Studying and achieving robust learning with PSLC resources

LearnLab
Pittsburgh Science of Learning Center

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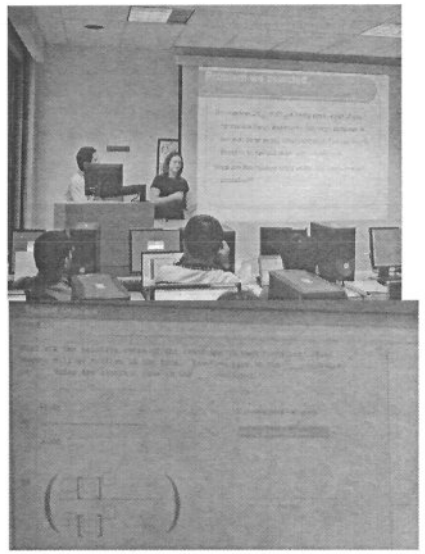
National Science Foundation
WHERE DISCOVERIES BEGIN

6th Annual Pittsburgh Science of Learning Center Summer School

- 10th overall
  - ITS was focus in 2001 to 2004
- Goals:
  - Learning science & technology concepts & tools
  - Hands-on project => poster on Fri



Vision for PSLC

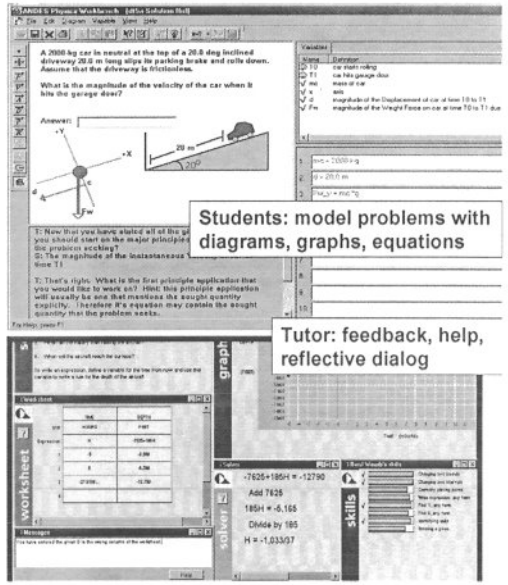
"rigorous, sustained scientific research in education" (NRC, 2002)

- Why? *Chasm* between science & practice
  Indicators: Ed achievement gaps persist,
  Low success rate of randomized controlled trials
- Underlying problem: Many ideas, too little sound scientific foundation
- Need: *Basic* research studies in the *field*

=> PSLC Purpose: Identify the conditions that cause robust student learning
- Field-based rigorous science
- Leverage cognitive & computational theory, educational technologies

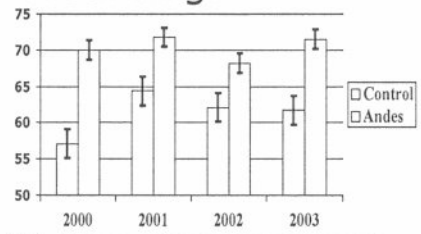
Builds off past success: Intelligent Tutors Bringing Learning Science to Schools!

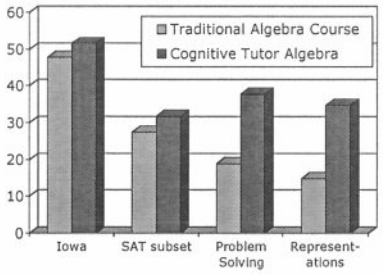
- Intelligent tutoring systems
  - Automated 1:1 tutor
  - Artificial Intelligence
  - Cognitive Psychology
- Andes: College Physics Tutor
  - Replaces homework
- Algebra Cognitive Tutor
  - Part of complete course



Tutors make a significant difference in improving student learning!

- Andes: College Physics Tutor
  - Field studies: Significant improvements in student learning
- Algebra Cognitive Tutor
  - 10+ full year field studies: improvements on problem solving, concepts, basic skills
  - Regularly used in *1000s of schools* by *100,000s of students*!!





President Obama on Intelligent Tutoring Systems!

"we will devote more than three percent of our GDP to research and development. .... Just think what this will allow us to accomplish: solar cells as cheap as paint, and green buildings that produce all of the energy they consume; *learning software as effective as a personal tutor;* prosthetics so advanced that you could play the piano again; an expansion of the frontiers of human knowledge about ourselves and world the around us. We can do this."

How close to this vision are we now?
What else do we need to do?

