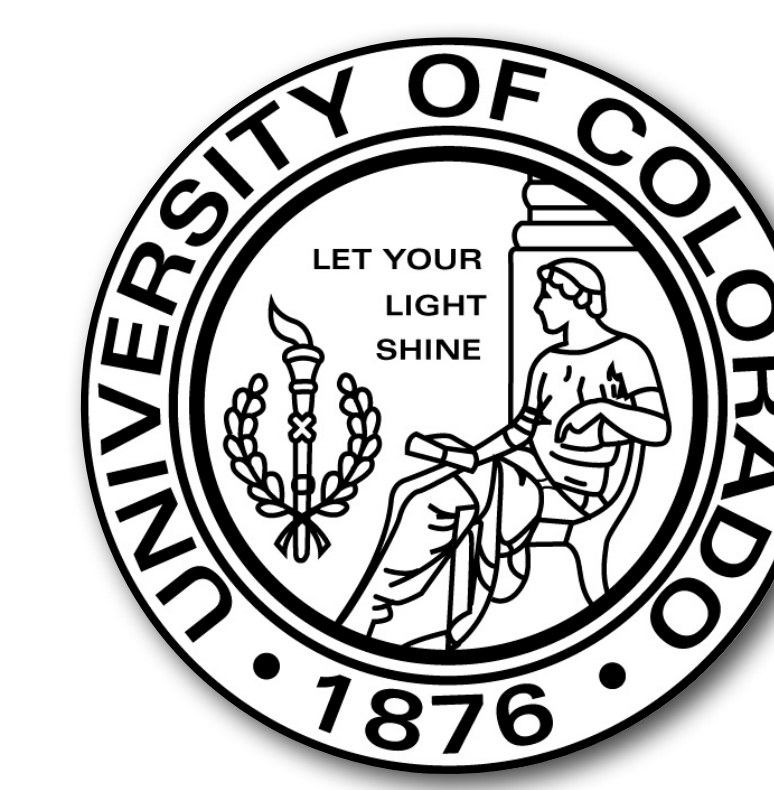




Computational Modeling as a Promoter of Cognitive Transfer: Pilot Study

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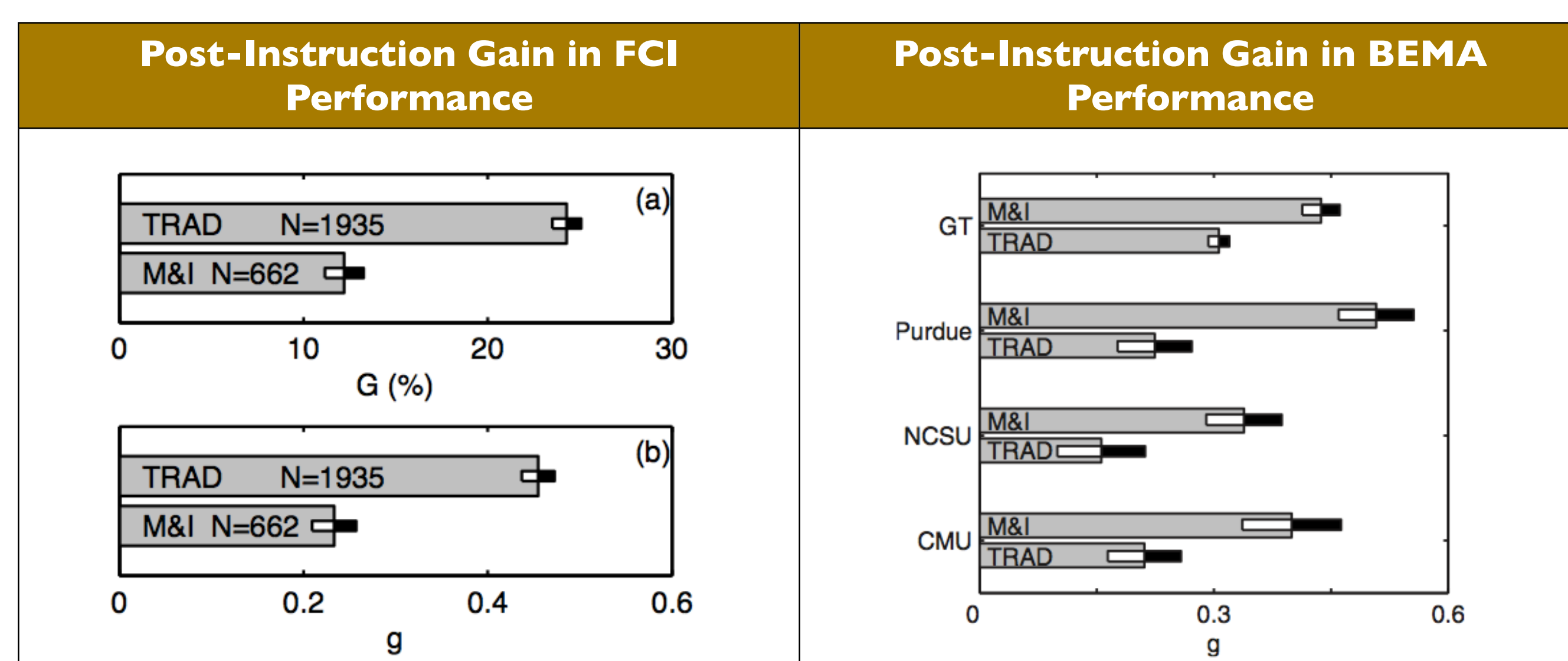
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Abstract

