Causal Model Search in Educational Research

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1. INTRODUCTION

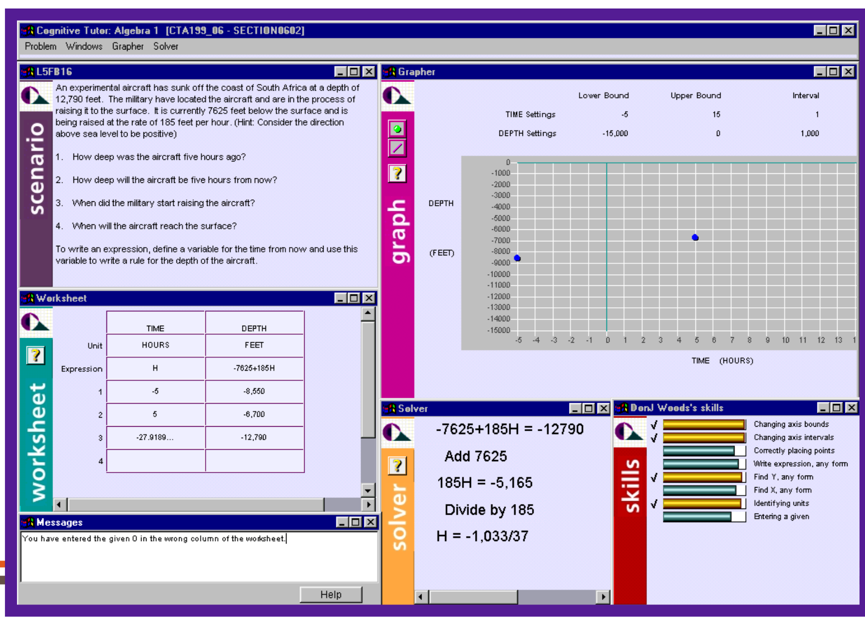
“Online” Educational Data

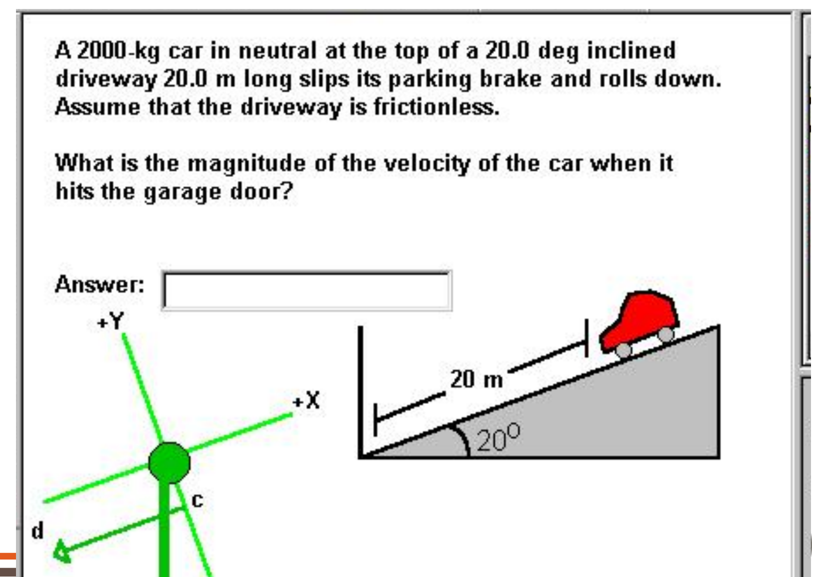
Data Pouring in From:

- Computer Tutors
- Online courses
- Virtual Labs

Pittsburgh Science of Learning Center
http://www.learnlab.org

- NSF center on learning science (1 of 6)
- Cognitive Tutors (Algebra, Physics, Geometry, etc.)
  - ~600,000 HS students
  - Recent independent evaluation (180 schools): twice as much algebra learned
- Datashop
  - ~500 publicly accessible datasets in standardized format
  - Analytic tools for analyzing these data





Online Course

CMU: The Open Learning Initiative

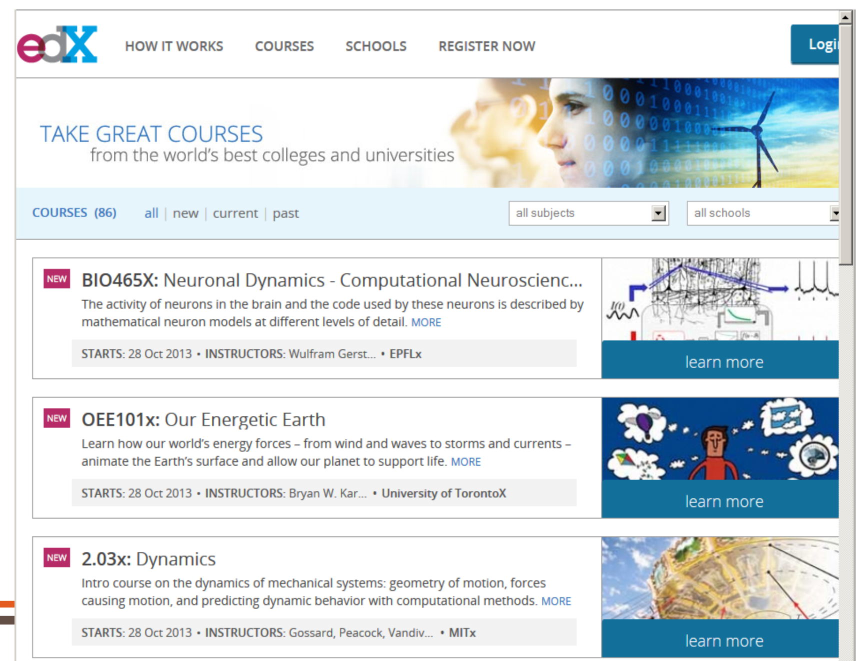
www.cmu.edu/oli

- Since 2002
- 25 College courses
- Automatic data logging
- Dozens of research studies

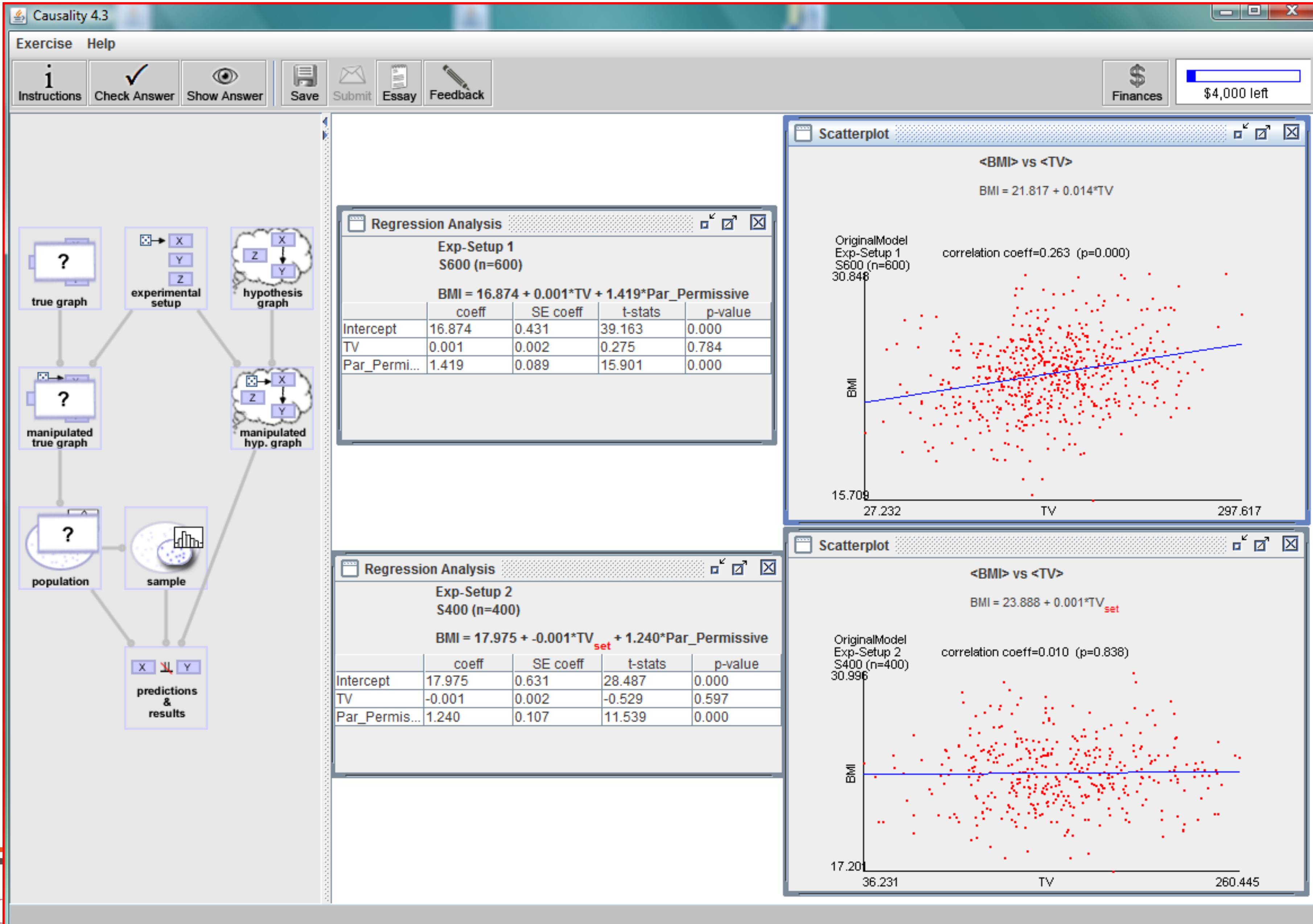
EdX

https://www.edx.org/

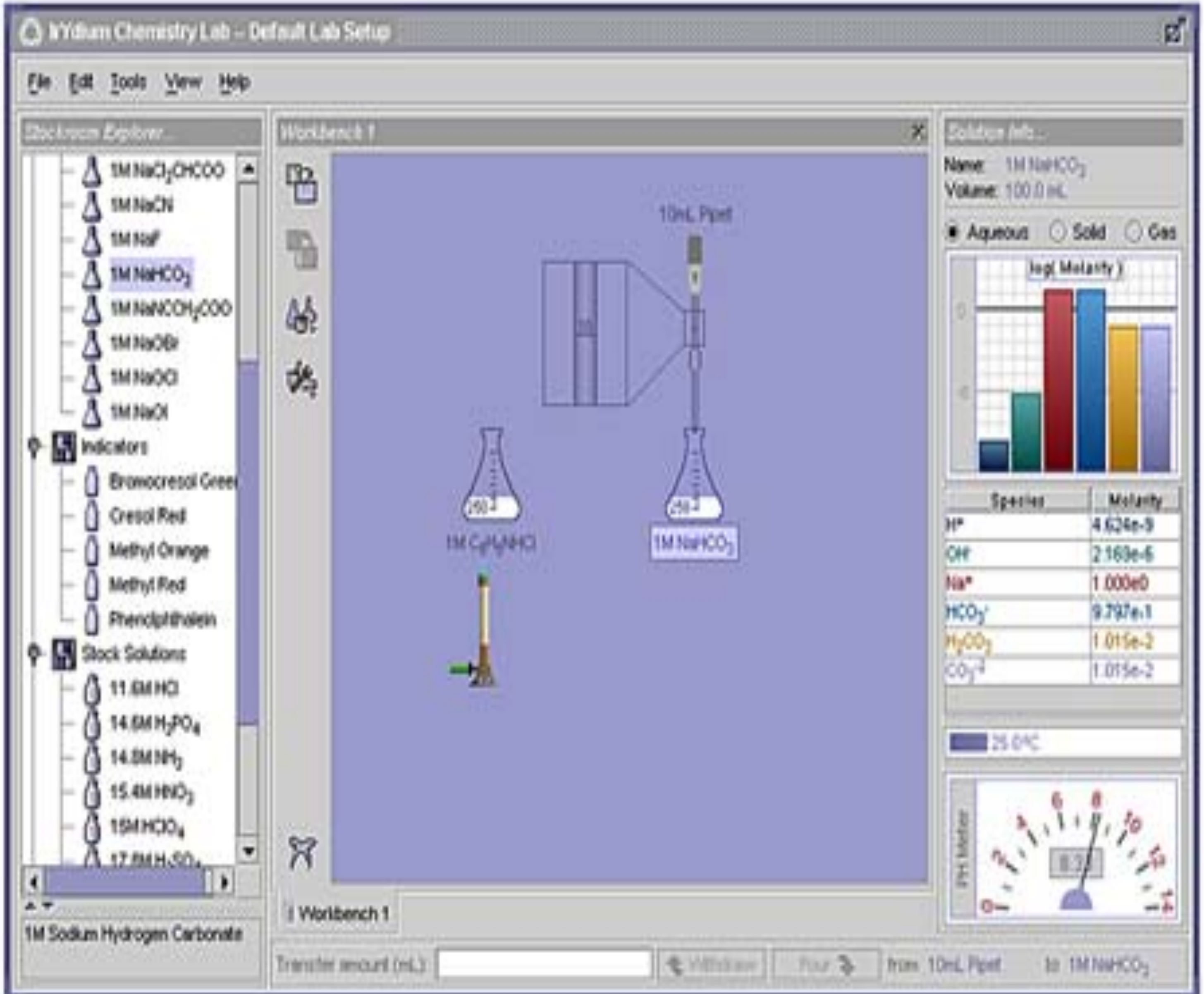
- MIT, Harvard, Berkeley, UT
- > $ 50 million in start-up funding
- Data collection being made public
- Data mining being prioritized



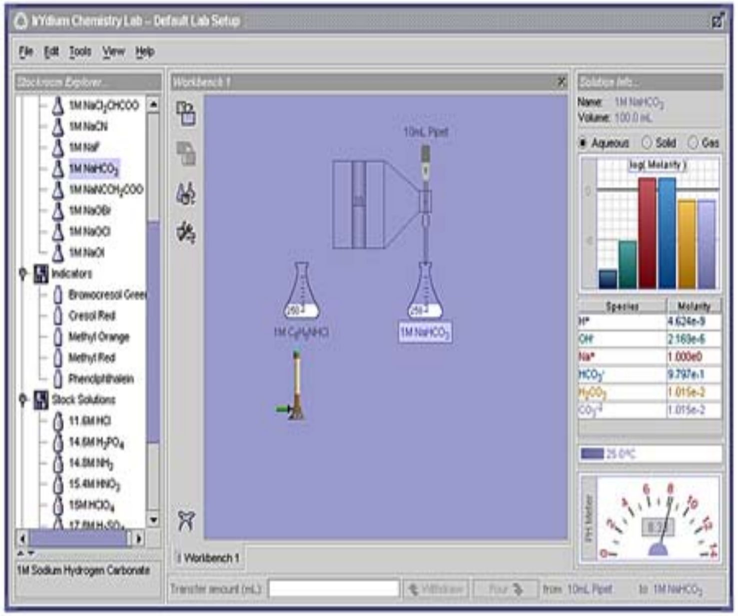
Virtual Labs: Causality Lab



Virtual Labs: Chem Lab



Virtual Labs: Chem Lab



- Number of engaged actions ⇒ 48% of the post-test variation

- # interactions with the virtual lab outweighed ALL other factors including gender and SAT score as the predictor of positive learning outcome.

Kinds of Data

1. Log data – time stamped events:

   login, page request, glossary, quiz attempt, score request, video, etc

2. Assessment data -
   - Pre-test scores
   - Intermediate assessments (low stakes, high stakes)
   - Midterm score
   - Final exam scores

3. Problem Solving Data:

   a) Unstructured Virtual Labs --> Customized Data

   b) Structured Cognitive Tutors --> PSLC Data Shop

Log Data: Edx MOOC Example

User	Res	Time	Resp1	Resp2	Count1	Count2
9	video	2m 30s	- -	- -	- -	- -
9	answer	10m 5s	correct	correct	1	1
10	book	4m 41s	- -	- -	- -	- -
10	book	40s	- -	- -	- -	- -
10	answer	20s	incorr.	- -	1	- -
10	answer	15s	incorr.	- -	2	- -
10	answer	1m 8s	incorr.	incorr.	3	1
10	answer	28s	- -	correct	- -	2
10	video	2m 10s	- -	- -	- -	- -
10	answer	6s	correct	- -	4	- -

