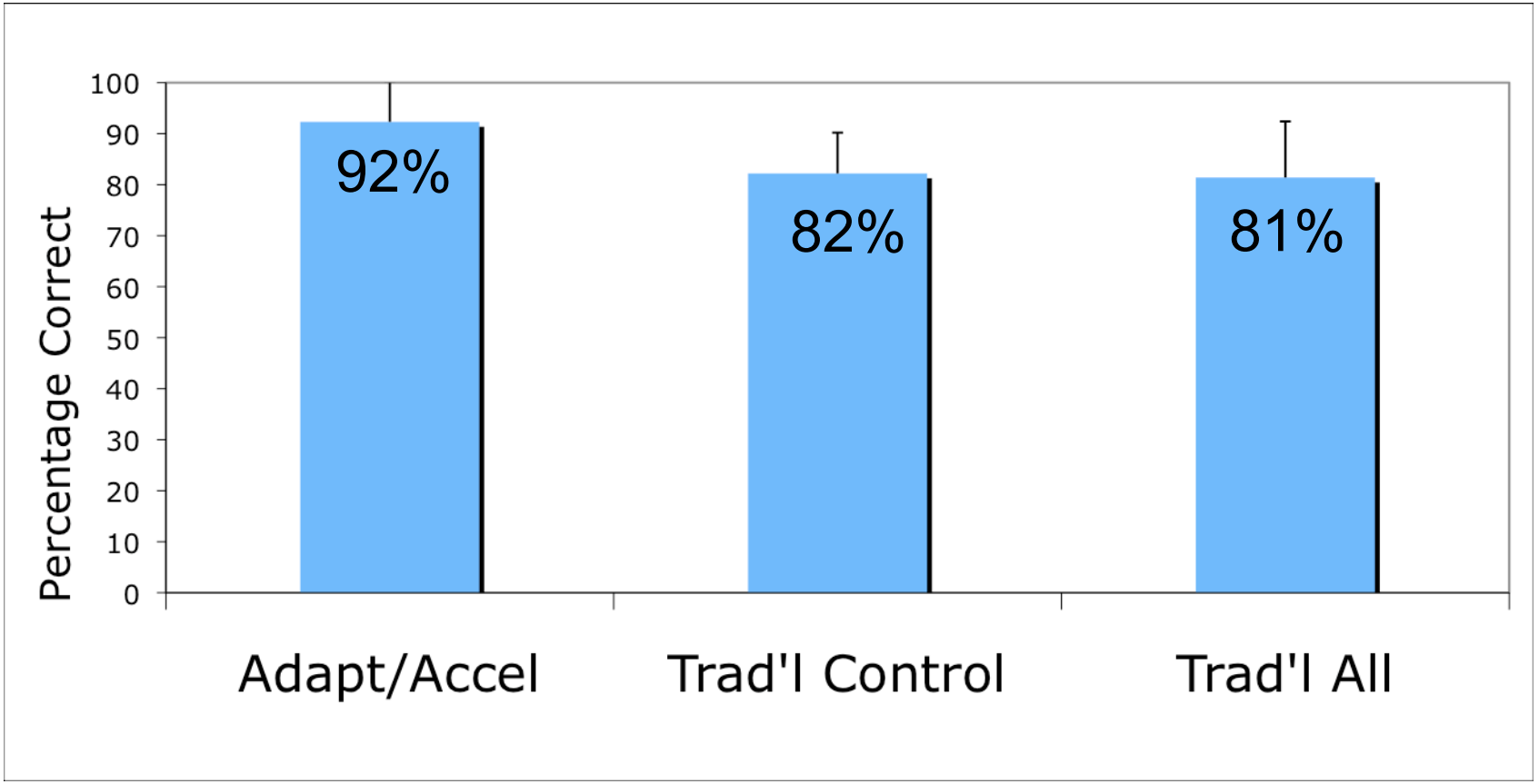
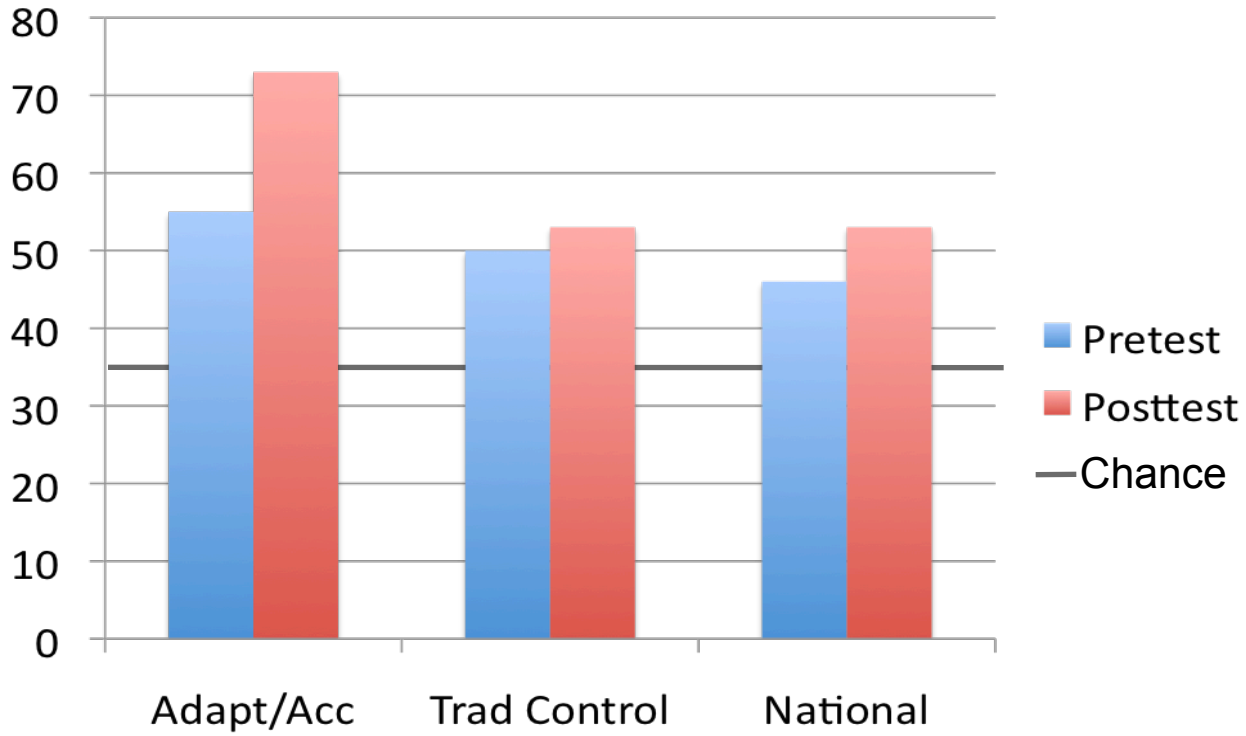
Final Exam Performance



