Calculating Expertise in Bioengineering Education

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***Abstract* - A previously hypothesized formula for calculating components of adaptive expertise (AE= 0.10F + 0.40C + 0.50T, where F = Factual knowledge, C= Conceptual knowledge, and T = Transfer) was tested and the weighting adjusted based on analysis undertaken using 2-group MANOVA with the original study data. This data included measures of change along three facets of adaptive expertise: factual knowledge, conceptual knowledge and transfer. Analysis of the univariate effects reveals a significant difference in the transfer gain (F=10.573, p= .004) but no significant difference on gains in conceptual knowledge (F= .920, p= .349) or factual knowledge (F= 3.104, p= .094). The linear combination that maximally separated the two groups was: 0.14F - 0.36C + 1.27T. The relative magnitudes of the weights share the same ordinal trend (F < C < T) as the original formula. The formula has theoretical underpinnings in *How People Learn* and attempts to describe points along the trajectory of novice to expert development in bioengineering education.**

Index Terms – Adaptive Expertise, Bioengineering education

INTRODUCTION

Much of the research and educational activities ongoing in the Vanderbilt-Northwestern-Texas-Harvard-MIT (VaNTH) Engineering Research Center for Bioengineering Educational Technologies are based on the belief that the How People Learn (HPL) [1] framework can provide a strong foundation for significantly improving bioengineering education. Research on the development of expertise has shown that experts' knowledge is connected and organized around big ideas or core principles of the expert's discipline [2]. Although expert knowledge rests on a foundation of factual knowledge about the content area [3, 4, 5], experts' knowledge cannot be reduced to a set of isolated facts, but instead is conditionalized to reflect the contexts in which it is applicable [6, 7] and organized into conceptual schema such that it is readily accessible [8, 9, 10]. Experts notice features about a given problem that are different from those noticed by novices [1, 3]. Finally expertise may involve the ability to apply knowledge to solving problems in a variety of contexts by recognizing the underlying similar concepts or principles that govern the given situation; this ability is called transfer [1]. Adaptive experts not only have knowledge that is well organized, but also display the ability to transfer their knowledge, skills, beliefs, and attitudes to new situations. Thus, adaptive expertise is a combination of factual knowledge, conceptual knowledge and the ability to transfer that knowledge to novel situations [1].

INSTRUCTION FOR ADAPTIVE EXPERTISE

Previous research into adaptive expertise in the context of biomechanics led to the generation of a metric for quantifying adaptive expertise [10]. This research involved a comparison of gains in the three facets of expertise for two groups of students (control and experimental). The experimental group completed biomechanics and muscle physiology modules in which they were expected: (a) to be able to define and calculate the velocity and acceleration of a point on a body segment; (b) to be able to apply the Impulse-Momentum method to find the velocity and acceleration of the center of mass of the body; (c) to be able to define and calculate the net muscle moment acting about a joint; (d) to be able to describe and explain the relationship between a joint moment, muscle force, and muscle lever arm; and (e) to be able to describe and

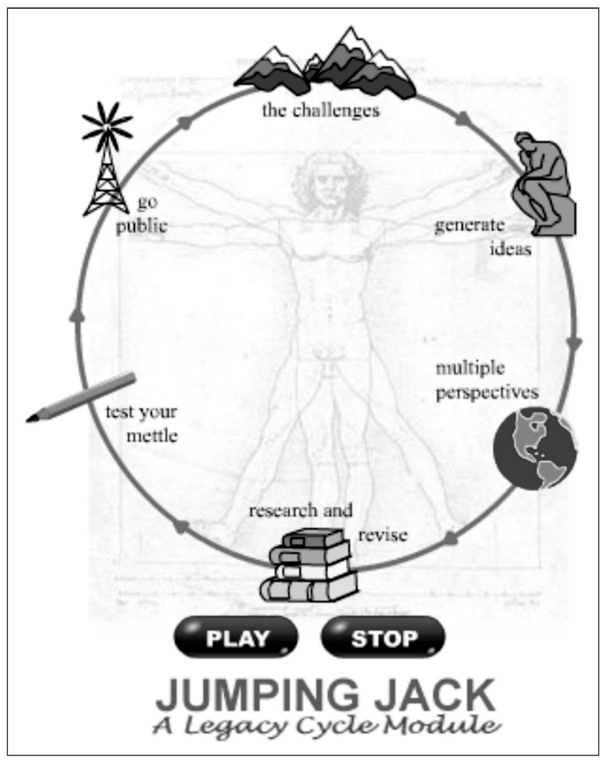

Figure 1. Screen shot showing the various steps of the Legacy Cycle, which was used to integrate the four types of learning environments (learner centered, knowledge centered, assessment centered, and community centered) defined by the HPL framework.

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explain the dependence of muscle force on length, contraction velocity, and activation level.

