行政院國家科學委員會專題研究計畫　成果報告

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International Conference on

Broadening Research At International Network (BRAIN)

sponsored by:

Department of Science Education, National Science Council, Taiwan

CONFERENCE PROGRAM

KEYNOTE PAPERS & ABSTRACTS

May 25 & 26 2006

at College of Science Campus, National Taiwan Normal University

organized by the

Department of Earth Sciences

at National Taiwan Normal University, Taiwan

CONTENTS

BACKGROUND

The Department of Science Education (DSE), National Science Council of Taiwan, has recently urged research of interdisciplinary studies in science and mathematics education. The purpose of this proposed conference is to invite individuals from different background including science and mathematics education, cognitive science, psychology and/or learning sciences for developing a framework aiming at conducting future interdisciplinary studies. The conference is designed to address important issues and key challenges and provide directions and conceptual framework for conducting interdisciplinary research in science and mathematics education.

背景

行政院國家科學委員會科學教育發展處，近期推動跨領域之數理教育研究。此研討會的目的在於邀請來自不同背景的學者，其中包含數學或科學教育、認知科學、心理及學習科學，以發展未來跨領域之研究架構。此研討會旨在深入討論重要及關鍵的研究問題，為未來跨領域之數理教育研究提供探討方向及概念架構。

PROGRAM

✧ May 25, 2006 (Thursday)

08:00 - 08:30	Reception
08:30 - 08:40	**Opening Ceremony** *Tung-Yi (Tony) Lee, Dean of The Office of Research & Development, NTNU*
08:40 - 10:10	**Keynote Speech I: Cognitive Research** Science learning and teaching for the 21st century: Impacting students' learning & teachers' assessment and pedagogical practices *Speaker: Janice Gobert* *Chair: Chun-Yen Chang, Dept. of Earth Sciences, NTNU*
10:10 - 10:30	Refreshment
10:30 - 12:00	**Keynote Speech II: Learning Sciences** Beyond Compartmentalized Curricula in Science and Mathematics: Implications of Complex Systems for the Learning Sciences and for Education *Speaker: Michael J. Jacobson* *Chair: Chin-Chung Tsai, Institute of Education, National Chiao Tung University*
12:00 - 14:00	Lunch
14:00 - 17:00	**Workshop**

PROGRAM

✧ May 26, 2006 (Friday)

08:00 - 08:30	Reception
08:30 - 10:00	**Keynote Speech III: Epistemology** Understanding students' epistemic beliefs in science and mathematics: An overview of constructs, measures, and research *Speaker: Barbara K. Hofer* *Chair: Fang-Ying Yang, Dept. of Earth Sciences, NTNU*
10:00 - 10:30	Refreshment
10:30 - 12:00	**Keynote Speech IV: Neurocognitive research** The neural mechanisms of visual/spatial imagery and their implications for science education *Speaker: Maria Kozhevnikov* *Chair: Chia-Ju Liu, Graduate Institute of Science Education, National Kaohsiung Normal University*
12:00 - 13:30	Lunch
13:30 - 14:30	**Keynote Speech V: Science Teacher Education** Developing a Science Teacher Professional Development Research Agenda *Speaker: James P. Barufaldi* *Chair: Chun-Yen Chang, Dept. of Earth Sciences, NTNU*
14:30 - 15:00	Refreshment
15:00 - 17:00	**Workshop**

KEYNOTE SPEECH I – ABSTRACT / PAPER

The text of the abstract/paper has been printed as received; no editing has been done.

Science learning and teaching for the 21st century: Impacting students' learning & teachers' assessment and pedagogical practices

Janice D. Gobert

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Introduction

The book Science for All Americans (Rutherford & Alhlgren, 1990) is party responsible for changing the way we think about who gets educated in science. Post the Sputnik era, we are no longer interested in science for only the "best and the brightest" students. We need a broad base of citizens who are scientifically literate so they can make decisions that affect their everyday lives, i.e., (e.g., radon testing in their homes, etc.). Being scientifically literate includes various forms of knowledge (Perkins, 1986), including: Content knowledge, to us, this knowledge is in the form of models, Process skills, i.e., inquiry, evaluation of evidence, communication, etc., to this we add modeling skills, Understanding the nature of science, i.e., that it is a dynamic discipline, and to this we add understanding the nature of models (Gobert & Discenna, 1996; Schwarz & White, 1998).

Information technologies provide a promising path to scientific literacy: 1) Computers are becoming more ubiquitous, thus, problems of access are lessening; 2) computers are a powerful computation medium which can run complex simulations beyond textbook diagrams, 3) the world wide web allows students access to authentic, real-time data and visualizations, and 4) learning environments and technology infrastructures are becoming widely available to support students in their science inquiry, support teachers in assessment, and support researchers in data analysis and, in turn, theory development. Furthermore, information technologies are making major contributions to Cognitive Science, to Intelligent Tutoring Systems, and to Science education in terms of reform efforts in many ways. In this paper we specifically address the affordances of learning environments, which log students' actions while they are learning. Logging has important implications, as follows: 1) For Cognitive Science because logging provides a bird's eye view into the "black box" regarding students' learning processes with greater validity than previous measures (Ericsson & Simon, 1984); 2) For Intelligent tutoring systems because it is an essential component of intelligent tutoring systems which can fade scaffolding as a student's skill level increases (Dede & Lewis, 1995), and 3) For Science

Education because log files provide formative assessment data for teachers to make curricular decisions in real time as well as for curriculum designers generally.

The Modeling Across the Curriculum project (mac.concord.org; IERI # 0115699).

The Modeling Across the Curriculum project is a scalability project for which we have developed a technology platform, a reporting system, and curricular materials. There are four levels of research being conducted. Level 1 focused on improving the scaffolding design through individual interviews of students and teachers. Level 2 focused on classroom-based studies to evaluate the impact of amount of scaffolding. Level 3 is a longitudinal study of our dependent variables (content, inquiry skills, attitudes towards science, and epistemology of models) with the same students across 3 years in all three domains in our partner schools. Level 4 addresses what supports are necessary to scale this to many more schools.

Our curricular activities present students with content using a progressive model-building approach (White & Frederiksen, 1990; Raghavan & Glaser, 1995; Gobert & Clement, 1999) in which simpler models (e.g., static representations of structural information) provide conceptual leverage for more complex models (e.g., causal models) of scientific phenomena. These, in turn, support model-based reasoning. We support students' model-based reasoning using scaffolds designed by our group (Gobert & Buckley, 2003) and in accordance with model-based learning theory (Gobert & Buckley, 2000); in doing so, we also draw on literature on students' difficulties in learning with models (Lowe, 1989).

The inquiry skills in national standards (NSES, 1996; U.S. Dept of Education, 1993) match pedagogically with model-based teaching and learning, the theoretical framework underlying our research, learning activities, and assessment (Gobert & Buckley, 2000). The tenets of model-based learning are based on the presupposition that understanding requires the construction of mental models, and that all subsequent problem-solving or reasoning are done by means of manipulating or 'running' these mental models (Johnson-Laird, 1983). Model-based reasoning also involves the testing, and subsequent reinforcement, revision, or rejection of mental models (Buckley & Boulter, 2000). This represents authentic science thinking in that it is analogous to hypothesis development and testing among scientists (Clement, 1989). The reasoning processes of hypothesis generation from the model, testing that hypothesis, and interpreting the data are among the higher order inquiry skills that are difficult to teach and are the type of reasoning needed in inquiry (Raghavan et al, 1995; Penner et al, 1997; White et al, 2002; Gobert, 2000).

Measuring Inquiry in situ

Inquiry is critical to science reform efforts as acknowledged by national standards (NSES, 1996; U.S. Dept of Education, 1993) but research on inquiry skills has been hampered by the difficulty and complexity of measuring inquiry, in particular, separating inquiry from its context.

Since inquiry skills are developed in rich scientific contexts, their assessment needs to be conducted within the scientific domains and contexts in which they are embedded (Mislevy et al., 2002). In the past, two approaches to measuring inquiry have been used: short answer tests of specific skills, and hands-on performance assessments. The former can be incorporated into large-scale standardized assessments but have been criticized because it is unclear whether decontextualized knowledge of the various skills that make up inquiry are sufficient to allow students to undertake inquiry (Pellegrino, 2001). The second option, performance assessment, appears to be more authentic because it requires a greater integration of specific skills to solve real problems (Ruiz-Primo & Shavelson, 1996) however, these are seldom used in schools, due largely to the difficulty of administering reliable assessments and the resulting high cost.

Our project uses a different approach that offers both the validity of performance tests and the simplicity demanded by large-scale assessments: that is, computer-based assessments of inquiry that are embedded in instructional activities. Using our scripted models which are based on scientific laws, the learner can ask a question of such a model, develop a plan of action for using the model to answer the question, run an experiment to test the model, collect the data, analyze the data, and communicate findings to other users.

Our technology has the following components. **Content Engines (BioLogica, Dynamica, Chemica, & Connected Chemistry)**-- These are implemented in Java, using model, view, controller architecture. They are Event-driven via action listeners. Actions may be initiated by user, via UI, or by model, via state change events. **Script Layer**--Our authoring environment uses node-and-arc representation of script structure. Nodes contain executable code and screen layout specification. Arcs implement flow control and node initialization and cleanup functions. State saving is achieved by designating alternative start nodes. **Pedagogica™**-- Links scripts to engines at runtime, using Java's introspection capability. These include generic objects such as questions, graphs, etc. They implement logging functions, including encryption and backup of log files. **CC Portal**-- Implements web-based school-topic-teacher-class-student registration process. It parses XML in student log files and populates MySQL database. It archives and maintains all data and provides browser-based online access to reports for administrators, teachers, and students. **Data mining tools**-- Produce customized reports for researchers. The output is exported to third-party statistics programs.

The advantages of using such a system to conduct empirically rigorous research on learning and assessment of inquiry skills are many, as follows. **Data collection**. Because all activities are on-computer, we can effortlessly and accurately monitor and record every user response and action. **Control**. Because we have complete control over the learning environment, we can simplify it to make the content more accessible and the experiments easier to perform than real systems. This can save time and increase the complexity of the science concepts studied. **Reproducibility.** All aspects of the assessment can be exactly reproduced—the experiment, the scaffolding, and the hints. Furthermore, there are no uncontrolled clues for the user, such as the tone of a human response or non-verbal clues. **Integration with instruction**. The same model and technical environment used for learning activities can be used for assessment. The assessment can be part of instruction, so that additional class time is not required; assessment is "seamless". **Convenience**. No equipment other than a computer is needed and no local training is needed for reliable results. **Scalability**. Because only a networked computer is needed, we can conduct this research anywhere and the resulting assessment tools can be used worldwide.

Inquiry Hot Spots

As previously stated, our computer models are hypermodels (Horwitz & Christie, 1999) which are scripted using Pedagogica ™ (Horwitz & Burke, 2002), a technological infrastructure that logs all students' interactions with our models and responds to learners based on their input. We log all students' interactions with models and use data from inquiry "hot spots", i.e., tasks that require deep reasoning and contain multiple components of model-based inquiry (representation, acquisition, integration, reasoning, and reflection) to characterize students' inquiry strategies on that task. We use students' log files on multiple inquiry hot spots across three domains to address how students' inquiry skills are developing both within and across domains. One measure of students' inquiry skills is how systematic students are in manipulating models to achieve a goal. Systematicity has been found to be a reliable measure of students' strategic learning and knowledge acquisition strategies (Gobert, 1994; Thorndyke & Stasz, 1980) and is a good measure with which to compare learners since it bears on their skill at estimating solutions (Paige & Simon, 1966). As we proceed with the project we will use students' data on inquiry hot spots and evaluate their relationship to both conceptual learning measurements, i.e., pre-post content tests and to measures of students' epistemologies of models and views of science since students' epistemologies of models have been found to influence science learning (Gobert & Discenna, 1997), thus, it is possible that students' epistemologies influence the manner in which students strategically manipulate models as well.

In this talk, **I** will describe logging and assessment tools developed by our group. Some of our current work on performance assessment of students' inquiry skills in different disciplines will be presented, namely Newtonian Mechanics, Genetics, and Gas Laws. Additionally, I will show, using logs, the relationship between students' specific inquiry strategies and their resulting conceptual understanding as measured by our conceptual post-tests.

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KEYNOTE SPEECH I – POWERPOINT

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The Concord Consortium

Science learning and teaching for the 21st century: Impacting students' learning & teachers' assessment and pedagogical practices.

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Modeling Across the Curriculum Team

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Overview

- Introduction: Information Technology & its implications
- MAC summary &Theoretical framework
- Technological Infrastructure & engines
- Model-based reasoning & inquiry leaning with technology
- MAC Data collected (surveys, etc).
- Data: content learning & inquiry skills~ example of hot spots
- Synergistic activities and future vision

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Information Technology & Scientific Literacy

- The book *Science for All Americans* is party responsible for changing the way we think about WHO gets educated in science.
- Post the Sputnik era, we are no longer interested in science for only the "best and the brightest students", we need a broad base of citizens who are scientifically literate so they can make decisions that affect their everyday lives, i.e., (e.g., radon testing in their homes, etc.).
- Being scientifically literate includes various forms of knowledge (Perkins, 1986):
  - ⇒ Content knowledge; to us, this knowledge is in the form of models.
  - ⇒ Process skills, i.e., inquiry, evaluation of evidence, communication, etc.; we add modeling skills).
  - ⇒ Understanding the nature of science, i.e., that it is a dynamic discipline.
  - ⇒ We add, understanding the nature of models (Gobert & Discenna, 1996; Schwarz & White, 1998).

Information Technology provides a promising path to scientific literacy…

- Computers are becoming more ubiquitous, thus problems of access are lessening.
- Powerful computation medium--> can run complex simulations beyond textbook diagrams.
- WWW allows students access to authentic, real-time data and visualizations.
- Learning environments and technology infrastructures are becoming widely available to support students in their science inquiry…

Information Technology & Broader Implications

Information technologies are making major contributions to Cognitive Science, to Intelligent Tutoring Systems, and to Science education in terms of reform efforts in many ways.

Here we specifically address the affordances of learning environments which log students' actions while they are learning.

Logging has important implications for: 1) Cognitive Science, 2) Intelligent Tutoring Systems, and 3) Science Education…

1) provides a bird's eye view into the "black box" regarding students' learning processes with greater validity than previous measures (Ericsson & Simon, 1980).

2) is an essential component of intelligent tutoring systems which can fade scaffolding as a student's skill level increases (Dede & Lewis, 1995).

3) is critical for formative assessments for teachers to make curricular decisions in real time as well as for curriculum designers generally.

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Modeling Across the Curriculum Project Summary

As part of a scalability effort funded by the Inter-Agency Education Research Initiative (IERI), we have developed qualitative model-based tools for inquiry as a means to promote scientific literacy on a broad scale.

We postulate that this promotes model-based learning in students. Model-based knowledge is more generative, transferable, and can be applied to everyday life (e.g., radon testing in our homes, etc.).

Currently, we have 13 Member schools and 400+ contributing schools.

MAC Research Overview

Four types of studies/questions originally proposed

- individual interviews of students and teachers to formalize scaffolding and surveys.
- classroom-based studies to evaluate the impact of amount of scaffolding.
- a longitudinal study of our dependent variables in a 3-year implementation of materials.
- how can this technology be scaled to include many more schools?

Instructional Design of Activities and Scaffolding are based on…

Model-based learning (Gobert & Buckley, 2000) as well as other literature….

- cognitive and perceptual affordances of learning with technology-based representations (Gobert, 2005; Larkin & Simon, 1987)
- progressive model-building (White & Frederiksen, 1990; Raghavan & Glaser, 1995)
- students' difficulties in learning with models (Sweller, et al, 1990; Gobert, 1994; Lowe, 1989; Head, 1984).

Thus, scaffolding is designed to…

- guide search, supports perceptual cues, and inference-making from perceptual cues (Larkin & Simon, 1987).
- elicit prior knowledge, support integration with new knowledge, and support reflection & reification of knowledge.

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What is Model-based reasoning?