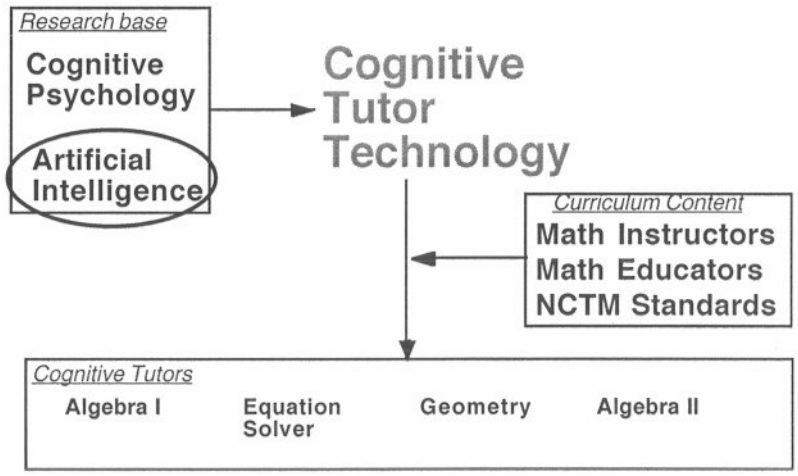
Overview

LearnLab
Pittsburgh Science of Learning Center

Next

- PSLC Background
  - Intelligent Tutoring Systems
  - Cognitive Task Analysis
- PSLC Methods & Tech Resources
  - *In vivo* experimentation
  - LearnLab courses, CTAT, TagHelper, DataShop
- PSLC Theoretical Framework

Cognitive Tutor Approach



Cognitive Tutor Technology

- Cognitive Model: A system that can solve problems in the various ways students can

Strategy 1:	IF the goal is to solve a(bx+c) = d THEN rewrite this as abx + ac = d
Strategy 2:	IF the goal is to solve a(bx+c) = d THEN rewrite this as bx + c = d/a
Misconception:	IF the goal is to solve a(bx+c) = d THEN rewrite this as abx + c = d

Cognitive Tutor Technology

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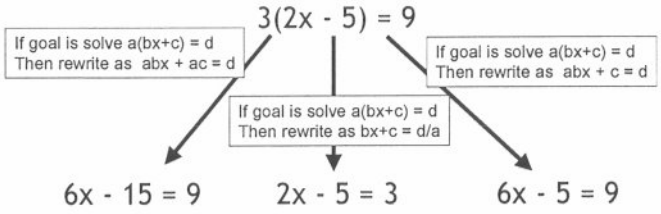
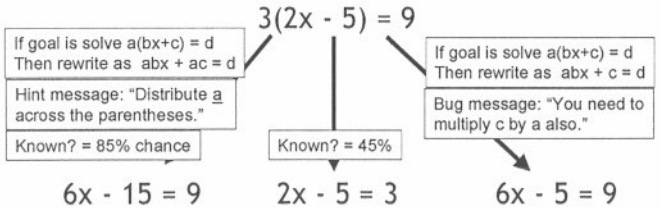


- Model Tracing: Follows student through their individual approach to a problem -> context-sensitive instruction

Cognitive Tutor Technology

- Cognitive Model: A system that can solve problems in the various ways students can

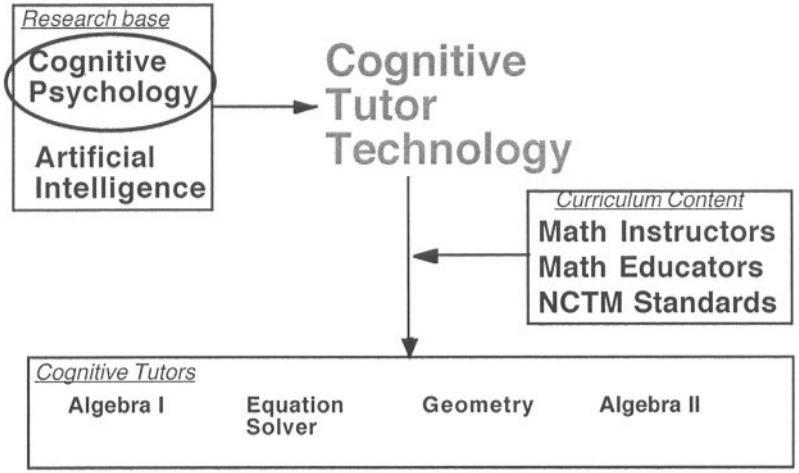


- Model Tracing: Follows student through their individual approach to a problem -> context-sensitive instruction
- Knowledge Tracing: Assesses student's knowledge growth -> individualized activity selection and pacing

Cognitive Tutor Course Development Process

1. Client & problem identification
2. Identify the target task & "interface"
3. *Perform Cognitive Task Analysis (CTA)*
4. Create Cognitive Model & Tutor
   a. Enhance interface based on CTA
   b. Create Cognitive Model based on CTA
   c. Build a curriculum based on CTA
5. Pilot & Parametric Studies
6. Classroom Evaluation & Dissemination

Cognitive Tutor Approach



Difficulty Factors Assessment:

Discovering What is Hard for Students to Learn

Which problem type is most difficult for Algebra students?

