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Using Early Warning Signs to Predict Academic Risk in Interactive, Blended Teaching Environments

Julie Schell, Brian Lukoff, Cassandre Alvarado

Introduction

Growing evidence in higher education suggests that interactive teaching leads to more robust student learning outcomes than lecture-based instruction (see Crouch & Mazur, 2001; Hake, 1998; Lasry, Mazur, & Watkins, 2008; Nicol & Boyle, 2003). This phenomenon transcends geographic and disciplinary boundaries, and institutions across the globe are investing in initiatives to support interactive pedagogical models (Becerra-Labra, Gras-Marti, & Torregrosa, 2012). As online learning becomes more accessible, interactive teaching often includes web-facilitated and blended learning (Allen & Seaman, 2014) to drive engagement. As a result, instructors can drive student success more effectively in and out of class.

In what seems to be universal pushes for technology-driven educational reform there is one reality that is under-studied and under-acknowledged: Even in classes where master instructors use interactive methods with the most effective online tools, there remain students who do not succeed. This is the research problem of this study: even when state-of-the art pedagogies and technologies are used, there are still students who do not succeed. For example, there still exist students who do not exhibit sufficient levels of gain in conceptual understanding of subject matter, academic performance, engagement in course activities, and beliefs and attitudes about academic competence. In this paper, we define those underachiev-ing students in interactive classrooms as at-risk. As educational reformers continue to emphasize interactive, blended learning as a critical element of change in higher education, the lack of extant effort to address the needs of *at-risk* students in such environments is an important research problem. Is there something educators can do to help these at-risk students? That is the underlying question of this study.

In the *NMC Horizon Report 2014 Higher Education Edition* (Johnson et al., 2014), the authors lament that higher educators have not yet "embraced" the potential to use extensive educational data generated by students to improve college student success. In this paper, we demonstrate how we used on and off-line data to chart a path early on in the semester for improving course-level student success in a blended, flipped physics classroom. The purpose of this study is to offer an evidence-based process for identifying characteristics correlated with student academic underachievement at the course level in blended, interactive teaching environments that qualify as *early* warning signs and to recommend early intervention points. We hypothesize that students' beliefs that they can reach a high level of achievement in a course, defined as their self-reported, perceived academic self-efficacy, will have a strong relationship with later course performance, as will a number of other simple measurements that are available in the first few weeks of instruction. We explore this hypothesis with the purpose of presenting a simple process that instructors can use to identify at-risk students in inter-

active, web-facilitated and/or blended classrooms early in the semester so that their teachers may intervene and address the specific needs of potentially at-risk students in interactive classrooms.

Conceptual Framework

The concepts that frame this study are as follows: interactive teaching, blended learning, self-efficacy, and Peer Instruction. We describe our research-based definitions of these concepts below.

Interactive Teaching

The pedagogical approach in such classrooms is generally based on constructivist theories of learning: "the contemporary view of learning…that people construct new knowledge and understanding based on what they already know" (Bransford, Brown, & Cocking, 2000 p. 10). Interactive teaching is a concept that lacks definitional clarity in the higher education literature. It is most often used in contrast to didactic, lecture-based teaching and researchers often attach the use of technology to conceptualizations of interactive teaching (see Sessoms, 2008). However, while there are numerous examples of interactive teaching that incorporate technology, there are just as many that do not; rather than technology serving as determinant in conceptualizations of interactive teaching, we posit that it is the pedagogical approach that is the most salient, defining feature.

In a typical classroom where interactive teaching is in use, an observer would witness numerous discursive actions occurring through multi-directional feedback loops among students, teachers, and other course staff. The pedagogical approach in such classrooms is generally based on basic constructivist theories of learning: "the contemporary view of learning people… that construct new knowledge and understanding based on what they already know" (Bransford, Brown, & Cocking, 2000 p. 10). Prevailing constructivist views of learning do not imply that "teachers should never tell students directly, but instead should always allow them to construct knowledge for themselves" (Bransford, Brown, & Cocking, p. 11), but rather that learning is a social and cognitive process that depends on the prior knowledge state of the student (Ambrose et al., 2010; Bransford et al., 2000; Darling-Hammond, Rosso, Austin, Orcutt, & Martin, 2003; Piaget, Green, Ford, & Flamer, 1971; Vygotsky, 1998). Constructivists also privilege the power of social learning theory (Vygotsky, 1998), which emphasizes the idea that "all learning…involves social interactions" (Vygotsky, referenced in Darling-Hammond et al., 2003).