Log Data: Fractions Tutor Example

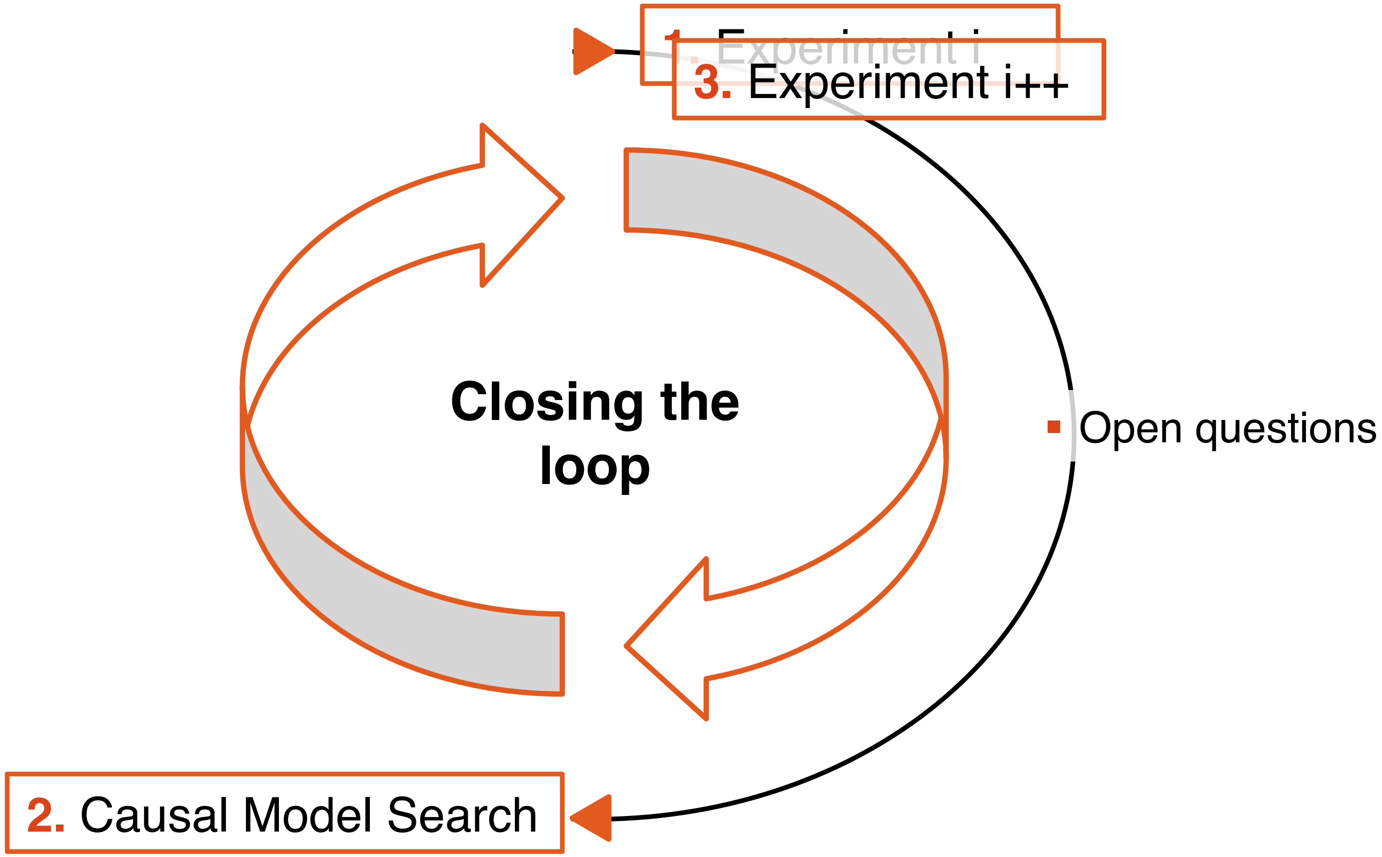
Student Id	Time	Duration (sec)	Student Response Type	Tutor Response Type	Problem Name	Step Name	KC Model	Attempt At Step	Outcome	Selection	Action	Input
Student1	5/14/13 14:09	1	ATTEMPT		1					NtpDate	NtpTimeCheck	2013-05-14 10:09:23.551 -0400
Student1	5/14/13 14:09	32	ATTEMPT	RESULT	1	fract1_numMultiply1 UpdateTextArea	equivMultiplyNum	1	Correct	fract1_numMultiply1	UpdateTextArea	3
Student1	5/14/13 14:10	4	ATTEMPT	RESULT	1	fract1_denomMultiply1 UpdateTextArea	equivMultiplyDenom	1	Correct	fract1_denomMultiply1	UpdateTextArea	3
Student1	5/14/13 14:10	4	ATTEMPT	RESULT	1	_root goToStep		1	Correct	_root	goToStep	2
Student1	5/14/13 14:10	18	ATTEMPT	RESULT	1	fract3_num UpdateTextArea	equivNameNumFract	1	Correct	fract3_num0	UpdateTextArea	1
Student1	5/14/13 14:10	3	ATTEMPT	RESULT	1	fract3_denom UpdateTextArea	equivNameDenomFract	1	Correct	fract3_denom0	UpdateTextArea	3
	5/14/13 14:10	6	ATTEMPT	RESULT	1	fract4_num UpdateTextArea	equivNameNumFract	1	Correct	fract4_num0	UpdateTextArea	3

“Online”Educational Data

Questions/Challenges:

- Raw Log Data → Meaningful Variables
- Which curricular or tutorial interventions cause learning?
- Which (influencible) student behaviors facilitate learning?
- By what mechanisms do successful interventions cause learning?

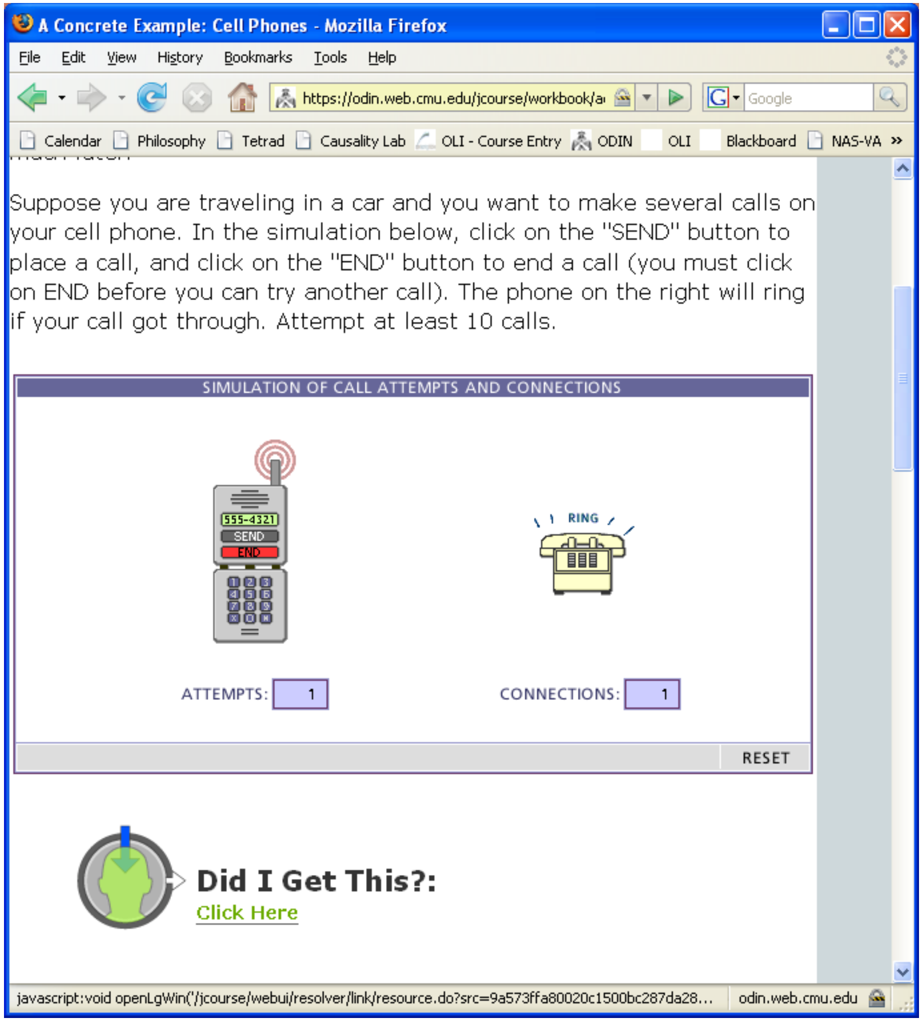
Motivation

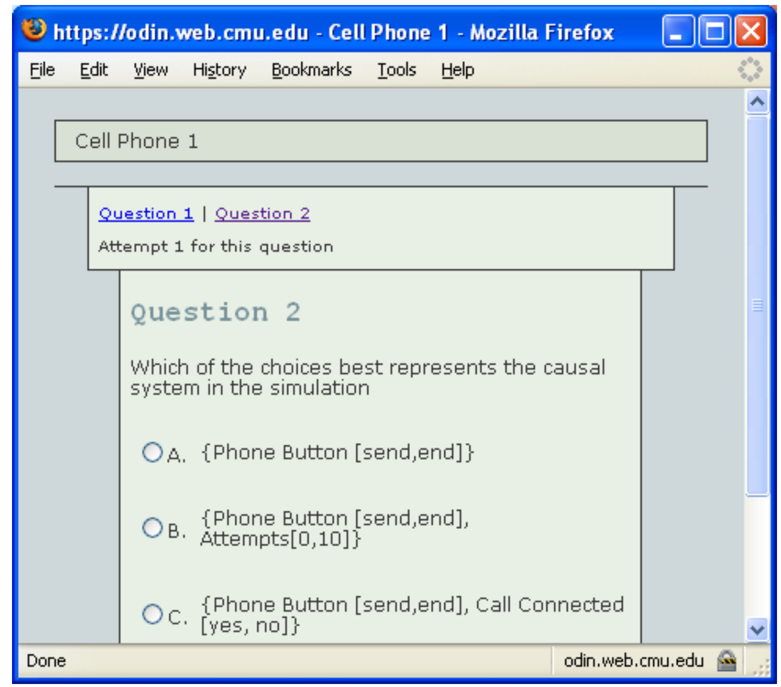


1. Experiment i
3. Experiment i++
Closing the loop
Open questions
2. Causal Model Search

2. MODEL SEARCH: ONLINE COURSE BEHAVIORS

Causal and Statistical Reasoning



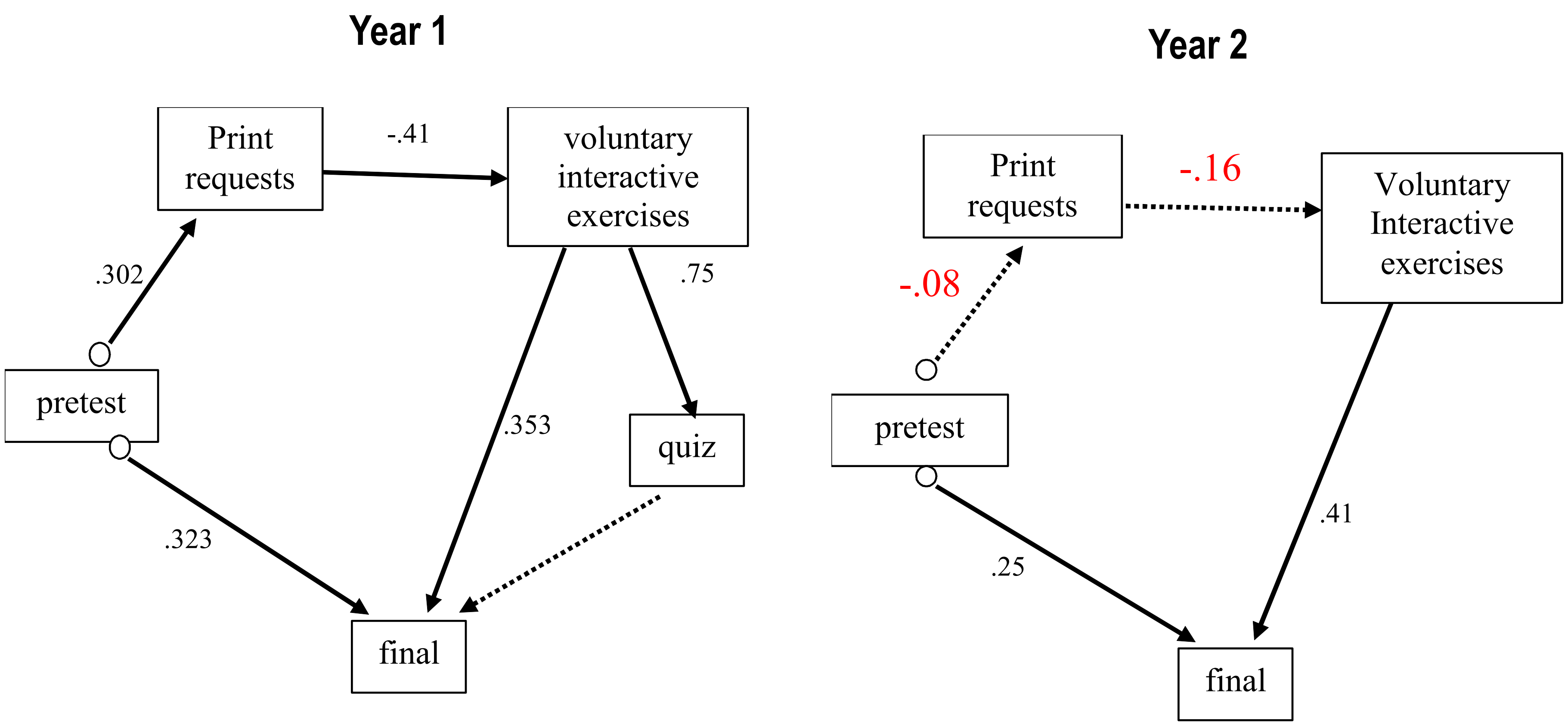


Student & Log Data

- Pre-test (%)
- Midterm1 (%)
- Gender
- Race
- Computer-comfort
- Final Exam (%)

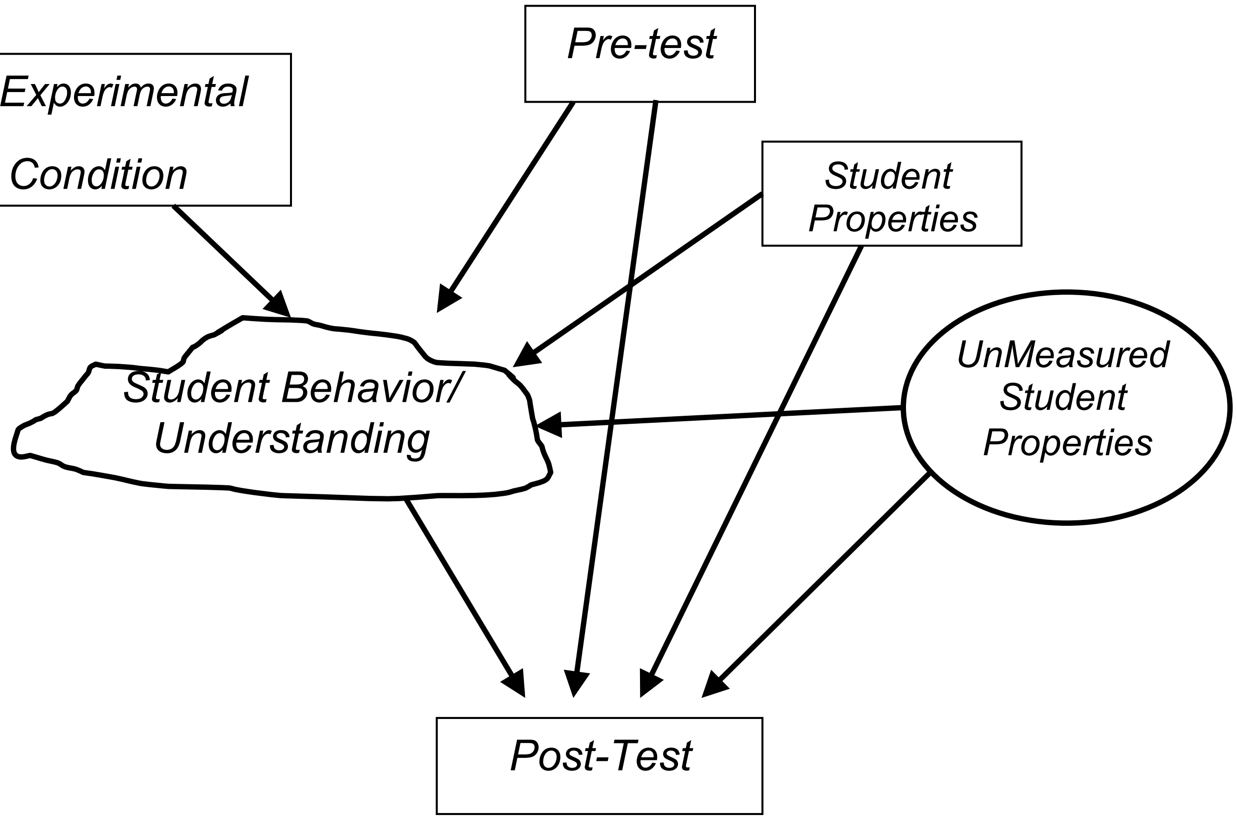
- Logged in time
- Voluntary-exercise completion (%)
- Quiz Scores (avg. %)
- Print-requests (% of modules)
- 12 others

Interaction → Learning

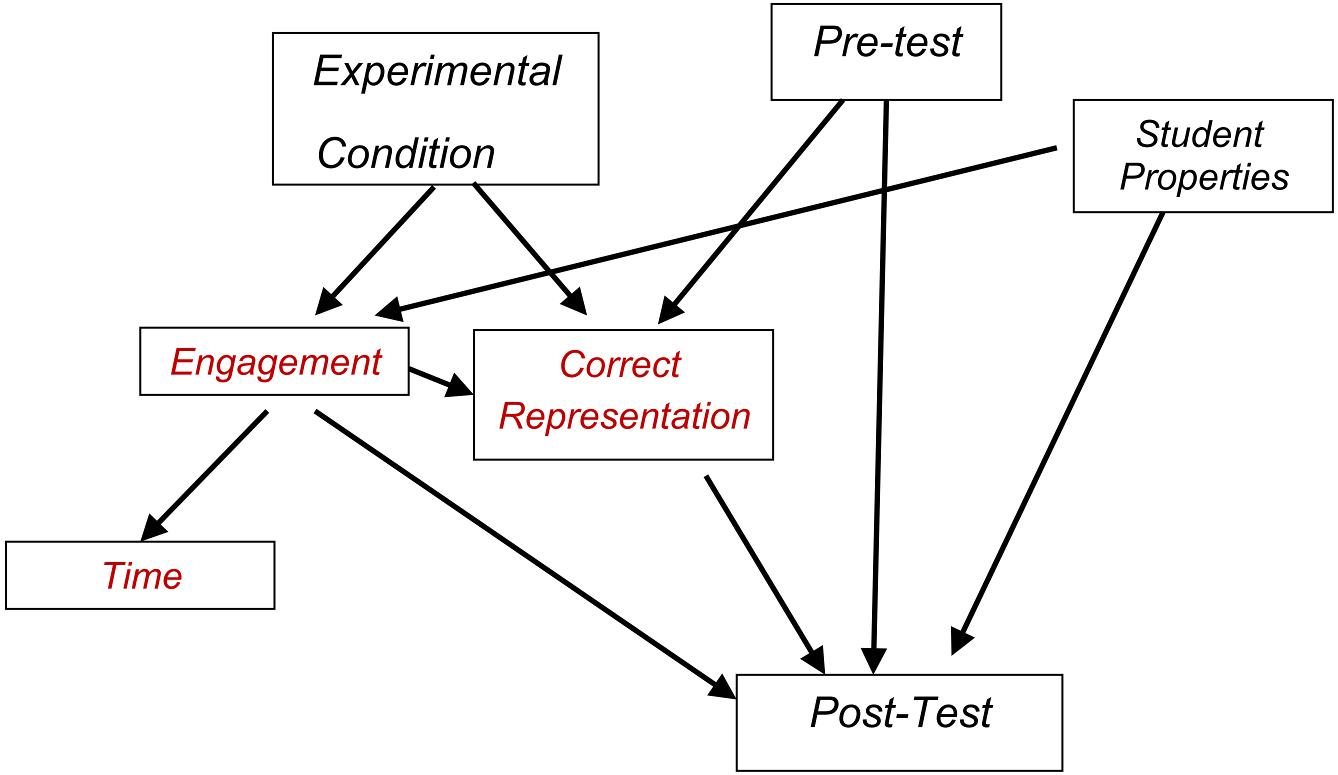


3. SEARCHING FOR MECHANISMS/MEDIATORS

What are the Mediators?



