Center for Innovative Teaching and Learning
Grant Application Cover Page

What kind of grant are you applying for?

_____ Active Learning Grant

__**X**__ Scholarship of Teaching and Learning (SOTL) grant

_____ Service-Learning Faculty Fellowship

_____ Student Learning Analytics Fellowship (SLAF)

_____ Summer Instructional Development Fellowship (SIDF)

_____ Summer Writing-Teaching Grant

_____ Other (please describe): _____

Title of project: Improving Teaching Through Enhanced Analysis of Teaching Evaluations

Name of Principal Investigator: Richard A. Hullinger

Department/School: Psychological and Brain Sciences

Email address for contact purposes: rahullin@indiana.edu

Please note that the CITL limits instructors to **one CITL-funded project at a time** in order to support as many instructors as possible. Funded projects include grants, faculty learning communities, fellowships, and any other program for which instructors receive financial support from the CITL. **Therefore we ask that you apply for only one type of grant in a given funding cycle.**

If you are currently participating in any CITL-funded program or project, please complete the table below by placing an X next to the type of funding you are currently receiving, and providing the information requested.

Current funding	Type of grant or other funded project	Title of grant, name of FLC, or description of project	Anticipated completion date
	Active Learning Grant		
	SOTL grant		
	Service Learning Faculty Fellowship		
	SLAF		
	SIDF		
	Summer Writing-Teaching Grant		
	Funded Faculty Learning Community		
	Other (please describe in the box to the right)		

SOTL Grant Application

In addition to the Grant Application Cover Page, please provide the following information. Submit all information (the Cover Page, the information on this page, and the parts of the application itself: the abstract, project description, budget narrative, research plan and timeline) in a single document to citl@indiana.edu by Monday, Feb. 27, 2017. The short CVs and the chair's nominating letter may be submitted separately.

If you have questions about your grant application, or would like to talk with a CITL consultant about your proposal, please contact Lisa Kurz (kurz@indiana.edu).

1. Name(s) and departmental affiliation(s) for all co-PIs:

PI: Rick Hullinger – Psychological and Brain Sciences
Co-PI: John Kruschke – Psychological and Brain Sciences
Co-PI: Ben Motz – Psychological and Brain Sciences

2. Funding level requested (Phase I, Phase II, Phase III):

Phase II

3. Duration of funding period:

May 2017 – July 2017

When it comes to student evaluation data, even the most skeptical psychologists' statistical reasoning skills seem to fail them. We place undue weight on whether a mean score is above or below the department's mean score, with practically no concern for variability or the magnitude of the difference (Boysen, 2015). We propose a new method of both analyzing student evaluation data and visually representing the results of the analysis to instructors. Our approach, based on Bayesian modeling of raw student response data, avoids well-documented problems associated with results based on the mean response values for an individual course's data. Instructors' rating data will be displayed in a graphical format which will enhance their understanding of their scores relative to their peers and will make it easier to see which areas should be the focus of increased efforts. We are requesting Phase II funding to cover support for one graduate student over the summer of 2017. If funded, we plan to create the new system using existing course evaluation data, pilot the dashboard, and assesse its effectiveness within Psychological and Brain Sciences during the Fall 2017 semester.

Improving Teaching Through Enhanced Analysis of Teaching Evaluations

One of the primary ways that instructors receive feedback about their performance in the classroom is through end-of-semester student evaluations of teaching (SETs). Universities, instructors, and students devote considerable time and effort to the collection of SET data each semester. Instructors who are committed to excellence in teaching may also invest substantial time looking at their results and using the feedback to learn how to improve their teaching (Nassar & Fresko, 2002). This is, indeed, the way the process should work. But the entire enterprise relies on the assumption that the feedback that is presented to the instructors is both accurate and easy to interpret.

Unfortunately, end of semester teaching evaluation reports are not nearly as accurate or as easy to interpret as they could be. Abrami (2001) warns against making evaluative judgments by comparing mean evaluation scores. Small differences in mean values, between two instructors' scores or between an instructor's score and a departmental average, may not indicate actual differences in performance. Yet in almost all reports, the instructor's ratings for a given question are summarized with an average score and presented alongside departmental and institutional mean values, which invites direct comparison. Based on the distribution of the data, some small differences between mean values may indicate very large actual differences in performance, and some large differences in mean values may be meaningless. Indiana University's Online Course Questionnaire (OCQ) reports include information on the standard deviation of the data to provide some context for interpreting the mean values, but we will argue below that these additional summary statistics only add to potential confusion about the results.