Adaptive/Accelerated had highest exam scores, but they were not statistically different from Traditional.

Standardized Test Results

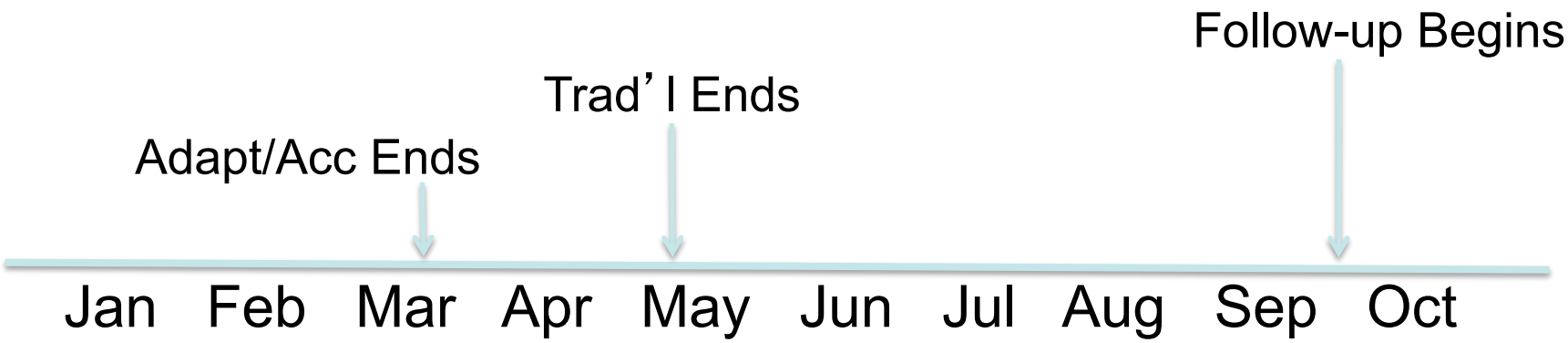


Adaptive/Accelerated group gained significantly more pre/post than the Traditional Control group, 18% vs. 3%