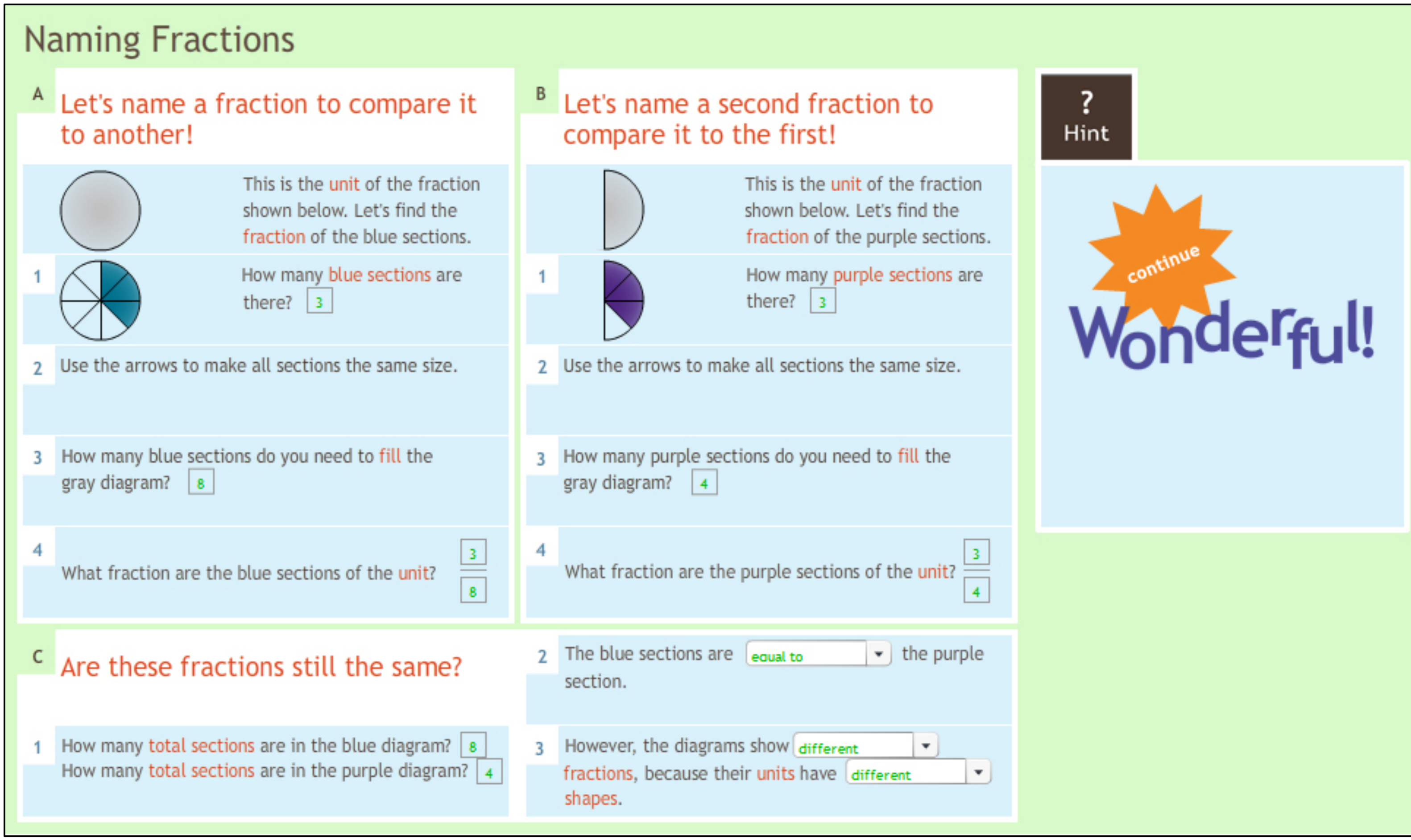
What are the Mediators?



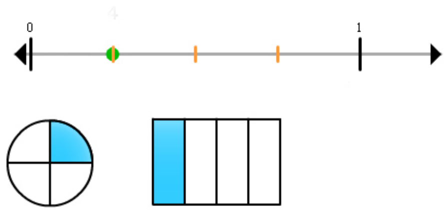
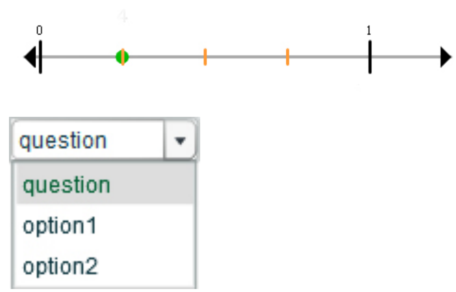
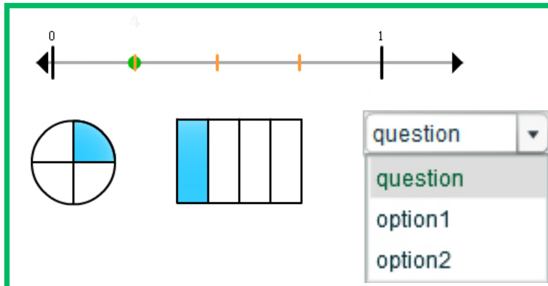
Exp. Condition _||_ Post-Test | {Pre-test, Student Properties, Engagement, Correct Rep}

Exp. Condition ~~_||_~~ Post-Test | {Pre-test, Student Properties, Time, Correct Rep}

Fractions Tutor

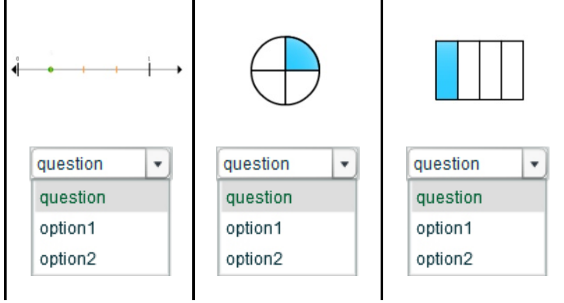
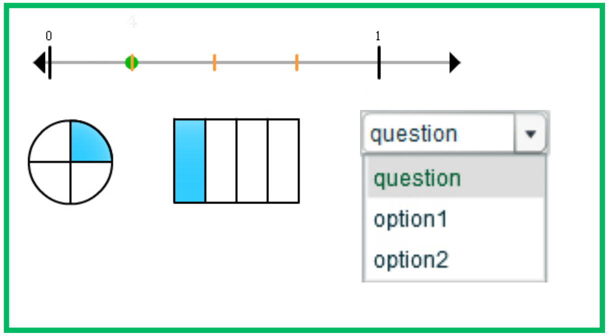


Experiment 1

	Single graphical representation	Multiple graphical representations
No self-explanation prompts		
Self-explanation prompts		

N = 110 6th-grade students, 2.5h
[Rau et al., AIED 2009, best student paper]

Experiment 2

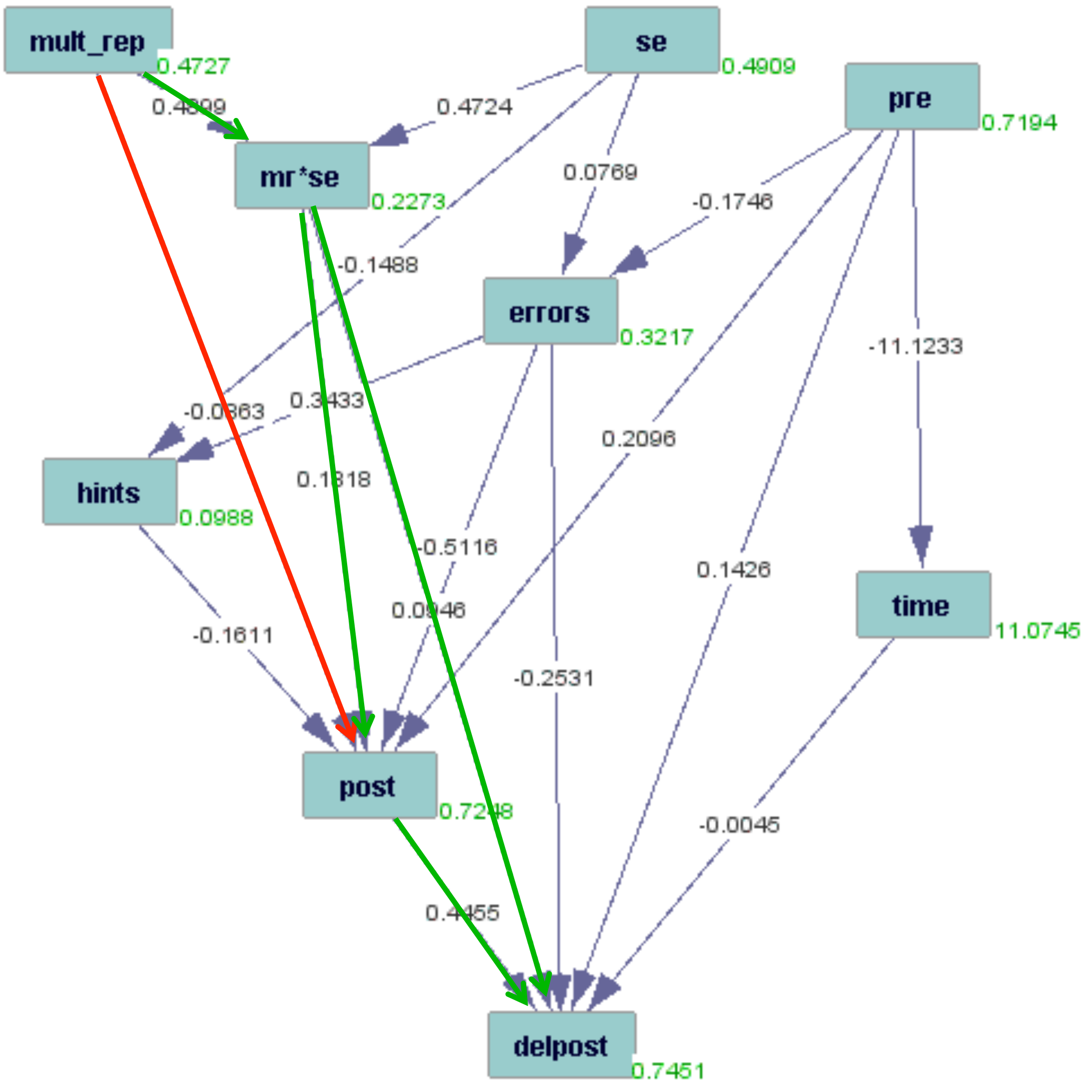
	Single graphical representation	Multiple graphical representations
Self-explanation prompts		

N = 290 4th- and 5th-grade students, 5h
[Rau et al., ICLS 2012]

Learning with Multiple Representations

- Multiple representations $\Rightarrow$ Learning √
- Mechanisms?
- Standard in ITS (Intelligent Tutor Systems):
  - *Error-rate*
  - *Hint-use*
  - *Time-spent*