Instead, Abrami (2001) argues that the correct interpretation of teaching evaluations requires a full statistical analysis incorporating data across multiple classes. Looking at a single course in isolation runs the same risk as conducting a study with only a single observation, $n = 1$. The mean value presented in a report is derived from a sample of the students in that course, and that course is one sample of the instructor's overall teaching. There are many avenues for considerable random error to influence that single value (e.g. Had students just gotten exam scores back? Was the most recent material particularly interesting?). Combining a teacher's ratings across multiple courses that she has taught, and across multiple semesters if possible, provides a more robust view of performance. An instructor's aggregate data can be sensibly interpreted and compared to departmental or institutional distributions using appropriate statistical methods. Again, IU's current system falls short in this regard. Even within a single semester, an instructor's results for each class are published in separate documents. Without access to the underlying data, post hoc synthesis of the summary statistics from multiple classes into a single clear view of teaching effectiveness is practically impossible.

The impact of these problems would be reduced if faculty members and administrators understood the limitations of the evaluation summaries and could adjust their interpretation of the results accordingly. Unfortunately, studies have shown that both instructors and administrators over-interpret small differences in mean evaluation scores and that these errors in interpretation persist even when the evaluators are explicitly warned about the pitfalls of over-interpretation before analyzing reports (Boysen, Kelly, Raesly & Casner, 2014; Boysen, 2015).

Additional problems compound the difficulties of interpreting the current course evaluations. The first is an untested assumption that the Likert-type response options (e.g. “Very Effectively”, “Effectively”, “Somewhat Effectively”, and “Not at all Effectively”) can be mapped onto a linear numeric scale (4, 3, 2, and 1, respectively). This transformation is only valid if the psychological distance between “Not at all Effectively” and “Somewhat Effectively” is the same as the distance between, say “Effectively” and “Very Effectively”. If the perceived distances between the neighboring response options are not equal – and there is little reason to believe that they are – then treating the values as sequential integers and using those values to generate an average score is not an accurate representation of the students’ perceptions.

Another problem is that the primary metrics used to summarize the overall response of the class are the mean and the standard deviation of the individual responses. Those methods of describing a data set are excellent choices for summarizing data if and only if the data being summarized fit a normal, or at least symmetric and unimodal distribution. If the data are heavily skewed, that is, if the majority of the students gave very positive evaluations and relatively few were on the lower-end of the scale, then the mean and standard deviation would be very misleading statistics. Unfortunately, teaching evaluation responses show a strong negative skew. The bulk of the student responses are at the high end of the scale, with a long tail of responses trailing out towards the lower end of the scale. In preliminary work towards the goals of this project, Ben Motz has been collaborating with BEST and has arranged for our department to receive anonymized, student-by-student raw responses for every course evaluation submitted for our classes in the past three semesters. This dataset has allowed us to look at the actual student responses and determine the shape of the underlying distribution of responses. This analysis revealed strong and consistent skews in the data (See Figure 1). Thus, reports that provide mean values and standard deviations can suggest conclusions that the underlying data do not support. For example, the Fall 2016 OCQ report lists a departmental mean value of 3.6 with a standard deviation of .3 points. An instructor with a score of 3.5 may feel that he is right around the average, so doing fine, when in fact that score would put him in the lower quartile of all instructors in the department. An instructor with an average score of 3.8 – 2/3rds of a standard deviation above the departmental average – might feel that she is near the very top of the distribution, when that score is actually only in the 58th percentile.

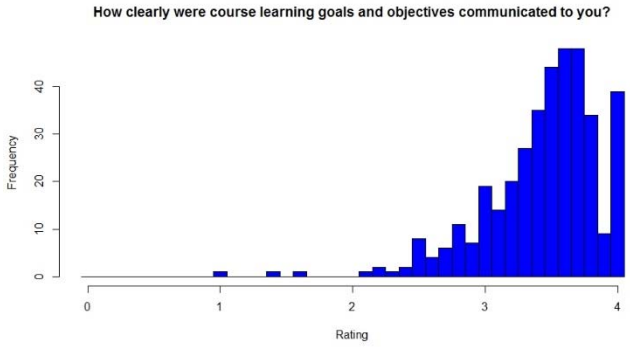


Figure 1 Results from OCQ question about communication of learning goals for all the fall 2016 classes taught by Psychological and Brain Sciences. All other response distributions show a similar strong negative skew.