The modules are based on the Star Legacy Cycle [6], which is designed to scaffold student inquiry. These challenge-based modules include various stages: 1) Look Ahead, 2) The Challenge, 3) Generate Ideas, 4) Multiple Perspectives, 5) Research & Revise, 6) Test Your Mettle, and 7) Go Public (Figure 1).

Changes in student achievement were quantified using pre-test (PRE) and post-test (POST) questionnaires designed to measure changes in three facets of adaptive expertise: (a) factual knowledge (F), which gauges a student's ability to retain key facts and principles; (b) conceptual knowledge (C), which measures a student's ability to grasp the underlying principles of the material taught as well as his or her quantitative skills (i.e., ability to manipulate mathematical symbols and numbers to arrive at the correct answer); and (c) transfer (T), which measures a student's ability to extend his or her knowledge to new and unfamiliar situations [1]. To this end, a rubric was developed that allowed each facet to be scored individually.

PARTICIPANTS AND INITIAL METHODS

Previous classroom assessment was conducted using students from a senior-level undergraduate biomechanics course (ME 354M) taught in the Department of Mechanical Engineering at The University of Texas at Austin. Approval for this study was obtained from the Institutional Review Board at The University of Texas at Austin. The assessment was based on a two-group design, in which the class of twenty-five students was divided randomly into a control group and an experimental (HPL) group. The control group received traditional instruction comprised of lectures and example problems solved in class. The HPL group received the first challenge of the module.

Students in both the control and HPL groups first received an introductory half-hour lecture. Students in the HPL group were given two class periods, each 1.5 hours long, to complete Challenge 1 of the jumping module. Students in the control group received lectures on jumping biomechanics over these same two class periods. In addition to the lectures, several examples on how to calculate jump height using equations of projectile motion and vertical ground force were worked through.

The data collected in the initial study were evaluated to for generating the initial metric, and re-evaluated for this study.

INITIAL METRIC

In order to quantify adaptive expertise in movement biomechanics, a metric was formulated based on a linear combination of weighted factual and conceptual knowledge and transfer [11]. The weightings were chosen based on the relative importance of each facet of expertise consistent with the HPL approach. Specifically, transfer was weighted most heavily, accounting for 50 percent of the total score on a given question, with the remainder divided between conceptual and factual knowledge in the proportions of 40 percent and 10 percent, respectively. These weightings were chosen to reflect one of the main tenets of the HPL approach—the ability to grasp key concepts (conceptual knowledge) and to apply those concepts in solving novel problems (transfer) is much more important to the development of adaptive expertise than is the ability to recall facts. Thus, adaptive expertise in movement biomechanics was quantified as:

$$AE = 0.10F + 0.40C + 0.50T,$$

where F = Factual knowledge, C = Conceptual knowledge, T = Transfer.

METHODS

A previously hypothesized metric for calculating adaptive expertise in biomechanics was tested using 2-group MANOVA and the original data. The original data measured changes in student achievement along three facets of adaptive expertise: (a) factual knowledge (b) conceptual knowledge; and (c) transfer. The weightings were adjusted based on this analysis.

RESULTS

Dependent Variables

i. Transfer Gain, T = Q3POST + Q2POSTT – Q2PRET
ii. Conceptual Knowledge Gain, C = Q3POSTC + Q2POSTC + Q1POSTC – Q2PREC – Q1PREC
iii. Factual Knowledge Gain, F = Q3POSTF + Q2POSTC + Q1POSTF – Q2PREF – Q1PREF

Between-subjects Factor
HPL vs. Control condition

Where Q1 stands for the first question, Q2 for the second, and Q3 for the third, PRE stands for pre-test and POST for the post-test, and F stands for factual knowledge, C for conceptual knowledge, and T for transfer.

Box's M Test was not significant suggesting model assumption of homoscedasticity holds good (F = .818, p = .556).

The overall multivariate effect of between-subjects factor was significant (F = 3.99, p = .025) with a large effect size (partial eta-squared = .413) but moderate power (power = .737).

Analysis of the univariate effects suggest that there is a significant difference in the transfer gain between the two groups (F = 10.573, p = .004). This effect had a large effect size (partial eta-squared = .358) as well as high power (power = .869). In other words, students in the treatment condition (M = 1.73, SD = 1.10) achieved significantly higher transfer gains than those in the control group (M = .40, SD = .70).

There was no significant difference between the groups on gains in conceptual knowledge (F = .920, p = .349) or factual knowledge (F = 3.104, p = .094). Although, the gain on factual knowledge may be considered to be of marginal significance.

Exactly one canonical dimension maximally separated the two groups. The linear combination that maximally separated the two groups was:

$$AE=0.14F - 0.36C + 1.27T$$

When contrasted with the paper's linear combination, AE= 0.10F + 0.40C + 0.50T, one can see that the relative magnitudes of the weights share the same ordinal trend ($F < C < T$). One can also see that the weight of T, relative to F and C, ought to be much larger than what was proposed in the original metric, though the results are generally consistent with the original metric. However, the effect of conceptual knowledge is reversed. In other words, controlling for the gains in Factual Knowledge and Transfer, higher scores on Conceptual Knowledge yield lower differences between the two groups.