We describe a study of the role of computational modeling in recognizing underlying similarities in different problems, a process called cognitive transfer. Previous studies have shown that this crucial process is highly sensitive to context, suggestion, and familiarity with the subject matter. We propose that courses emphasizing computational modeling, in which students repeatedly employ similar lines of code to model different physical systems, foster a more generalized cognitive transfer ability. We performed a think-aloud study on several students (some from a course involving computational modeling, others from a traditional physics course), exposing them to ordered pairs of problems of varying degrees of separation in specific details (molecular mechanics vs. projectile motion) and solution methods (numerical vs. analytical). With these data, we attempt to separate the influence of long-term instruction in computational modeling from the immediate priming effect of solving computational problems, and relate both to the promotion of cognitive transfer.

Computation Makes a Difference



Gain in student performance on two standard physics understanding measures for M&I and Traditional students (Force Concepts Inventory at Georgia Tech, left; Brief Electricity and Magnetism Assessment at four institutions, right). Note that the gain in FCI performance at Georgia Tech is less for M&I students than for traditional students. Reproduced from [1] and [2], respectively.

Why These Differences?

Could computational modeling be influencing **cognitive transfer**? If so, is it because long-term instruction in modeling makes students better at transfer, or is it because the short-term effects of doing a modeling problem prime students to think about transfer?

Cognitive Transfer

Task-Oriented Transfer (Thorndike, 1901)	Subject-Oriented Transfer (Judd, 1908)
Doing task A influences your performance on task B insofar as A and B share similar elements.	The relationship between your performance on A and B is largely determined by how you approached A. [3]
M&I computational modeling exercises admit both sorts of transfer.	

Study Design

Think-Aloud Protocol

(In a think-aloud study, the subject speaks his or her thoughts aloud continuously) [4]

1: Warm-Up Question: Imagine there were a standard kitchen faucet in this room. If I were to turn it all the way on, how long would it take this room to fill completely with water?

2: Two Physics Questions:

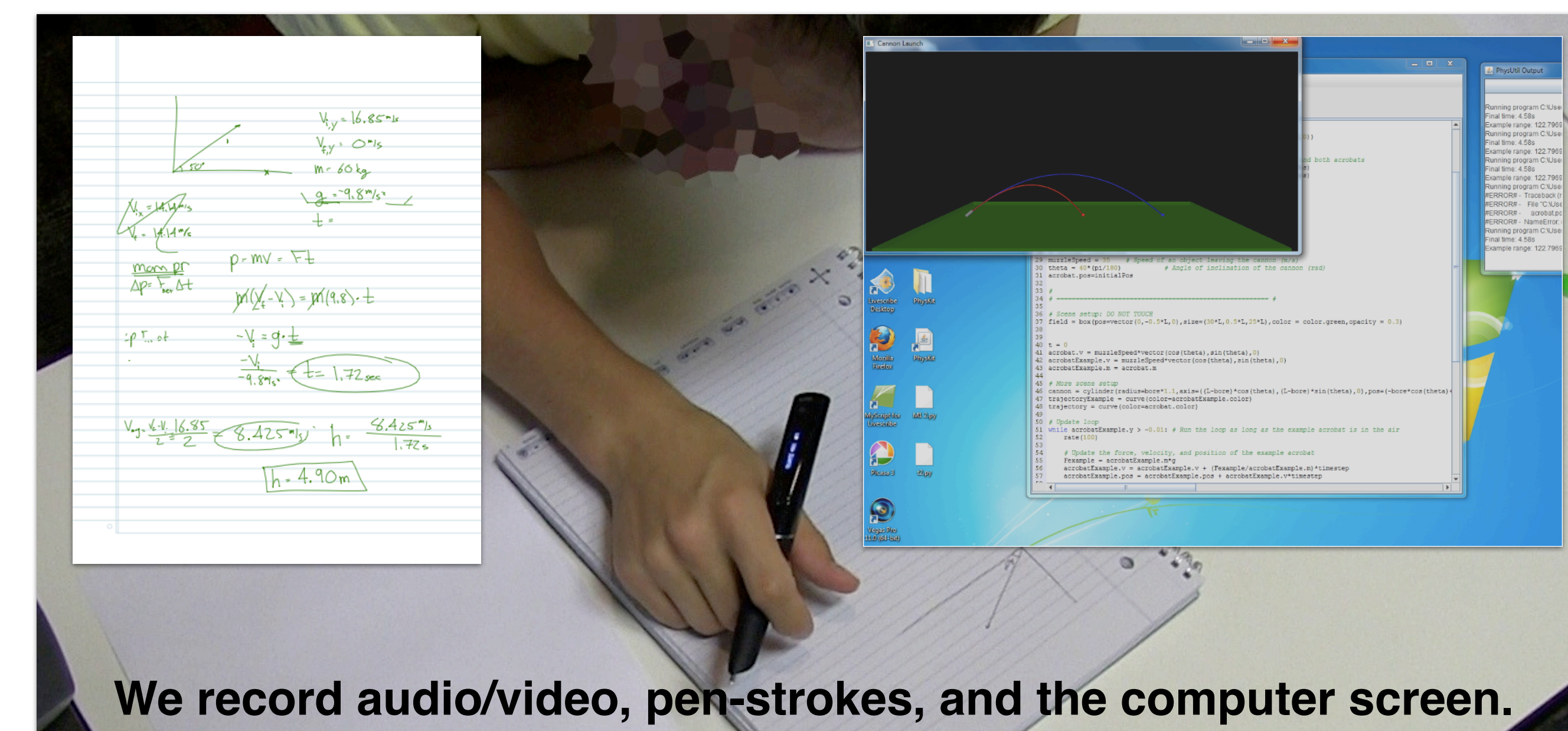
	Projectile	Molecular
Analytical	A	A*
Computational	C	C*

3: Retrospective Question: Were these two problems similar? Can you describe their important similarities and important differences?

(We expect cross-domain transfer to be more difficult)

4 Traditional Students	1 M&I Student*	2 Experts	Full Study in Fall 2012
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*GA Tech's scheduling is such that many M&I students are off-campus during the summer



Preliminary Results

- Evidence of transfer is detectable! One subject (who happened to be the only M&I student) actually used an explicit analogy.
- The problems are well-suited to the abilities of the participants; not too hard, not too easy.
- Both subjects who were primed with a C problem also used the computer to solve their A problem.

References

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Acknowledgments

Thanks to Wendy Newstetter, Richard Catrambone, and Mark Guzdial at Georgia Tech for their guidance and support. Special thanks to Joe leDoux for the use of his recording lab, and extra special thanks to Alisha Waller for facilitating the use of the lab.