Follow-up: Retention & Transfer

Goal: Study students' retention and transfer in both groups

Students were recruited at the beginning of the following semester



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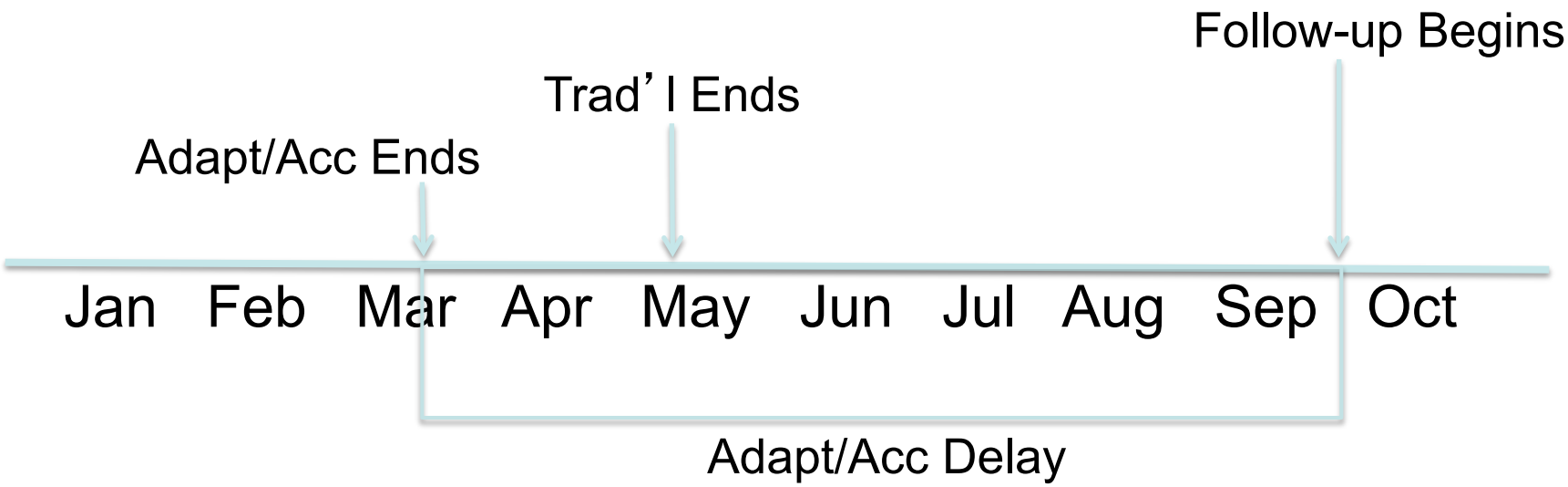