Web-facilitated and Blended Learning

According to the report, Grade Change-Tracking Online Education in the United States (Allen & Seamen, 2014), web-facilitated learning is typically "a course that used web-based technology to facilitate what is essential a face-to-face course." An online course is one where at least 80% of the content is delivered online. The course we studied for this research was a blended, flipped classroom: "a course that blends online and face-to-face delivery", where between 30-79% of the content is delivered online, and students do engage in continuous learning before, during, and after class.

Self-efficacy

Theories of self-efficacy (Bandura, 1977, 2003) lay the groundwork for this study. We define self-efficacy as the belief

that one can successfully complete a task (Bandura, 2003). Theories of self-efficacy suggest that the courses of action that individuals take in their lives are driven by their beliefs about their own abilities. In particular, researchers use self-efficacy to explain academic, career, and life decisions and outcomes (Lent, Brown, & Larkin, 1984; Multon, Brown, & Lent, 1991). The basic theory suggests that an individual's perceptions of their own ability or competence (i.e., their perceived self-efficacy), regardless of accuracy, will lead them toward specific courses of action and not others.

The present study was designed with self-reported perceived academic self-efficacy as a unit of analysis, whereby academic self-efficacy is defined by students' beliefs about their academic competence (Pajares, 1996; Pajares & Miller, 1994). In a review article, Pajares (1996) documented the literature demonstrating positive relationships between self-reported academic self-efficacy, academic performance, and choice of college major. In particular, Hackett and Betz (1989) suggested that self-reported academic self-efficacy is more predictive of mathematics interest or choice than actual performance (Hackett & Betz, 1989). We used the theory of self-efficacy to guide our investigation into early predictors of academic success or the lack thereof.

Peer Instruction

One interactive teaching method that has gained international prominence is Peer Instruction, developed by Eric Mazur at Harvard University in the 1990s (Mazur, 1997). Peer Instruction is often used with the web-facilitated pedagogy, Just-in-Time Teaching, to create a "flipped classroom," which incentivizes students to prepare before class by completing online pre-class assignments that require them to interact

with the subject matter and reflect on their understanding prior to the class period. Instructors then use feedback from students' pre-class assignments to plan class time. During class, instructors pose a series of questions often, but not always, using web-facilitated learning tools, such as classroom response systems. These questions pushed to students through technology serve to elicit, confront, and resolve (ECR) their misunderstandings and misconceptions (Heron, Shaffer, & McDermott, n.d.). In Peer Instruction, teachers use short, conceptually based questions called ConcepTests to facilitate the ECR technique (Mazur, 1997). The implementation of interactive teaching throughout the course for this study, included facilitating Peer instruction using a cloud-based classroom response system called Learning Catalytics. Students use their own devices (smartphones, tablets, or laptops) to interact and response to the questions. While Peer Instruction does not require the use of technology, the basic protocol for in-class questioning with Peer Instruction using a web-based response system is as follows:

1. Instructor gives a mini-lecture on selected concept.
2. Instructor poses a question using Learning Catalytics, which delivers the question to each student's personal device.
3. Students are given time to think individually about their response.
4. Students submit first-round responses using their personal devices.
5. Instructor reviews first-round feedback and data using an instructor-only dashboard through Learning Catalytics.
6. Instructor uses Learning Catalytics to pair students with someone with a different answer. The instructor

encourages students and to either defend their answer or to convince them that their own response is correct.

7. Students submit second-round responses after discussion.
8. Instructor reviews second-round feedback using the Learning Catalytics dashboard.
9. Instructor guides a closure activity for explaining the correct answer.

Instructors elicit misconceptions in steps 1-4, confront those misconceptions in steps 5-7, and resolve those misconceptions in steps 8-9. (If too few or too many students answer correctly in the first round, then there may be no significant misconceptions, and the process would jump from step 5 to step 9.) By building on students' prior knowledge derived from pre-class reading assignments submitted online and engaging them in constant social learning opportunities, Peer Instruction qualifies as a leading, internationally recognized interactive, web-facilitated teaching method. Indeed, in a study of 722 physics professors, Henderson and Dancy (2010) found that Peer Instruction was the most well-known and most tried interactive teaching method, with "more than 64% of respondents reporting familiarity" (p.1057).