Story Problem

As a waiter, Ted gets $6 per hour. One night he made $66 in tips and earned a total of $81.90. How many hours did Ted work?

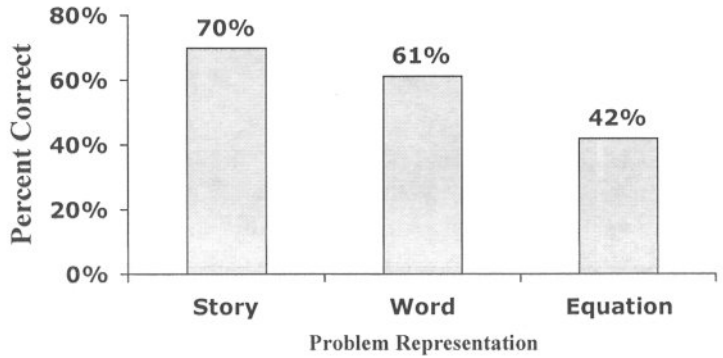
Word Problem

Starting with some number, if I multiply it by 6 and then add 66, I get 81.90. What number did I start with?

Equation

x * 6 + 66 = 81.90

Algebra Student Results: Story Problems are Easier!

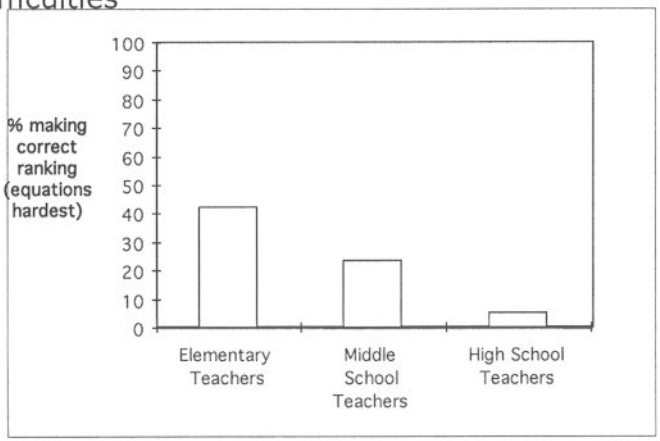


Koedinger, & Nathan, (2004). The real story behind story problems: Effects of representations on quantitative reasoning. *The Journal of the Learning Sciences*.

Koedinger, Alibali, & Nathan (2008). Trade-offs between grounded and abstract representations: Evidence from algebra problem solving. *Cognitive Science*.

Expert Blind Spot:

Expertise can impair judgment of student difficulties



Nathan, M. J. & Koedinger, K. R. (2000). An investigation of teachers' beliefs of students' algebra development. *Cognition and Instruction, 18*(2), 207-235

"The Student Is Not Like Me"

- To avoid your expert blind spot, remember the mantra:

  "The Student Is Not Like Me"

- Perform Cognitive Task Analysis to find out what students *are* like

Tutors make a significant difference in improving student learning!

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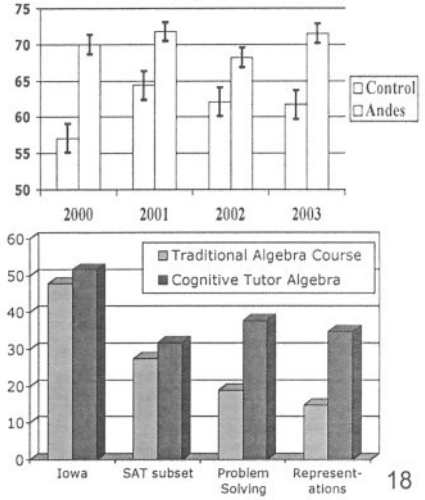

Prior achievement: Intelligent Tutoring Systems bring learning science to schools

A key PSLC inspiration: Educational technology as research platform to generate new learning science

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PSLC Statement of Purpose

Leverage cognitive and computational theory to identify the instructional conditions that cause *robust student learning*.

What is Robust Learning?

- Robust learning is achieved through the development of *both:*
  - conceptual understanding & sense-making skills
  - procedural fluency with basic skills
- *Robust Learning* is measured by
  - transfer to novel tasks
  - retention over the long term, and/or
  - acceleration of future learning

PSLC Statement of Purpose

Leverage cognitive and computational theory to *identify the instructional conditions that cause* robust student learning.