- Modeling research at the Concord Consortium organizes learning activities, assessment, and research around model-based learning (Buckley, 2000; Gobert & Buckley, 2000), a theory of science learning that integrates basic research in cognitive psychology and science education.
- Its tenets are that understanding requires the construction of mental models and all subsequent problem-solving, inferencing, or reasoning are done by means of manipulating or 'running' these mental models (Johnson-Laird, 1983).
- Model-based reasoning also involves the testing, and subsequent reinforcement, revision, or rejection of mental models.

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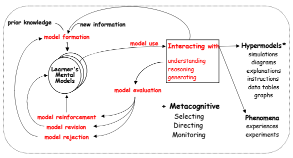
Model-Based Learning in situ

Intrinsic Learner Factors

Epistemology of models
(SUMS, Treagust et al, 2002)

Attitudes & Self-efficacy
(VASS, Halloun, 2001)



Intrinsic Teacher Factors

Epistemology of models
(adapted from Grosslight et al, 1991)

Teaching experience Background
(adapted from Fishman, 1999)

Classroom Factors
Implementation of MAC activity use
(logged)
Teacher practices
(reported via Classroom Communique)

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Model-based Inquiry a la MAC

MAC supports 5 strands of model-based inquiry. These are more specific than the NSES (1996) inquiry standards which were are not specific to current technology-based learning.

- **Representational Competence:** view and understand a representation or features of the domain.
- **Model pieces acquisition:** understand & reason with pieces of models (spatial, causal, functional, temporal).
- **Model pieces integration:** combine model components in order to come to a deeper understanding of how they work together as a causal system.
- **Model based reasoning:** reasoning with models or pieces of models.
- **Reconstruct, Reify, & Reflect:** reify knowledge and transfer it to another context or level of understanding.

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Model-based learning, inquiry, assessment & technology!

- **Currently reform efforts call for the development of inquiry skills by learners.**
- **However, there lacks efficient, reliable means of assessing inquiry skills in part because it is difficult to separate inquiry skills from the context in which they were developed (Mislevy et al., 2002).**
- **In MAC, our activities require deep, authentic model-based inquiry, are enacted over many days while seamlessly integrated with instruction, thus, we have an efficient, reliable way of assessing inquiry skills.**

Types of Data Collected

- School demographics & available technology
- Teachers
  - Science Background
  - Modeling survey
    - *(adapted from Gobert & Discenna, 1997)*
  - Classroom Communiqués regarding pedagogy used alongside software.
- Students
  - SUMS (Student Understanding of Models Survey; Treagust et al, 2002, adapted from Grosslight et al, 1991)
  - VASS (Views About Science Survey; Halloun and Hestenes, 1998)
    - *Comparable forms for biology, physics, and chemistry*
  - Content Pre and Post tests
  - Log files from our curricular activities (includes embedded & performance assessments)~ in particular, HOT SPOTS

Technology Overview

Our Engine

- We use Pedagogica, a powerful runtime and authoring environment which~
  - has general purpose software tools, manipulable models, and assessments
  - controls all aspects of the learners' interactions with the tools
  - provides formative and summative assessment (for teachers) and performance assessments (log data for researchers).

Content Models

Four content areas:

- Genetics (BioLogica)
- Gas Laws (Connected Chemistry)
- Newtonian Mechanics (Dynamica)
- Atomic Structure (Chemica)

- Our models are hypermodels whereby interactive models are coupled with rich embedded assessments that students learn through exploration and scaffolded inquiry; thus, assessment is seamlessly integrated with instruction. Hypermodels logs all actions, allowing performance-based assessment of students' inquiry strategies and content learning.

KEYNOTE SPEECH I – POWERPOINT

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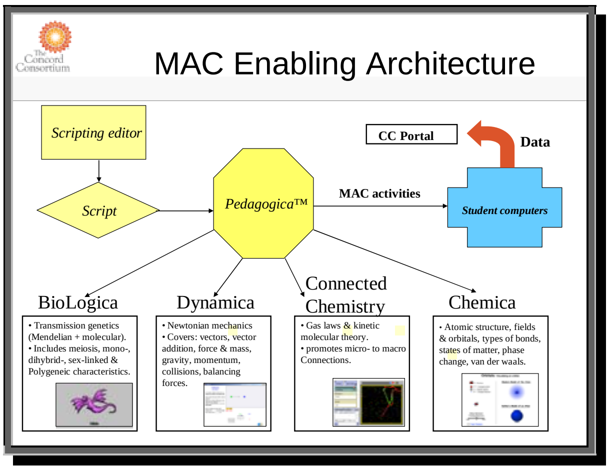
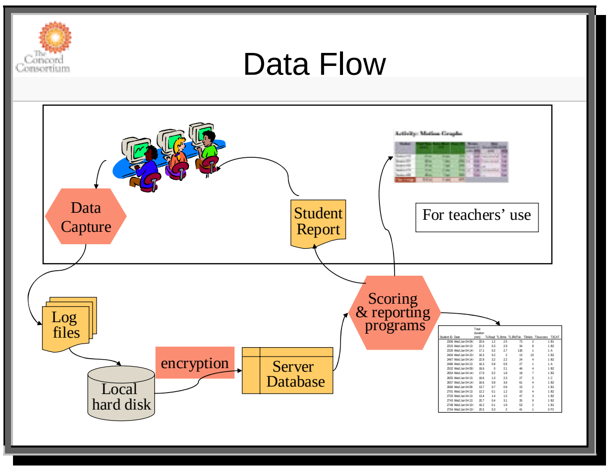
What's under "the hood"?

- Pedagogica™
  - Links scripts to engines at runtime, using Java's introspection capability
  - Includes generic objects such as questions, graphs
  - implements logging functions, including encryption and backup of log files
- Content Engines
  - Implemented in Java, using Model, View,Controller architecture
  - Event-driven via action listeners
  - Actions may be initiated by user, via UI, or by model, via state change events
- Script Layer
  - Authoring environment uses node-and-arc representation of script structure
  - Nodes contain executable code and screen layout specification
  - Arcs implement flow control and node initialization and cleanup functions
  - State saving achieved by designating alternative start nodes
- CC Portal
  - Implements web-based school-topic-teacher-class-student registration process
  - Parses XML in student log files and populates MySQL database
  - Archives and maintains all data
  - Provides browser-based online access to reports for administrators, teachers, and students
- Data mining tools
  - Produce customized reports for researchers
  - Output can be exported to third-party statistics programs





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Technology & Affordances for Research & Assessment

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Technology:

Log files on students' interactions with models capturing students'…

- Data on duration and sequence
- Actions and choices with models
- What info or help they seek
- Responses to questions

Affordances

Implementation data -- which activities were used, pattern of use (consecutive or intermittent days) at classroom level & student level.

Finer-grained log data can be used for

- Measure of students' systematicity and inquiry skills.
- Test for interactions with prior knowledge & epistemology.

These data are used to derive student reports….

Embedded & Performance Assessments with models & questions…

- Generate profile for students at "pivotal" points in curriculum
- Responses to questions

- Formative assessments
- Summative assessments
- Performance assessments

Inquiry "Hot Spots"

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- Currently we are focusing on analyzing log file data from inquiry hot spots as indices of students' model-based inquiry skills.

Hot spots are:

- Tasks or parts of tasks that contain multiple components of model-based inquiry (representation, acquisition, integration, reasoning, and reconstruct, reify, and reflect).
- Tasks or parts of tasks that require deep reasoning.

Fine-grained analysis, one hot spot at a time, is necessary in order for us to code the various process variables we plan to aggregate and focus on.

With these data, we can assess transfer from one domain to another and assess how a student's inquiry skills are progressing "independent" of content learning.

Analysis of hot spots (cont'd)

The Concord Consortium

- Since our activities are enacted over multiple days and in three domains, we avoid the problems faced by earlier studies of inquiry in which there were not enough data to get at students' inquiry skills (Shavelson et al, 1999).

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Overview of Data Analysis of Hot Spots

Tracking students' systematicity in learning with models is one important facet of inquiry skills and conceptual learning. To us, inquiry skills co-evolve with content learning but each can be measured separately (sort of).

Theory driving this is based on…

- expert problem-solving for estimating solutions (Paige & Simon, 1966)
- experts vs. novices search and knowledge acquisition strategies (Gobert, 1994, 1999; Thorndyke & Stasz,1980).

Relationship of log data to:

- conceptual learning measurements, i.e., pre-post content tests
- measures of students' epistemologies of models and views of science since students' epistemologies influence learning (Songer & Linn, 1991; Gobert & Discenna, 1997).

Steps for Analysis of Log Data

- Analysis protocols for log file were developed via a reiterative process of
  - validation of log files
  - development of rubrics
  - hand scoring
  - computer scoring
  - validation of scoring
  - hand summarization
  - computer processing
  - validation of summary/concise reports
  - statistical analyses: relationship to content learning, and other dependent variables.

Data to be presented

From Dynamica on inquiry hot spot coding and validation using Carnegie-Mellon University production rules approach.

If there is time, data from BioLogica on inquiry hot spot coding and relationship to content learning and from Connected Chemistry on students' strategies on hot spots.

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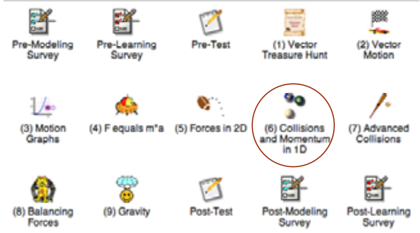
Activities in Dynamica & hot spots presented here

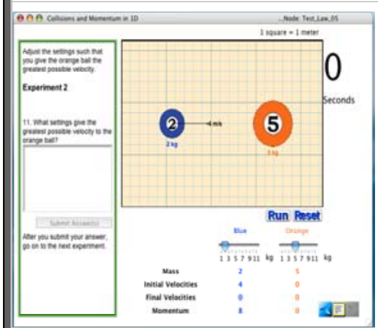


- 9 activities
- Pre and post tests and surveys
- Here we focus on **hot spots** from Collisions and Momentum in 1D

Types of data Data logged for Hot Spots

Item format	Data
Multiple choice Survey questions	Students' choices (Auto Scored)
Constructed text responses	Full text of responses
Numerical values *Arrows, sliders, boxes*	Value(s) (Auto Scored)
Simulation tasks	Values entered for each trial Number of trials Process variables Success

Hot spot from Collisions task 5: Student sets mass of two balls



- The challenge: adjust the masses of the two balls to make the orange ball move as fast as possible after the collision.

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Strategies for Inquiry

Preliminary analysis based on human coding identified 2 different inquiry patterns:

1. haphazard
2. Systematic

(Also, there are students who got it correct on first trial, sometimes with explicit test).

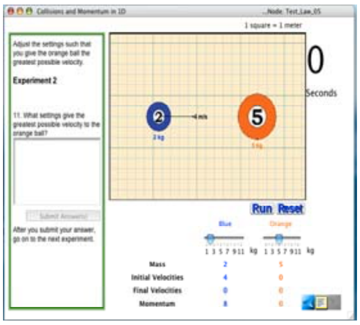
These are consistent with literature:

~ experts vs. novices search and knowledge acquisition strategies (Thorndyke & Stasz,1980; Gobert, 1994, 1999).

~ expert problem-solving for estimating solutions (Paige & Simon, 1966).

Examples …

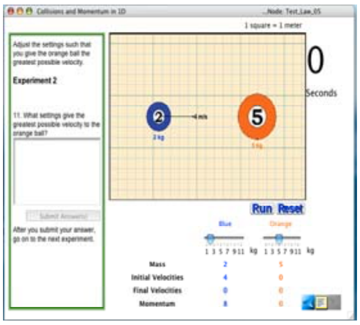
Haphazard Strategy- this student obtained the correct answer (11.0; 1.0) on trials 2,10,(& 15) but did not know it!



Student 12116 made 15 trials:

Blue Ball	Orange ball
11.0	11.0
11.0	1.0
11.0	3.0
11.0	4.0
1.0	1.0
1.0	11.0
8.0	7.0
11.0	2.0
11.0	11.0
11.0	1.0
11.0	5.0
3.0	5.0
1.0	5.0
1.0	8.0
11.0	1.0

Systematic Strategy, e.g.,vary one ball at a time (a good strategy in the absence of prior knowledge).



Student 18115 had a plan:

Blue Ball	Orange ball
11.0	11.0
5.0	11.0
10.0	11.0
11.0	1.0

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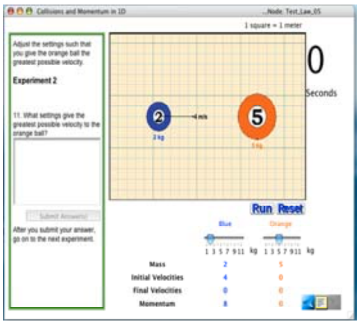
Correct on first trial with a trial to be sure (likely that this student started with high prior knowledge)



Student 18185 got it right the first time:

Blue Ball	Orange ball
11.0	1.0
1.0	11.0
11.0	1.0

Collaboration with Carnegie-Mellon University

- In collaboration with Ken Koedinger & Bruce McLaren, we investigated whether we could use production rules to code students' strategies (n= 96) on this task.
- We developed specifications for scoring students' strategies:
- "Strong" productions rules (i.e., content knowledge) in Newell's terms (1990) fired when the student maximized the mass of A and/or minimized the mass of B.
- "Weak" rules (i.e., inquiry strategies) in Newell's terms (1990) fired when students' varied the mass of one ball at a time, did not repeat incorrect experiments, and stopped when the fastest possible velocity had been obtained.

Table 1: Weak and Strong Scores for the Cognitive Model

Cognitive Model	
Strong Methods	
For	*0.71 (71/100)*
Against	*0.44 (238/539)*
Weak Methods	
For	*0.57 (138/240)*
Against	*0.33 (37/111)*
Partial-For	*0.43 (78/183)*
Neutral	*0.68 (26/38)*

• A "Correct one trial" protocol would be evidence the student used strong methods since s/he apparently had the knowledge to immediately solve the problem with no inquiry necessary.

• A "Correct one trial" protocol would provide no evidence for whether the student used weak methods since not enough data is available ("neutral" was assigned in this case).

• A "Correct and systematic" protocol provides evidence the student did not use strong methods, since multiple trials were needed and the strong rules discussed above were apparently not used, but it provides clear evidence for the use of weak methods.

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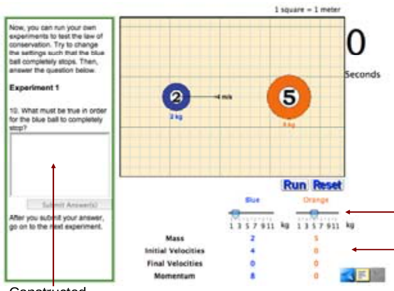
Findings from CMU collaboration (cont'd)

- the "For" evidence (0.71) is higher than the "Against" evidence (0.44), indicating that the strong rules appeared to model the "For" categories (e.g., "Correct one trial", "Correct two trials") better than it did the "Against" categories (e.g., "Correct and systematic").
- The difference between the "For" and "Against" scores of the Weak Methods is a bit smaller (0.57 versus 0.33, respectively) but still high enough to be encouraging.
- These scores for "strong" and "weak" strategies corresponded very well with human coding.
- Thus, the production rules were successful at predicting both strong and weak methods (Horwitz, Gobert, & Koedinger, 2005).
- This gives us added confidence that the log data we acquire in this project will enable us to track students' learning trajectory as they follow our progression of models.

Hot Spot 2: Concord's algorithms for auto-scoring Task 3: "What settings cause the blue ball to stop when it collides with the orange ball?"



- Student has to "estimate" the mass of the hidden ball based on velocity of red ball.
- Track students' iterations of this as index of systematicity in inquiry.

Input sliders

Numerical data from run

Constructed text response

CC's approach for Task 3- Additional Categories for coding & 4 students' data.