For over twenty years, studies in classrooms all over the globe consistently indicate that there are positive learning outcomes associated with Peer Instruction. Prominent research includes Fagen et al. (2002), which found from a study of 384 Peer Instruction users and 30 courses at 11 universities a positive correlation between Peer Instruction and increased scores on standardized assessments of conceptual understanding. Mazur (1997) reported that students performed better on both course-specific exams and stan-

dardized tests of conceptual understanding when taught using Peer Instruction instead of with the traditional method (see Mazur, 1997, p. 16). Smith et al. (2009) reported that in a Peer Instruction environment, "peer discussion enhances understanding, even when none of the students in a discussion group originally knows the correct answer." Watkins (2010) reported that Peer Instruction is correlated with increased persistence (staying) in science majors and a reduction in the gender gap and the gap between racial and ethnic minorities on tests of conceptual understanding in physics.

Despite its successes, there remain students in Peer Instruction and other constructivist-based, interactive, blended classrooms that do not achieve at the levels proponents of interactive teaching and blended learning hope for. In this study, we examine if we can predict students that are at-risk in blended Peer Instruction classrooms early, with the intention of using those early warning models to recommend early interventions to instructors utilizing Peer Instruction and other interactive teaching methods. In this study, we posit that pre-course self-efficacy may be one such non-content related early warning sign.

Methods

We studied N = 89 students in a medium-sized introductory physics course at a large private university in the Northeast taught using Peer Instruction and Just-in-Time Teaching by a highly experienced instructor. Most implementations of Peer Instruction facilitate the mechanics of responding to ConcepTests using clickers or other audience response systems; as aforementioned, the course we studied used Learning Catalytics, a cloud-based response system (developed

by one of the authors) that permits the instructor to pose non-multiple-choice ConcepTests to students (e.g., sketch a graph) and then can use student responses to automatically group students for discussion.

Peer Instruction Self-Efficacy Instrument

To measure self-efficacy, both in general and in a Peer Instruction environment, we developed a set of 25 Likert-scale items aimed at measuring various qualities related to self-efficacy, including qualities that we believed would be unique to a Peer Instruction environment. These items were based on Fencl and Scheel's (2003) Sources of Self-efficacy in Science COurses (SOSESC). The statements, such as "When I come across a tough physics problem, I work at it until I solve it" were designed to gather data about students' self-reported beliefs their abilities in physics and in a Peer Instruction environment.

As this was the first time the instrument was used, this study simultaneously served as an opportunity to use measurements from this instrument as covariates as well as an opportunity to gather some initial validation data from the study. We later extracted two subscales that we used as variables in the study. The first subscale was a seven-item set that conceptually covered general self-efficacy; Cronbach's coefficient alpha reliability for this subscale was 0.85 when the scale was administered at the beginning of the semester (pretest) and 0.83 when it was administered at the end of the semester (posttest). The second subscale was a six-item set that conceptualized our notion of "Peer Instruction self-efficacy." Unsurprisingly, since the notion of self-efficacy in a Peer Instruction environment is

a new concept, this subscale proved to be somewhat less reliable, with coefficient alpha values of 0.53 for the pretest and 0.68 for the posttest. The fifteen items used in these subscales (as well as the other ten items that were ultimately not used in this analysis) appear in Appendix A.

Data Set

Our data set included all performance data for students over the semester, including:

- Summative assessment data collected over the semester, including scores on problem sets (eight over the course of the semester), three midterm exams, and the final exam.
- Pre and post-test scores on the Conceptual Survey of Electricity and Magnetism (Maloney, O'Kuma, Hieggelke, & Van Heuvelen, 2001), a conceptual inventory measuring understanding of fundamental concepts in electricity and magnetism.
- Pretest and posttest data from a non-cognitive assessment, developed by the authors, to measure students' self-efficacy in a Peer Instruction environment as well as attitudes towards science and education. Seven items measured general self-efficacy; Cronbach's coefficient alpha reliability for this subscale was 0.85 for the pretest and 0.83 for the posttest. Eight items measured Peer Instruction self-efficacy; this subscale proved to be somewhat less reliable, with coefficient alpha values of 0.66 for the pretest and 0.73 for the posttest.
- Formative assessment data consisting of student responses to ConcepTests asked by the instructor in class. These

questions were administered using Learning Catalytics and consisted of a mix of constructed-response and multiple-choice questions.