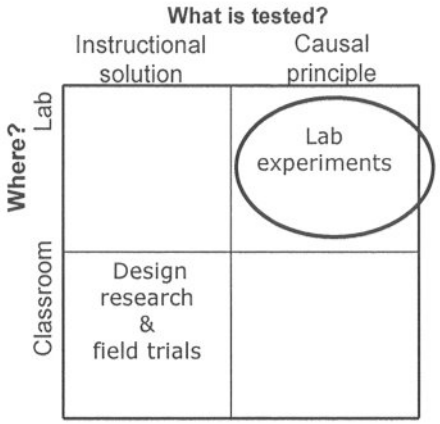
In Vivo Experiments

Principle-testing laboratory quality in real classrooms

In Vivo Experimentation Methodology

Methodology features:

- What is tested?
  - Instructional solution vs. causal principle
- Where & who?
  - Lab vs. classroom
- How?
  - Treatment only vs. Treatment + control
- Generalizing conclusions:
  - *Ecological validity*: What instructional activities work in real classrooms?
  - *Internal validity*: What causal mechanisms explain & predict?



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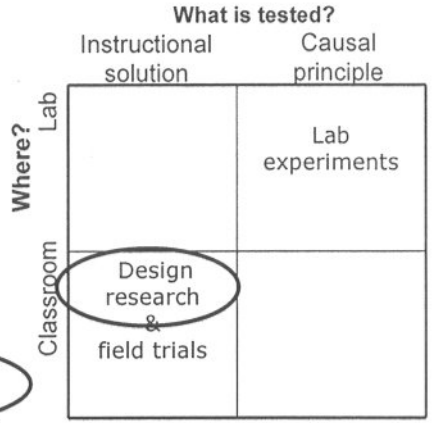

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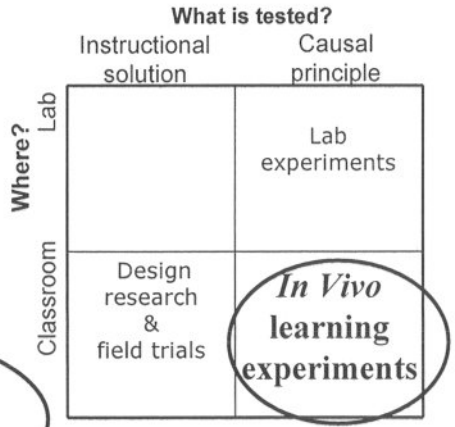
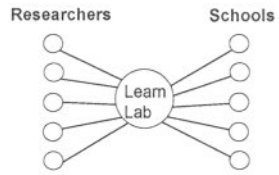


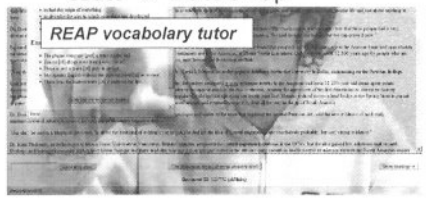
LearnLab

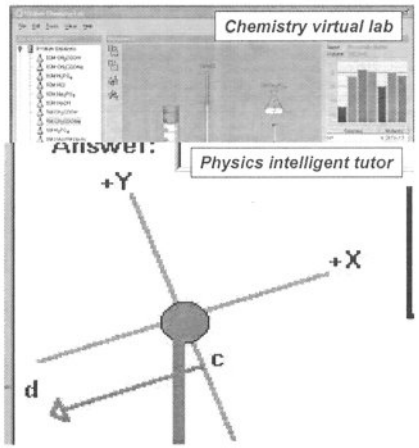
A Facility for Principle-Testing Experiments in Classrooms

LearnLab courses at K12 & College Sites



- 6+ *cyber-enabled* courses: Chemistry, Physics, Algebra, Geometry, Chinese, English
- Data collection
  - Students do home/lab work on tutors, vlab, OLI, ...
  - Log data, questionnaires, tests → DataShop



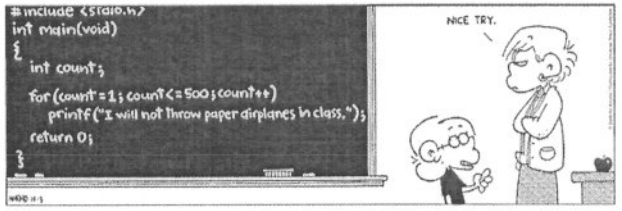


PSLC Statement of Purpose

Leverage cognitive and computational theory to identify the instructional conditions that cause robust student learning.

PSLC Technology Resources

- Tools for developing instruction & experiments
  - CTAT (cognitive tutoring systems)
    - SimStudent (generalizing an example-tracing tutor)
  - OLI (learning management)
  - TuTalk (natural language dialogue)
  - REAP (authentic texts)
- Tools for data analysis
  - DataShop
  - TagHelper



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KLI Framework: Designing Instruction for Robust Learning

The conditions that yield robust learning can be decomposed at three levels:

Knowledge components

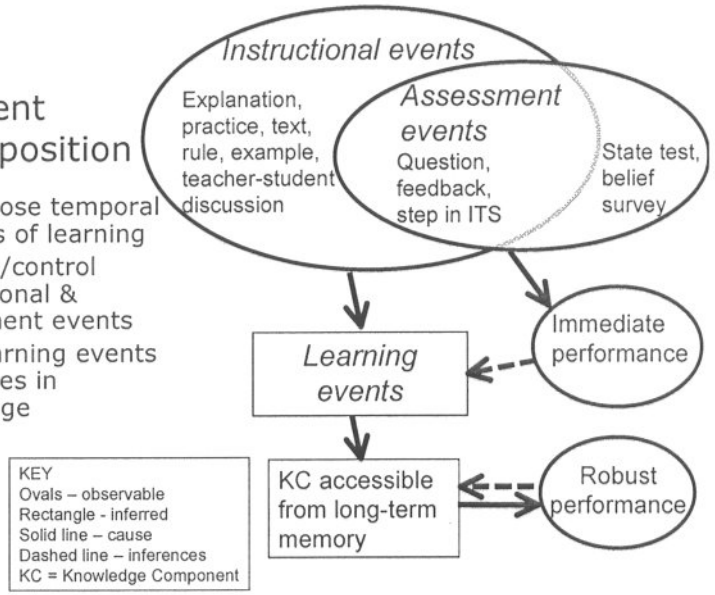
Learning events

Instructional events

Get framework report at learnlab.org

KLI Event Decomposition

- Decompose temporal progress of learning
- Observe/control instructional & assessment events
- Infer learning events & changes in knowledge



KLI Framework: Designing Instruction for Robust Learning

The conditions that yield robust learning can be decomposed at three levels:

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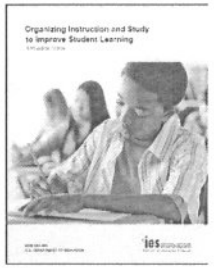
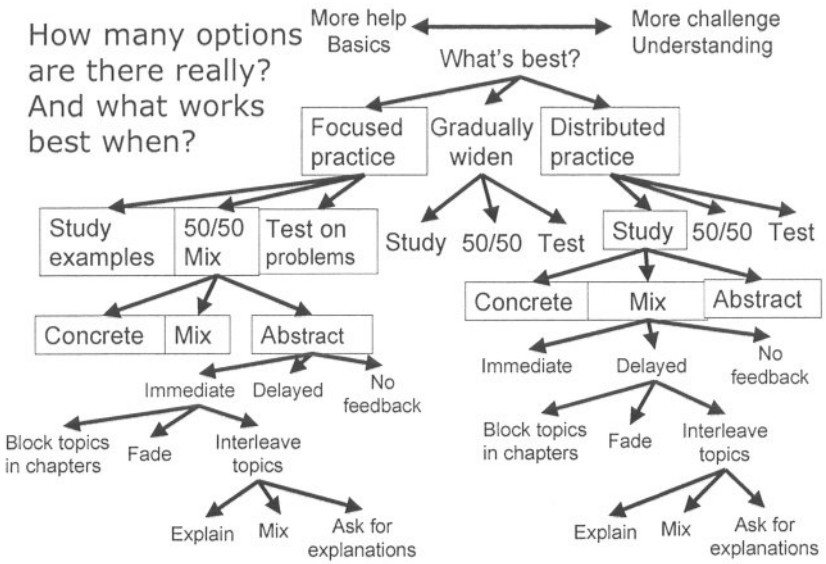
What's the best form of instruction? Two choices?



- More assistance vs. more challenge
  - Basics vs. understanding
  - Education wars in reading, math, science…
- Researchers like binary oppositions too. We just produce a lot more of them!
  - Massed vs. ***distributed*** (Pashler)
  - Study vs. ***test*** (Roediger)
  - ***Examples*** vs. problem solving (Sweller,Renkl)
  - ***Direct instruction*** vs. discovery learning (Klahr)
  - Re-explain vs. ***ask for explanation*** (Chi, Renkl)
  - ***Immediate*** vs. ***delayed*** (Anderson vs. Bjork)
  - ***Concrete*** vs. ***abstract*** (Pavio vs. Kaminski)
  - …

Koedinger & Aleven (2007). Exploring the assistance dilemma in experiments with Cognitive Tutors. *Ed Psych Review*.

How many options are there really? And what works best when?



Derivation:
- ➢15 instructional dimensions
- ➢ 3 options per dimension
- ➢ 2 stages of learning
- => 3^{15*2} options

205,891,132,094,649

"Big Science" effort needed to tackle this complexity

Cumulative theory development

Field-based basic research with microgenetic data collection

An example of some PSLC studies in this space

- Researchers like binary oppositions too. We just produce a lot more of them!
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  - ...

Learn by doing or by studying?