Model Search: Experiment 1

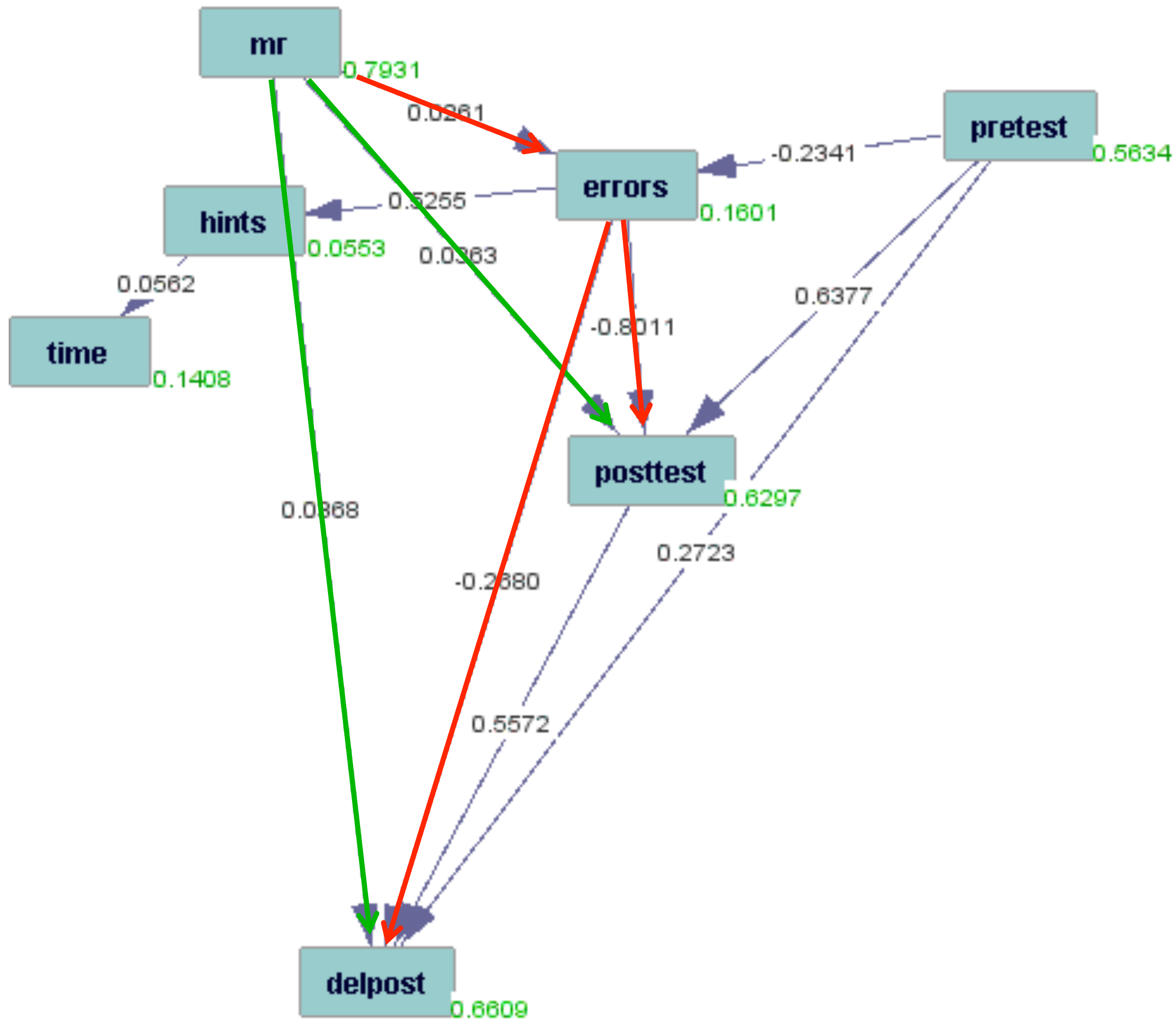


No mediation of multiple representations on learning

$\chi^2 = 22.11$, df = 19, $p = .29$

Model Search: Experiment 2

Error-rate mediates negative effect



Positive direct effects

Carnegie Mellon University

$\chi^2 = 6.89$, df = 10, $p = .74$

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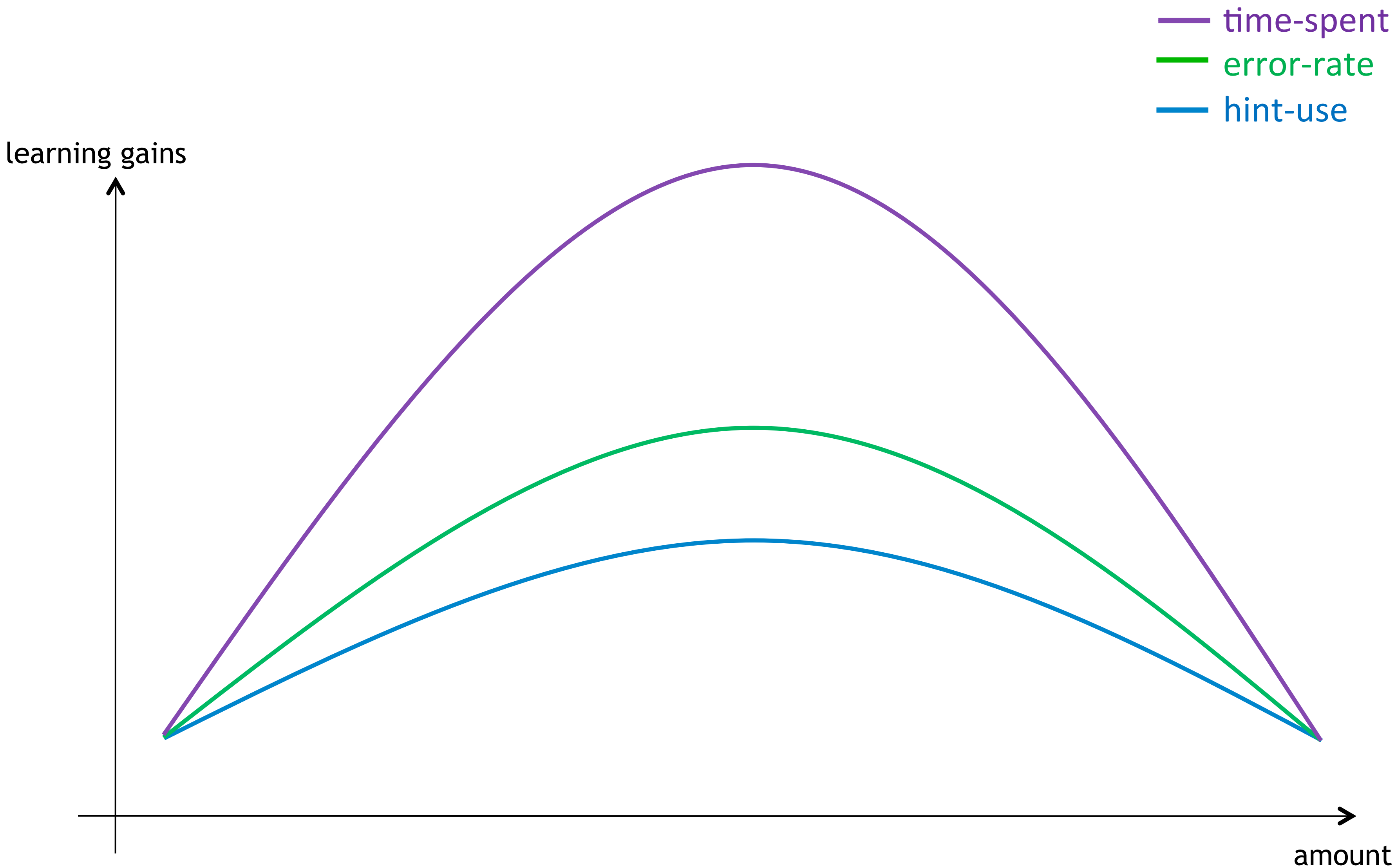
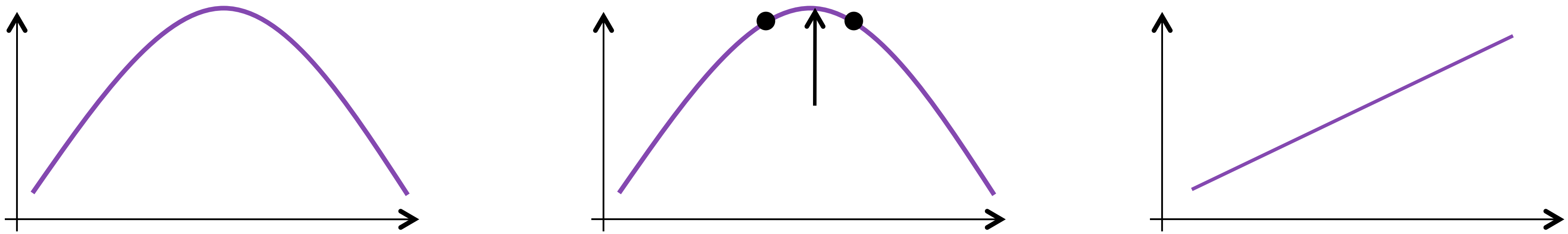
Mediator Variables: Non-monotic?



Tranforming/Defining Variables

Raw data (non-monotonic) → Transformation → Transformed Var. (monotonic)



Raw measures of error-rate, hint-use, time-spent,

Identification of 'optimal level' of error-rate, hint-use, time-spent

transformation: distance (squared distrance) from optimum

Transforming Variables: No help

- Result: raw variables no worse, perhaps better
- Models using the raw variables explained slightly more variance than models with the transformed variables

[Rau & Scheines, EDM 2012]

Experiments 1&2 Conclusions

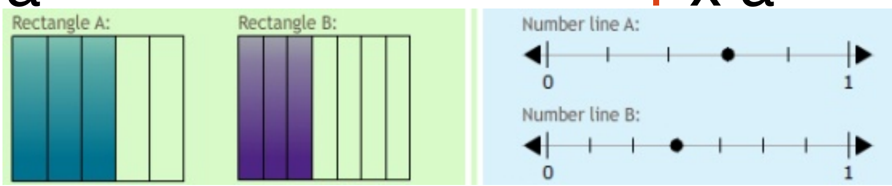
- Multiple representations increase learning
- Standard Variables: *Time*, *Error*, and *Hints* do ***not*** seem to be mechanisms through which multiple representations *increase* learning

4. INFORMED MEDIATORS

Motivation

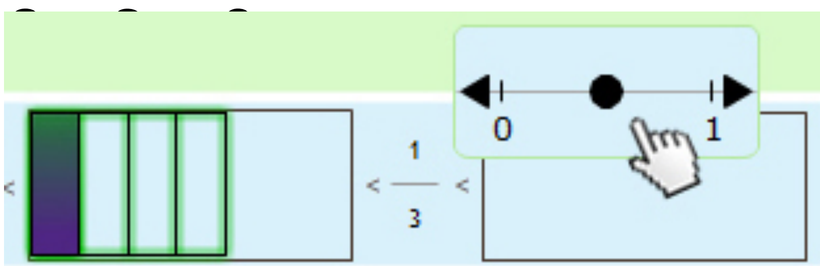
- Learning processes [Koedinger et al., 2012]:
  - Understanding: sense-making processes

a = 1 x a



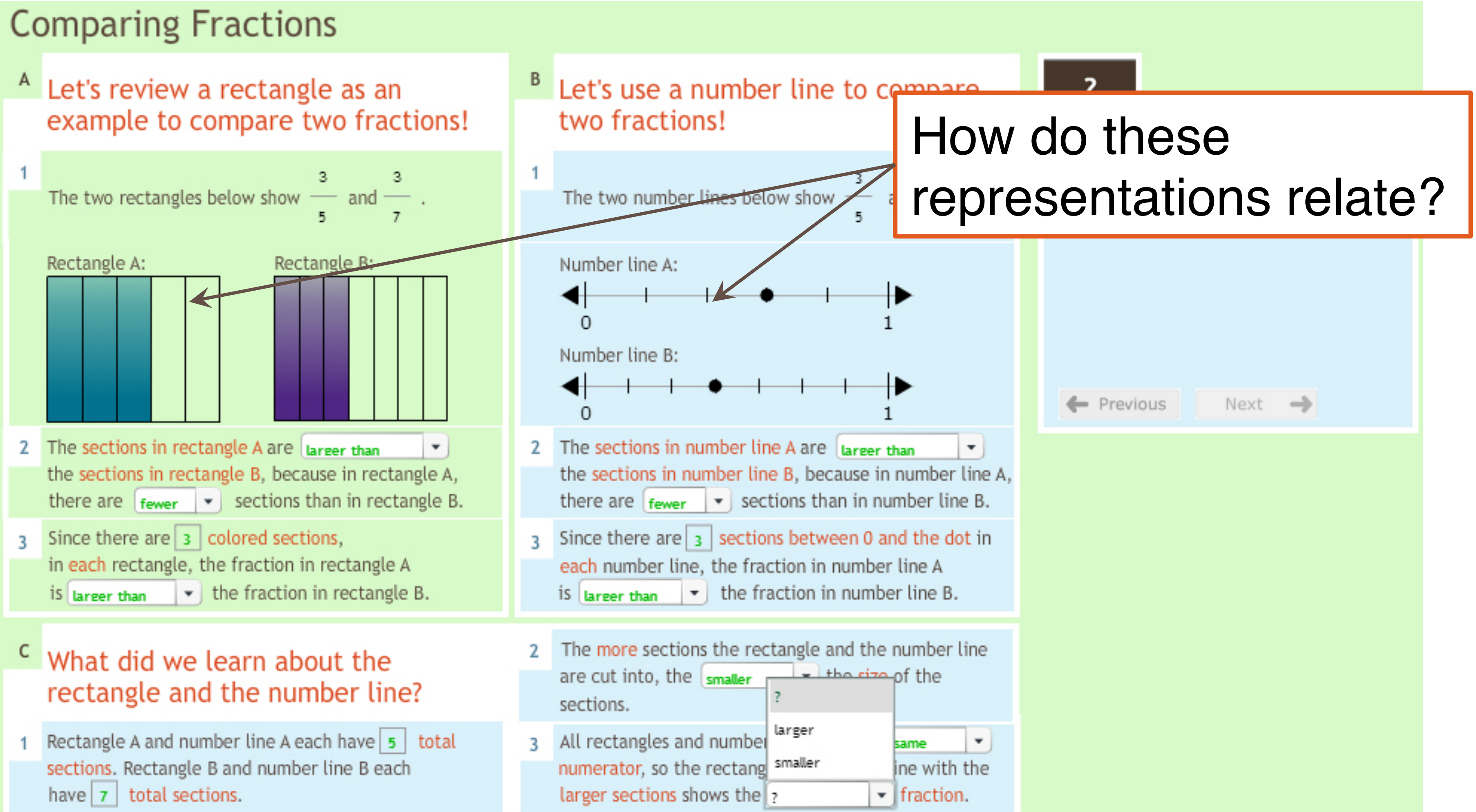
… …

  - Fluency: fluency-building processes

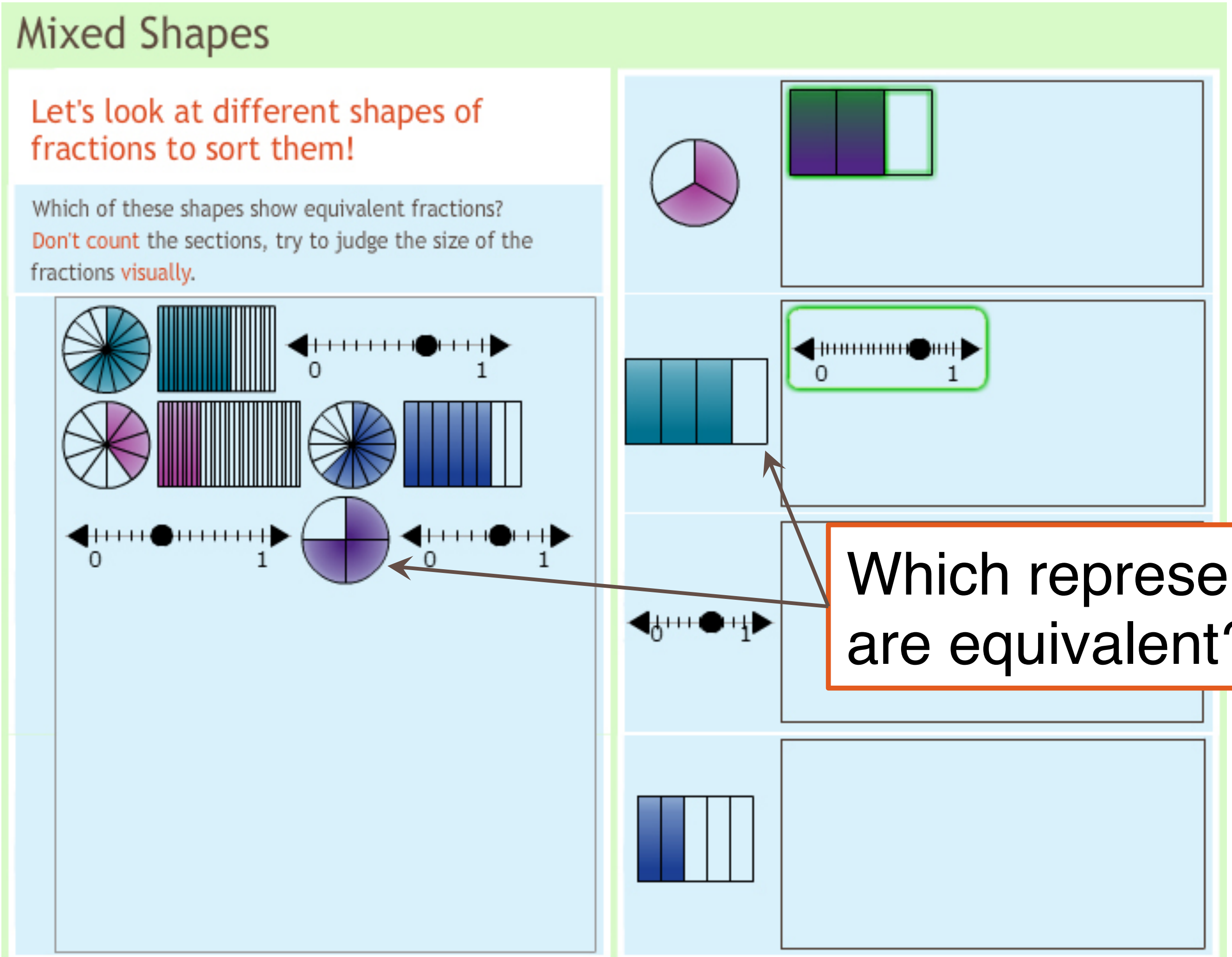


…

Fractions Tutor: Sense-making

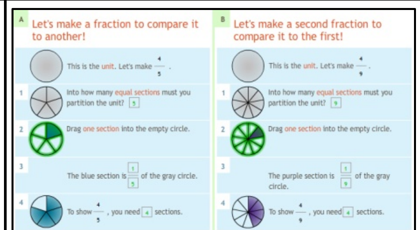
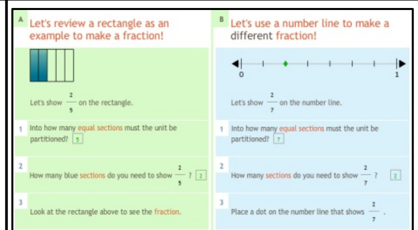
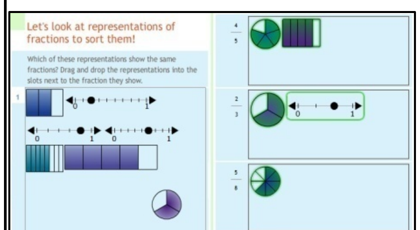
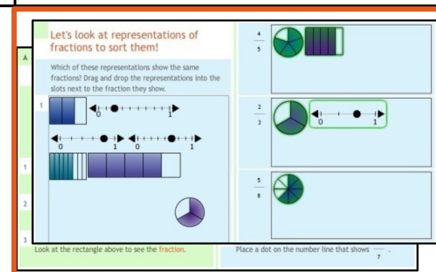
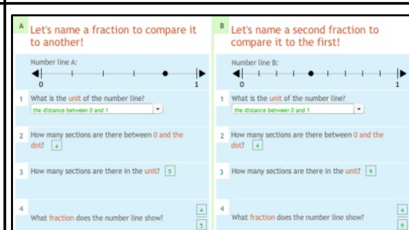


Fractions Tutor: Fluency-building



Which representations are equivalent?

Background: Experiment 3

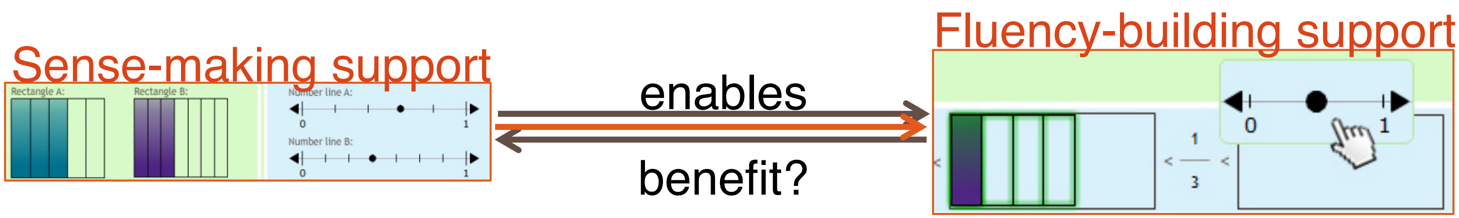
		Sense-making problems	
		no	yes
Fluency-building problems	no		
	yes		
Control			

- N = 599 4th-/5th-graders

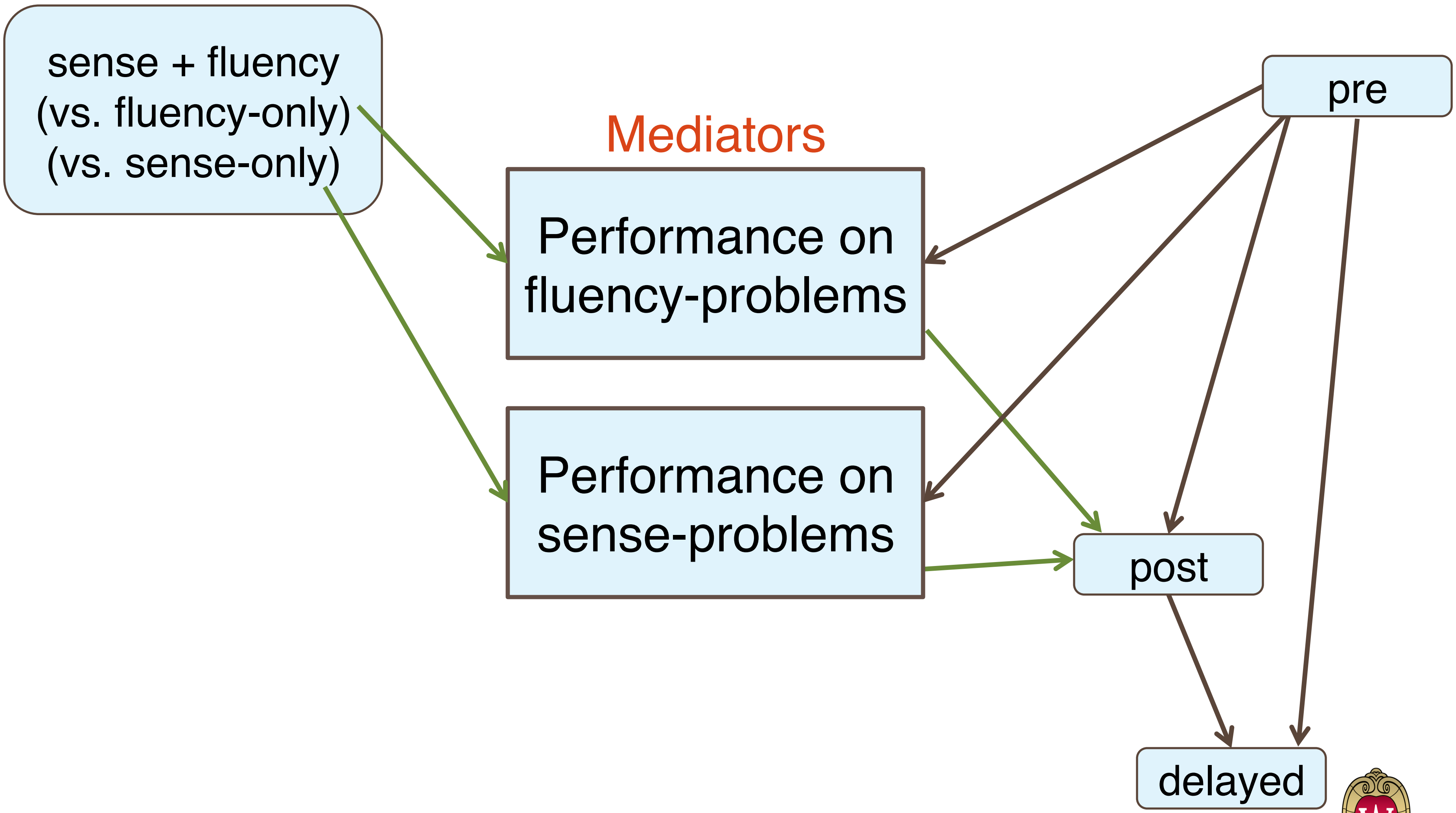
[Rau et al., ITS 2012]

Mediator hypotheses

- How do sense-making processes and fluency-building processes interact?
  - Understanding hypothesis:



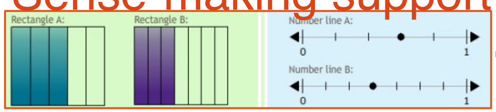
Mediation hypothesis



Mediation Hypotheses

- How do sense-making processes and fluency-building processes interact?
  - Understanding hypothesis:

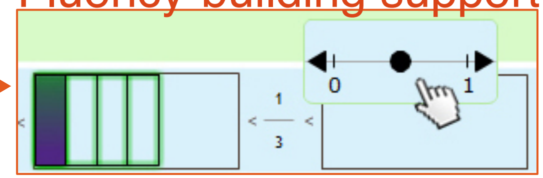
Sense-making support



enables

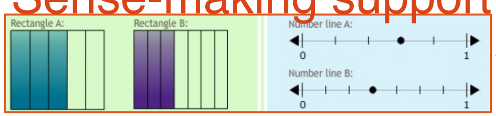
benefit?