TL3 time	TL3 RdTsk	T3 trials	T3 values	T3 Vx	T3 #rtPr	T3 success	Q10A	T3 %vary1	T3 %rpt	T3 #eqPr	T3 #extrem Pr	T3 %clg	T3 %frg	T3 %goal Flips	T3 CAT
2.5	73	2	2.0 v 5.0 5.0 v 5.0	-1.7, 0.0,	1	1	that they must have have equal masses	1	0	1	0	1	0	0	B1
2.9	34	8	2.0 v 5.0, 4.0 v 11.0, 1.0 v 4.0, 11.0 v 11.0, 6.0 v 7.0, 5.0 v 7.0, 3.0 v 7.0, 7.0 v 7.0,	-1.71, -1.87, -2.4, 0.0, - 0.31, - 0.67, - 1.6, 0.0,	2	1	they have to both have to be the same size	0.43	0	2	0	0.29	0.71	0.43	B2
2.7	130	1	5.0 v 5.0,	0.0,	1	1	match the orange	0	0	1	0	0	0	0	A
2	13	10	2.0 v 5.0, 1.0 v 5.0, 11.0 v 5.0, 8.0 v 5.0, 8.0 v 11.0, 7.0 v 11.0, 6.0 v 11.0, 7.0 v 10.0, 11.0 v 10.0, 10.0 v 10.0,	-1.71, -2.67, 1.5, 0.92, - 0.63, - 0.89, - 1.18, - 0.71, 0.19, 0.0,	1	1	The mass must be almost as big as the other ball	0.89	0	1	0	0.67	0.33	0.33	B2

Additional categories we auto-coded are % of trials in which
~ set the masses as equal
~ set the masses as extremes
~ closer the the goal, further from the goal,
~ goal flips.

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Performance Assessments of Inquiry in Dynamica: Findings thus far

- These tasks are well-suited to assessing students' systematicity because of the well-defined domain, and numerical data inputted by students.
- We have developed analysis protocols & auto-coding for 4 inquiry hot spots in Dynamica.
- These are auto-scorable, except for textual responses, i.e., explanation tasks.
- Systematicity is machine-detectable in students' actions, i.e., in the inputs they assign to objects, etc.
- Systematicity can be calculated across tasks but the domain needs to be very finely specified (i.e., velocity not Newtonian Mechanics). This likely reflects students' conceptual knowledge building piece by piece, at the concept level (acceleration, not Newton's laws).

Performance Assessments of Inquiry in Dynamica: Plans for Aggregating Hot Spot data

Evaluating whether inquiry skills improve over time will involve aggregating hot spots.

Aggregation & analysis can be done in 2 ways (and within each domain):

- type of hot spot (involves the same model-based inquiry strands), i.e., do kids get better at similar types of model-based inquiry tasks?
- type of inquiry skill, i.e., do kids get better at making predictions, using evidence, etc?

We assume that the skill development to which we refer here (as measured by hot spots) are skills that are difficult to hone, thus, aggregating them over multiple activities is a better way to assess their development.

Overall Research Goals

- Evaluating whether inquiry skills improve over time.
- Investigate relationship between inquiry and content learning.
- Test for development of inquiry strategies across domains (physics, biology, chemistry)
  ~ complicated by task difficulty increasing over time
  ~ complicated by the co-evolution of the development between domain-knowledge and inquiry strategies
  ~ complicated by the likelihood that students build knowledge in small, conceptual pieces, i.e., about acceleration or velocity as opposed to about Newton's Laws).
- Investigate whether we can bootstrap inquiry in service of content learning.
- Lastly, using log files we seek to identify at risk students- i.e., students whose inquiry strategies are buggy (proposal pending with CMU; Horwitz, Gobert, & Koedinger, 2005).

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General affordances of this approach

- **Data collection**. Because all activities are on-computer, we can effortlessly and accurately monitor and record every user response and action.
- **Control.** Because we have complete control over the learning environment, we can simplify it to make the content more accessible and the experiments easier to perform than real systems. This can save time and increase the complexity of the science concepts studied.
- **Reproducibility.** All aspects of the assessment can be exactly reproduced—the experiment, the scaffolding, and the hints. Furthermore, there are no uncontrolled clues for the user, such as the tone of a human response or non-verbal clues.

Affordances (cont'd)

- **Integration with instruction.** The same model and technical environment used for learning activities can be used for assessment. The assessment can be part of instruction, so that additional class time is not required; assessment is "seamless".
- **Convenience**. No equipment other than a computer is needed and no local training is needed for reliable results.
- **Scalability.** Because only a networked computer is needed, we can conduct this research anywhere and the resulting assessment tools can be used worldwide.

Other synergistic activities

- Building on previous technologies of Pedagogica and the Web-based Inquiry Science Environment (WISE), in the TELS project (telscenter.org), the Concord Consortium, UC-Berkeley, and University of Toronto (Jim Slotta) are developing a powerful new open source authoring system that allows researchers or developers to create highly interactive java-based activities that are delivered to classrooms via the Internet.
- This system emphasizes interoperability with other java-based learning tools, thanks to a new Scalable Architecture for Interactive Learning (SAIL) that has guided our development.
- Easy to use authorware allows teachers to customize curriculum activities to their specific classroom needs. This authoring environment can work with various content engines.
- Activities can be downloaded from an open content library and reshaped by authors who can add or subtract curriculum or assessment elements.

KEYNOTE SPEECH II – ABSTRACT / PAPER

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Beyond Compartmentalized Curricula in Science and Mathematics: Educational and Research Implications of Complex Systems[1]

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"The central task of a natural science is to make the wonderful commonplace: to show that complexity, correctly viewed, is only a mask for simplicity; to find pattern hidden in apparent chaos."
-- Herbert Simon

The teaching and learning of science and mathematics in the 21st century faces many challenges. Of these, two are arguably fundamental. First, many current science and mathematics curricula have been criticized for superficially covering too many subjects, with the consequence that students typically fail to achieve a solid understanding of even a single domain (National Research Council, 1996, 2000). A second challenge, which conflicts with the first, is that there is approximately a 20 to 30 year gap that exists between the articulation of new scientific knowledge and the integration of these ideas into mainstream education. Further, with respect to the second challenge, it seems unlikely that conceptually challenging concepts and skills from 21st century sciences can be merely "added" to the already bloated and over-stretched science and mathematics curriculum.[2]

One approach for addressing these challenges is to look carefully at trends in the nature of 21st century scientific inquiry. Such an analysis could consider ways that (a) the classroom teaching of science and mathematics and (b) the conduct of scientific research in the learning sciences and in science and mathematics education might be at variance with new scientific ideas and methods. This paper briefly considers these two areas in turn.

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[1] This paper synthesizes material from Jacobson and Wilensky (2006).

[2] There is also a "meta-challenge" related to a theme of this workshop, that is, what should be the basis for cross-domain research that will investigate challenges to learning science and mathematics such as these?

The Nature of Modern Scientific Inquiry and Complex Systems Curricular Integration in Science Education

Over a decade ago, Stewart Kauffman (1995) observed that the relentless reductionism (i.e., increasingly fragmented and narrowly defined and isolated subspecialties) of the past 300 years in the history of science may be coming to an end. Instead, what appears to be emerging is a new kind of science (Bar-Yam, 1997; Gell-Mann, 1994; Holland, 1995; Kauffman, 1995; Wolfram, 2002) in which scientists in multidisciplinary fields study various types of complex physical and social systems. These investigations employ a similar set of conceptual perspectives or principles (e.g., multi-scale hierarchical organization, emergent patterning, dynamical attractors, scale-free networks) and methods of doing science (e.g., computational modeling, network analysis) that function as a shared framework for the discourse and representations used in the conduct of scientific inquiry (Jacobson & Wilensky, 2006). These new theoretical conceptual perspectives about complex systems in conjunction with rapid advances in computational technologies, enable researchers to study aspects of the real world for which events and actions have multiple causes and consequences, and where order and structure co-exist at many different scales of time, space, and organization. Using what may be called a complex systems framework for science, critical behaviors of systems that were systematically ignored or over-simplified by classical science can now be included as part of routine scientific inquiry in the physical and social sciences (Bar-Yam, 1997; Gell-Mann, 1994; Kauffman, 1995; Prigogine & Stengers, 1984).

However, little of the conceptual power embodied in the rapidly developing perspectives and tools of complex systems has informed the educational experience of students at any level, save that of graduate students in selected scientific areas. This absence from mainstream education creates many missed opportunities for building links between new 21st century scientific knowledge and what students learn in schools. Further, given the integrative function of complex systems ideas in actual scientific research, there is also the potential for this knowledge to help provide unifying conceptual frameworks to address the problems of fragmented and compartmentalized curricula in science and mathematics.

There are many ways that complex systems concepts might be infused into the curricular content of school subjects that could form the basis of a new type of scientific literacy (Jacobson, 2001). Across many domains, concepts derived from a complex systems analytical perspective have the potential to provide organization to the otherwise bewildering properties of diverse phenomena in the physical and social sciences. For example, complex systems concepts such self-organization and positive feedback may be seen to apply in biological systems such as insect colonies (Dorigo & Stuetzle, 2004; Resnick, 1994) in social science systems such as economics (Anderson, Arrow, & Pines, 1988; Epstein & Axtell, 1996), and in engineering (Amaral & Ottino, 2004; Ottino, 2004). Research is needed to explore if the use of appropriate pedagogies, curricular materials, and learning tools helps students understand that complex systems conceptual perspectives have relevance across what have traditionally been taught as separate compartmentalized subject areas in the natural sciences such as chemistry and biology as well as the social sciences such as psychology and sociology. If so, then this would help justify the need for curricular reforms at the college and pre-college levels in order to obtain conceptual and curricular coherence and interconnectedness. In particular, cognitively powerful cross domain links may be fostered by the design of modeling and simulation tools that scaffold structural and functional similarities between traditionally regarded distinct sets of physical and social science phenomena. For instance, at first glance, there is no reason to believe that a network capturing a cell's genetic network and a network capturing the topology of the World Wide Web would have much in common. It has been demonstrated, however, that many physical and social networks are similar in the sense that their degree distribution is scale-free (Barabasi & Albert, 1999). This similarity is explained by an agent-level mechanism of growth and preferential attachment. Another area of research could explore whether a complex systems infused curriculum allows both for depth of coverage of traditional physical and social science subjects and for cross-disciplinary conceptual and cognitive "hooks" that may support far transfer of knowledge to dramatically new situations and problems.

In addition, complex systems phenomena are well suited to problem- and inquiry-centered learning approaches that implement constructivist models of learning and teaching. Thus research could investigate whether a learner centered curriculum that integrates complex systems perspectives helps address the unfortunate situation whereby many students view science as rote memorization of isolated and decontextualized facts for which they often see little use in their daily lives. Research could also explore if such a curricular approach helps make cross-disciplinary connections easier for teachers to teach and cognitively easier for students to appreciate and to learn, while also employing content in the physical and social sciences that is conceptually principled and current for the 21st century.

Implications of the Sciences of Complex Systems for the Learning Sciences

In addition to the curricular and learning implications of complex systems ideas, there are important theoretical and methodological issues for the learning sciences and for science and mathematics education that are raised by what might be called the complex systems framework of conceptual perspectives and principles. We use the term "framework" as it does not appear that there is a general "theory of complex systems" at this time. Rather, the multidisciplinary fields that study various types of complex systems use a set of conceptual perspectives or principles (e.g., multi-scale hierarchical organization, emergent patterning, dynamical attractors, scale-free networks) and methods of doing science (e.g., computational modeling, network analysis) that function as a shared framework for the discourse and representations used in the conduct of scientific inquiry. As such, various fields can formulate specific theoretical perspectives of relevance to the study of particular complex systems of interest that still share common elements due to their grounding in the complex systems framework.

As Jacobson and Wilensky (2006) argue, complex systems perspectives provide new methods and insights for learning science research related to how students come to understand challenging ideas. As an example, let us consider how complex systems perspectives may enhance or extend theory and research in the learning sciences and science and mathematics education through the use of computational modeling of learning and education systems.

It has been argued that there has been a recent major shift in what constitutes legitimate sources of scientific information (Jackson, 1996). The origins of modern science are often credited to Aristotle and his use of careful observations to obtain information upon which to make informed decisions rather than the logical argumentation of philosophical beliefs. The next metamorphosis in the conduct of inquires we now regard as "science" occurred with the intellectual contributions of Brahe, Galileo, Newton, Kepler, Liebniz, and Euler who not only advanced the field of mathematics, but who also demonstrated how new scientific discoveries could be made through the use of information derived from mathematical manipulations of observational data. The remarkable scientific achievements of the ensuing 300 years were predicated on these two sources of scientific information. Indeed, observational and mathematically derived information have been the norm in virtually all of the published research in the learning and cognitive sciences and in education to date.

However, Jackson (1996) has proposed that we are in the midst of a second historical metamorphosis in the conduct of science, one that involves the use of computational tools to generate a third legitimate source of scientific information. In addition, others, such as Pagels (1988), have observed how the use of computational tools in science allows dramatically enhanced capabilities to investigate complex and dynamical systems that otherwise could not be systematically investigated by scientists. These computational modeling approaches include cellular automata, network and agent-based modeling, neural networks, genetic algorithms, Monte Carlo simulations, and so on that are generally used in conjunction with scientific visualization techniques. Examples of complex systems that have been investigated with advanced computational modeling techniques include climate change (West & Dowlatabadi, 1999), urban transportation models (Balmer, Nagel, & Raney, 2004; Helbing & Nagel, 2004; Noth, Borning, & Waddell, 2000), and economics (Anderson et al., 1988; Arthur, Durlauf, & Lane, 1997; Axelrod, 1997; Epstein & Axtell, 1996). New communities of scientific practice have also emerged in which computational modeling techniques, in particular agent-based models and genetic algorithms, are being used to create synthetic worlds such as artificial life (Langton, 1989, 1995) and artificial societies (Epstein & Axtell, 1996) that allow tremendous flexibility to explore theoretical and research questions in the physical, biological, and social sciences that would be difficult or impossible in "real" or non-synthetic settings.

The typical approach used by researchers involved with computational science tools such as agent-based modeling is to articulate a model of the system of interest in terms of hypothesized rules that define the interactions between agents and between agents and their environment. In scientific computational modeling work, as opposed to explorations of modeling by mathematicians, there generally is an existing body of observational and mathematical information about the system that allows (a) an initial specification of the parameters for the model and (b) a validity check of the articulated model with the real world data, generally with iterative revisions to the model in terms of the parameters or rules the agents in a model follow in their interactions in the synthetic world. Once the researcher has demonstrated a valid model for a particular system compared to available data, it is then possible to run "computational experiments" in which what-if scenarios about the behavior of the system may be explored to understand the system under different conditions than the observed data and to perhaps envision different possible futures for how the system might behave over time. It is important to understand, however, that nearly all examples of complex systems have important random or chaotic (i.e., sensitivity to initial conditions) factors that mean there is a high probability each run of the model may be different, sometimes in small ways but perhaps in dramatically large and chaotic ways (i.e., the "butterfly effect").

Given the development of sophisticated computational modeling tools and their increasing acceptance in a wide range of scientific fields in the physical and social sciences, we argue that there is great potential to accept computationally generated information as part of research in the learning and cognitive sciences that explores complex learning, socio-cognitive, and educational systems. We believe that such work has enormous potential in four broad ways. First, the articulation of models, particularly those that are "bottom-up" such as agent-based models, often helps researchers distill their qualitative intuitions about critical factors that might be most responsible for the behavior of the system of interest. This "analytical catalyst" function of computational model building is often quite valuable when confronting systems of multi-dimensional and multi-level complexity. Second, complex systems models then become scientifically inspectable artifacts that, as mentioned above, may be compared to real world data and iteratively revised to improve the fit of the model. Third, models validated with one or more datasets may be used to explore the behavior of the system by varying model parameters (ideally with multiple runs involving all parameter combinations to investigate stochastic properties of the system). Fourth, such models may function as a tool to help generalize the findings from the observed and modeled system(s) to similar types of systems that probably have different specific local features.