DISCUSSION

The purpose of this study was to propose an updated metric for adaptive expertise in biomechanics based on data from past research involving the development and implement of new multimedia-based learning modules. The weightings of the new metric reported in this study may be interpreted in a number of ways.

One possible explanation for this could be that in solving post-test question three, students used additional facts without using any additional concepts.

A second explanation is at the heart of the argument. We are making an assumption that there exists a linear combination of F, C, and T that gives us a metric for measuring AE. This is quite a plausible assumption, however, we are also making the additional assumption that difference between the two groups is due to AE. If the first assumption is true, then the data clearly do not support the second assumption. This is because only when both the assumptions are true can one attribute the linear combination from the analysis to substantively represent the construct of AE. It is conceivable that the true difference between the HPL and control groups is not entirely manifested in terms of AE.

Finally, one could also attribute this to a very small sample size, especially when there are 3 dependent variables. Any interpretation must be constrained by the small sample size.

While our results for the effectiveness of the HPL approach are encouraging, there remain some limitations that bear mentioning; these impact both findings as well as the metric presented here. First, our sample size was somewhat limited (n =25). Coinciding with this limitation was the fact that the original study was conducted in a single college classroom. We would like to address both of these issues in our next iteration as we seek a greater sample size and an increase in the number of participating classrooms. Thirdly, the original intervention lasted only a few class sessions. In the future, we plan on including more challenges to better assess the true differences between the HPL and non-HPL classes on affect, factual, conceptual, and transfer dimensions. Finally, we realize our adaptive expertise formula is tied to only a small data set and yet attempts to describe a complicated construct. As such, we will pursue greater fidelity of measure and welcome comments and critiques from interested colleagues.

CONCLUSION AND FUTURE WORK

This paper describes the refinement of a formula for quantifying adaptive expertise and is an outcome of a multimedia-based learning module focused on biomechanics. The modules are based on a model of learning and instruction known as the How People Learn (HPL) framework. This study draws upon research undertaken to test the hypothesis that the HPL approach increases adaptive expertise in movement biomechanics.

The original data, which included student achievement scores on pre- and post-test questionnaires designed to measure changes in three facets of adaptive expertise: factual and conceptual knowledge and transfer inspired the original metric and was analyzed with two-group MANOVA to generate a more accurate metric. The linear combination that maximally separated the two groups was:

$$AE=0.14F - 0.36C + 1.27T$$

The assessment study is currently being extended to include participation from a greater number of students, to include all three challenges of the module, and to evaluate the efficacy of the module in more than one course and across several institutions. Also of interest to us are the generalizability and validity of this metric; future research will address to what extent it could be applied to other areas of engineering and beyond.

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REFERENCES

[1] Bransford, J.D., A.L. Brown, and R. Cocking, (Eds.), (2000) *How People Learn: Brain, Mind, Experience and School*. Washington, DC: National Academy Press.

[2] Bruer, J., (1993) *Schools for Thought: A Science of Learning in the Classroom*, Cambridge, MA: MIT Press.

[3] Chi, M.T.H., P.J. Feltovich, and R. Glaser, (1981) “Categorization and Representation of Physics Problems by Experts and Novices,” *Cognitive Science*, Vol. 5, pp. 121–152.

[4] deGroot, A.D., (1965) *Thought and Choice in Chess*, The Hague, The Netherlands: Mouton.

[5] Chase, W.G., and H.A. Simon, (1973) “Perception in Chess,” *Cognitive Psychology*, Vol. 1, pp. 33–81.

[6] Blumenfeld P.C., E. Soloway, R.W. Marx, J.S. Krajcik, M. Guzdial, and A. Palincsar, (1991) “Motivating Project-based Learning: Sustaining the

Doing, Supporting the Learning," *Educational Psychologist*, Vol. 26, No. 3–4, pp. 369–398.

[7] Williams, S.M., (1992) "Putting Case-based Instruction into Context: Examples from Legal and Medical Education," *Journal of the Learning Sciences*, Vol. 2, No. 4, pp. 367–427.

[8] Driver, R., (1983) "Learning Science and Theories of Cognitive Development," *The Pupil as Scientist*? Berkshire, UK: The Open University Press.

[9] Driver, R., H. Asoko, J. Leach, E. Mortimer, and P. Scott, (1994) "Constructing Scientific Knowledge in the Classroom," *Educational Researcher*, Vol. 23, No. 7, pp. 5–12.

[10] Pandy, M., Petrosino, A., Austin, B., Diller, K. (2004). *Assessing Adaptive Expertise in Undergraduate Biomechanics*. Journal of Engineering Education

[11] Lawson, A.E., (1979) "The Developmental Learning Paradigm," *Journal of Research in Science Teaching*, Vol. 16, No. 6, pp. 501–515.