Our project will address all of these problems by creating an easy-to-use web-based application (“dashboard”) that will provide instructors with accurate and easily interpretable information about their teaching ratings and will help them pinpoint areas to target for improvement. These reports, which will be CAS protected to insure privacy, will combine results across multiple classes and multiple semesters and will use statistical methods appropriate for heavily skewed, Likert-scale response data to present graphical results to instructors. These results will give our instructors a clearer view of how they

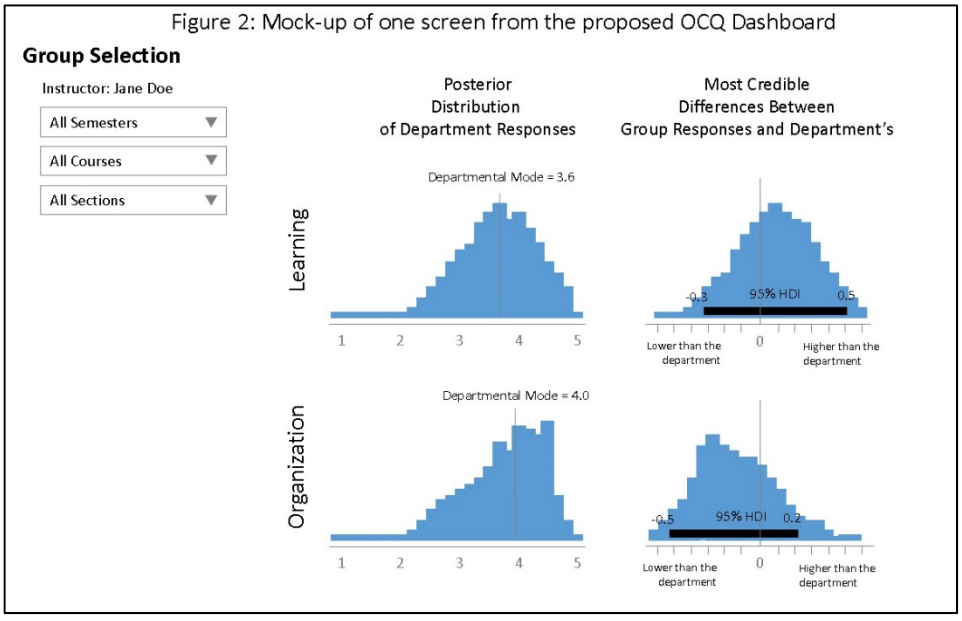
measure up to specific, departmental, or possibly institution-wide norms and allow them to make valid inferences about their performance.

Because we have been given access to the raw student response data, we have the ability to create sophisticated statistical models of students' responses. These models will be tailored to the specific details of our OCQ data, and will:

- Combine data from across semesters and courses to provide more accurate estimates of a single instructor's relative strengths and weaknesses.
- Factor out the influence of random effects that an instructor cannot control, such as class size and course level.
- Provide a statistical framework that correctly deals with skewed data and Likert scale responses.

The best way to build models that accomplish these goals is through Bayesian modeling of the student responses. Once created, these models can be used to analyze instructors' individual response data, either aggregated across all courses that the instructor has taught or reasonably selected subsets of the courses. The dashboard can then be used to analyze the data and display any credible differences between the instructor's distribution of evaluation results and the department's distribution. Figure 2 shows a mock-up of one potential view of the dashboard for an instructor. The instructor will be able to filter his data in meaningful ways and then see a set of graphs that show the expected distribution of results for the correct comparison group across the department (or institution if institution-wide data are available) as well as a clear indication of the 95% highest density interval (HDI) – the Bayesian version of a confidence interval that indicates the range of scores that are likely to include the instructor's actual evaluation. If the credible difference interval is shifted to the high end of the departmental distribution, then there is evidence to support the instructor's excellence in that area. If the HDI is roughly in line with the departmental distribution, then the instructor is performing within the typical range or expected results. This graphical approach that presents ranges of credible evaluation scores removes the problems of over-interpreting small mean differences between comparison groups.