In research into science and mathematics education and the learning sciences to date, there have been few examples of computational modeling along the lines discussed in the previous paragraph. For example, Lemke and Sabelli (2004) have proposed building "SimSchool" or "SimDistrict" simulation programs that would not just model existing school or school district systems, but also could be used to create synthetic schools and district systems and to study their evolution over time in terms of needs, problems, and probable outcomes. Recently, actual systems have been developed along these lines. For example, researchers have done agent-based simulations in areas of educational policy such as school choice where parents and school officials are agents in the simulation (Lauen, 2004; Maroulis & Wilensky, 2005, 2005). Researchers are also using network analysis methods to study topics ranging from how social structure impacts technology adoption in schools (Frank, Zhao, & Borman, 2004) to the role of social structure on student achievement (Maroulis, Griesdorn, & Gomez, 2005). Overall, there would seem to be great potential for complex systems and computational modeling techniques to enhance science and mathematics educational and learning sciences research involving micro and macro levels of cognitive, learning, and educational systems, such as the evolution of cognitive representational networks, design experiments of technology interventions in classrooms, and social network analysis of collaborative interactions patterns.

Conclusion

The teaching and learning of science and mathematics faces two fundamental challenges that conflict with each other. First, the fragmented and superficial coverage of too many subjects is widely criticized for contributing to poor student learning in science. Second, there has typically been a decades long gap between the generation of new scientific knowledge and its integration into college and pre-college curricula. In this paper, it is argued that one way to address these challenges is to infuse knowledge from emerging multi-disciplinary scientific research, in particular work related to the study of complex systems, into K-16 curricula in the physical and social sciences. It is also argued in this paper that there is considerable potential for complex systems conceptual perspectives and methodological tools, such as agent-based modeling, to enhance research in science and mathematics education and in the field of the learning sciences. The overall goal, of course, is for students and citizens of the new century to understand many of these exciting new ideas and perspectives about how the world works, or, in the words of Nobel Laureate Herbert Simon (1996), "to make the wonderful commonplace: to show that complexity, correctly viewed, is only a mask for simplicity; to find pattern hidden in apparent chaos."

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KEYNOTE SPEECH II – POWERPOINT

The text of the PowerPoint has been printed as received; no editing has been done.

Beyond Compartmentalized Curricula in Science and Mathematics: Implications of Complex Systems for the Learning Sciences and for Education

Michael J. Jacobson, Ph.D.
Singapore Learning Sciences laboratory

Broadening Research at International Networks: Developing a Cross Domain Framework for Science and Mathematics Education

Taipei

Overview

- What are complex systems?
- Why complex systems in education?
- Ways of thinking about complex systems
- Learnability
- Universal acid for curricula and research?

"The real voyage of discovery lies not in finding new landscapes, but in having new eyes."
-- Marcel Proust

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What are Complex Systems? Examples

- Traffic jams
- Ants foraging for food
- Birds flocking
- Immune system
- Rain forest
- "Butterfly Effect" in weather
- Singapore educational system
- Counter example: Is a watch a complex system?

What are Complex Systems? The Simple in the Complex

- *Agents* or elements
- Interactions based on often *simple rules*
- *Self-organization* occurs based on agent interactions
- *Chaos* or sensitivity to initial conditions
- *Selection, evolution*, and *co-evolution* of biological or artificial agents
- *Emergent properties* at macro level, often with different characteristics than agents at micro-level

My Complex Systems Trajectory…

- NSF funded research on learning difficult biological concepts with hypermedia in early-middle 1990s
- NSF 1996 *Cognition, Technology, & Complex Systems* project
- Organizing Committee for NSF funded *Planning Documents for a National Initiative on Complex Systems in K-16 Education* (New England Complex Systems Institute) in 1999
- Organizing Committees for *International Conference on Complex Systems*, 2000, 2002
- Author (with Uri Wilensky) of lead paper for complex systems special issue in *Journal of the Learning Sciences* (2006)

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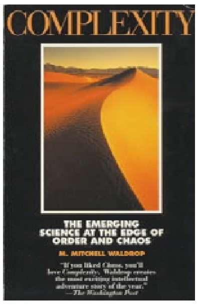
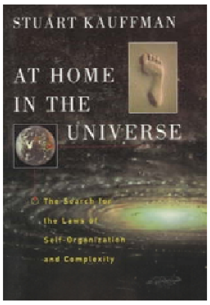
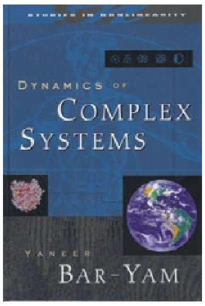
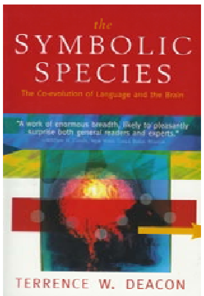
Early and Recent Good Reads





Early and Recent Good Reads





Why Complex Systems in Education?

Emerging 21st Century Science

- Integration of ideas and methods from many disciplines into the study of complex physical and social systems
- Excitement among scientists, policy-makers, business leaders, and segments of the public
- Concepts and new computational techniques provide new research tools for understanding real world:
  - Events and actions have multiple causes and consequences
  - Order and structure co-exist at many different scales of time, space, and organization
  - Behaviors ignored or over simplified by classical science may now be included in natural and social science research

KEYNOTE SPEECH II – POWERPOINT

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Why Complex Systems in Education? Integrative Conceptual Perspectives

- Complex systems concepts being integrated into conceptual frameworks of many 21st century professions:
  - Engineering, medicine, business, finance, and management
- Examples:
  - *Interdependence* and *co-evolution* in ecosystems, with emergent patterns formed by self-organization, now equally important as competitive selection in understanding biological evolution
  - *Interdependence* and *self-organization* in social systems informs corporate managers about their employees and about their relationships with other corporations
  - El Niño to the Internet/WWW and the global economy
- Variety of complex systems impact the day-to-day lives of individuals, organizations, and countries in the 21st century

Why Complex Systems in Education? Gaps in 21st Century Education

- Complex systems knowledge the province of research and advance graduate students in a few scientific areas
- Little of the conceptual power and tools of complex systems in mainstream 21st century education
- Potential consequences:
  - *Educational gap* between current best understandings and analytical tools in the physical and social sciences
  - *Working knowledge gap* of professionals, policy makers, and an informed citizenry
- Challenge: How to shorten the typical 20-30 year gap between new scientific understandings and integration into mainstream learning experiences?

Before Education: Cognition and Learnability

- Students' underlying intuitions about how world "works" quite different than many scientific perspectives
- "Traditional" scientific ideas pose significant learning challenges
  - Newtonian "laws" of motion
  - Evolution by natural selection
- Can K-16 level students understand and learn "non-traditional" complex systems scientific conceptual perspectives?

KEYNOTE SPEECH II – POWERPOINT

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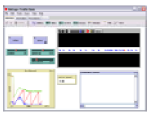
Just Plain Folks & Experts: Complex Systems and Ways of Thinking

- Paper in journal *Complexity* (2001)
- Are there expert-novice differences in ways of thinking about complex systems?
- Subjects
  - University undergraduate students
  - Complex systems scientists and professionals

Sample Problem and Answers



- Why do traffic jams form?
- University student answers:
  - Stupid drivers!
  - Accidents
- Complexity scientist:
  - Because of **random patterns** in fluid motion that generate **statistical anomalies** at irregular periods
  - Because of an **anomaly** in traffic flow (e.g., accident, stall) that causes a bottleneck
- Differences in beliefs about *linear versus non-linear causality, predictability versus randomness*

Coding Scheme for Complex Systems Problem Solving Ontologies & Mental Models

Beliefs	Clockwork Mental Model	Complex Systems Mental Model
Control	• centralized	• de-centralized
Causes	• single	• multiple
Linearity	• small action - small effect	• small action - big effect
Agent actions	• predictable	• stochastic
Agent features	• homogeneous	• heterogeneous
Purposefulness	• teleological	• non-teleological
Processes	• static structures, events	• equilibration processes

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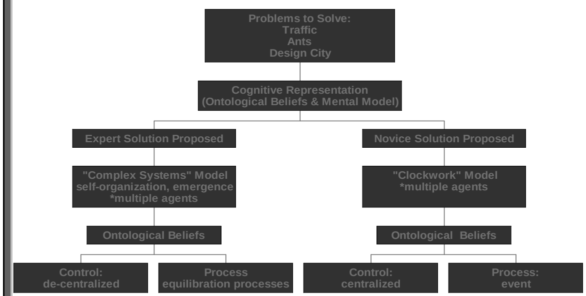
Theory of Ways of Thinking about Complex Systems



Ontological Belief Networks: Expert-Novice Differences

- Novice used few complex systems concepts
- Significant differences in ontological beliefs
- Novice ontological beliefs network
  - Reductive, order through centralized control, predictive, linear effects
- Expert ontological beliefs network
  - Non-reductive, order through decentralized interactions, randomness, nonlinear effects
- Implications:
  - May need to enrich the learner's network of ontological beliefs before students may be able to learn higher order complex system concepts

Overview of Learning Research: General Findings and Challenges

- Suggests pre-graduate level students can learn core complex systems knowledge
  - Resnick &Wilensky (1993), Wilensky's group (1995-2006), Charles (2002, 2003), Penner (2000, 2001), Goldstone & Sakamoto (2003), Chi (2005)
- However, conceptual challenges remain
  - Bias toward "top-down" rather than "bottom-up" explanations
  - Bias towards central control and linearity

KEYNOTE SPEECH II – POWERPOINT

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Complex Systems & Learning:
Research Opportunities

- *Pushing the theoretical and research envelop for exploring how people learn* (Richard Lesh)
- Dynamics of cognitive re-organization and transformation (i.e., conceptual change)
- Fostering *far transfer* of knowledge (Goldstone, 2006; Goldstone & Wilensky, in preparation)

Learning Implications

- Potential problem with directly "teaching" (learning) complex systems concepts
- Foster understanding of appropriate ontological beliefs *before* learning complexity concepts
- Research to enrich ontological beliefs
  - Participatory simulations (Wilensky, Resnick, Stroup)
  - Chi (2003; in preparation)
  - Problem based learning with contrasting cases supported with ontological and conceptual scaffolding
  - Enriching ontologies in multi-user virtual environments (MUVE)

Darwin's Dangerous Idea: Evolution & the Meanings of Life

- Amazing book by Daniel Dennett
- Darwinism (natural selection) not just for biology anymore
- Darwinism as an intellectual "universal acid"
- What container can hold an universal acid?
- Answer (of course) is *none*
- *But both the container and the acid are transformed into something new*

Can complex systems ideas and methods be a universal acid for educational curricula and learning sciences research?

KEYNOTE SPEECH II – POWERPOINT

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Universal Acid for Subject Silos in Science & Social Science Education?

- Potential for deep integrative learning about physical and social systems by using complex systems ideas across different subject areas
- Provide organization to bewildering properties of diverse systems spanning various school subjects
- Self-organization & positive feedback relevant to:
  - Biological systems such as social insect colonies
  - Social science systems such as segregation patterns, economics, and income distribution patterns
- Over time, students learn complex system perspectives:
  - Relevant to separate subject areas in *both* the physical and social sciences
  - Support deeper understanding of "traditional" subject area concepts

Universal Acid for Educational Theories?

- Potential to transform current theoretical silos in education and learning sciences
  - Neuro-brain, cognitive, situated, policy theories
  - Theories tend to focus at one "level" of analysis (e.g., cognitive, social-cultural)
- Core complex systems ideas as "theoretical Lego blocks:"
  - Agent interactions, self-organization, selection, emergence, feedback, non-linearity
  - Conceptual tools for new theories that bridge micro-macro levels of complex human and social systems relevant to learning
- Way to bridge the "cognitive" and "socio-cultural" theoretical divide.

Universal Acid for Educational Research Methods?

- Santa Fe Institute Working Paper by Atlee Jackson: *The Second Metamorphosis of Science*
- Legitimate sources of scientific information
  - Observations: Aristotle, 600 BC
  - First metamorphosis: Mathematical models: Newton, Keplar, 17th century
  - Second metamorphosis: Computational modeling: late 20th century

KEYNOTE SPEECH II – POWERPOINT

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Complex Systems Modeling in Educational & Learning Sciences Research

Second metamorphosis of science has yet to occur in learning sciences & educational research

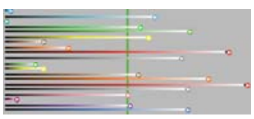
- Current learning sciences and educational research
  - Observations: quantitative & qualitative research
  - Mathematical models: quantitative

Computational Modeling in Learning Sciences Research

- *Analytical catalyst*:
  - Make explicit and distill ideas about factors of importance in a particular system of research interest
  - Data about agent behaviors to create models exploring emergent properties at macro system levels
- *Scientific inspectable artifacts*
- *Computational science research* with validated model under different settings impossible to change in "real world"
- *Model-based generalized findings* from one modeled system to other similar systems

Piaget/Vygotsky (Abrahamson-Wilensky)

- ABM for theory of learning
  - "Runnable" thought experiment
  - Flexible parametrization
  - Explicit (proceduralized)
  - Enables critique/compare (accompanies paper)
  - *Lingua franca* for intra/inter-disciplinary discourse
- ***Agent***: *marbles player*
- ***Emergent Phenomena***: *group-learning patterns*



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New Learning Science Research In Action (1)

Hi Uri, After we talked over lunch at AERA on Saturday about the modification I made to the model of Vygotskian learning that you and Dor Abrahamson created, it occurs to me that there's an interesting observation to make about the modified model. On each trial, here's a pairing of the agents. In the original model, the less well performing of the pair modifies its behavior to model the better performing if the better performing agent was within the specified "zpd". But there is no modification of the better performing agent based on the interaction.

New Learning Science Research In Action (2)

Now with the "-t" modification, half of the agents each turn (the better performing agent of each pair) perform worse than they know how to, in order to help the less performing agent of the pair learn to perform better. Yet despite the fact that half of the agents perform worse each cycle, the overall learning of the whole set of agents proceeds faster than otherwise. This emergent global property might be called "the teacher effect". ;-) Education generally can be seen as a sort of "investment", in which short term costs lead to longer term benefit. Perhaps this simple model can help us explore this aspect of education, teaching, and learning. -- Jim Levin

Conclusion

- Overview of arguments presented in recent *Journal of the Learning Sciences* paper and conference symposia (AERA & ICLS)
- Very early stages of theory and research focusing on fundamental issues in the fields of the learning sciences and education
- Hope these perspectives stimulate new scientific thinking and ideas to advance education
- Conversations!

KEYNOTE SPEECH II – POWERPOINT

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P.S. Demo Complex Systems Knowledge Mediator

- Problem-based e-Learning environment about complex systems
- Set of 6 cases and 8 complex systems related concepts and ideas
- http://lsl1.lsl.edu.sg/cskmdemo.htm

KEYNOTE SPEECH III – ABSTRACT / PAPER

The text of the abstract/paper has been printed as received; no editing has been done.

Understanding Students' Epistemic Beliefs in Math and Science: An Overview of Constructs, Measures, and Research

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Abstract prepared for BRAIN conference (Broadening Research At International Network: Developing a Cross-Domain Research Framework for Science and Math Education), National Taiwan Normal University, Taipei, Taiwan, May 2006. Please do not cite without permission of the author: Barbara K. Hofer, Psychology Department, Middlebury College, Middlebury, VT 05753, bhofer@middlebury.edu.

Individuals' conceptions of knowledge and knowing have been shown to influence learning in multiple ways (Hofer, 2001), and what has been called "personal epistemology" has been investigated by developmental psychologists, educational psychologists, teacher educators, higher education researchers, and science and math educators. Researchers have typically been interested in how individuals come to know, the theories and beliefs they hold about knowing, the patterned sequence in which such conceptions develop, and the manner in which learners' epistemologies are a part of and an influence on the cognitive processes of thinking and reasoning.

In this talk, I will provide an overview of the general construct and its relation to learning and education, examine the issues of domain generality and domain specificity, and then focus on epistemic understanding in mathematics and science. I will review some of the conceptual background and research and discuss multiple methodological approaches for investigating this construct in math and science, with suggestions for researchers. I will also provide examples from my own research and will discuss two recent projects in my research lab, one examining students' epistemic metacognition as they conduct an online search for a science assignment, and another on how students view the theory of evolution and how this is related to epistemic beliefs, science education, and conceptual change. Throughout the talk I will provide opportunities for interaction and discussion.