Results

The predictive models are shown in Table 1, along with the R2 value and the root mean squared error (RMSE) for each; this latter value gives roughly the "expected error" from using the model to predict final exam score given the predictors.

Model 1 demonstrates that just knowing students' conceptual understanding at the beginning of the semester is surprisingly predictive of their final course grades, with 29% of variance explained and a RMSE of 6.9. Adding in knowledge of students' self-efficacy at the beginning of the semester (Model 2) adds significantly to the model, raising $R2$ to 34%. The coefficient for CSEM score is (unsurprisingly) positive in Model 1 but remains positive in Model 2, indicating that conceptual understanding at the beginning of the course is positively associated with final grade even among students with the same level of self-efficacy.

Model 3 indicates that Peer Instruction self-efficacy does not add to the predictive quality of the model above and beyond CSEM score and general self-efficacy. (Surprisingly, Peer Instruction self-efficacy did not correlate at all with final grade; r = 0.13, p > 0.05.) However, Models 4 and 5 demonstrate that by adding early indicators of student performance it is possible to substantially increase the predictive quality of the model. Model 4 adds as an indicator the number of Learning Catalytics questions (ConcepTests) answered correctly in the first three weeks of instruction, while Model 5 replaces that with students' average scores on their first two problem sets, which

also occur within the first three weeks of instruction.

Since Model 5 is a stronger predictor of final grades than Model 4, early problem set scores are retained in the later models. Models 6-8 add in successive scores on the three midterms. Not surprisingly—at least in part because midterm scores are a significant part of students' final grades—the addition of each midterm to the model substantially increases the model's predictive quality. We include these last three models in part because of the impact on the coefficient for self-efficacy: it decreases upon addition of each midterm exam score to the model, eventually becoming non-significant. This suggests that over the course of the semester, students' self-efficacy—which begins the semester simply as a thought process—starts to crystallize into better or worse performance; students' midterm grades essentially are likely accounting for students' prior self-efficacy. A similar pattern is evident with students' CSEM scores, which may be the result of the same sort of process: students' background knowledge about the subject domain starts to show up strongly in their exam performance.

Finally, Table 2 shows two models that regress final grades on gender and (in the second model) self-efficacy at the start of the course. These analyses show that male students had course grades that were on average almost 5 points higher than those of female students, but that the difference becomes statistically insignificant when controlling for self-efficacy.

Discussion

Our first set of analyses demonstrate that it is possible to use a simple set of early measures, content and non-content related—accessible within the first three weeks of the semester—to predict

Table 1. Regression models predicting final course grades

	Model 1	*Model 2*	*Model 3*	*Model 4*	*Model 5*	*Model 6*	*Model 7*	*Model 8*
CSEM score	0.24***	0.20***	0.20***	0.17***	0.14**	0.07	0.04	0.04
Self-efficacy (pretest)		2.89*	3.34*	2.14	3.39**	2.41*	0.92	0.40
Peer-instruction self-efficacy (pretest)			-1.11					
Early Learning Catalytics responses				0.33**				
Early problem sets					0.83***	0.57**	0.34*	0.30*
Midterm 1						0.64**	0.31	0.30
Midterm 2							0.81***	0.73***
Midterm 3								0.18*
R^2	0.29	0.34	0.35	0.42	0.53	0.60	0.75	0.77
RMSE	6.9	6.7	6.7	6.3	5.7	5.3	4.3	4.1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. Regression models predicting final course grades as a function of gender and self-efficacy

	Model 1	*Model 2*
Gender	4.69*	2.45
Self-efficacy (pretest)		3.82**
R^2	0.07	0.15
RMSE	8.49	8.19

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

final course performance with some reasonable level of accuracy. This result suggests that instructors ought to make this information known to students, ideally through a computerized early detection system that automatically alerts instructors when the model predicts that a student may fail the course. Such a system ought to also be available to students, both to help students stay on track in the course and to help students learn and internalize the important metacognitive skills of self-monitoring.

Our analysis of the relationship between gender, self-efficacy, and course performance suggests a different understanding of the gender gap in physics. Female students' lower levels of self-efficacy (a mean of 3.2 on a 5-point scale, compared to 3.8 for their male counterparts) suggest that self-efficacy differences may be at least partly responsible for the gender gap. This suggests that an important next study is to examine in detail what factors lead to the gender gap of self-efficacy in science.