Fluency-building support



  - Fluency hypothesis:

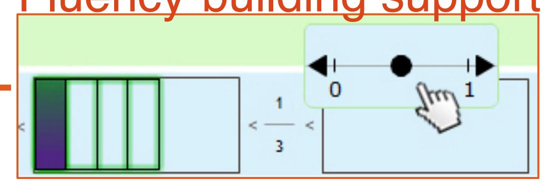
Sense-making support



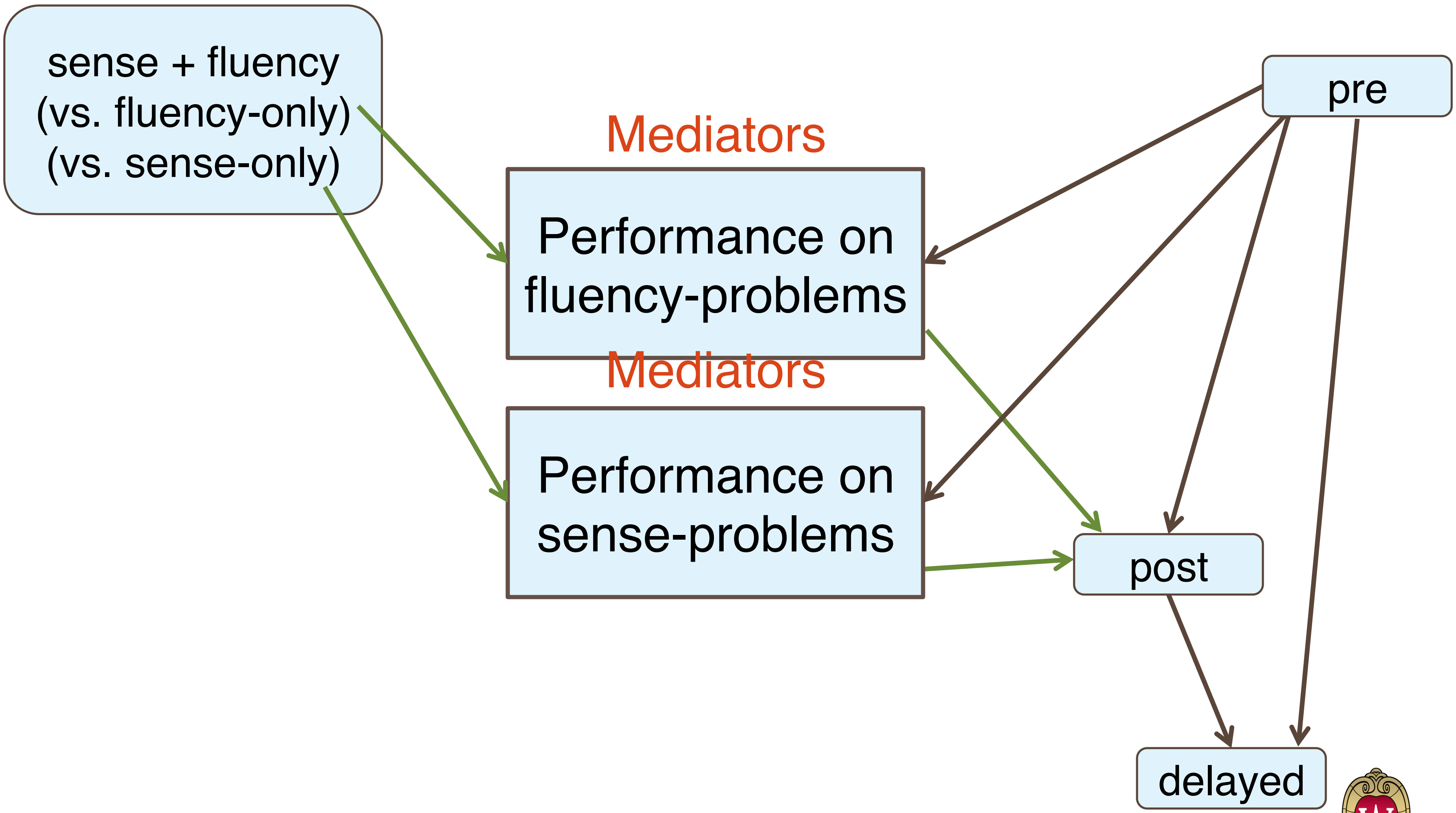
enables

benefit?

Fluency-building support



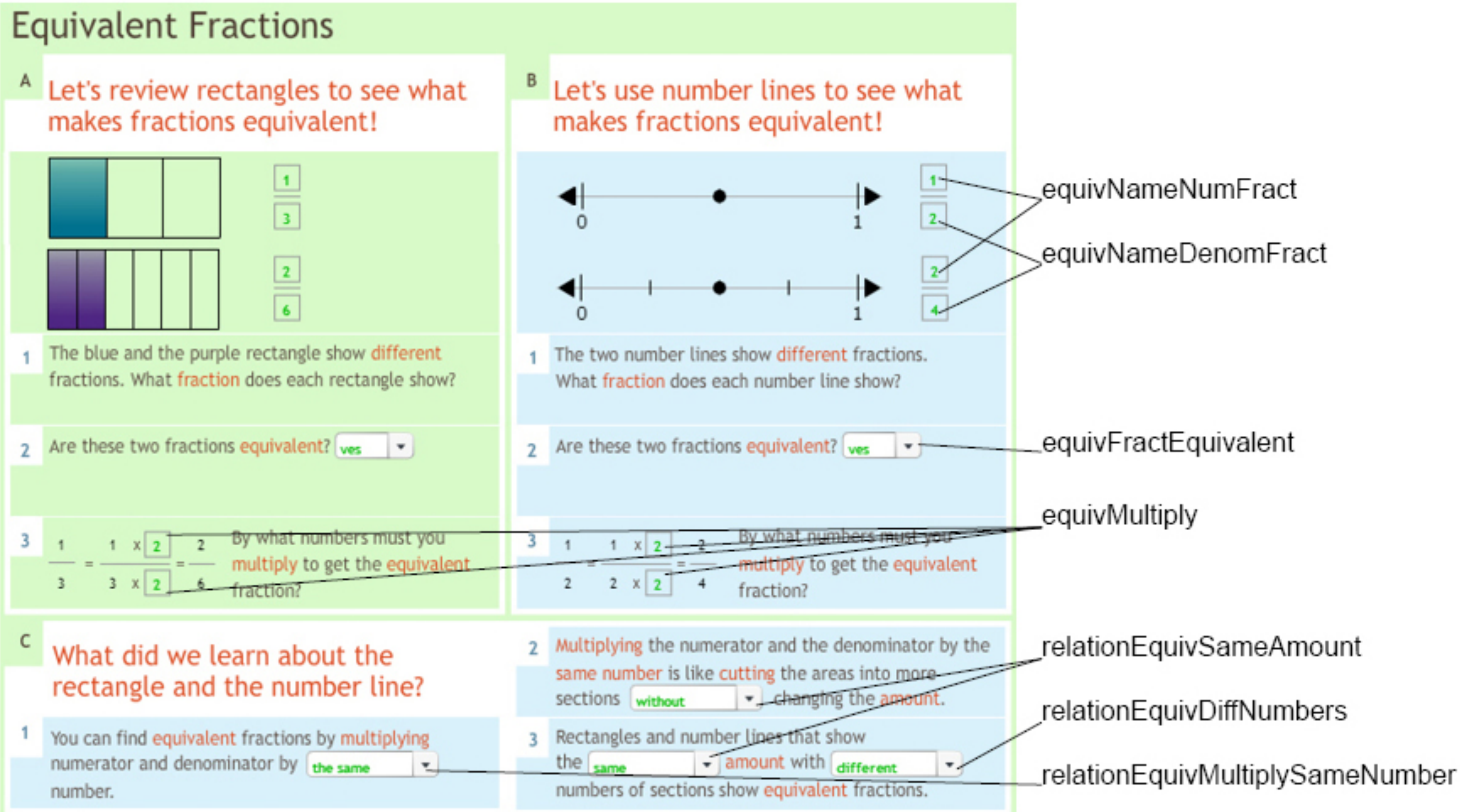
Mediation Hypotheses



Variable identification

- Search among large number of potential variables
  [Rau et al., EDM 2012]
- Based on knowledge component model

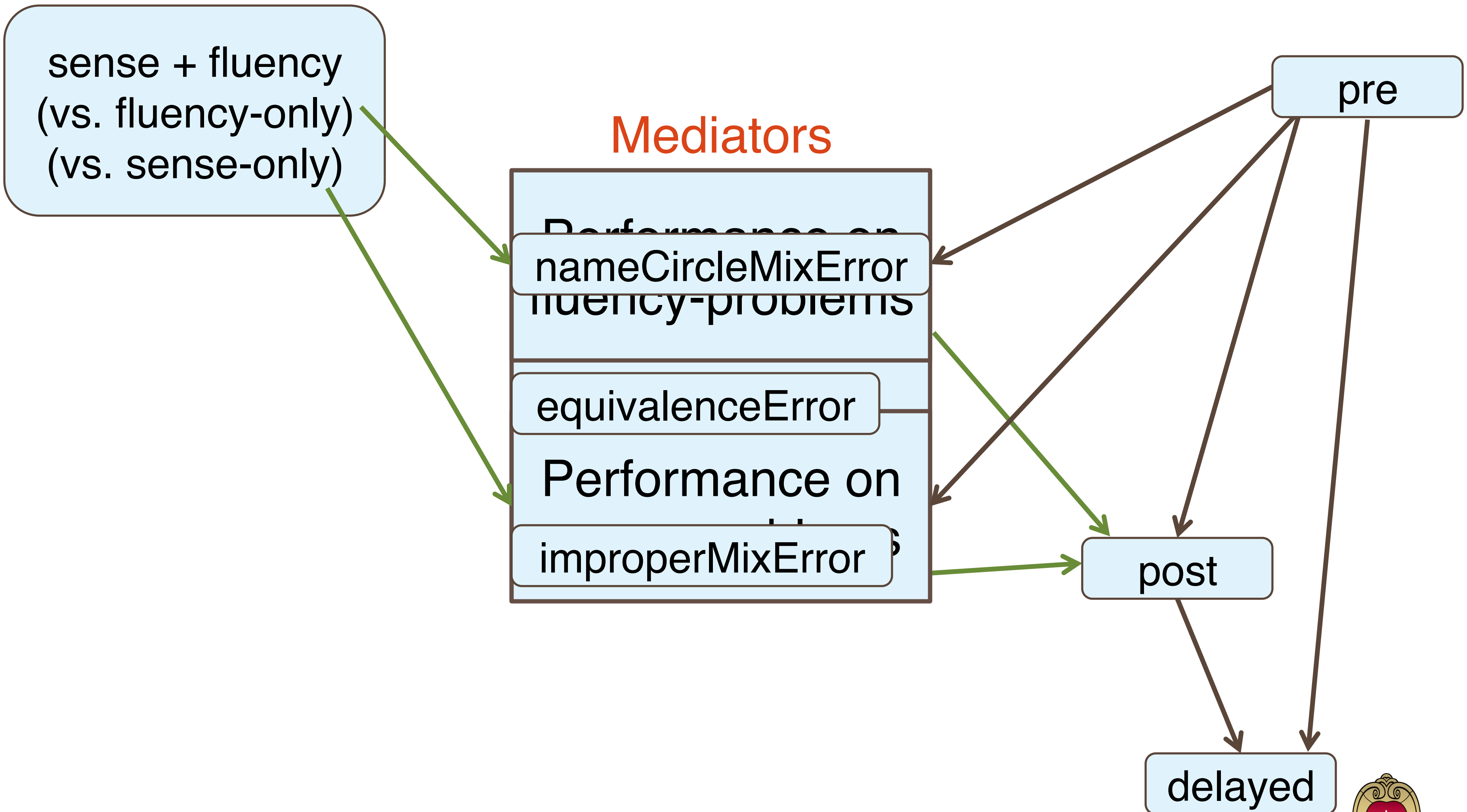
Knowledge Component Model



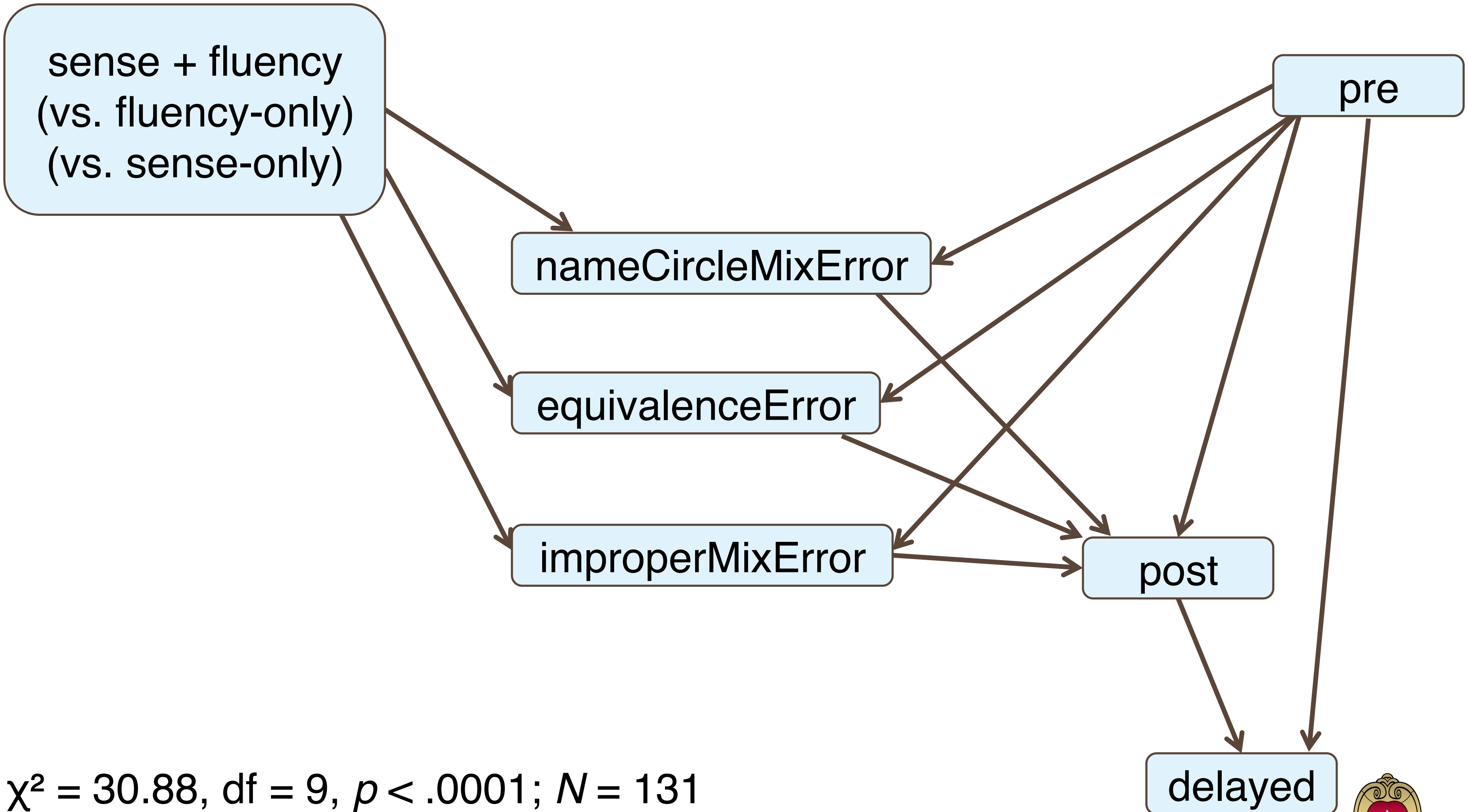
Variable identification

- Search among large number of potential variables
  [Rau et al., EDM 2012]
- Based on knowledge component model
  - Significant predictors of posttest performance
  - Significant differences between conditions