There is compelling evidence to suggest that individuals hold both general and domain specific epistemic understanding (Hofer, in press; Muis, Bendixen, & Haerle, in press). Early research in this field addressed epistemology as either a developmental construct (Baxter Magolda, 1992; Belenky, Clinchy, Goldberger, & Tarule, 1986; King & Kitchener, 1994; Kuhn, 1991; Perry, 1970) or a system of beliefs (Schommer, 1990), both with the presumption that learners' epistemologies were domain general. Researchers have since investigated whether these epistemic beliefs differ by discipline (Buehl, Alexander, & Murphy, 2002; Hofer, 2000), and it appears that the structure of epistemic understanding is consistent, but that there are mean differences in beliefs, for example, in regard to the perception of the certainty of knowledge within a discipline. A third line of research includes beliefs that are particular to disciplines, such as history (Wineburg, 1991), math (Hofer, 1999; Schoenfeld, 1983, 1992), or science (Bell & Linn, 2002; Conley, Pintrich, Vekiri, & Harrison, 2004). Thus, as noted elsewhere (Hofer, in press), individuals can be queried about their general epistemic beliefs (e.g., "Truth is unchanging"), disciplinary perspective on beliefs (e.g., "Truth is unchanging in this subject"), and discipline-specific beliefs (e.g. "A good way to know if something is true is to do an experiment"). Such distinctions are increasingly important in understanding the relations among beliefs, cognition, and academic performance, and are critical in addressing beliefs of both teachers and students.

In terms of the scope of what is included within this construct at the domain-general level, a review of the literature (Hofer & Pintrich, 1997) suggested that there are four dimensions that appear consistently within the early primary literature on personal epistemology and that are congruent with the philosophical definition of epistemology. These four dimensions are organized into two areas, beliefs about the nature of knowledge, which includes the dimensions of certainty and simplicity of knowledge, and about the nature of knowing, which includes the source of knowledge and justification for knowing. This excludes beliefs that appear in some schemes and which may well be related, such as beliefs about the role of the instructor (Baxter Magolda, 1992), or about intelligence or the speed of learning (Schommer, 1990), or beliefs about learning preferences. Such beliefs are not represented across models nor typically considered a part of epistemology by philosophers. Although these are important constructs in learning, I think we are likely to develop better and more precise models of the relation between epistemic understanding and other beliefs, attitudes, values, dispositions and strategies for learning, if we err on the side of parsimony, coherence, and philosophical clarity. This is by no means an issue confined to domain-general models, as some of what is discussed as epistemological within the disciplines also lies outside these bounds.

Beliefs about what it means to know and do math and science have been a particular fruitful avenue of inquiry for researchers interested in math education (Muis, 2004) and science education (Songer & Linn, 1991; Southerland, Sinatra, & Matthews, 2001; C.-C. Tsai, 2000; C. C. Tsai, 1999b). Although there is no firm agreement as yet about either the dimensionality of these constructs or about reliable forms of measurement, there is reasonable overlap with some of the dimensions suggested above. I will provide a brief overview of work in this area and discuss various methodological approaches. In addition, we will examine current "nature of science" (NOS) research (Abd-El-Khalick & Akerson, 2004; Abd-El-Khalick, Bell, & Lederman, 1998; Lederman, 2004) and discuss how this may be utilized by researchers in understanding both students' and teachers' epistemic understanding. We will also examine how math beliefs have been codified and studied (De Corte, Eynde, & Verschaffel, 2002; Muis, 2004; Schoenfeld, 1992).

The importance of this work in understanding student learning has been demonstrated in a series of studies, providing evidence that beliefs can influence learning in powerful ways. Epistemic beliefs influence text comprehension, (Schommer, 1990), strategy use, cognitive processing (Kardash & Howell, 2000), conceptual change (Andre & Windschitl, 2003; Mason, 2003; Mason & Boscolo, 2004; Qian, 2000; Windschitl & Andre, 1998), and motivation (Buehl & Alexander, 2005), for example. I will describe similar ongoing research in my lab involving investigations into students' understanding and acceptance of the theory of evolution, and how this is related to epistemic beliefs, science education, and conceptual change.

Additional methodological approaches to investigating beliefs about math and science have also included case study analysis of videotaped science lessons, with examination of epistemological stances of teachers, tasks, and practices. This has included various levels of schooling, including elementary school science classes (Louca, Elby, Hammer, & Kagey, 2004), secondary school physics classes (C. C. Tsai, 1999a), and college chemistry courses (Hofer, 2004b). As part of our discussion of this approach, we will examine a videotape of a typical U.S. science lesson and in small groups discuss the underlying epistemological assumptions of science suggested by the teacher and the tasks and how the students may interpret this.

Epistemic understanding of science can also be explored as a form of metacognition, which creates the possibility of integrating multiple perspectives of the construct. Viewed as a form of meta-knowing (Kitchener, 1983), or knowing about knowing, personal epistemology can be conceptualized as a set of beliefs, organized into theories, operating at the metacognitive level (Hofer, 2004a). From this perspective, epistemic theories develop in interaction with the environment, are influenced by culture and education and other context variables, operate at both the domain-general and domain-specific level, are situated in practice, and are activated in context. The primary methodological approach for exploring the metacognitive nature of epistemic assumptions and beliefs has been the think-aloud protocol, used, for example, in the investigation of epistemological thinking about history (Wineburg, 1991, 1998). Coupled with retrospective interviews (Wineburg, 1998), this technique has considerable power. Recent research using think-aloud protocols during online searching for a simulated class assignment suggests that students do metacognitively monitor the epistemological nature of their learning, and that at some level this is accessible to researchers (Hofer, 2004a). I will provide a brief overview of this approach with examples from research in my lab.

My goals for this session are to provide an overview of multiple approaches to investigating learners' epistemologies in math and science, to illustrate the importance of this work, and to provide opportunities for discussion among researchers.

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KEYNOTE SPEECH IV – ABSTRACT / PAPER

The text of the abstract/paper has been printed as received; no editing has been done.

The Neural Mechanisms of Object versus Spatial Imagery. Implications for Education

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In neuroscience, considerable progress has been made in understanding the neural underpinnings of the essential skills taught by educators, such as numeracy, literacy, and visual/spatial reasoning. However, this progress is mostly theoretical, and not bridged yet with the development of science education research as well as with educational practice. For instance, still there are many "pervasive neuromyths that have taken root in education and which give a flavor of the information being presented to teachers as neuroscientific facts" (Goswami, 2006). One of such myths, originated from an over-literal interpretation of hemispheric specialization, suggests that children should be identified as either 'left-brained' or 'right brained' learners. Teachers are told that the left brain dominates in the processing of language, logic, mathematical information, while the right brain is said to dominate in the processing of spatial transformations, images and pictures. The other myth suggests that children's cognitive styles should be identified as either visual or verbal, and that learning materials should fit a child's preferred cognitive style. Many in education accept claims such as these as established facts. The current presentation will focus on the current neuroscience findings on visual/spatial imagery and visual cognitive style, and their relevance to educational practice.

The neural correlates of object versus spatial imagery

It is now well-established that both visual imagery and visual perception rely on sets of distinct subsystems (Kosslyn, 1994), and a major concern of neuroimaging studies that identified the cerebral bases of visual imagery has been to assess the extent to which visual imagery and visual perception share common cerebral structures (Kosslyn, Thomson, & Alpert, 1997).

It has been established that both visual perception and visual imagery rely on "what" and "where" pathways, also called the object and spatial relations pathways (Haxby et al., 1991;

Ungerleider & Mishkin, 1982). As shown in Figure 1, the object pathway runs from the occipital lobe down to the inferior temporal lobe (area 37). The spatial relations pathway runs from the occipital lobe up to the posterior parietal lobe (areas 7, 39, 40). According to this dichotomy, object (figurative) aspects of both imagery and perception, such as shape and color, are processed along the ventral route areas, while the dorsal route processes object localization. spatial attributes, and guiding movements. For example, Farah et al. (1988) demonstrated that lesions in the temporal cortex disrupted performance of tasks that rely on mental images of objects and their properties, whereas such lesions did not disrupt spatial imagery. In contrast, lesions in posterior parietal cortex had the reverse effects (see also Farah et al., 1988). Similarly, in neuroimaging studies, spatial and object imagery tasks led to very different patterns of brain activity (Kosslyn, Ganis & Thompson, 2001). For example, when participants visualized a route on a map that they had memorized prior to the experiment, the parietal lobes were activated, but when participants visualized faces or colors, the temporal lobes were activated (Uhl et al., 1990). However, this distinction is not absolute, since most of the neuroimaging studies that dealt with spatial imagery not only reported dorsal activation but also activation along the ventral route and vice versa.

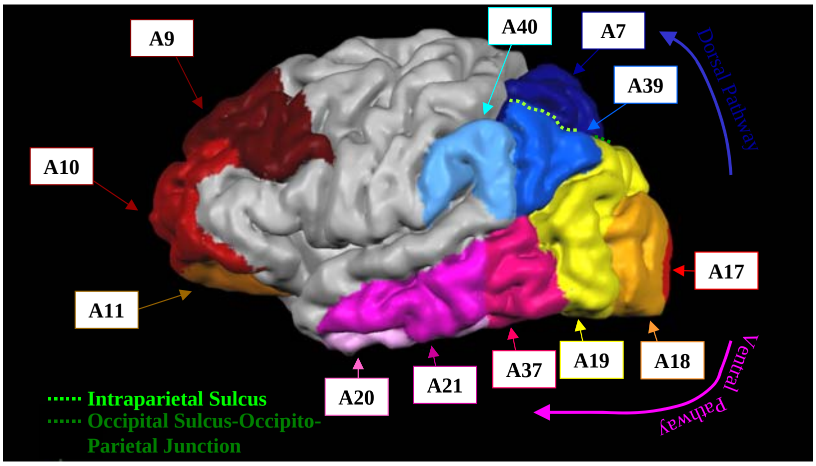

Figure 1. Areas activated during visual imagery. A17: early visual cortex (V1, calcarine sulcus); A18: ; A19; : A37: occipito-temporal junction; A21: medial temporal cortex; A20: inferior temporal cortex; A7: superior parietal cortex; A39: inferior parietal cortex (angular gyrus); A40: inferior parietal cortex (supramarginal gyrus); A9: parts of the superior and middle frontal gyri; A10: parts of the superior and middle frontal gyri; A11: the orbital gyrus, gyrus rectus, and parts of the superior frontal gyrus.

Divergent neuroimaging results were reported regarding the involvement of the early visual cortex (Broadmann area 17, 18) during visual imagery (see Figure 1). Some researchers reported activation of early visual cortex, whereas others have not (Roland & Gulyas, 1994; Kosslyn, Ganis, Thomson, 2001; Mellet at al, 1998). The early visual cortex had been proposed to be a key-part of the neural substrate of the so-called visual buffer (Kosslyn, 1994). This buffer would be shared by both perception and imagery and is thought to implement a topographic representation of either a perceptual or mental image. Recent results confirm that the type of imagery is a crucial feature from explaining discrepancies. Most of the studies dealing with spatial imagery indeed have not reported early visual cortex activation, whereas in those studies in which activation was noted, object imagery tasks were used (Mazard et al., 2004).

Individual differences in object versus spatial imagery

Dissociation between object and spatial imagery also has been found in research on individual differences in imagery (Hegarty & Kozhevnikov, 1999; Kozhevnikov, Hegarty, & Mayer, 2002; Kozhevnikov, Kosslyn, & Shepard, 2005). Kozhevnikov et al. (2005) reported that verbalizers (i.e., those who prefer to use verbal-analytical coding versus imagery) typically performed at an "intermediate" level on imagery tasks, whereas visualizers (i.e., those who reported strong and consistent preferences for processing information visually) could be divided into a group that scored poorly on spatial imagery tasks (e.g., mental rotation task) but excelled on object imagery tasks (e.g., degraded pictures task) and a group that excelled on spatial imagery tasks but scored poorly on object imagery tasks (see Figure 2). Thus, two types of imagers were identified: object imagers who tend to construct colorful, pictorial, and high-resolution images of individual objects, and spatial imagers who tend to use imagery to schematically represent spatial relations among objects and to perform complex spatial transformations. Kozhevnikov et al. also found that object imagers encoded and processed images holistically, as a single perceptual unit, whereas spatial imagers generated and processed images analytically, part by part.

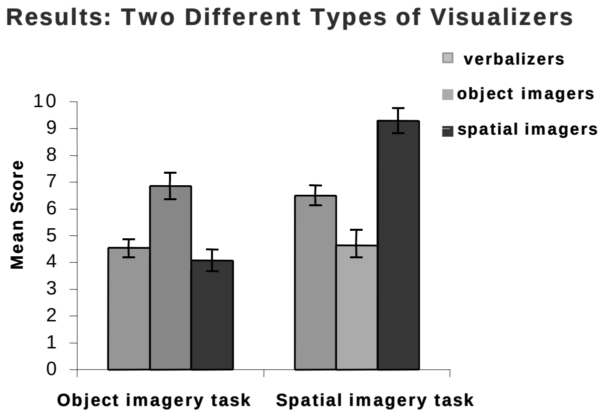

Figure 2. Performance of object visualizers, spatial visualizers, and verbalizers on object (degraded pictures) and spatial (mental rotation) imagery tasks

Blajenkova et al. (2005) reported that scientists and engineers tended to be spatial imagers, while visual artists tended to be object imagers. Furthermore, visual artists' object imagery scores tended to be above average when compared with the rest of the professional groups, yet their spatial imagery scores tended to be below average. Scientists' spatial imagery scores, on the other hand, tended to be above average, but their object imagery scores tended to be below average. The finding that professional domain, where work involves extensive use of object or spatial imagery, differentially predicted scores on object and spatial imagery measures provides ecological validation of the distinction between object and spatial imagers. The analyses also revealed that none of the professional groups showed above average proficiency in both types of imagery, supporting the idea of the existence of a trade-off between object and spatial imagery abilities (Kozhevnikov et al., 2005). Even architects, whose work requires both object and spatial imagery skills were not good imagers in general, scoring high both on both types of imagery measures. Indeed, the data are consistent with previous research suggesting that characterizing one as a "good" or "bad" imager is inappropriate, and the present research specifically demonstrates the importance of distinguishing between object and spatial imagery abilities. Furthermore, the results of Hegarty & Kozhevnikov (1999) revealed that the use of spatial images was associated with success in mathematical problem solving, whereas use of pictorial images was negatively correlated with success. Furthers studies by Kozhevnikov, Hegarty & Mayer (2002) showed that object imagers have difficulties understanding science graphs, tending to interpret them as concrete pictures, but spatial imagers tended to interpret science graphs as abstract spatial representations and correctly.

Recent neuroimaging provided data that the two groups of imagers differ qualitatively in their visual processing. Motes et al (2006) found that object imagers showed greater activation, bilaterally, in parts of the occipito-temporal junction (A19-37), and they also showed greater activation in parietal areas (A7 and A40) than spatial imagers. Spatial imagers, on the other hand, showed significantly greater activation, bilaterally, in the occipito-parietal junction (A7/19), occipital (A17-18), superior temporal (A22), posterior cingulate, and frontal/prefrontal areas. Spatial visualizers also showed significantly greater activation in parts of the left occipito-temporal junction (A37/21). The results suggest that the greater parietal activations occurring for the object imagers and the greater left occipito-temporal activations occurring for the spatial imagers might be due to the groups trying to compensate for processing "weaknesses."

Bridging Neuroscience Findings to Science Education

Numerous studies have been carried out to understand the role of visual-spatial representations in learning. However, most studies investigating the effect of mental imagery on learning have treated imagery as a general and undifferentiated skill, yet the research cited above challenges this view. Kozhevnikov et al (2002) found that a large group of college students, object imagers, had serious difficulty interpreting graphs as abstract schematic representations and instead interpreted them as pictorial representations. These students will clearly have difficulty solving science and mathematics problems that involve processing or creating abstract, schematic, spatial representations (e.g., graphs). How might we best teach these students to solve such science and mathematical problems?