The success of the very short (seven-item) self-efficacy measure suggests that there may be other noncognitive characteristics that might also be predictive of later

student performance. We were surprised to discover that students' self-efficacy of their performance in the Peer Instruction environment did not help to predict students' final grades, especially since both general self-efficacy and students' actual performance on the ConcepTests both were highly predictive. One avenue of future work is to refine our instrument for measuring Peer Instruction self-efficacy so that it might be more predictive of final grades. Another is to examine other noncognitive abilities that can be measured early on and that are predictive of course outcomes (e.g., study skills and habits, attitudes towards learning and the discipline, etc). Even though our analysis was retrospective and does not demonstrate causality between self-efficacy and course outcomes, the results do suggest that the development of an intervention to help improve students' self-efficacy may be worthwhile, especially for women. Further, given that our study was conducted in one classroom at one institution, future work that replicates and expands on these findings across a range of disciplines and institutions would be valuable in helping to shape what a successful intervention would look like.

Conclusion

This study demonstrates that there remain students at risk in interactive teaching, blended learning environments, even those taught by master teachers, but that there are key early warning signs that are easily identifiable. The major findings of this study suggest that simple, easy to measure methods can reasonably predict student achievement in interactive teaching environments that feature blended delivery, offering an opportunity for faculty to intervene early with students who are at risk along content and non-content related dimensions.

Pertaining to non-content related dimensions, with Bandura as a guide and subsequent research studies as further support, we propose that in order to demonstrate academic achievement, at-risk students must also believe they are "capable of identifying, organizing, initiating, and executing a course of action that will bring about a desired outcome" (Bandura, as cited in Ambrose et al., 2010 p. 77). The impact of perceived self-efficacy raises interesting questions about strategies for early intervention with students in interactive teaching environments. Given the impact of self-efficacy on final course grades, even in light of prior knowledge, we posit that perceived self-efficacy described by Bandura (2003) creates either bridges or barriers to the construction of knowledge and ultimately academic success. It is not clear how a positive self-efficacy assists in knowledge acquisition and transfer or academic success. What is clear from this study, however, is that while they may be important in general, an exclusive focus on content interventions for at-risk students in interactive teaching environments—such as tutoring or extra study sessions—may fail to address a key, non-content-specific element of student success: self-efficacy. Self-efficacy specific interventions may be particularly important for women. Future research should examine specific tools for intervening on the non-content, attitudinal level of self-efficacy as well as at the content level for students, such as emphasizing the importance of homework. Because the Peer Instruction Self-Efficacy Instrument was used for the first time in this study, future work must include validation. For concurrent work exploring interactive teaching using this instrument see Miller, Schell, Ho et al. (in press).

This study demonstrates that even in interactive teaching environments using state-of-the art online tools, there are students who remain at risk of not reaching key academic milestones that may determine how they proceed in their academic careers. It also offers a practical procedure for identifying risk factors and points of intervention. International educational reform efforts recommending interactive teaching methods, such as blended Peer Instruction, should venture forward with understanding of, acknowledgement of, and clear strategies to help groups of students who may otherwise be left behind.

References

Allen, E. & Seaman, J. (2014). *Grade Change: Tracking Online Education in the United States, 2013*. Babson Survey Research Group, Babson Park, MA.

Ambrose, S., Bridges, M. W., Dipietro, M., Lovett, M. C., Norman, M. K., & Mayer, R. E. (2010). *How learning works: Seven research-based principles for Smart Teaching.* San Francisco: Jossey-Bass.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, 84(2), 191–215. doi:10.1037/0033-295X.84.2.191

Bandura, A. (2003). *Self-efficacy: The exercise of control* (6th ed.). New York: Macmillian.

Becerra-Labra, C., Gras-Marti, A., & Torregrosa, J. (2012). Effects of a Problem-based Structure of Physics Contents on Conceptual Learning and the Ability to Solve Problems. *International Journal of Science Education, 34*(8), 1235–1253.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (Eds.). (2000). *How people learn: Brain, mind, experience, and school: Expanded Edition.* Washington, DC: National Academy Press.