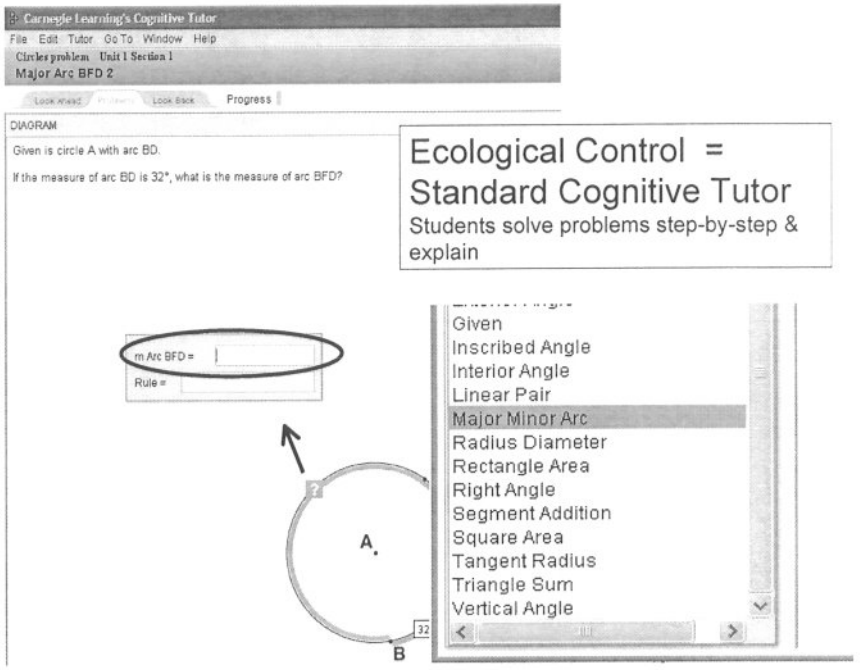
- Testing effect (e.g., Roediger & Karpicke, 06)
  - "Tests enhance later retention more than additional study of the material"
- Worked example effect
  - "a worked example constitutes the epitome of strongly guided instruction [aka optimal instruction]"
  - Paas and van Merrienboer (1994), Sweller et al. (1998), van Gerven et al. (2002), van Gog et al. (2006), Kalyuga et al. (2001a, 2001b), Sweller et al. (1998), Ayres (2006), Trafton & Reiser (1993), Renkl and Atkinson (2003), ... the list goes on ...
- Theoretical goal: Address debate between desirable difficulties, like "testing effect", and direct instruction, like "worked examples"
- Limitation of past worked example studies have weaker control, untutored practice
  - PSLC studies compare to tutored practice

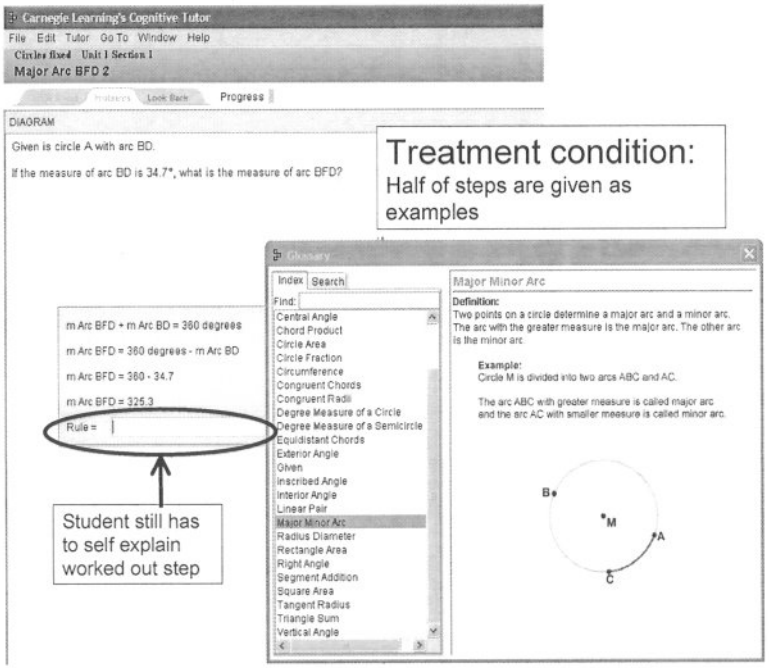
Kirschner, Sweller, & Clark (2006). Why minimal guidance during instruction does not work:...failure of... problem-based...teaching.

Worked Example Experiments within Geometry Cognitive Tutor

(Alexander Renkl, Vincent Aleven, Ron Salden, et al.)