One possible approach is to teach object imagers represent and solve science and mathematics problems by using verbal-analytical strategies rather than spatial strategies requiring spatial imagery abilities that they do not have. Another possible way of teaching object imagers is to give them explicit instruction on how visual, schematic, and verbal representations relate to each other. For example, interactive computer simulations (e.g., White, 1993) that include verbal representations, schematic graphics, and iconic representations, might be effective for these students. Having all these types of representations available and demonstrating how each of them translates into the others might help object imagers translate concrete pictorial representations into a more schematic spatial form. Furthermore, instruction could be aimed explicitly at teaching students to construct and interpret different types of representations and to translate between different representations of the same phenomenon, for instance, microcomputer-based learning (MBL) technologies designed specifically to pair physical events with their graphical representations in real time and provide students with the possibility of exploring connections between them. Students immediately see the graph made by a moving object with the results appearing instantly on the graph with each move made by the object. Researchers have found a significant change in students' ability to interpret kinematics graphs and overcome graph-as-picture misconceptions after MBL intervention (e.g., Kozhevnikov & Thornton, 2006; Linn, Layman, & Nachmias, 1987; Mokros & Tinker, 1987; Thornton & Sokoloff, 1990).

However, we must note that although concrete pictorial images do not contribute to science problem solving, this type of imagery has been found to be very useful for enhancing memory (Presmeg, 1986), as well as in social studies classes (Danzer & Newman, 1992). Such images provide a quick means of recall and can help to illuminate the subject. Thus, the utility of a particular type of imagery depends in part on the task; it is not likely that any type of imagery is necessarily or universally superior to any other type. In summary, the results highlight the need for research that characterizes which type of imagery facilitates learning and reasoning in specific domains. We not only propose that instructional strategies not only be designed to teach students to construct and interpret different types of visual-spatial representations but that different students can be taught strategies for translating material to representations that are compatible with their own preferred cognitive style.

In summary, recent neuroscience data reject the myth about “right” hemisphere responsible for visual processing, since it occurs in both hemispheres. Also, it will not be useful to debate whether visualizers are more successful in learning than verbalizers or whether imagery in general enhances or impairs performance on cognitive tasks. In order to make optimal use of the strengths of visual-spatial processing, we need to explore the relationships between different types of imagery and performance in various domains. Moreover, the question remains why people who are good at object imagery tend not to develop their spatial imagery ability, and vice versa. One way to grapple with this issue is to discover whether people can be trained to use their less-preferred type of imagery effectively.

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KEYNOTE SPEECH IV – POWERPOINT

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Object vs. Spatial Mental Imagery:
The Neural Mechanisms and Implications for Science Education

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National Science Foundation
Science of Learning Centers Program

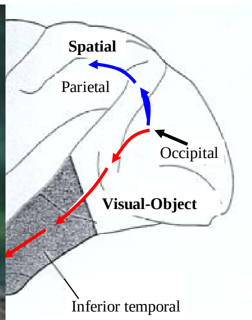
Educational "neuromyths"

1. Children could be identified as either "left-brained" or "right-brained". Left brain dominates in processing language, logic, mathematical formulas, whereas right brain dominates visual processing.

2. Children's cognitive style could be identified as either visual and verbal. Visualizers prefer to process information by imagery means, while verbalizers by verbal/analytical means. Curriculum materials should match individuals' cognitive style.

Neuroscience data: Dissociation Between Object vs. Spatial Visual Systems:

(Jonides & Smith, 1997; Kosslyn & Koenig, 1992; Underleiger and Mishkin, 1982)



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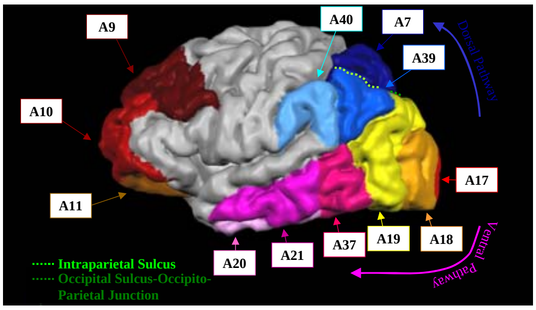
Evidence from brain lesion studies: the same dissociation in imagery (Farah et. al., 1988)

Imagery

Visual-object	Spatial
Visualizing object properties in color and detail:	Visualizing spatial relations and transformations:
Visualizing the sun rising above the horizon	*Mental rotation of a three dimensional figure*

Neural correlates of visual imagery



Dissociation between object and spatial imagery exists in individual differences in imagery ***(Kozhevnikov, Kosslyn, & Shephard, 2005)***

Object Imagers ← Visualizers → Spatial Imagers

Especially good at constructing vivid, pictorial, and detailed images of individual objects

Excel in creating images that represent spatial relations among objects and imagining spatial transformations

KEYNOTE SPEECH IV – POWERPOINT

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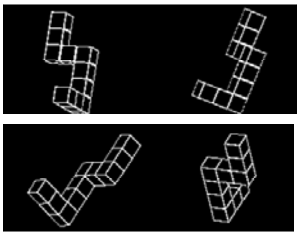
Experimental Study

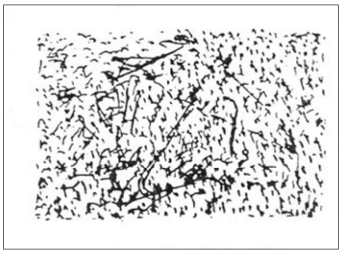
162 psychology undergraduates were given a battery of spatial and object imagery ability tests:

Mental Rotation Spatial Imagery Task



Are the figures in each pair the same or different?

Object Imagery Task



Results: Two Types of Visualizers

Visualizers show bimodal distribution on imagery tasks, that is, most of the visualizers are <u>either of high spatial imagery or high object imagery ability</u> with almost no visualizers with average imagery abilities.

Most verbalizers show average performance on object and spatial imagery tasks.

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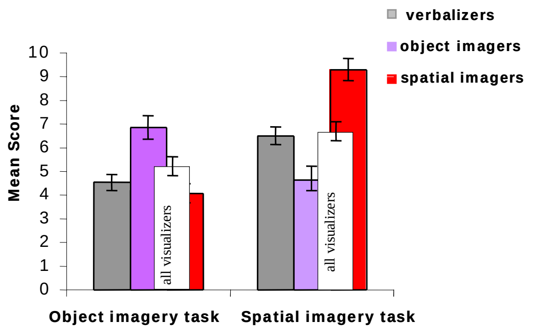
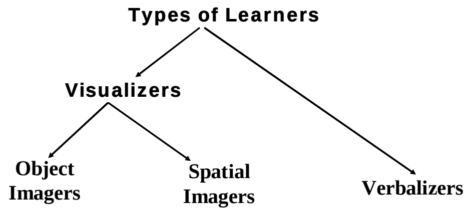
Results: Two Different Types of Visualizers



New Approach to Cognitive Style

(*Kozhevnikov, Kosslyn, & Shepard, 2005*)



New instruments to assess students' visual cognitive style and differentiate between three types of learners were designed and validated (*Blajenkova, Kozhevnikov, & Motes 2006: Applied Cognitive Psychology***).**

Neural underpinnings of individual differences in imagery

Neuroimaging data provided evidence that the two groups of imagers differ qualitatively in their visual cognitive style:

Seven *spatial imagers and seven object imagers were administered Embedded Picture Test, while scanned on fMRI. Our predictions were that the most significant differences between the two groups of participants in the inferior temporal versus posterior parietal lobes (e.g., ventral vs. dorsal pathways) (Motes et al., 2006)*

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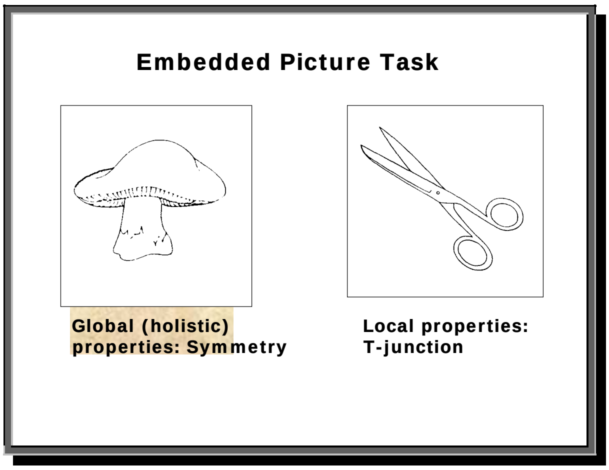

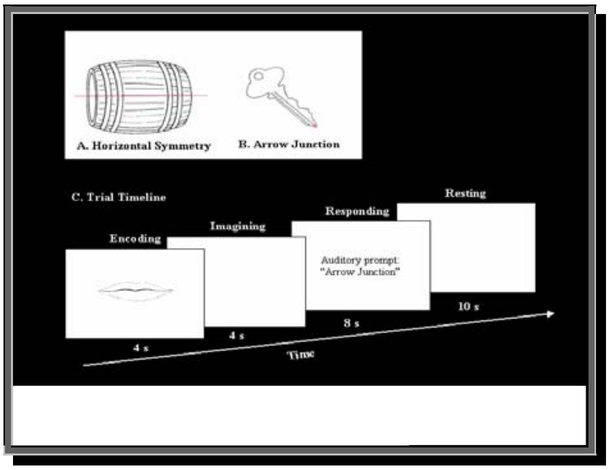

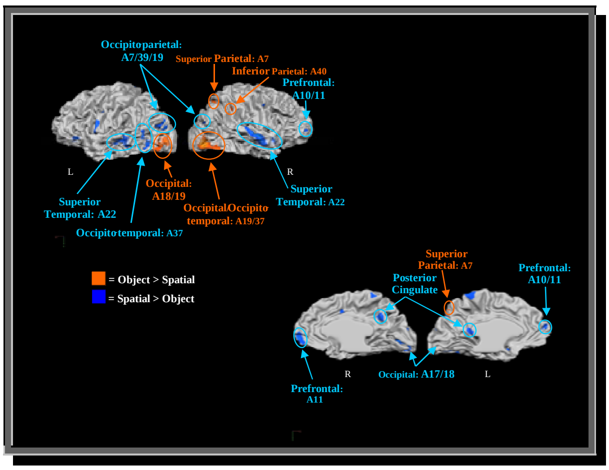

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fMRI studies: Conclusions

The data are consistent with the idea that individual differences in object versus spatial representations are related to the differential use of regions in the dorsal and ventral visual processing streams. Hemispheric differences also have significance.

We suggest that the greater parietal activations for the object imagers and the greater left occipito-temporal activations for the spatial imagers are due to the groups trying to compensate for processing “weaknesses.”

Ecological validity of visual cognitive style: Imagery within various professional domains

- Visual artists & designers are better at object imagery tests
- Architects? Good in both?

- Scientists & engineers are better at spatial imagery tests

- Linguists & philosophers use less imagery

Participants

Visual Artists, designers N = 19	Scientists (physicists and engineers) N = 24
Architects N = 12	Linguists and philosophers N = 23

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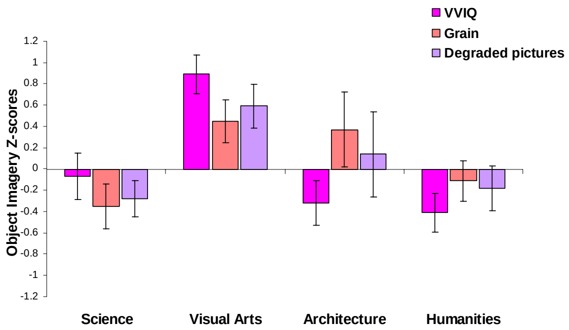
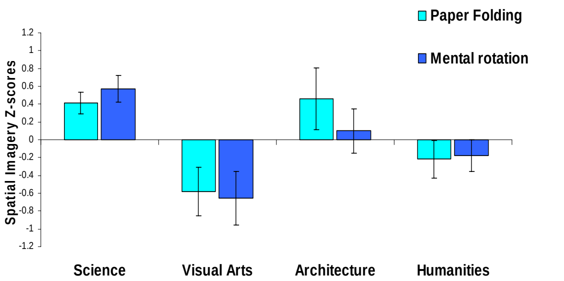
Results: Object Imagery Tasks



Blajenkova & Kozhevnikov (In submission), Psychonomic Bulletin & Review

Results: Spatial Imagery Tasks



Blajenkova & Kozhevnikov (In submission), Psychonomic Bulletin & Review

Ecological validity of visual style: Conclusions

It will not be useful to debate whether visualizers are more successful in learning than verbalizers or whether imagery in general enhances or impairs performance on cognitive tasks.

In order to make optimal use of the strengths of visual-spatial processing, we need to explore the relationships between different types of imagery and performance in various domains.

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Object and spatial imagery in science problem solving and arts

The goal of the next studies was to compare how object imagers, spatial imagers, and verbalizers, as well as members of different professions process and interpret abstract visual information (Hegarty & Kozhevnikov, 1999; Kozhevnikov, Hegarty & Mayer, 2002, Blajenkova et al., 2006)

Imagery strategies in science problem solving

Participants

The participants were: 25 psychology undergraduates; every student was assigned to one of the four groups:

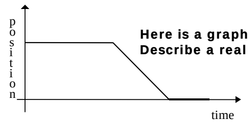
6 object imagers
7 spatial imagers
6 verbalizers of low spatial ability
6 verbalizers of high spatial ability

Plus 66 members of different professions from the previous study (visual artists, linguists and philosophers, and scientists)

Method

The materials included three graph problems depicting an object motion. Participants were asked to visualize and then write down a story that describes a situation depicted on the graph.

Categorization of students' answers



Here is a graph of an object's motion. Describe a real situation depicted on the graph.

Students' answers were categorized into three categories (Interjudge reliability - 0.89) :

•**literal (graph-as-picture)**: "a ball rolled along a level surface, then down a ramp onto another level surface"
• **no image or irrelevant:** "an object is moving constantly in a circle", "a toy plane is gliding into the air"
• **schematic:** "an object is at rest on the first interval and moves at the second interval and stops again"

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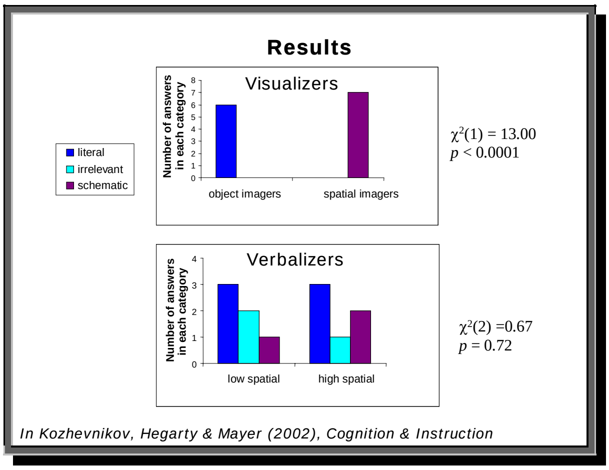

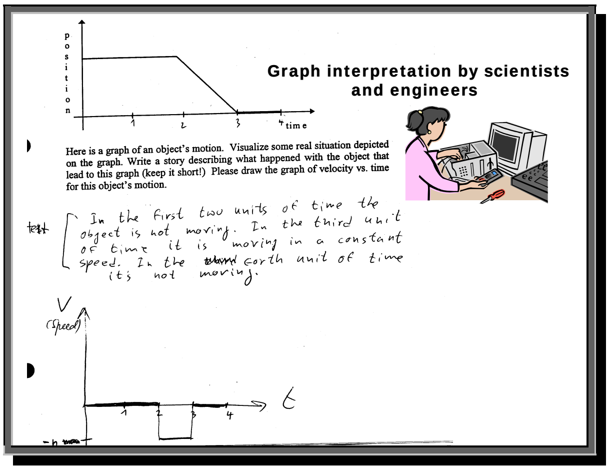

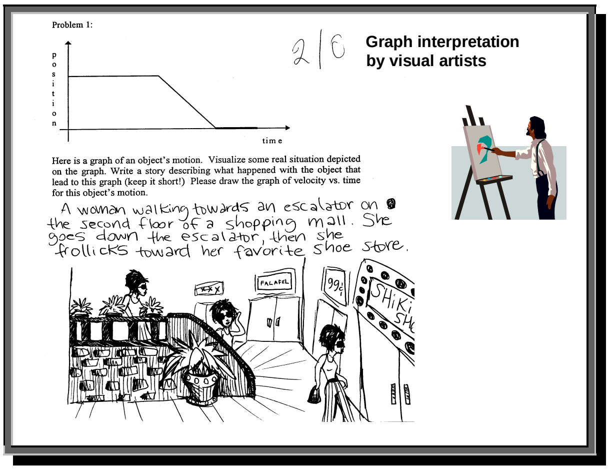

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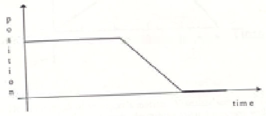
Graph interpretation by linguists and philosophers



Here is a graph of an object's motion. Visualize some real situation depicted on the graph. Write a story describing what happened with the object that lead to this graph (keep it short!) Please draw the graph of velocity vs. time for this object's motion.