Crouch, C. H., & Mazur, E. (2001). Peer Instruction: Ten years of experience and results. *American Journal of Physics*, 69(9), 970–977.

Darling-Hammond, L., Rosso, J., Austin, K., Orcutt, S., & Martin, D. (2003). How People Learn: Introduction to Learning Theory. Annenberg Learner. Retrieved from http://www.learner.org/courses/learningclassroom/support/01_intro.pdf

Fencl, H., & Scheel, K. (2003). Sources of Self-Efficacy in Science Courses Scale.

Hackett, G., & Betz, N. E. (1989). An exploration of the mathematics self-efficacy/mathematics performance correspondence. *Journal of Research in Mathematics Education, 20*(3), 261–273.

Hake, R. R. (1998). Interactive-engagement versus traditional methods: A six-thousand-student survey of mechanics test data for introductory physics courses. *American Journal of Physics, 66,* 64–74.

Heron, P., Shaffer, P. S., & McDermott, L. C.

(n.d.). Identifying and addressing student conceptual difficulties: An example from introductory physics. *National Academy Press.* Retrieved from http://www7.nationalacademies.org/bose/Heron_CommissionedPaper.pdf

Johnson, L., Adams Becker, S., Estrada, V., Freeman, A. (2014). *NMC Horizon Report: 2014 Higher Education Edition.* The New Media Consortium: Austin, TX.

Lasry, N., Mazur, E., & Watkins, J. (2008). Peer instruction: From Harvard to the two-year college. *American Journal of Physics, 76*(11), 1066. doi:10.1119/1.2978182

Lent, R. W., Brown, S. D., & Larkin, K. C. (1984). Relation of self-efficacy expectations to academic achievement and persistence. *Journal of Counseling Psychology, 31*(3), 356–362. doi:10.1037/0022-0167.31.3.356

Maloney, D. P., O'Kuma, T. L., Hieggelke, C. J., & Van Heuvelen, A. (2001). Surveying students' conceptual knowledge of electricity and magnetism. *American Journal of Physics, 69*(S1), S12. doi:10.1119/1.1371296

Mazur, E. (1997). *Peer instruction: A user's manual.* Upper Saddle River, New Jersey: Prentice Hall.

Miller, K., Schell, J., Ho, A., Lukoff, B., & Mazur, E. (in Press). Response switching and self-efficacy in Peer Instruction classrooms. *Physical Review Special Topics – Physics Education Research.*

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology, 38*(1), 30–38.

Nicol, D. J., & Boyle, J. T. (2003). Peer Instruction versus Class-wide Discussion in Large Classes: a comparison of two interaction methods in the wired classroom. *Studies in Higher Education, 28*, 457.

Pajares, F. (1996). Self-efficacy beliefs in academic settings. *Review of Educational Research, 66*(4), 543.

Pajares, F., & Miller, M. (1994). Role of self-efficacy and self-concept beliefs in mathematical problem solving: A path analysis. *Journal of Educational Psychology, 86*(2), 193–203.

Piaget, J., Green, D. R., Ford, M. P., & Flamer, G. B. (1971). The Theory of Stages in Cognitive Development. In *In Measurement and Piaget* (pp. 1–11). New York: McGraw-Hill.

Sessoms, D. (2008). Interactive instruction: Creating interactive learning environments through tomorrow's teachers. *International Journal of Technology in Teaching and Learning, 4*(2), 86–96.

Vygotsky, L. S. (1998). The collected works of L. S. Vygotsky: Vol.5. *Child Psychology*. In R. W. Rieber (Ed.), M.J. Hall (Trans.). New York: Plenum Press.

Appendix A : Self-efficacy items

1. I have taught or tutored a class before

2. I enjoy learning about science
3. I enjoy learning about physics
4. I often do well in science courses
5. I often do well in non-science courses
6. I identify with students who do well on exams and quizzes in science courses*
7. I expect to receive an A- or higher in this course*
8. I am confident I can do the work required for this course*
9. Doing laboratory experiments and write-ups comes easy to me*
10. I am often able to help my classmates with physics in the laboratory or in section
11. I usually don't worry about my ability to solve physics problems*
12. When I come across a tough physics problem, I work at it until I solve it*
13. I get a sinking feeling when I think of trying to tackle difficult physics problems*
14. I like hearing about questions that other students have about the reading
15. I am usually confident of my answers to the EARS† questions before I talk to a neighbor**
16. I am usually confident that I can convince my neighbor of my answer to EARS questions**
17. I know how to explain my answers to EARS questions in a way that helps others understand my answer**
18. My peers know how to explain their answers to EARS questions in a way that helps me understand their answer**
19. Listening to my neighbors talk about their answers increases my confidence when responding to the same EARS** question a second time
20. Practicing answering EARS questions in class makes it easier for me to do physics problems at home**
21. I can communicate science effectively
22. I can communicate physics effectively
23. I am an outgoing person
24. I often feel compelled to multi-task in science courses
25. I often feel compelled to multi-task in non-science courses