- 8 studies in US & Germany
  - Random assignment, vary single principle
  - Over 500 students
  - 3 *in vivo* studies run in Pittsburgh area schools
- Cognitive Science 08 IES Best Paper Award

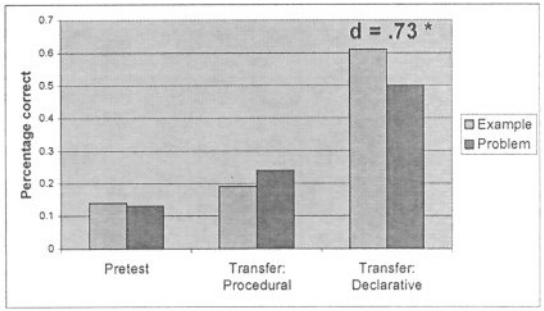




Worked examples improve efficiency & understanding

Lab results

- 20% less time on instruction
- Conceptual transfer in study 2



In Vivo

- *Adaptively fading* examples to problems yields better long-term retention & transfer

Worked example effect generalizes across domains, settings, researchers

- Geometry tutor studies
- Chemistry tutor studies *in vivo* at High School & College (McLaren et al)
  - Same outcomes in 20% less time
- Algebra Tutor study *in vivo* (Anthony et al)
  - Better long term retention in less time
- Theory: SimStudent model (Matsuda et al)
  - Problems provide learning process with negative examples to prune misconceptions
- Research to practice
  - Influencing Carnegie Learning development
  - New applied projects with SERP, WestEd

Processes of *Learning* within the KLI Framework

The conditions that yield robust learning can be decomposed at three levels:

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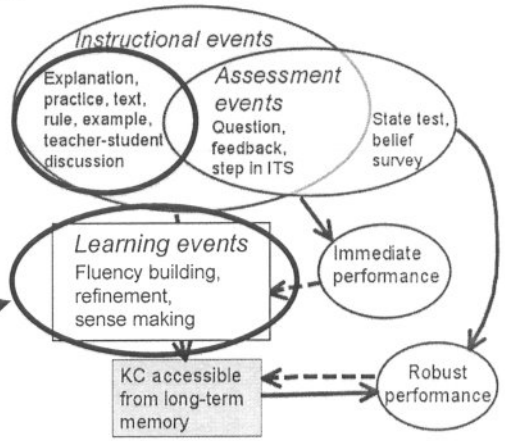
Instructional events



Learning Events in the Brain & reflected in Dialogue

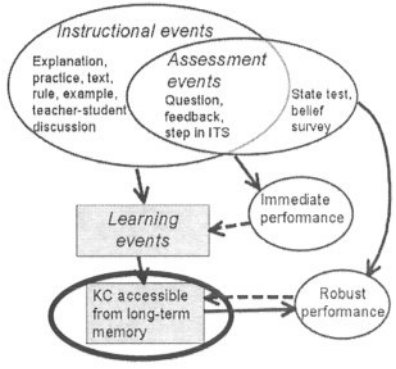
- Fluency building
  Memory, speed, automaticity
- Refinement processes
  Classification, co-training, discrimination, analogy, non-verbal explanation-based learning
- Sense-making processes
  Reasoning, experimentation, explanation, argument, dialogue

Some PSLC Examples

- ACT-R models of spacing, testing effects & instructional efficiency (Pavlik)
- SimStudent models of learning by example & by tutoring
  - Inductive logic prgrming, probabilistic grammars (Matsuda, Cohen , Li, Koedinger)
- Transactivity+ analysis of peer & classroom learning dialogues (Rose, Asterhan, Resnick)

Knowledge components carry the results of learning

- Knowledge component = a unit of cognitive function or structure that can be inferred from performance on a set of related tasks.
- Used in broad sense of a knowledge base
  - From facts to mental models, metacognitive skills



Kinds of Knowledge Components

Task Features	Response	Relationship	Rationale	Labels
constant	constant	implicit	no	association
constant	constant	explicit	no	fact
variable	constant	implicit	no	category
variable	constant	explicit	no	concept
variable	variable	implicit	no	production, schema, skill
variable	variable	explicit	no	rule
variable	variable	explicit	yes	principle, rule, model

- Other kinds of KCs
  - Integrative, probabilistic, metacognitive, misconceptions or "buggy" knowledge

Example KCs with different features

- Chinese vocabulary KCs:
  const->const, explicit, no rationale
  - If the Chinese pinyin is "lao3shi1", then the English word is "teacher"
  - If the Chinese radical is "日", the English word is "sun"
- English Article KCs:
  var->const, implicit, no rationale
  - If the referent of the target noun was previously mentioned, then use "the"
- Geometry Area KCs:
  var->var, implicit & explicit, rationale
  - If the goal is to find the area of a triangle, and the base <B> and the height is <H>, then compute 1/2 * <B> * <H>
  - If the goal is to find the area of irregular shape made up of regular shapes <S1> and <S2>, then find area <S1> and <S2> and add

Integrated KCs for mental models, central conceptual structures, strategies & complex planning

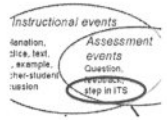
Knowledge components are not just about domain knowledge

- Examples of possible domain-general KCs
- Metacognitive strategy
  - Novice KC: If I'm studying an example, try to remember each step
  - Desired KC: If I'm studying an example, try to explain how each step follows from the previous
- Motivational belief
  - Novice: I am no good at math
  - Desired: I can get better at math by studying and practicing
- Social communicative strategy
  - Novice: When an authority figure speaks, remember what they say.
  - Desired: Repeat another's claim in your own words and ask whether you got it right