Understanding hypothesis
Mediation hypothesis

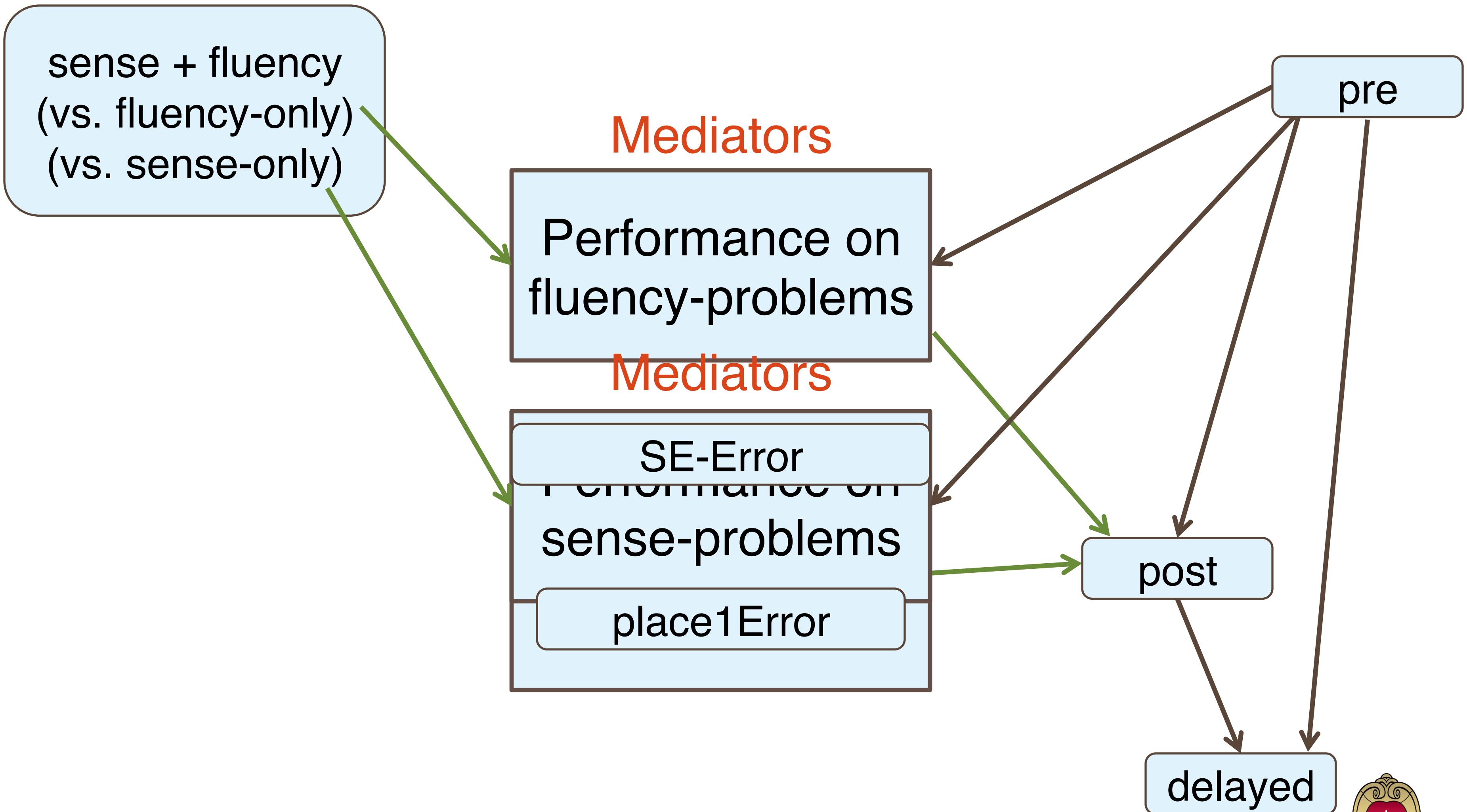


Understanding hypothesis

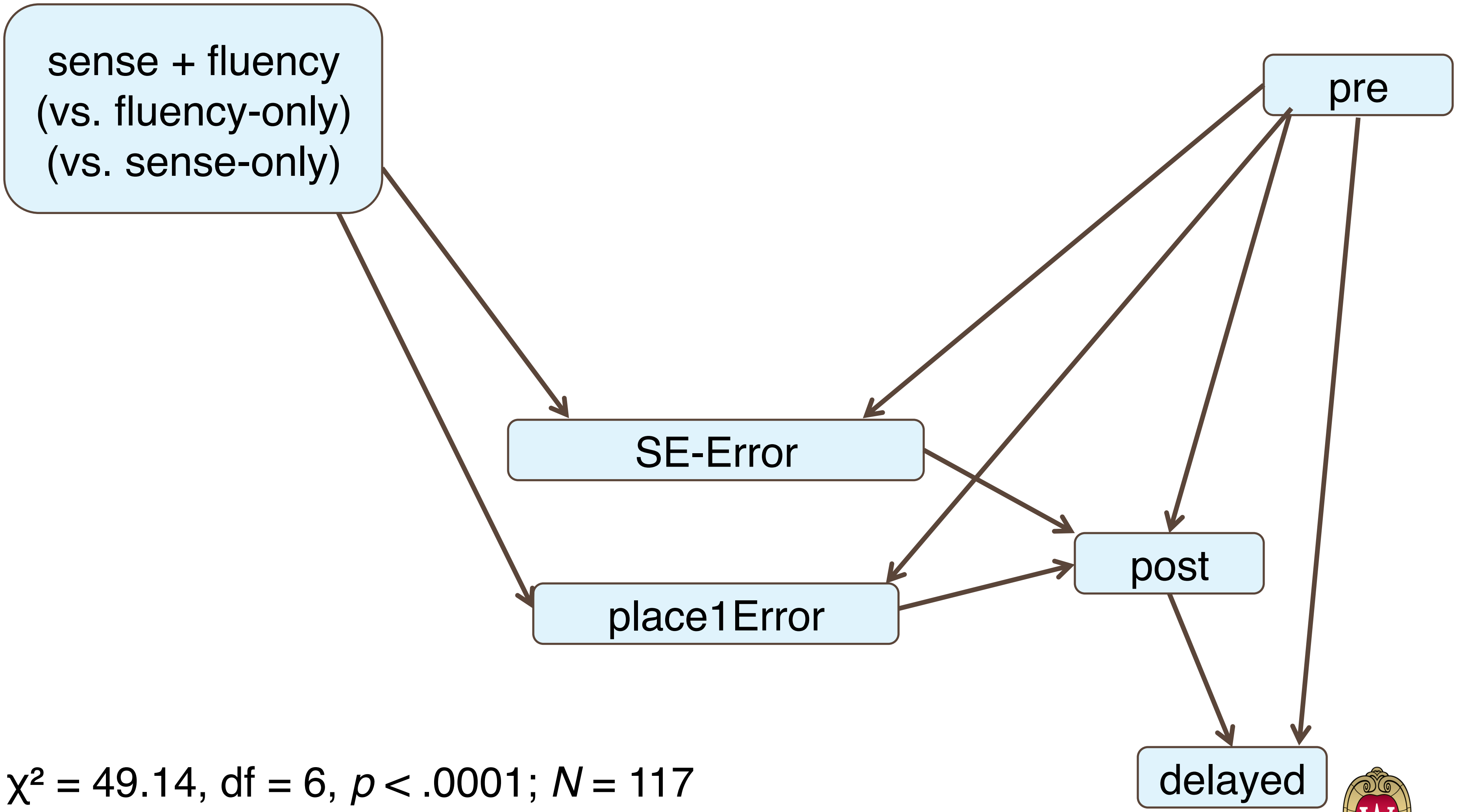


$\chi^2 = 30.88$, df = 9, $p < .0001$; $N = 131$

Fluency hypothesis

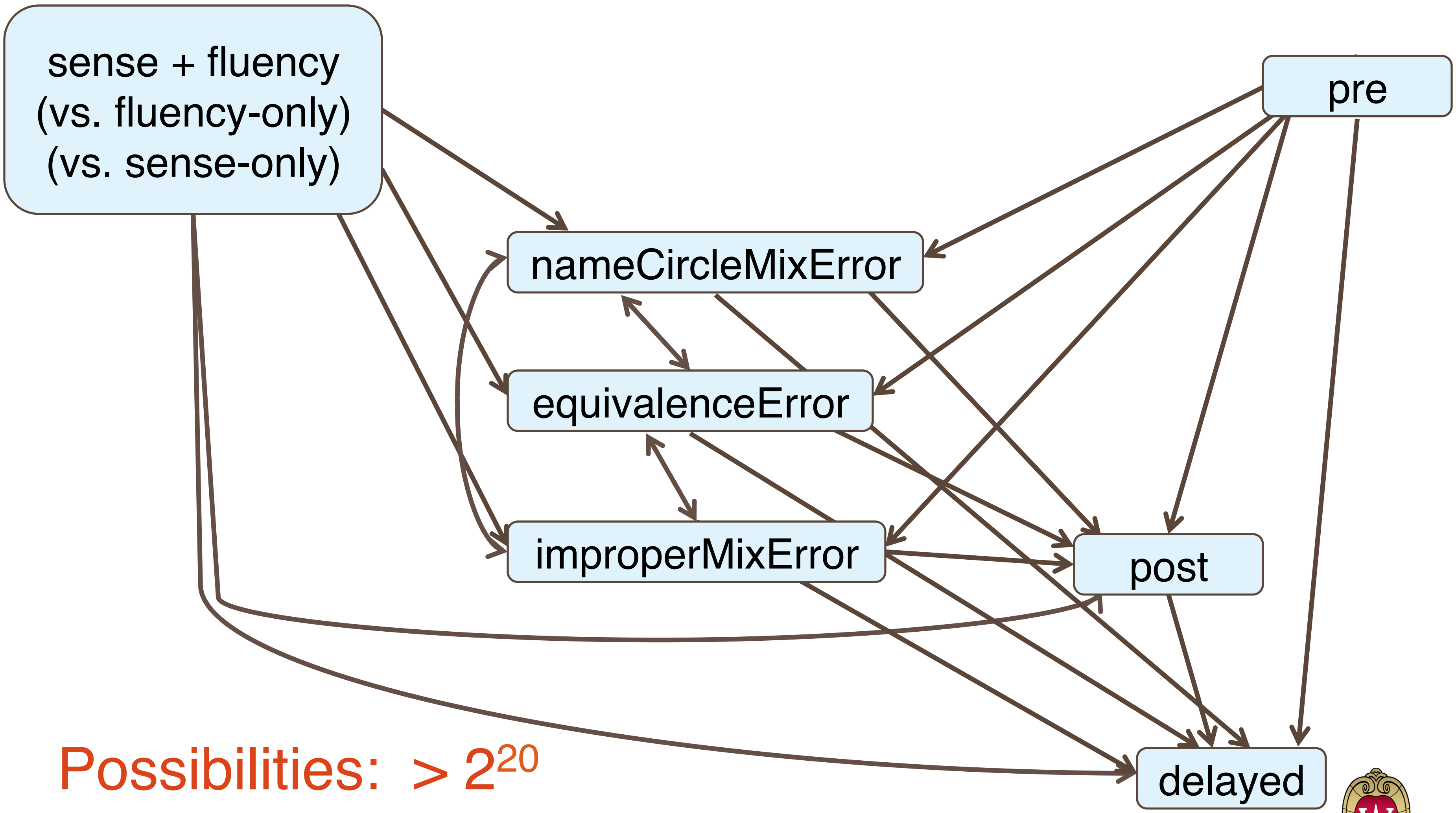


Fluency hypothesis



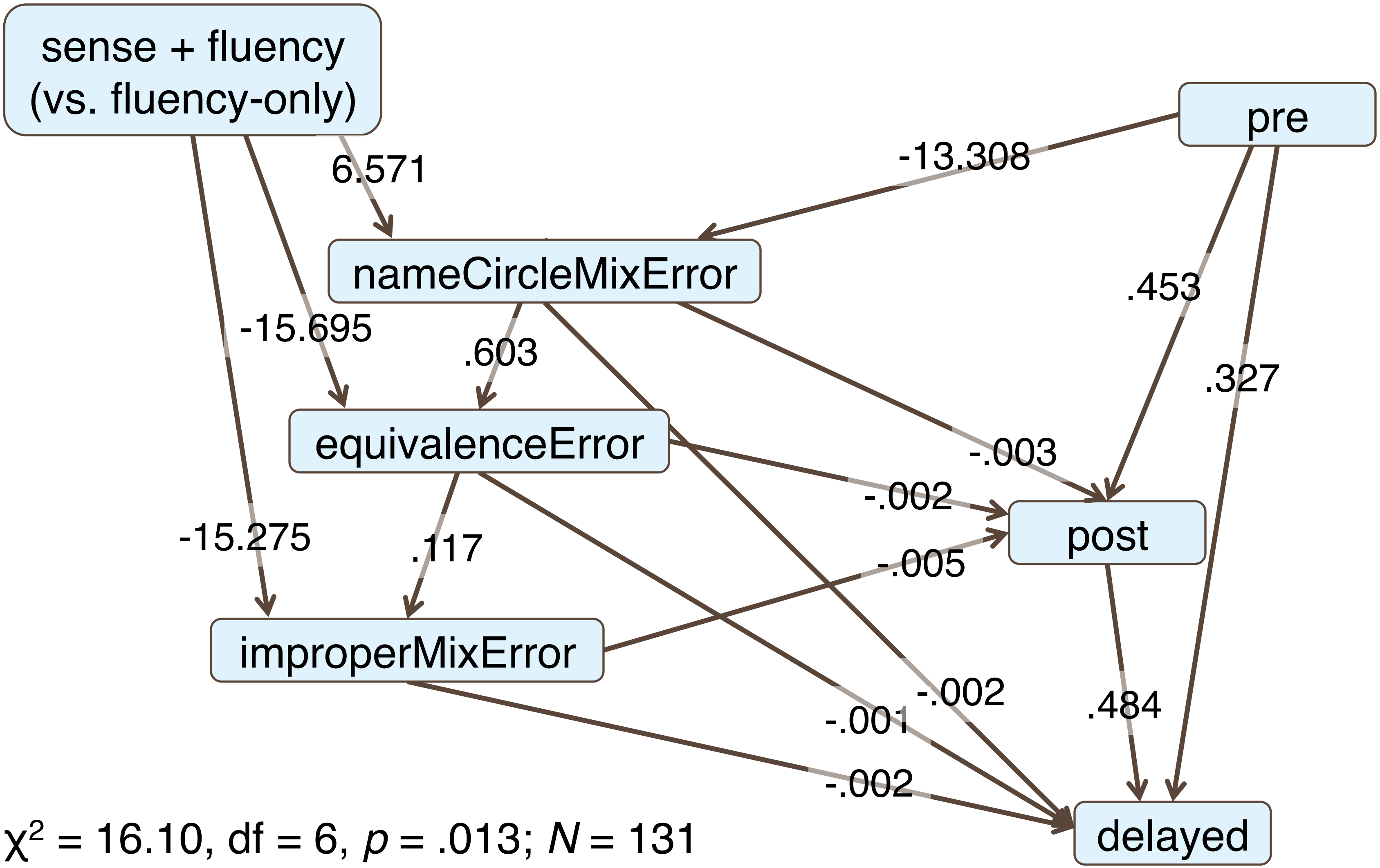
$\chi^2 = 49.14$, df = 6, $p < .0001$; $N = 117$