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* Used in general Self-Efficacy subscale
** Used in Peer Instruction Self-Efficacy subscale
† EARS was an early name for Learning Catalytics.

About the Authors

Julie Schell is the Director of OnRamps and Strategic Initiatives at The University of Texas at Austin's (UT-Austin) Center for Teaching and Learning where she leads signature, dual-credit curricular innovations that extend the reach of the University. In 2014, she was identified by Teachers College, Columbia university as an Early Riser in Higher Education for her contributions to the field. She is also a Clinical Assistant Professor at UT-Austin's top ranked College of Education, where she teaches a new graduate course, Technology and Innovation in Higher Education. With UT, she currently holds a dual appointment as an associate in the Mazur Group at the School of Engineering and Applied Sciences at Harvard University, where she generates and tests ideas for scaling innovative teaching methods. She completed a three-year postdoctoral fellowship under Eric Mazur at Harvard University. She has over 15 years of experience in higher education, has written and presented widely on Peer Instruction, and has held positions at the nation's top research universities including Stanford, Yale, Columbia, Harvard and most recently The University of Texas at Austin. Dr. Schell is an expert in educational innovation and a recipient of a Longhorn Innovation Fund for Technology award in 2013. She was awarded the Dissertation of the Year from the American Educational Research Association, Postsecondary Education Division in 2010. She holds a doctorate in Higher and Postsecondary Education from Teachers College, Columbia University and an M.S. in Counseling and Educational Psychology, with an emphasis in instructional technology, from the University of Nevada, Reno.

Brian Lukoff is an educator, technology designer, and engineer with a passion for assessment and innovation. I am Program Director for Learning Catalytics at Pearson Education. In 2013, Pearson acquired Learning Catalytics, a company that I founded with Eric Mazur and Gary King that produced a cloud-based educational assessment and engagement platform. Learning Catalytics grew out of research work I engaged in as a Postdoctoral Fellow in Technology and Education at the School of Engineering and Applied Sciences at Harvard University. Previously, I was a software engineer at adap.tv, a video advertising startup in Silicon Valley. I received a Ph.D. from the Stanford University School of Education where I studied educational measurement and technology. I also hold an M.S. in statistics from Stanford University and a B.A. in mathematics from Cornell University.

Cassandre Giguere Alvarado is a Clinical Assistant Professor in the Department of Educational Administration at The University of Texas at Austin, and also serves in the Office of the Executive Vice President and Provost, directing initiatives in student success and enrollment management. Dr. Alvarado's teaching, research and professional practice focuses on college readiness and student retention and success. She currently directs the PACE (Path to Admission through Co-Enrollment) Program, an innovative co-enrollment program with Austin Community College. She is the College Readiness Special Advisor to the Texas Higher Education Coordinating Board (THECB) and frequently works with national organizations on issues of readiness and retention. Her current research focuses on understanding college readiness, including the development and testing of readiness assignments designed to introduce students to the content knowledge and cross-disciplinary skills needed for success. A 20-year

veteran of university administration, Dr. Alvarado's signature program at The University of Texas at Austin was the creation of the First year Interest Groups (FIGS), a learning community initiative she began in 1998. The initiative focuses on bringing together the many facets of university life in one nexus for each student in an effort to maximize their success. The university now offers a learning community to all incoming first year students. Additionally, Dr. Alvarado led the University's major Quality Enhancement Plan initiative, providing the blueprint and assessment of the University's first major curriculum reform in the last 30 years. An alumna of Leadership Texas (LT'10), Dr. Alvarado has served as a member of the committee of the board for the Foundation for Women' s Resources. Dr. Alvarado holds a bachelor of journalism, master of education and doctor of philosophy degree from The University of Texas at Austin.