I am really having trouble understanding what I should be doing. The only thing this possibly reminds me of is a stock market chart showing how prices have plummeted. This isnot, however, the answer you are looking for (the direction indicate the actual object). OK: if I have to think about actual objects rather than abstractions – the physical objects – the closest thing I can think of is that a mountain-climber started at a certain elevation (on the side of a small mountain, perhaps) and then walked down it in a certain amount of time.

Imagery in abstract visual art interpretation

Berryhill "Breakthrough"

Visual artists

What images this picture bring about to your mind? What is drawn here? What feelings does this picture evoke?

Extreme tension; catastrophe, people, explosion, fire; breakthrough; eruption; war, explosion; burst through, anxiety and tension; crash and liberation; death

KEYNOTE SPEECH IV – POWERPOINT

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Scientists and engineers

What images this picture bring about to your mind? What is drawn here?

Abstract painting; eye-catching; different colors: blue, black, red, yellow, white; sharp edges in red; crystals of ice; window to the sky; pieces of ice (glass)

What feelings does this picture evoke?

Nothing; positive; Strange; everything happens together

Linguists and Philosophers

What images this picture bring about to your mind? What is drawn here?

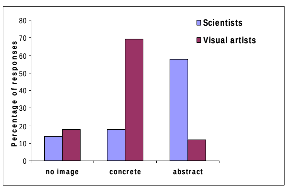
Nothing; diversity; pieces of cloths thrown together with some picture of a cloudy sky; don't see anything; no image.

What feelings does this picture evoke?

Nothing; neutral; no feelings; confusion

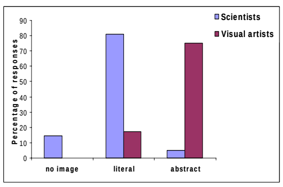
Interpretations of abstract visual representations by artists and scientists

Graph interpretation



$\chi 2(2) = 11.21$; $p < 0.01$

Abstract art interpretation



$\chi 2(2) = 11.64$; $p < 0.01$

KEYNOTE SPEECH IV – POWERPOINT

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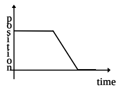
Different approaches in interpretation of visual representations

Type of visual information / Profession	Object (pictorial) imagery: Artistic works 	Spatial schematic imagery: Graphs 
visual artists & designers	Abstract interpretations	Concrete interpretations
scientists & engineers	Concrete interpretations	Abstract interpretations

•The distinction between object and spatial imagery could not be reduced to the difference between concrete versus abstract visual representations.

•Scientists significantly more often interpret abstract art literally (concrete objects), while visual artists interpret abstract art as conveying abstract ideas and complex emotions. Visual artists significantly more often interpret graphs literally (graph-as-picture), while scientists more often interpret graphs as abstract schematic representations.

We found that a large group of college students, object imagers, had serious difficulty interpreting graphs as abstract schematic representations and instead interpreted them as pictorial representations.

These students will clearly have difficulty solving science and math problems that involve processing or creating abstract, schematic, spatial representations (e.g., graphs).

How might we best teach these students to solve such science and mathematical problems?

Implication of Neuroscience to Science Education
Design Learning Technologies
MBLs and Immersive Virtual Realities

•One possible approach is to teach object imagers represent and solve science and mathematics problems by using verbal-analytical strategies rather than spatial strategies requiring spatial imagery abilities that they do not have.

•Another possible way of teaching object imagers is to give them explicit instruction on how visual, schematic, and verbal representations relate to each other.

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MBLs (in collaboration with Center for Science and Math Teaching, Tufts University)

Research Design

Participants: 84 undergraduates from Tufts University who studied mechanics based on MBL curriculum and 40 undergraduates who did not study any science courses (control group).

Materials: Spatial visualization test (paper-folding) (pre and post) and physics conceptual test including 12 kinematics graphs (pre and post).

Eliminating concrete graph misinterpretations with the help of MBL technology

	Concrete/literal interpretation	Schematic interpretation	Other interpretation
Pre-test	64	11	9
Post-test	9	75	0

Kozhevnikov & Thornton (2006), JSET

KEYNOTE SPEECH IV – POWERPOINT

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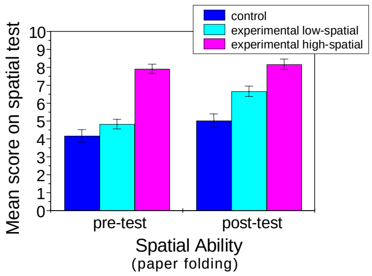
Increase in Spatial Ability



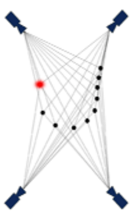
Immersive Virtual Realities

1) Investigating how various aspects of virtual reality (multisensory immersion, 3-d representations, shifting among different frame of references) support complex conceptual learning.

2) Examining the interaction between different virtual reality aspects and other factors such as a learner individual characteristics, domain-specific knowledge and interaction experiences

3) Creating educational software with focus on visualization processes

Virtual Reality Lab



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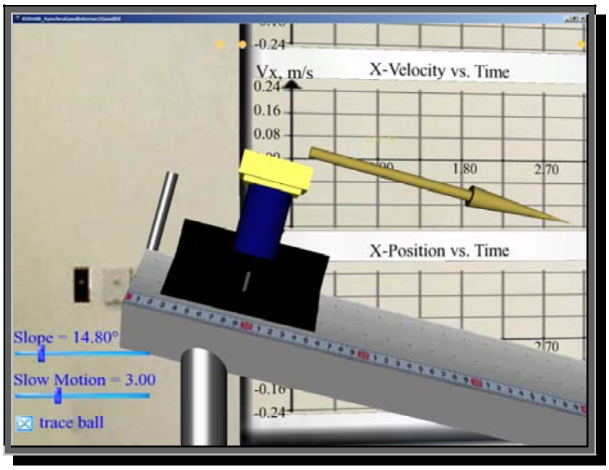

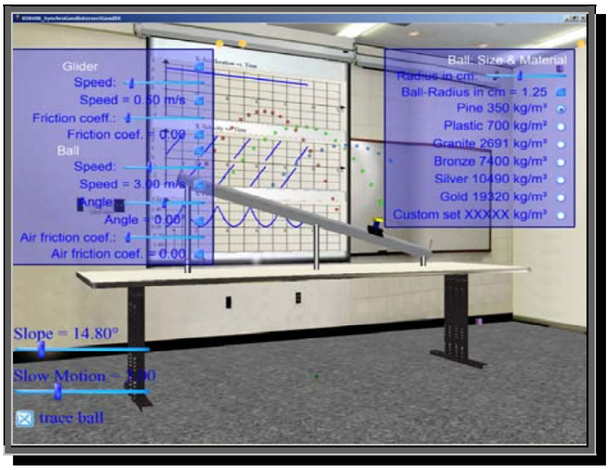

Conclusions

Interactive computer simulations that include verbal representations, schematic graphics, and pictorial representations, might be effective for object imagers .

Instruction should be aimed explicitly at teaching students to construct and interpret different types of representations and to translate between different representations of the same phenomenon.

Thus, the utility of a particular type of imagery depends in part on the task; it is not likely that any type of imagery is necessarily or universally superior to any other type.

KEYNOTE SPEECH IV – POWERPOINT

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More Conclusions

The results highlight the need for research that characterizes which type of imagery facilitates learning and reasoning in specific domains.

We propose that instructional strategies not only be designed to teach students to construct and interpret different types of visual-spatial representations but that different students can be taught strategies for translating material to representations that are compatible with their own preferred cognitive style.

Future research:

How education research can inform neuroscience?
What kind of educational questions are important to be tested in neuroscience labs?

Imagery training…

How does imagery practice change the brain activation over time as the participants receive training, and which changes predict improvement in solving spatial versus object imagery tasks?

KEYNOTE SPEECH V – ABSTRACT / PAPER

The text of the abstract/paper has been printed as received; no editing has been done.

Abstract
Developing a Science Teacher Professional Development Research Agenda

James P. Barufaldi, Ph.D.

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The purpose of the paper is to discuss characteristics of effective professional development programs and the need for research to document the effectiveness of such programs. Providers of professional development must carefully plan and promote their research agendas. Implementing research studies designed to document the effectiveness of their programs related to student learning in science is quite challenging. Many factors contribute to student learning such as socio-economic status, limited English proficiency and minority status of students, per-pupil spending, pupil teacher ratios, class sizes, and teacher quality. As noted by many researchers, teacher quality is highly correlated with student learning (Darling-Hammond; 1999), (Dufee & Aikenhead, 1992) and (Dreil, Beijard & Verloop, 2001). Since it appears that teacher quality is one of the most determinant factors for student learning, one must focus on ways to enrich teacher quality. Studies concerned with improving teacher quality must pay special attention to the kind of professional development that is provided to these teachers. Moreover, if the ultimate goal of improving teacher quality is to consequentially improve student learning, it is imperative to determine variables or characteristics of professional development programs that may impact student learning (Tinoca, 2005).

The paper will briefly discuss a series of strategies and activities suggested by Loucks-Horsley et al. (1998) that are helpful in conceptualizing a model professional development program. An overview of one such model professional development program, the Texas Regional Collaboratives for Excellence in Science Teaching (TRC), will be described (Barufaldi & Reinhartz, 2001). The unique components of the TRC will be compared with those proposed by Loucks-Horsley, Guskey (1986), and others. A theoretical framework for professional development will also be proposed. The TRC will be discussed in terms of the impact it has made on science teacher's learning, attitudes and changes in the ecology of the classroom. The

relationship between characteristics of professional development programs and student achievement in science will be discussed. In addition, the paper will provide a review of studies that have shown a positive relationship between characteristics of professional development programs and student achievement. Research studies focusing on professional development will be presented that have demonstrated no impact, minimal impact and considerable impact on student achievement in science. Finally, the paper will discuss challenges in documenting the effectiveness of professional development programs and provide an update of research conducted by the TRC staff.

KEYNOTE SPEECH V – POWERPOINT

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Developing a Science Teacher Professional Development Research Agenda

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A paper presented at the conference, Broadening Research at International Network (BRAIN)
National Taiwan Normal University - College of Science Campus
Taipei, Taiwan
May 26, 2006

Overview of the Presentation

- Purpose
- Conceptualizing a model professional development program
- Texas Regional Collaboratives for Excellence
- Impact on teachers
- Factors contributing to student learning
- Relationship between characteristics of professional development programs and student achievement in science
- Challenges in documenting the effectiveness of professional development programs

Purpose

- The purpose of the paper is to discuss characteristics of effective professional development programs and the need for research to document the effectiveness of such programs.

KEYNOTE SPEECH V – POWERPOINT

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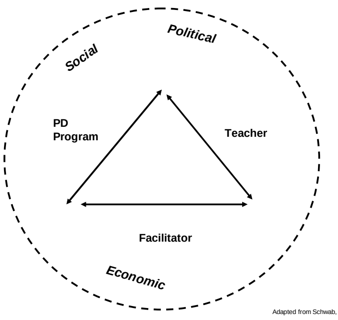
Factors contributing to student learning

- Socio-economic status
- Limited English proficiency and minority status of students
- Per-pupil spending
- Pupil teacher ratios
- Class sizes
- Teacher quality (Darling-Hammond, 1999)

Teacher Quality

- How does one enhance/develop teacher quality through professional development?
- How does teacher quality contribute to student learning?

Components of a Professional Development System



Adapted from Schwab, 1978, Borko, 2004

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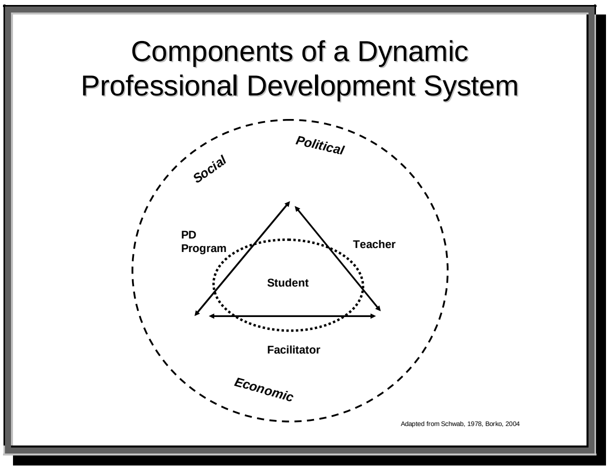

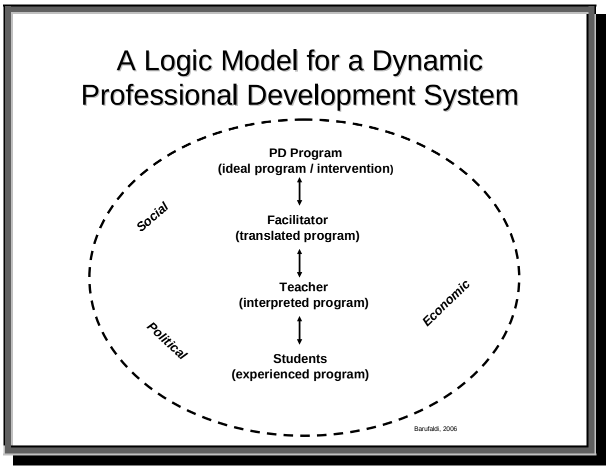

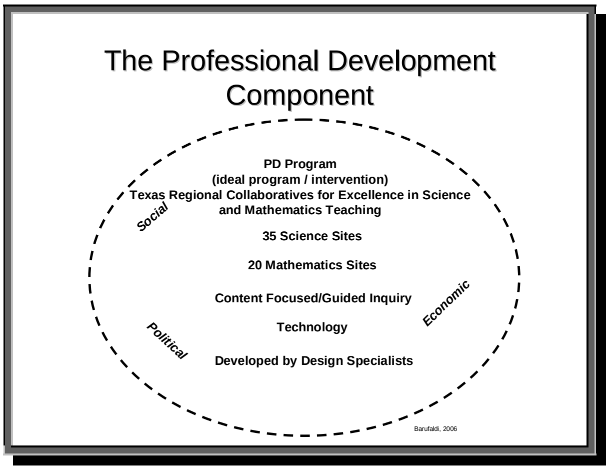

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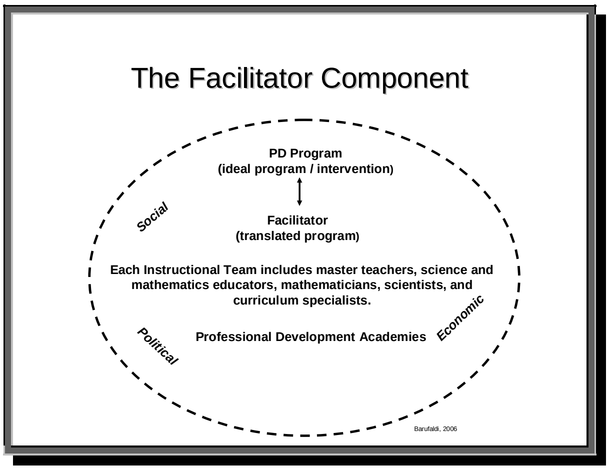

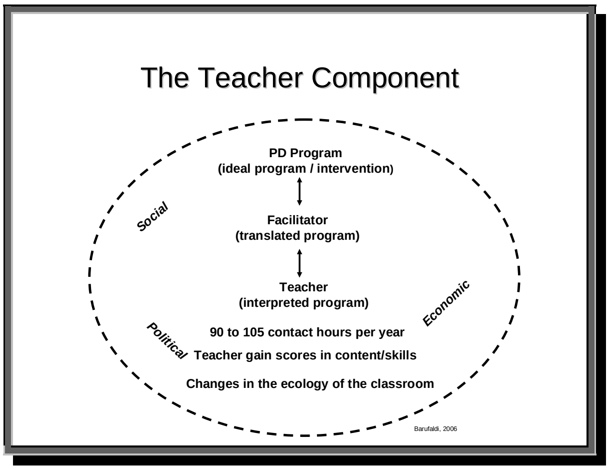

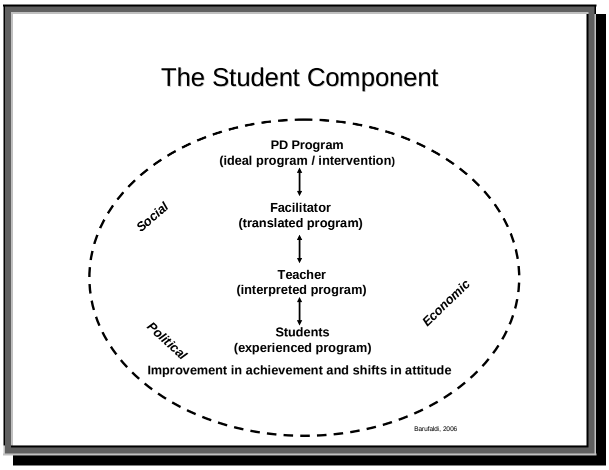

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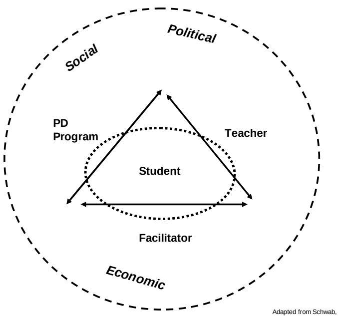
Why is the Texas Regional Collaboratives for Excellence in Science and Mathematics Teaching Program Successful?