Possible alternative models



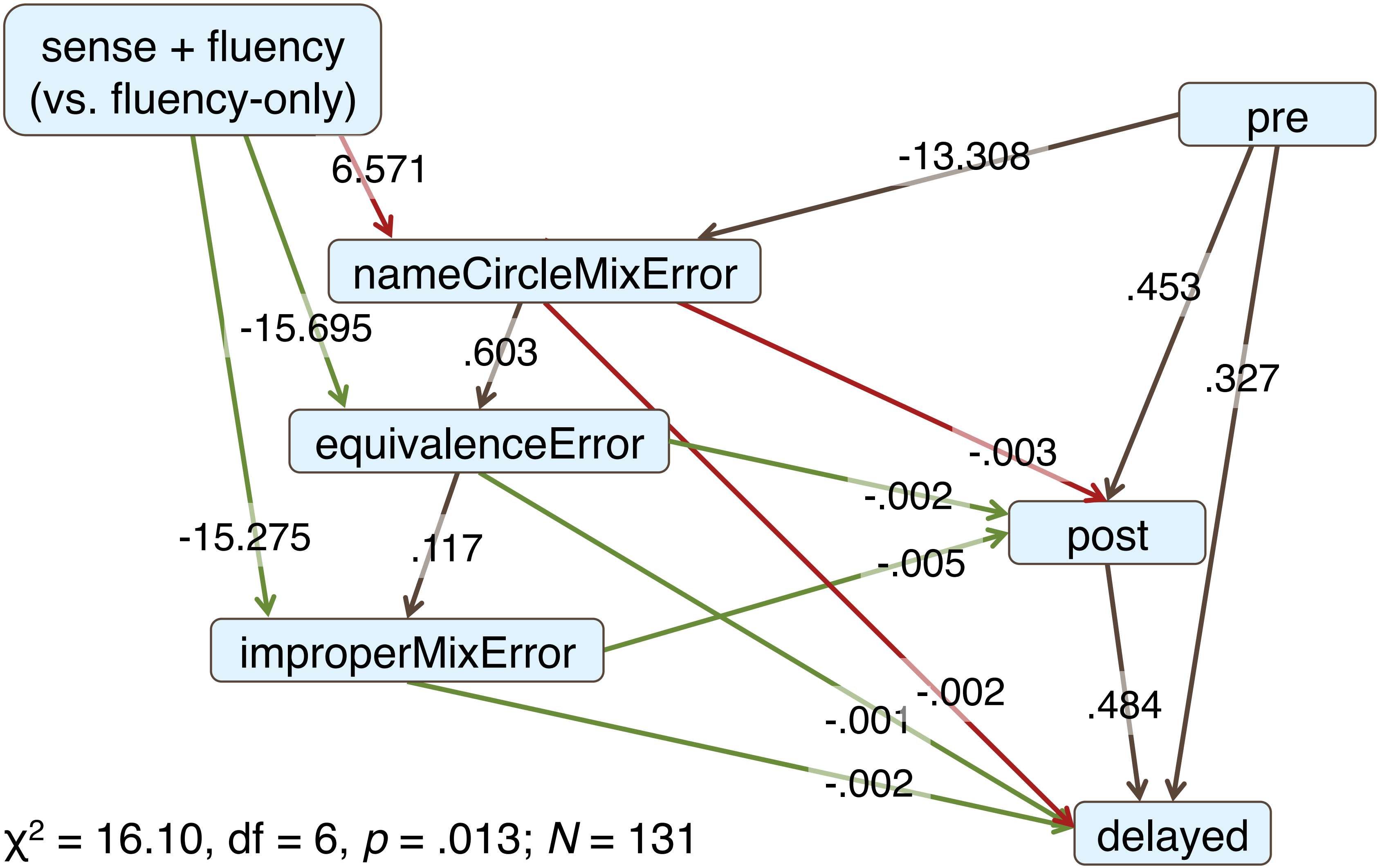
Possibilities: > 2^{20}

Model Search Results: Understanding model



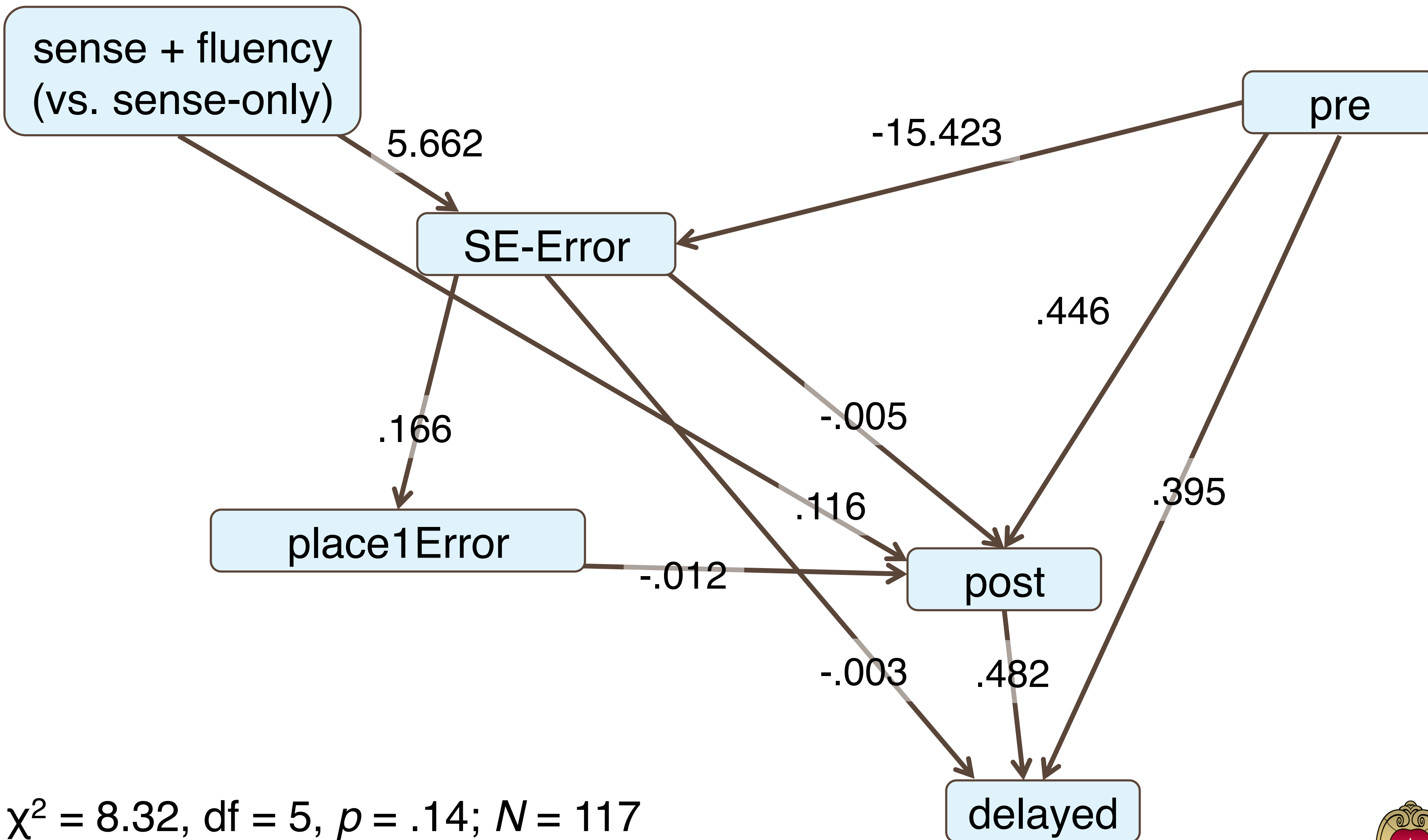
$\chi^2 = 16.10$, df = 6, $p = .013$; $N = 131$

Model Search Results: Understanding model



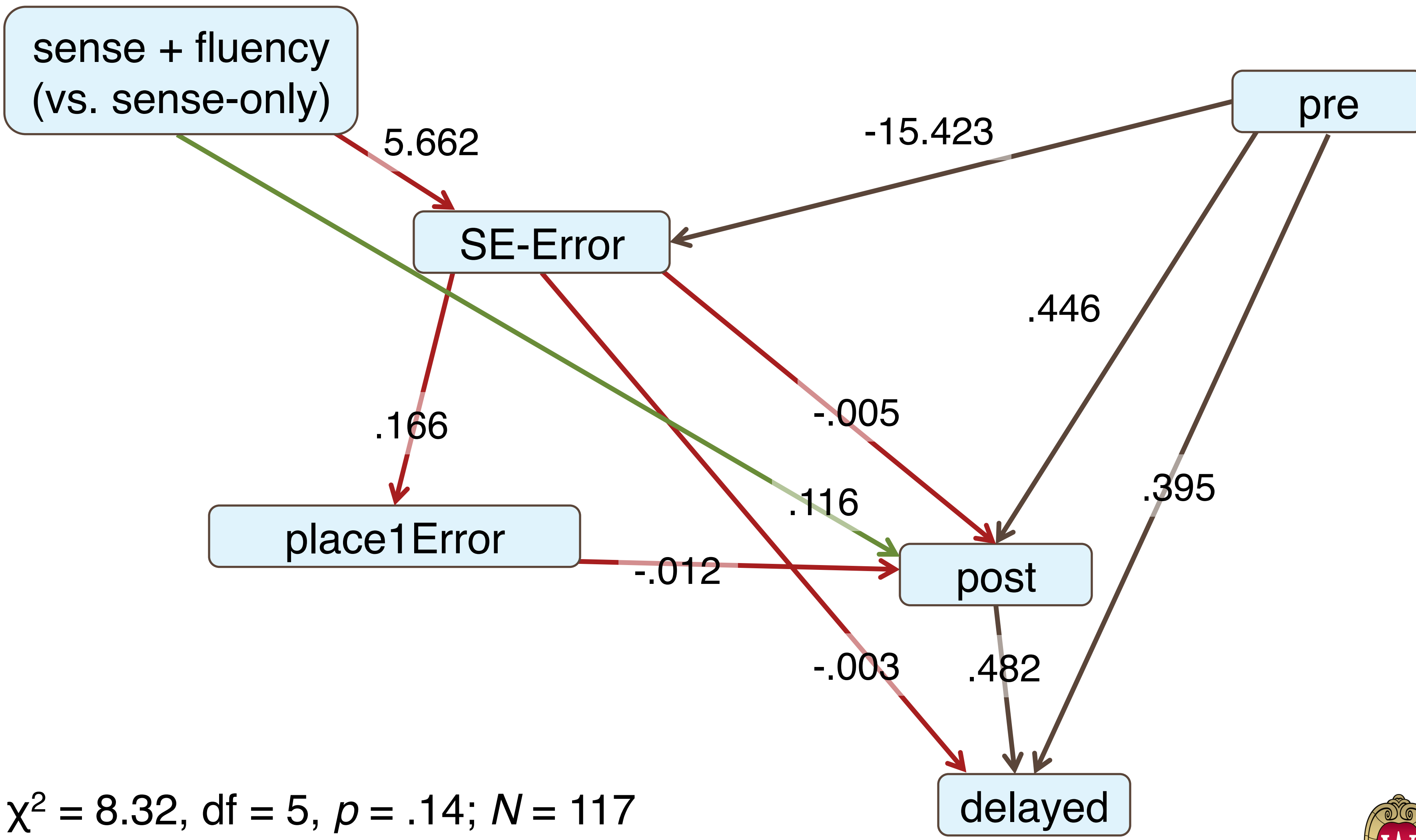
$\chi^2 = 16.10$, df = 6, $p = .013$; $N = 131$

Model Search Results: Fluency model



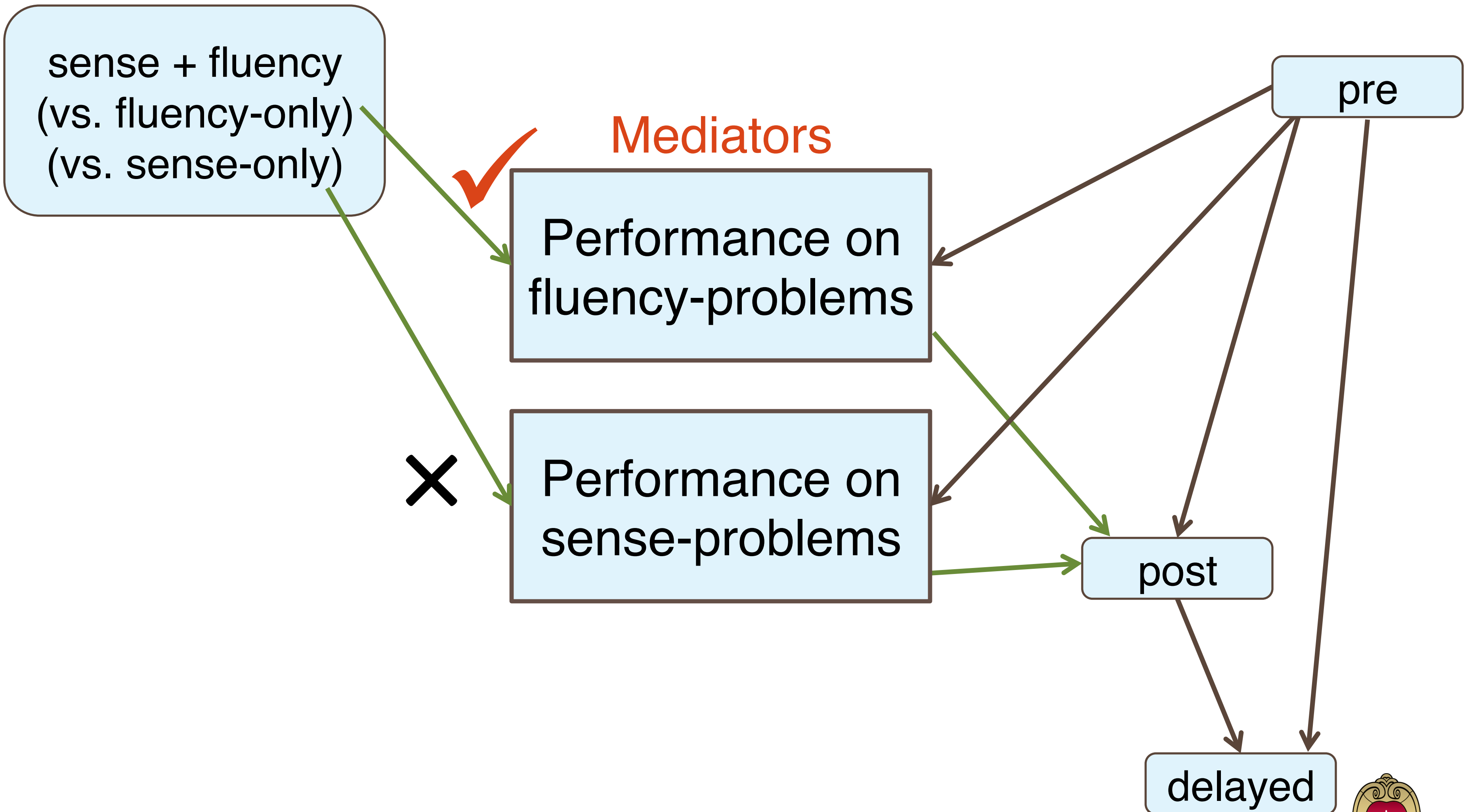
$\chi^2 = 8.32$, df = 5, $p = .14$; $N = 117$

Model Search Results: Fluency model



$\chi^2 = 8.32$, df = 5, $p = .14$; $N = 117$

Mediation hypothesis



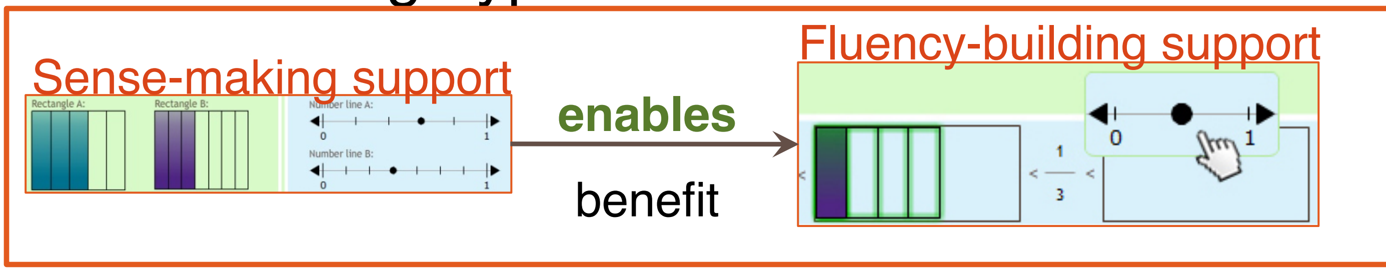
Taking Stock

- Results are in line with understanding hypothesis, but not with fluency hypothesis
  - Sense-making support reduces errors students make on fluency-building problems

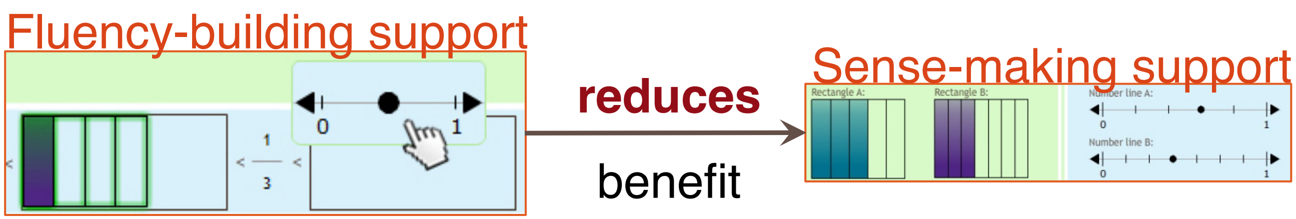
    [Rau, Scheines et al., EDM 2013, best paper]
- Limitations
  - Bound to fixed sequence: sense – fluency
  - Different results possible with sequence fluency – sense
- Makes testable predictions:
  - Sense-making support should be provided *before* fluency-building support

Experiment 4: Results

- Which process should instruction support first?
  - Understanding hypothesis:



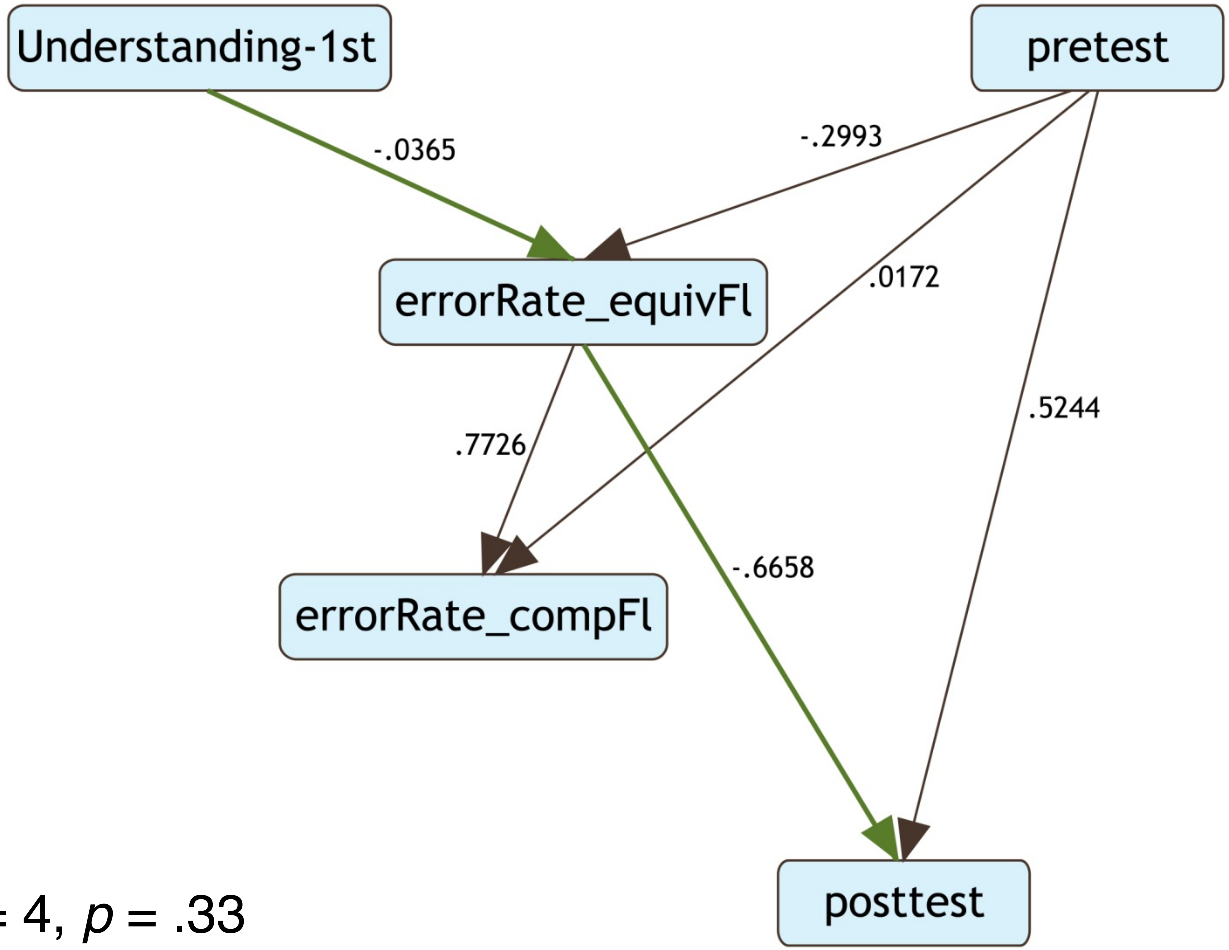
  - Fluency hypothesis:



[Rau et al., AIED 2013]

Experiment 4: Model Search Results

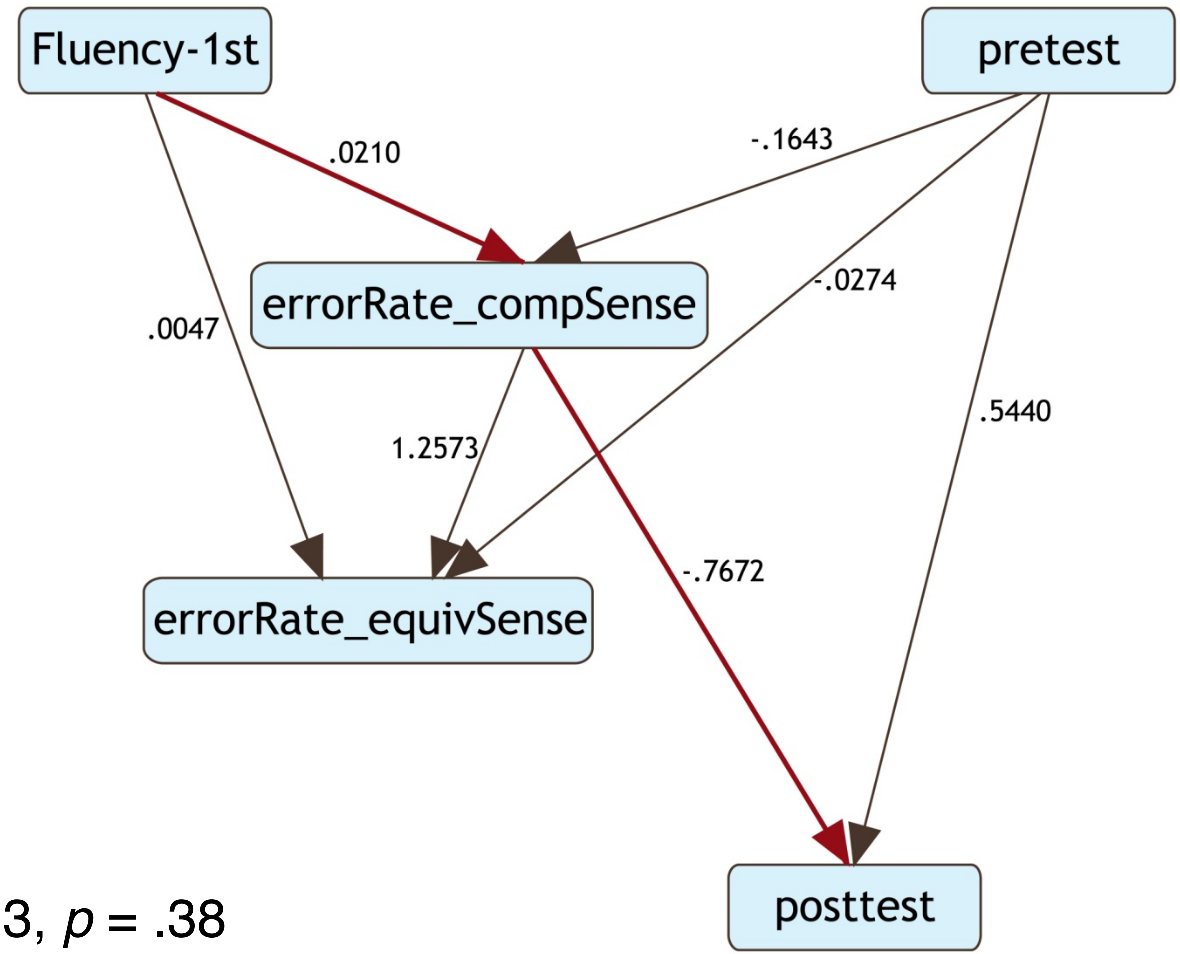
Fluency-building errors



$\chi^2 = 4.58$, df = 4, $p = .33$

Experiment 4: Model Search Results

Sense-making errors



$\chi^2 = 3.38$, df = 3, $p = .38$

5. CONCLUSION

Conclusion

- Both sense-making processes and fluency-building processes need to be supported
- Sense-making enhances fluency-building
- Sense-making support should be provided before fluency-building support
- Closing the loop!

1. Experiment 3

2. Causal path analysis

3. Experiment 4

Conclusion

- Overall measures of problem-solving behaviors were not successful at establishing mediation
- Informed mediators explained interaction between different learning processes
- Model search helped identify plausible models for our hypotheses
- Results from mediation analysis made testable predictions
- Results from follow-up experiment were in line with these predictions

Thanks!

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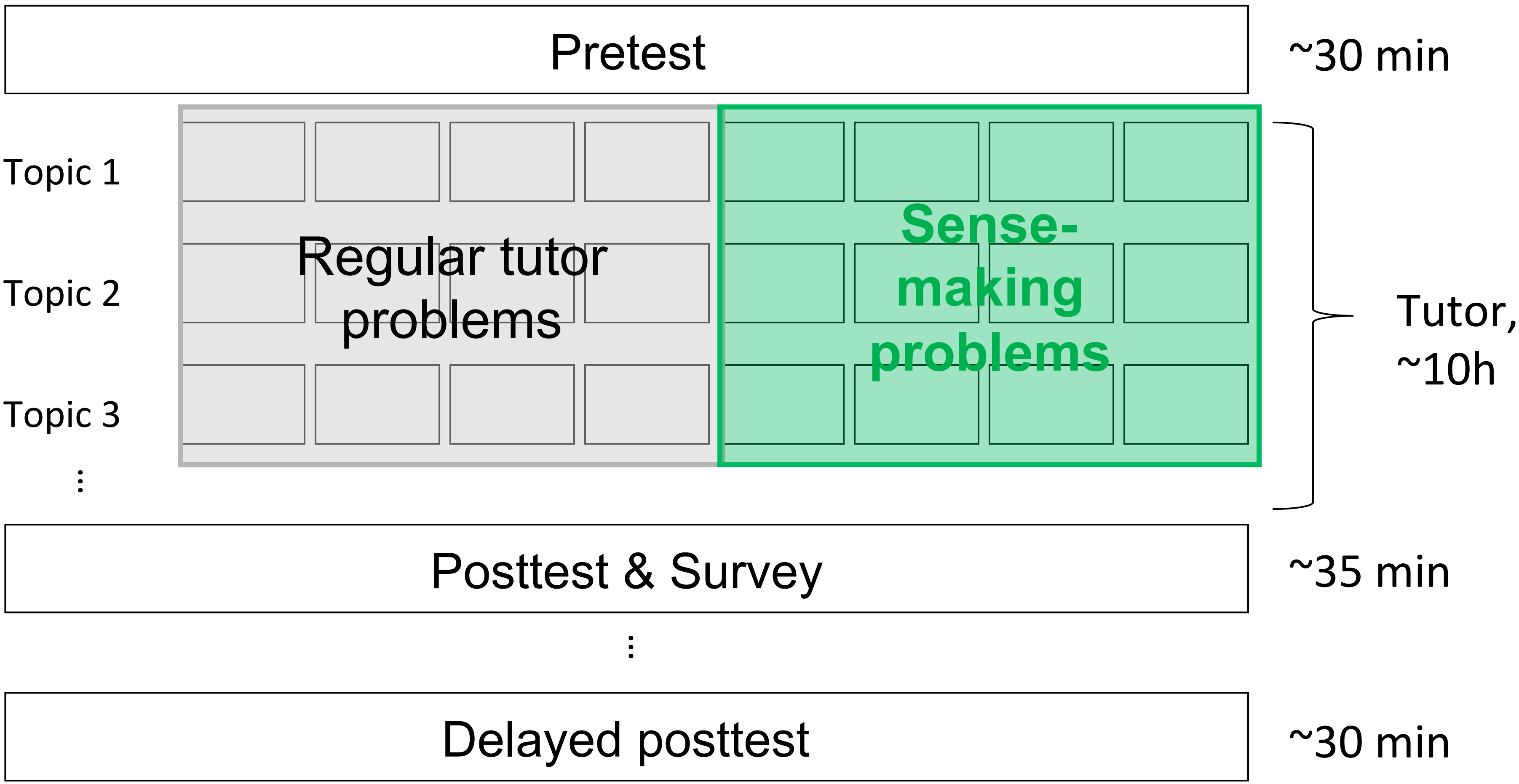
BACKUP SLIDES

Sense-only condition



Fluency-only condition

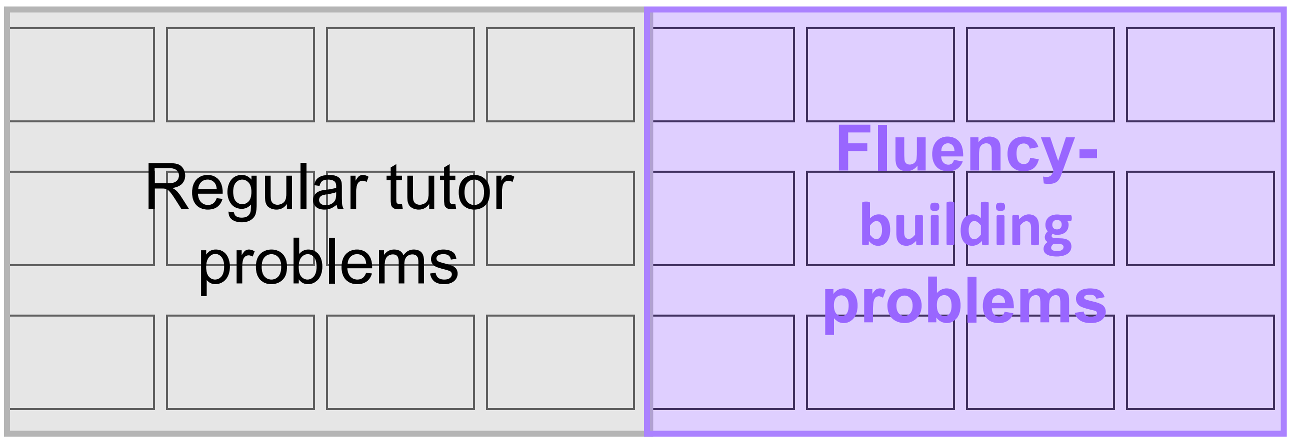
Pretest ~30 min

Topic 1

Topic 2

Topic 3

⋮



Tutor, ~10h

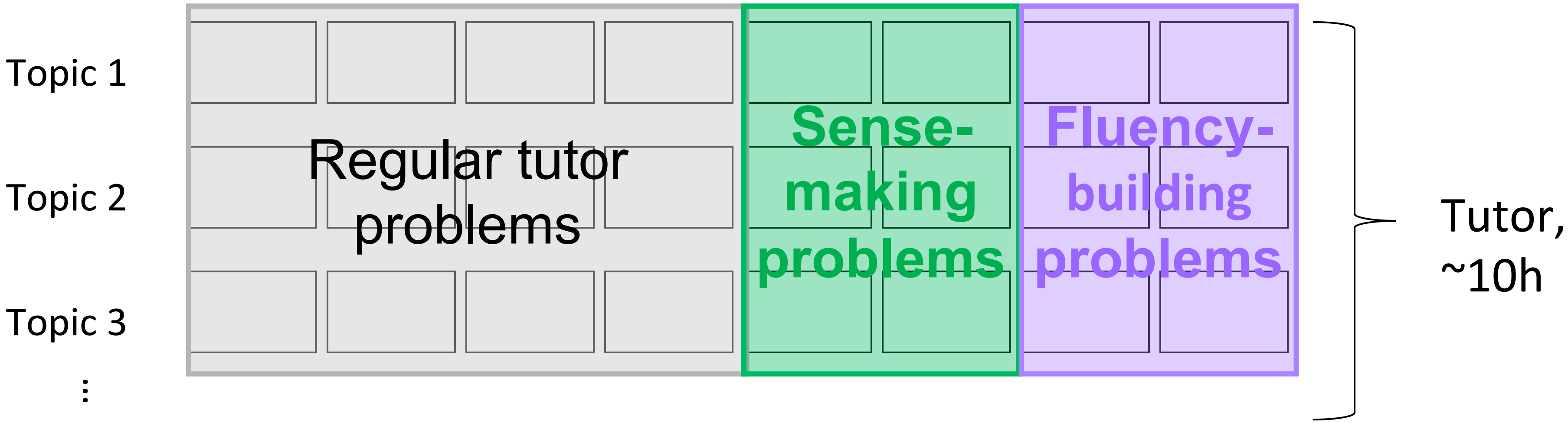
Posttest & Survey ~35 min

⋮

Delayed posttest ~30 min

Sense + fluency condition

Pretest ~30 min

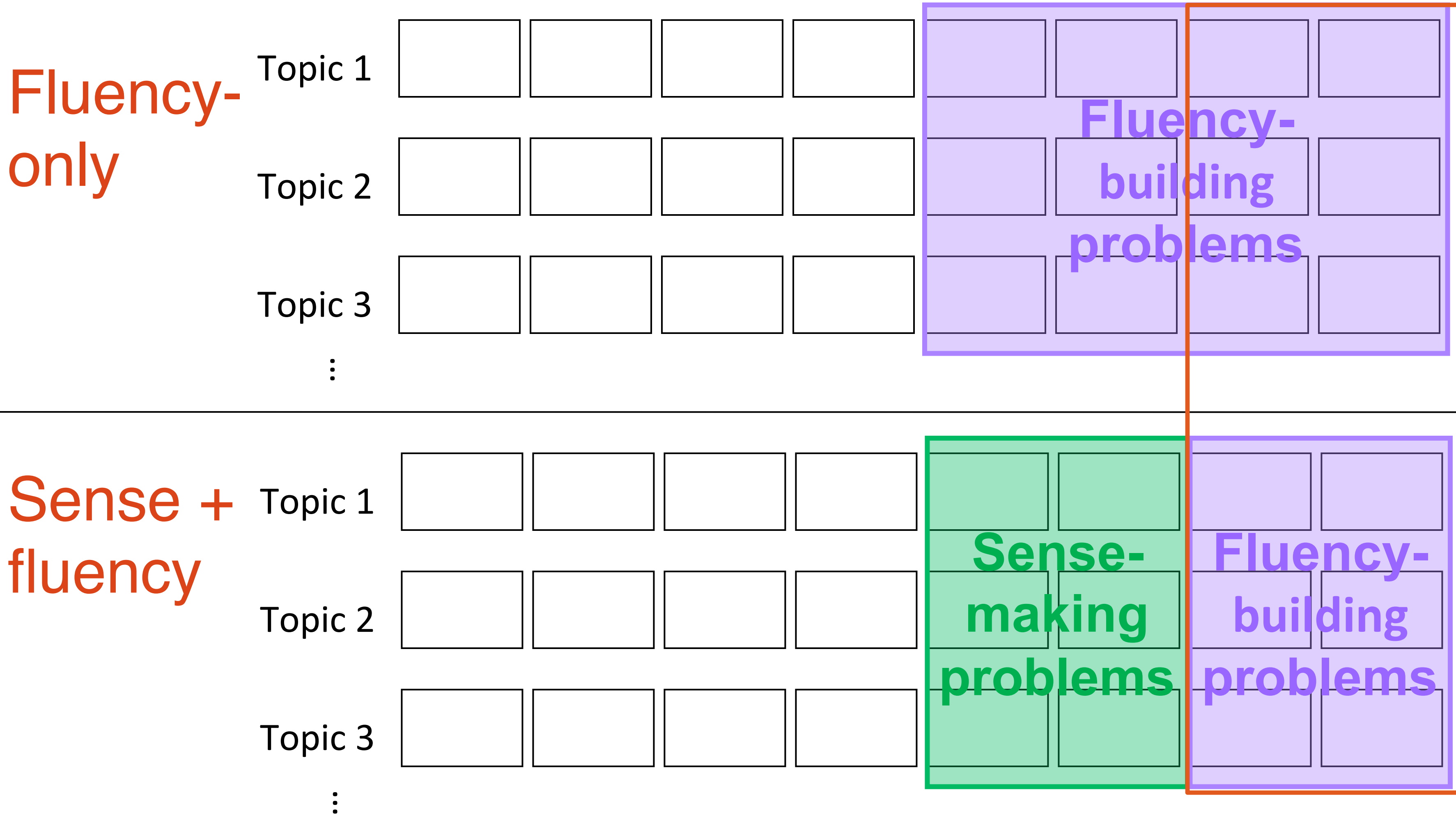


Posttest & Survey ~35 min

⋮

Delayed posttest ~30 min

Fluency-only vs. sense + fluency



Sense-only vs. sense + fluency