Figure 2: Mock-up of one screen from the proposed OCQ Dashboard



As the dashboard display is implemented, we will work closely with faculty members, including those who are less statistically savvy, to ensure that the data visualizations are intuitive and that they lead to correct interpretations of the underlying data. Our goal for the end-product is that using the dashboard and correctly interpreting its results require no understanding of Bayesian modeling or any advanced statistical knowledge whatsoever.

Along with that improved understanding comes the ability to make evidence-based decisions about how to change the structure, content, or style of instruction to improve performance in the classroom and student learning outcomes. In addition, once more instructors realize that the course evaluation data can be used to provide accurate and actionable feedback on their teaching, we believe that overall views of the course evaluation process will increase. Instructors who value the OCQ will be more likely to promote it in their classrooms. Students who see that their OCQ responses are leading to positive changes are more likely to take the initiative to fill out their evaluations. More student responses lead to more representative samples and more accurate analysis, and the cycle feeds itself.

These beliefs about how the dashboard will improve instructor understanding and lead to better teaching are empirical questions that must be tested. To that end, we are planning on four separate methods to assess the impact of our project:

1. We will perform multiple pre- and post-test surveys of our faculty. Survey questions will investigate the faculty's faith in the accuracy of their evaluation ratings, their understanding of their ratings as compared to other members of the department, and measures of how helpful they view the OCQ reports to be as a tool to improve teaching.
2. We will build instrumentation into the dashboard to collect and log data on its use. We will be able to use this data to explore, with great precision, what faculty would be doing with the evaluation summaries.
3. We will create focus groups with the faculty who use the system the most to to investigate how they used the information to improve their teaching. This feedback will be invaluable for refining the information displayed in the dashboard and for educating new faculty.
4. Once the dashboard is completed, we will perform a replication of Boysen, Kelly, Raesly & Casner's (2014) study of instructor's perceptions of rating differences. We can present the original test scenarios alongside two separate graphical displays, one similar to our standard OCQ reports and one using the new dashboard, to test the efficacy of our intervention.

As the results of our various studies become available, we will disseminate them to audiences within IU through SOTL talks and presentations as well as to a larger audience through publication in pedagogy and/or statistical journals.

In summary, we believe that the current method of reporting the results of end-of-semester teaching evaluations is statistically flawed and can easily result in instructors drawing inaccurate conclusions about their teaching effectiveness. We propose a new method of reporting that will analyze multiple semesters of response data using techniques that are appropriate for the specific types of data that are collected in our course evaluations. The results of our analysis will be available to instructors through a simple graphical interface designed to help them better understand how their performance lines up

with departmental or university-wide standards. This improved information will also promote better classroom performance.

References

Abrami, P. C. (2001). Improving judgments about teaching effectiveness using teacher rating forms. *New directions for institutional research*, *2001*(109), 59-87.

Boysen, G. A. (2015). Significant interpretation of small mean differences in student evaluations of teaching despite explicit warning to avoid overinterpretation. *Scholarship of Teaching and Learning in Psychology*, *1*(2), 150.

Boysen, G. A., Kelly, T. J., Raesly, H. N., & Casner, R. W. (2014). The (mis) interpretation of teaching evaluations by college faculty and administrators. *Assessment & Evaluation in Higher Education*, *39*(6), 641-656.

Nasser, F., & Fresko, B. (2002). Faculty views of student evaluation of college teaching. *Assessment & Evaluation in Higher Education*, *27*(2), 187-198.

Budget Narrative and Research Timeline

Date:	Expenditure:	Total Cost:
5/1/17 – 7/31/17	Full Time Graduate Student Summer Stipend	$4,000

Grant funds will be used to support one graduate student full-time during the summer of 2017. The student will be responsible for writing the software to analyze the course evaluation results and generate visualizations of the data for instructors. The PI and Co-PIs will remain actively involved in this project, aiding with design and development, although grant funds will not be used for PI support.

The initial planning and design phases of this project will begin in the second half of the spring semester. The PIs and graduate student will meet to explore the course evaluation data that we have collected and to determine the best methods for analyzing and displaying this information to instructors. Over the summer, the graduate student, with help from the PI and Co-PIs will develop, refine, and test the software. We believe that the software will be completed by the start of the Fall 2017 school year, and after internal (within Psychological and Brain Sciences) testing for a semester, would be ready for wider use in the spring of 2018.