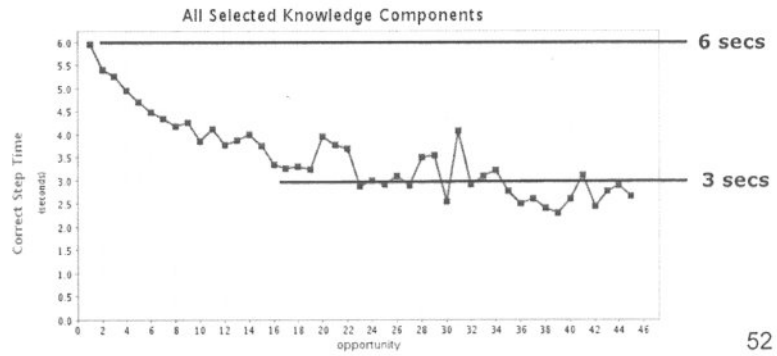
Can these be assessed, learned, taught? Broad transfer?

Learning curves: Measuring behavior on tasks over time

- Data from flash-card tutor
- Tasks present a Chinese word & request the English translation
- Learning curve shows average student performance (e.g., error rate, time on correct responses) after each opportunity to practice



Dataset: Chinese Vocabulary Spring 2007
Sample(s): All Data
KC Model: Default



Empirical comparison of KC complexity

Example KC types

Chinese vocabulary KCs
const->const, explicit, no rationale

English Article KCs
var->const, implicit, no rationale

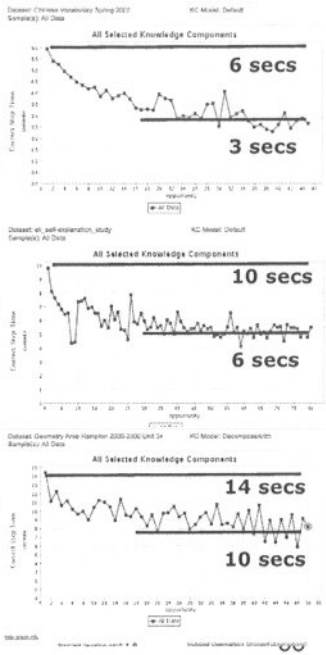
Geometry Area KCs
var->var, implicit/explicit, rationale

Time

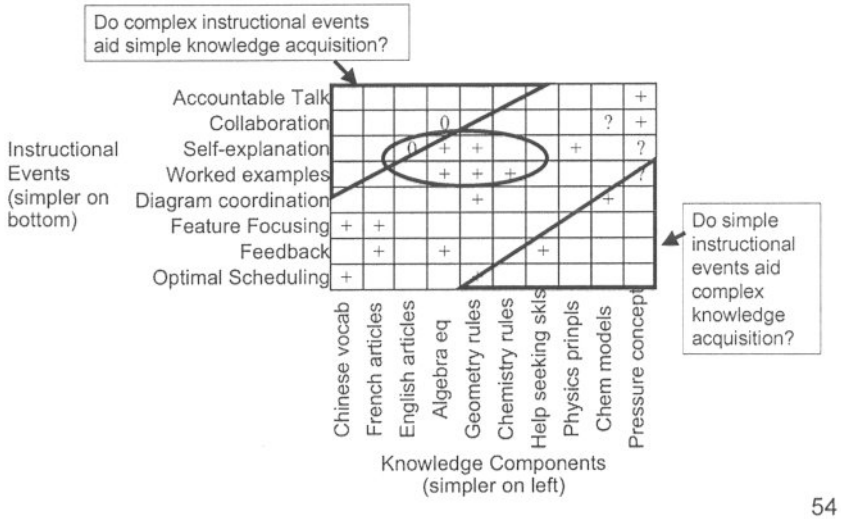
6 -> 3 secs

10 -> 6 secs

14 -> 10 secs



Which instructional principles are effective for which kinds of knowledge components?



Prompted self-explanation studies across domains

- Physics Course - field principles
  - Better transfer than providing explanations
- Geometry Course - properties of angles
  - Better transfer than just practice despite solving 50% fewer problems in same time
- English Course - article use
  - Pure practice appears more efficient; self-explanation may help for long-term retention & for novices
- *Cross-domain hypoth: Type of KC determines when self-explanation will be effective.*

Var->Var, explicit

Var->Const, implicit

Summary

- Obama: "learning software as effective as a personal tutor"
- How close to this vision are we now?
  - Many fielded Intelligent Tutors
  - Students learn as much or more
- What else do we need to do?
  - Expand to more areas => CTAT
  - More sophisticated interaction => CSCL
  - Use tutors to advance science & improve educational practice => In Vivo & EDM

In other words …

Take the PSLC Summer School!