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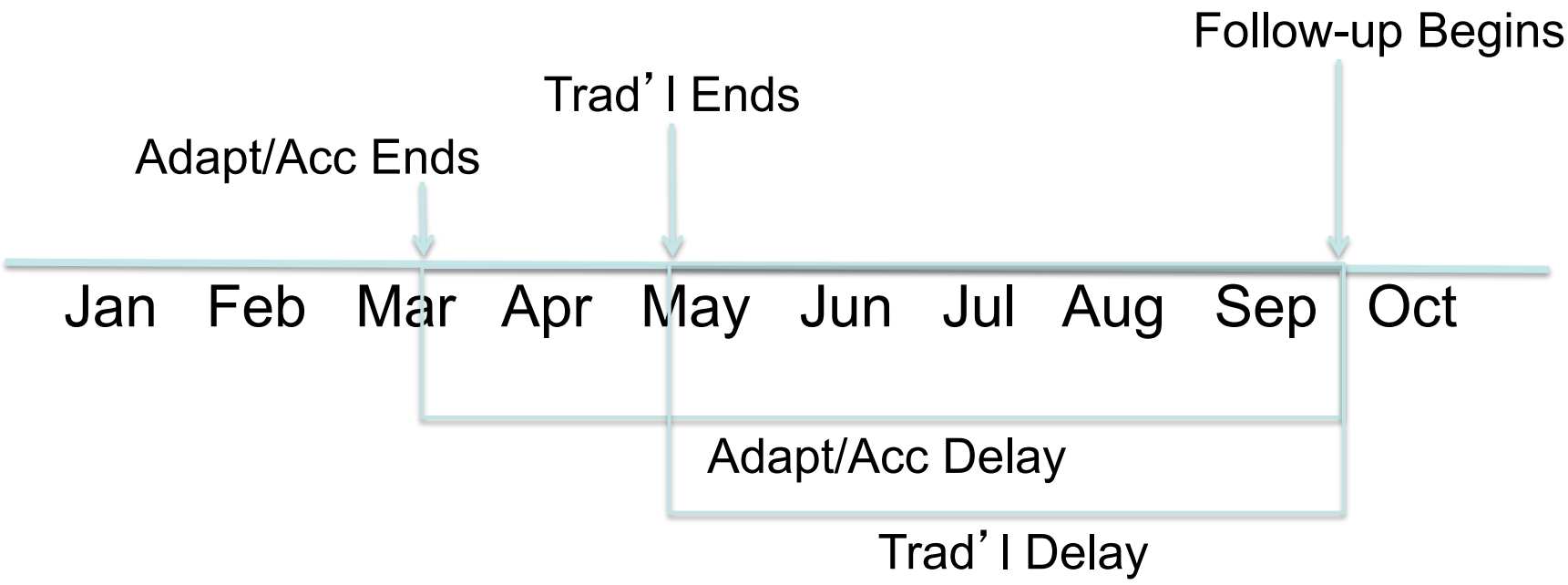
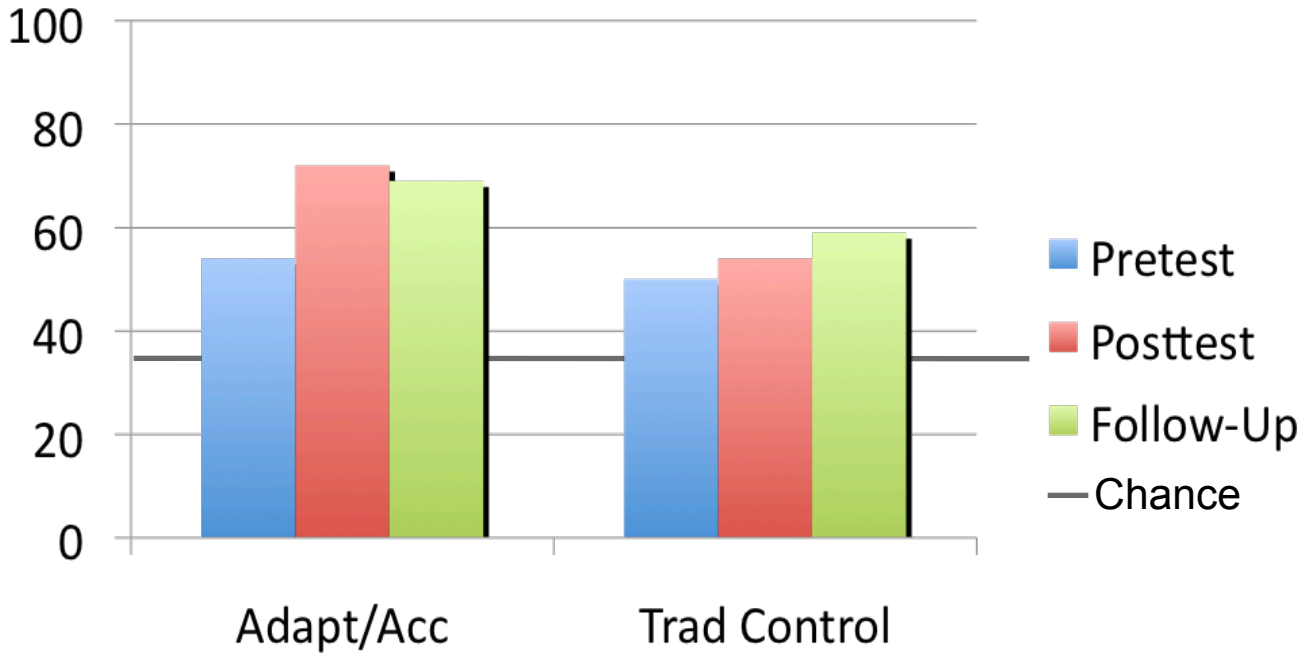
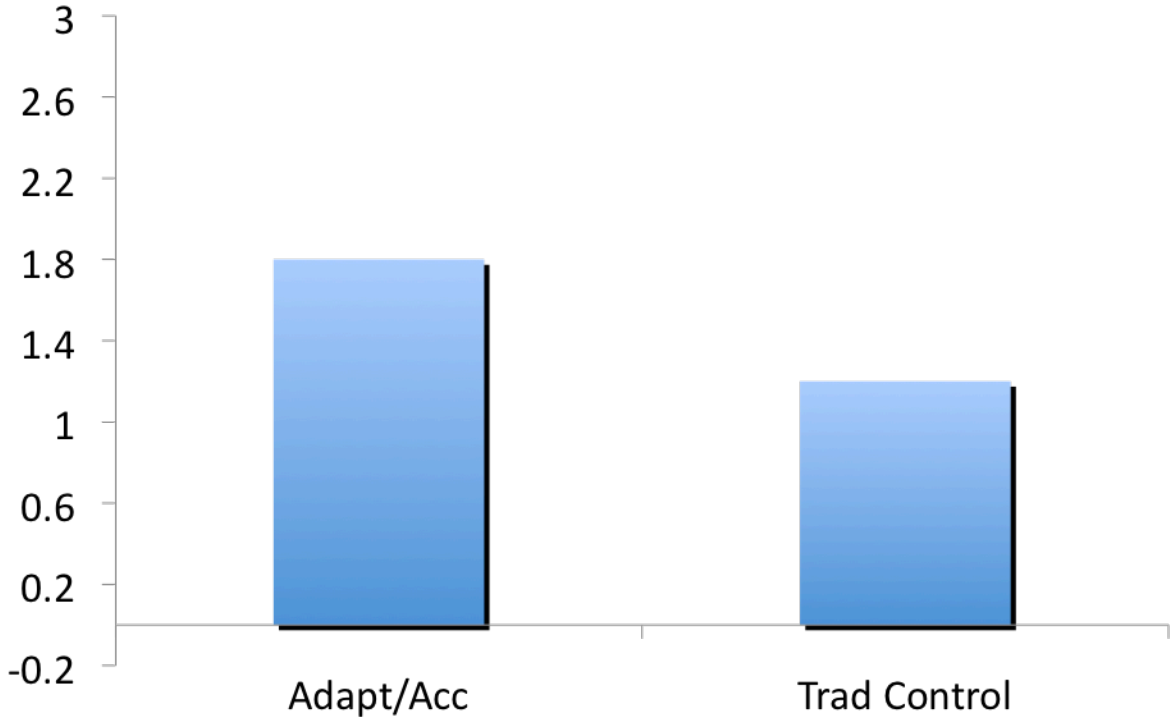


Retention: Standardized test



At 6-month delay, Adaptive/Accelerated group scored higher on CAOS than Traditional Control, $p < .01$.

Transfer: Open-Ended Data Analysis



Adaptive/Accelerated group scored significantly higher than Traditional Control.

Quotes

This is so much better than reading a textbook or listening to a lecture! My mind didn't wander, and I was not bored while doing the lessons. I actually learned something. – *Student in study*

The format [of the adaptive/accelerate course] was among the best teaching experiences I've had in my 15 years of teaching statistics. – *Professor from Study 1*

At the University of Maryland, Baltimore County, teacher Bonnie Kegan found one big advantage was the timely feedback the software gave by tracking students' answers to questions posed as they worked through each lesson. "You can drill down and see what questions they're missing," she says.

– from "Tapping Technology to Keep Lid on Tuition" by David Wessel, *Wall Street Journal,* July 19, 2012

Take-Home Points

- Currently, the rich data available from students' learning interactions are only barely being tapped.
- Cognitively informed models and sophisticated statistics add value to learning analytics.
- The *Learning Dashboard* contributes to significant improvements in teaching and learning: students' gains jump from 3% to 18%!