Richard A. Hullinger

Lecturer and Director of Pedagogy
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Updated January, 2017

Education

Ph.D. in Psychological and Brain Sciences and Cognitive Science, 2011
Indiana University, Bloomington, Indiana
Advisor: John K. Kruschke
Thesis Title: *An Evolutionary Analysis of Selective Attention*

B.S. in Physics, 1996
B.S. in Computer Science, 1996
Magna Cum Laude
Rensselaer Polytechnic Institute, Troy, NY

Teaching Experience

Director of Pedagogy, Indiana University:
- P211 Methods of Experimental Psychology, Spring 2015 – Spring 2017
- P335 Cognitive Psychology, Spring 2015
- P101 Introductory Psychology, Fall 2015
- K300 Statistical Techniques, Fall 2015, Fall 2016, Spring 2017
- P660 Teaching of Psychology, Spring 2015 – 2017

Lecturer, Indiana University:
- K300 Statistical Techniques, Fall 2013 – Fall 2014
- P335 Cognitive Psychology, Fall 2013 – Spring 2014
- C105 Brains & Minds, Robots & Computers, Fall 2013 & 2014
- P199 Planning Your Psychology Career, Spring 2014
- P101 Introductory Psychology, Fall 2014

Visiting Assistant Professor, Indiana University:
- K300 Statistical Techniques, Spring 2012 – Spring 2013
- Q301 Brain and Cognition, Spring 2013
- P335 Cognitive Psychology, Fall 2011 & 2012
- C105 Brains & Minds, Robots & Computers, Fall 2011 & 2012
- P199 Planning Your Psychology Career, Spring 2012 & 2013
- P102 Introductory Psychology, Fall 2011

Honors and Fellowships

Disability Services for Students Access Award – Indiana University, 2016
College of Arts and Sciences Trustees Teaching Award – Indiana University, 2014
Cognitive Science Outstanding Teaching Award – Indiana University, 2011

William Estes Summer Research Award – Indiana University, 2010
Award for Outstanding Teaching by a Graduate Student in Psychology – Indiana University, 2009

Research Interests

As an instructor, I am deeply interested in studying pedagogical issues in post-secondary education. Specifically, I am drawn towards the interface between technology and the classroom – electronic textbooks, student response systems, internet access during class time, interactive applets, etc. – and the effects that technology can have on learning.

I am also interested in a range of cognitive science topics with a primary focus on evolutionary simulations of attention and learning. I use simulated evolution as a means to investigate the types of environmental information structures that lead to the emergence of attention as an adaptive mechanism. I employ genetic algorithms to evolve simple connectionist networks in a range of environments. These environments may vary in terms of the underlying structure of the cues and responses, the temporal structure, or the amount of noise that is present in the environment. I then analyze the evolved agents to determine if they show signs of attentional behavior. The primary goal of this work is to explain attentional behaviors as adaptive evolved responses that can only be fully understood in the context of the environments that gave rise to them.

Publications

Hullinger, R. A., Kruschke, J. K. and Todd, P. M. (2015), An Evolutionary Analysis of Learned Attention. Cognitive Science, 39: 1172–1215. doi: 10.1111/cogs.12196

Kruschke, J.K., & Hullinger, R.H. (2010). Evolution of attention in learning. In: N. Schmajuk (Ed.), *Computational Models of Classical Conditioning*, pp. 10 – 52. Cambridge University Press.

Presentations

Hullinger, R.H., Kruschke, J.K., & Todd, P.M. (2010) *Evolution of Attention in Learning*. Talk presented at I.U. Cognitive Lunch Series, Bloomington, IN.

Kruschke, J. K. & Hullinger, R. H. (2009). *Evolution of Attention in Learning*. Invited presentation at the Workshop on Computational Models of Conditioning, Duke University, May 16, 2009.

Hullinger, R.H., & Kruschke, J.K. (2006). *Attention To Individuating Cues Obviates Dual Process Theories*. Talk presented at I.U. Cognitive Lunch Series, Bloomington, IN.

Service

College of Arts and Sciences

Faculty Task Force for the College's Office of Student and Career Success, Spring 2016
Academic Fairness Committee, Fall 2016 – Spring 2017
21st Century Task Force, Minors and Certificates sub-committee, Spring 2015

Psychological and Brain Sciences

Undergraduate Professional Development Committee, Fall 2016 – Spring 2017
Teaching Evaluation Committee, Fall 2016 – Spring 2017
Undergraduate Program Committee, Spring 2015 – Spring 2017

Professional Experience

Software Developer/Team Lead, Interactive Intelligence, Indianapolis, IN. 1999-2004. Responsible for the support, maintenance and new development of several client-side applications.