Comparison of Loucks-Horsley et al. (1998) Principles to the TRC

Loucks-Horsley Criteria
- Sustained contact
- Defined image
- Teachers build knowledge and skills
- Models for teachers to use with students
- Builds a learning community
- Leadership roles
- Links to the system
- Continuous self assessment

TRC Criteria
- 105 contact hours/yr
- Six systemic threads
- Professional development academies
- Training models best practice
- Network with teachers
- Science Teacher Mentors
- Teachers as professionals
- Access to most current information
- Yearly pre, post, and formative assessments

Collaboration is the Synergy



Adapted from Schwab, 1978, Borko, 2004

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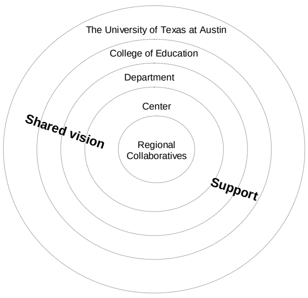
Texas Regional Collaboratives for Excellence in Science and Mathematics Teaching

Shared vision – to improve the teaching and learning of science and mathematics by providing teachers of Texas with sustained, exemplary opportunities to grow professionally.

The Dynamics of Collaboration



Relationship between Characteristics of Professional Development Programs and Student Achievement in Science

No impact on student learning

- Action research
- Study groups

Tinoca, 2005

KEYNOTE SPEECH V – POWERPOINT

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Minimal Impact on Student Learning

- Inquiry
- Case discussions
- Coaching and mentoring
- Partnerships with scientists

Tinoca, 2005

Considerable Impact on Student Learning

- Curriculum
- Replacement
- Implementation
- Development of partnerships/collaboration (Barufaldi & Reinhartz, 2001)
- Development of team leaders as professional developers (Fletcher & Barufaldi, 2001; Hobbs & Barufaldi, 2006)
- Sustained over time (Tinoca & Barufaldi, 2005; Meyer & Barufaldi, 2004)

Tinoca, 2005

Sustained Over Time

Factors impacting science teacher renewal/retention

- Creating professional environments for teachers
- Providing classroom lessons and materials
- Providing current information on educational issues
- Providing networking opportunities
- Building confidence to teach science
- Providing leadership opportunities

Meyer & Barufaldi, 2003

KEYNOTE SPEECH V – POWERPOINT

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Providing Leadership Opportunities

Empowerment

- What are those impacting events that contribute to teachers' overall sense of empowerment?
- What professional growth experiences do teacher recall as having a positive and pivotal impact on their empowerment?
- Is there a pattern to the experiences that is common to all empowered career science teachers?

Hobbs & Barufaldi, 2006

Challenges in Documenting the Effectiveness of Professional Development Programs

- Theoretical Framework
- The Intervention
- Experimental/Control Group Design
- Variables
- Teacher Quality Indicators
- Professional Development across Multiple Sites

Professional Development Across Multiple Sites

Borko (2005) states longitudinal studies in professional development that include multiple sites with multiple facilitators are nonexistent.

The TRC model is one example of this research agenda.

KEYNOTE SPEECH V – POWERPOINT

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Developing an Intellectual Agenda for Research of Professional Development

"Ideal Professional Development"
↓
Facilitators -Translated
↓
Teachers - Interpreted
↓
Students - Experienced

Concluding Thoughts

- If developers are serious about promoting student learning in science through professional development then the design of the program must be chosen with great care.
- Scholars of professional development agree that in order for exemplary professional development to occur, the program must be designed with the learning outcomes clearly defined (Gusky, 2005, Loucks-Horsley & Stiles, 2003).

THANK YOU

INVITED SPEAKERS

- **Janice D. Gobert**
  Senior Research Scientist, Concord Consortium, Concord MA
  North American Editor, International Journal of Science Education
  http://mtv.concord.org/publications/janice_gobert_cv.pdf

  Janice Gobert is a Research Scientist at the Concord Consortium. She is also a Research Associate at Harvard University in the Department of Learning and Teaching, and was recently appointed the North American Editor of the International Journal of Science Education. Her Ph.D. is in Applied Cognitive Science from the University of Toronto. Her primary interests are in visual models in science and how these support reasoning and inference-making. She is also interested in how technology can support students' inquiry with models. Janice is the Director of the Making Thinking Visible project, a collaborative effort with Marcia Linn at UC-Berkeley, and the Director of the Models of Plate Tectonics Project, both funded by the National Science Foundation. Janice is also Research Director of the Modeling Across the Curriculum project.

- **Michael J. Jacobson**
  Associate Professor, Learning Sciences and Technology Academic Group; Senior Research Scientist, Learning Sciences Lab
  National Institute of Education, Nanyang Technological University, Singapore
  http://mjjacobson.net/

  Michael J. Jacobson, Ph.D., is an Associate Professor with the Learning Sciences and Technology Academic Group at the National Institute of Education (NIE), Nanyang Technological University in Singapore. He is also a Co-Principal Scientist at the NIE Learning Sciences Lab where he heads up the Cognition and Beliefs About Learning research strand. Formerly he was the Senior Associate Director and an Associate Professor at the Korea University Center for Teaching and Learning in Seoul, Korea. Dr. Jacobson has also held faculty and research positions at the University of Illinois at Urbana-Champaign, Vanderbilt University, and The University of Georgia, and he has been involved with organizational and international consulting activities. His research has focused on the design of learning technologies to foster deep conceptual understanding, conceptual change, and knowledge transfer in challenging conceptual domains. Most recently, his work has explored cognitive and learning issues related to the design of learning technologies to help students understand new scientific perspectives emerging from the study of complex and dynamical systems. Dr. Jacobson received his Ph.D. in educational technology with a secondary emphasis in cognitive science from the University of Illinois at Urbana-Champaign in 1991.

INVITED SPEAKERS

- **Barbara K. Hofer**
  Associate Professor, Psychology Department
  Middlebury College, Middlebury VT
  http://www.middlebury.edu/academics/ump/majors/psych/hours/hofer/

  Dr. Barbara K. Hofer is currently associate professor of psychology at Middlebury College in Middlebury, Vermont. She is an expert on epistemic beliefs and development, and also is interested in motivation, self-regulation, and culture and cognition. Her research on epistemic understanding includes both quantitative and qualitative approaches, and recent studies include investigations of epistemic metacognition during online searching in science learning, students' epistemic beliefs about evolution, cross-cultural studies of knowledge and knowing, disciplinary differences in epistemic beliefs, and classroom level research on teacher and student beliefs. She was awarded the Research Review Award from the American Educational Research Association for her review of epistemological research with Paul Pintrich, and also received the American Psychological Association Early Career Teaching Award. She serves on the editorial boards of Educational Psychologist and Contemporary Educational Psychology and as an ad hoc reviewer for over twenty journals and is the secretary of the Division of Educational Psychology of APA. Dr. Hofer has served as a consultant and on advisory boards for the U.S. National Science Foundation and the Social Sciences and Humanities Research Council of Canada and currently is engaged in assisting with the NSF-funded Math and Science Partnership project at the University of Michigan, where she received her Ph.D. in 1998. During a recent sabbatical she was a Faculty Fellow at Doshisha University in Kyoto, Japan.

- **Maria Kozhevnikov**
  Associate Professor, Psychology Department
  George Mason University
  NSF Program Director for Science of Learning Centers
  http://psychology.rutgers.edu/~maria/

  Dr. Kozhevnikov is interested in neural mechanisms of visual/spatial imagery as well as in individual differences in basic information processing capacities (e.g., the ability to generate, inspect, or transform visual/spatial images). In addition, Dr. Kozhevnikov is interested in examining how these individual differences affect more complex activities, such as spatial navigation, learning and problem solving in mathematics and sciences as well as in exploring the ways to train visual/spatial imagery skills and design learning technologies that can accommodate individual differences and learning styles.

INVITED SPEAKERS

- **James P. Barufaldi**

Ruben E. Hinojosa Regents Professor, Department of Curriculum and Instruction
College of Education
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http://www.utexas.edu/education/facultyDetails.php?ID_PK=68D67753-07C6-639B-827F218D1097F15F

Dr. James P. Barufaldi is the Ruben E. Hinojosa Regents Professor and serves as Director of the Center for Science and Mathematics Education at The University of Texas at Austin. He also serves as Principal Investigator of the Texas Regional Collaboratives for Excellence in Science Teaching. In 2003 Barufaldi was selected as a member of the Academy of Distinguished Teachers at The University. He teaches undergraduate and graduate courses in science education. Barufaldi's special areas of interests are curriculum design, instructional strategies, implementation, evaluation, and science teacher education. He is currently investigating the process of building successful collaboratives in the science education community and variables, which may contribute to high intensity, sustained collaboration.

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于富雲 / Fu-Yun Yu Professor National Cheng Kung University
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Professor & Chair

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Professor

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📖 **楊芳瑩 博士**

Fang-Ying Yang, Ph.D.

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LIST OF THE BRAIN WORKING TEAM

The list is in alphabetical order

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曾煥格 / Frank Tseng

曾如詩 / Ju-Shih (Jenny) Tseng

王淑文 / Shu-Wen (Sophia) Wang

Graduate Students

黃俊傑 / Chun-Chieh Huang

黃晟庭 / Sheng-Ting Huang

洪逸文 / Yi-Wen Hung

李旻憲 / Min-Hsien Lee

李岱螢 / Tai-Ying Lee

林銘照 / Ming-Chao Lin

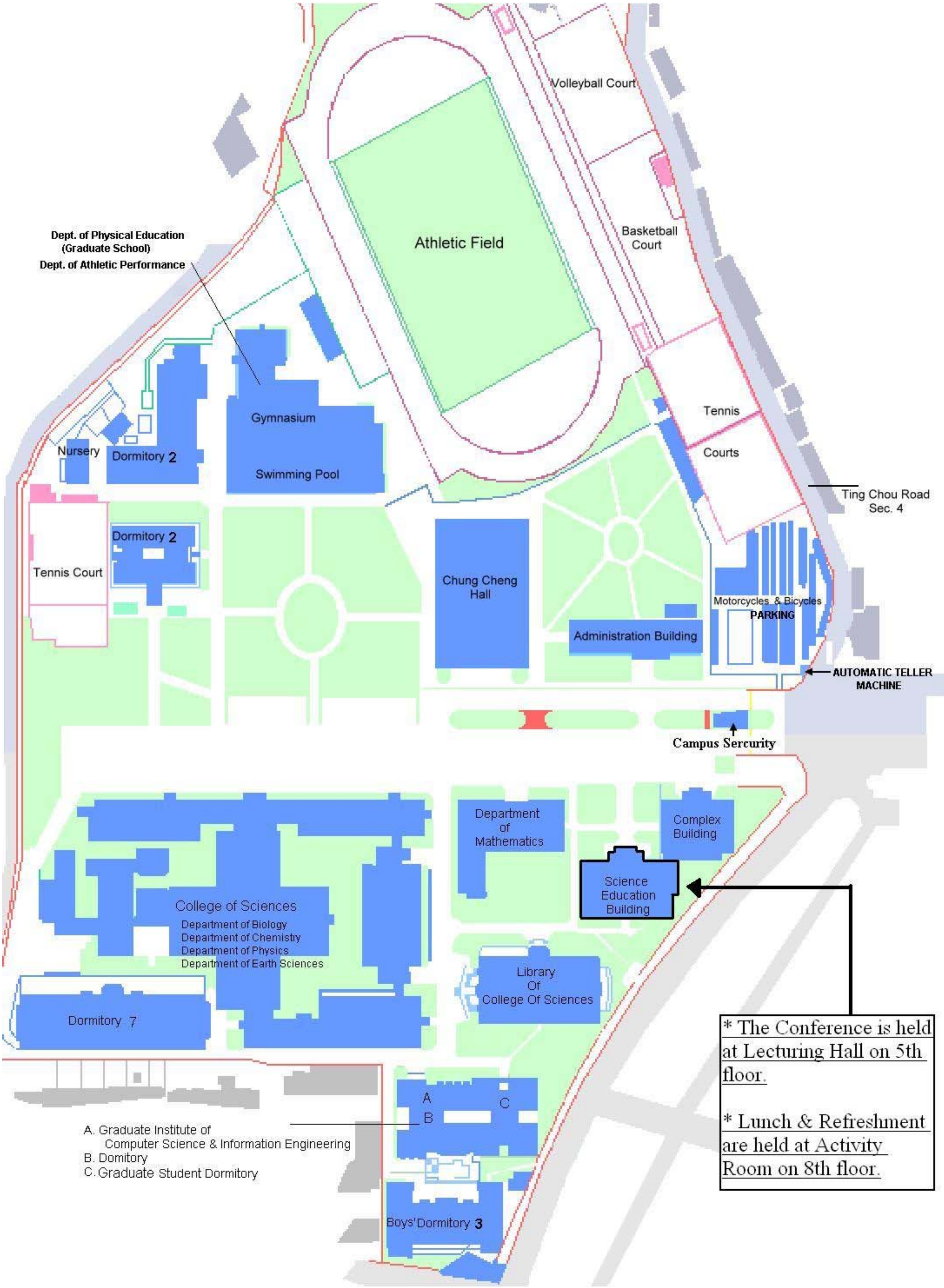
呂志峰 / Chih-Feng Lu

吳皇慶 / Huang-Ching Wu

吳穎沺 / Ying-Tien Wu

葉庭光 / Ting-Kuang Yeh

CAMPUS MAP


Volleyball Court
Athletic Field
Basketball Court
Dept. of Physical Education (Graduate School)
Dept. of Athletic Performance
Gymnasium
Swimming Pool
Tennis
Courts
Nursery
Dormitory 2
Dormitory 2
Tennis Court
Ting Chou Road Sec. 4
Chung Cheng Hall
Administration Building
Motorcycles & Bicycles PARKING
AUTOMATIC TELLER MACHINE
Campus Sercurity
Department of Mathematics
Complex Building
Science Education Building
College of Sciences
Department of Biology
Department of Chemistry
Department of Physics
Department of Earth Sciences
Library Of College Of Sciences
Dormitory 7
A
B
C
A. Graduate Institute of Computer Science & Information Engineering
B. Domitory
C. Graduate Student Dormitory
Boys' Dormitory 3
* The Conference is held at Lecturing Hall on 5th floor.
* Lunch & Refreshment are held at Activity Room on 8th floor.

Notes

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