Software Developer, Multiplicity Inc., Indianapolis, IN. 1998-1999.
Designed and developed the user interface for windows software to present historical and real-time data about server performance.

Software Developer, Westinghouse Corp., Pittsburgh, PA. 1996 – 1998.
Primary developer of the Prospector news analysis system for the automated capture and analysis of local news broadcasts.

Patents

"System for Analyzing Television Programs," U.S. Patent Number 6,295,092, issued Sept. 25, 2001. Inventors: R. Hullinger et al

Benjamin Motz

A. Professional Preparation

Indiana University Bloomington	BS in Cognitive Science, 2002
University of California San Diego	MS in Cognitive Science, 2005
Indiana University Bloomington	PhD in Cognitive Science, *In Progress* (planned 12/17)

B. Appointments

August 2008 – *current*	**Senior Lecturer**, Department of Psychological and Brain Sciences, Indiana University (Bloomington, Indiana)
January 2006 – June 2008	**Statistical Consultant**, Analytics, Rapp Collins Worldwide (El Segundo, California)

C. Publications

i. Up to 5 closely related to the proposed project

Motz, B., Busey, T., Rickert, M., & Landy, D. (submitted). Finding topics in enrollment data. *Journal of Educational Data Mining*.

Carvalho, P., Braithwaite, D., de Leeuw, J., **Motz, B.**, & Goldstone, R. (2016). An in-vivo study of self-regulated study sequencing in Introductory Psychology courses. *PLoS ONE 11*(3): e0152115. doi: 10.1371/journal.pone.0152115

Day, S., **Motz, B.**, Goldstone, R. (2015). The cognitive costs of context: The effects of concreteness and immersiveness in instructional examples. *Frontiers in Psychology, 6*(1876). doi: 10.3389/fpsyg.2015.01876

Motz, B., Teague, J., & Shepard, L. (2015). Know thy students: An institutional report that provides aggregate student data to instructors. *EDUCAUSE Review Online (Peer Reviewed Category)*. http://www.educause.edu/ero/article/know-thy-students-providing-aggregate-student-data-instructors

Motz, B., James, K. & Busey, T. (2012). The Lateralizer: A tool for students to explore the divided brain. *Advances in Physiology Education, 36*(3), 220-225. doi: 10.1152/advan.00060.2012

ii. Up to 5 other significant publications

de Leeuw, J. & **Motz, B.** (2016). Psychophysics in a Web browser? Comparing response times collected with JavaScript and Psychophysics Toolbox in a visual search task. *Behavior Research Methods, 48*(1), 1-12. doi: 10.3758/s13428-015-0567-2

Motz, B., Erickson, M. & Hetrick, W. (2013). To the beat of your own drum: Cortical regularization of non-integer ratio rhythms toward metrical patterns. *Brain and Cognition, 81*(3), 329-336. doi: 10.1016/j.bandc.2013.01.005

Motz, B. (2013). Fantasy football: A touchdown for undergraduate statistics education. In C. Williams, A. Ochsner, J. Dietmeier, & C. Steinkuehler (Eds.), *Proceedings of the*

*9th Annual Meeting of Games+Learning+Society (GLS)***,** Madison, Wisconsin. (pp. 222-228). Pittsburgh, PA: ETC Press.

Motz, B., Goldstein, M. & Smith, L. (2012). Understanding behavior from the ground up: Constructing robots to reveal simple mechanisms underlying complex behavior. *Psychology Learning and Teaching, 11*(1), 77-86. doi: 10.2304/plat.2012.11.1.77

Núñez, R., **Motz, B.**, & Teuscher, U. (2006). Time after time: The psychological reality of the Ego- and Time-Reference-Point distinction in metaphorical construals of time. *Metaphor and Symbol, 21*(3), 133-146. doi: 10.1207/s15327868ms2103_1

D. Synergistic Activities

Director of Undergraduate Instruction and Online Development
IU Department of Psychological and Brain Sciences – *2015-current*

Undergraduate Program Committee
IU Department of Psychological and Brain Sciences – *2009-current*
Chair, Ad Hoc Assessment Committee – *2013-2014*

Invited Member, Educational Policies Committee, IU Bloomington Faculty Council – *2014-current*

Active Learning Online Faculty Learning Community, IU CITL – *2015-2016*

Invited Member, Indiana University Faculty Leadership Institute, IU FACET – *2014-2016*

Director of Pedagogy, IU Department of Psychological and Brain Sciences – *2012-2014*

Elected Member, Student Academic Appointee Board of Review, IU Bloomington Faculty Council – *2014-5*

Organizer, Pedagogy Seminar, IU Department of Psychological and Brain Sciences – *2011-2014*

Preparing Future Professors Faculty Learning Community, IU CITL – *2010-2014*

E. Recent Grants and Honors

APS Fund for Teaching and Public Understanding of Psychological Science ($11,000) – APS, *2016*
Improving Student Motivation and Success with Social Norm Messaging

President's Award for Excellence in Teaching and Learning Technology – Indiana University, *2015*

Student Learning and Success in STIM ($30,000) - Bay View Alliance, *2014*
Charting Educational Outcomes Following P101 with Linear Modeling: Enabling Data-Driven Improvement of Introductory Psychology

Trustee Teaching Award – Indiana University, *2012, 2014*

Outstanding Teaching Award, Cognitive Science – Indiana University, *2013*

CITL Writing Program Summer Writing-Teaching Grant ($1,500) – Indiana University, *2012*

Brief Biographical Sketch

John K. Kruschke
Professor of Psychological and Brain Sciences, Adjunct Professor of Statistics, Indiana University
kruschke@indiana.edu

Positions:
Professor, 2000 – present; Associate Professor, 1996 – 2000; Assistant Professor, 1990 – 1996; Lecturer, 1989 – 1990; Department of Psychological and Brain Sciences, Indiana University, Bloomington.
Adjunct Professor, Department of Statistics, Indiana University, Bloomington; 2006 – present.
Core member of the Cognitive Science Program, 1989 – present.

Education:
Ph.D. 1990, Psychology, University of California at Berkeley
B.A. 1983, Mathematics, University of California at Berkeley

Recognitions:
Remak Distinguished Scholar Award, Indiana University, 2012
Indiana University Trustees Teaching Excellence Recognition Awards, 1997, 1998, 1999, 2008, 2009, 2010, 2011, 2012.
Fellow, Association for Psychological Science, 2012
Fellow, Eastern Psychological Association, 2012
Fellow, Society of Experimental Psychologists, 2006
Troland Research Award, National Academy of Sciences, 2002
National Institute of Mental Health FIRST Award, 1994–1999
Grants to Enhance Active Learning, Indiana University, 1997, 2005
Instructional Development Summer Fellowships, Indiana University, 1993, 2006
National Science Foundation Graduate Fellowship, 1983
The Berkeley Fellowship for Graduate Study, 1983
Phi Beta Kappa (U. C. Berkeley), 1982

Selected Publications (Full list at Google Scholar: https://scholar.google.com/citations?user=Im5IIiMAAAAJ&hl=en)
Book:
Kruschke, J. K. (2015). Doing Bayesian Data Analysis, Second Edition: A Tutorial with R, JAGS, and Stan. Academic Press / Elsevier.
Peer reviewed articles:
Kruschke, J. K., and Liddell, T. M. (2017). The Bayesian New Statistics: Hypothesis Testing, Estimation, Meta-Analysis, and Power Analysis from a Bayesian Perspective. Psychonomic Bulletin & Review. http://link.springer.com/article/10.3758/s13423-016-1221-4 or https://osf.io/preprints/psyarxiv/wntsa/.
Kruschke, J. K. (2013). Bayesian estimation supersedes the t test. Journal of Experimental Psychology: General, 142(2), 573–603.
Kruschke, J. K., Aguinis, H., and Joo, H. (2012). The time has come: Bayesian methods for data analysis in the organizational sciences. Organizational Research Methods, 15(4), 722–752. * Winner of Sage Best Article of the Year Award.
Kruschke, J. K. (2011). Bayesian assessment of null values via parameter estimation and model comparison. Perspectives on Psychological Science, 6(3), 299–312.
Hullinger, R. A., Kruschke, J. K., and Todd, P. M. (2015). An evolutionary analysis of learned attention. Cognitive Science, 39(6), 1172–1215. doi:10.1111/cogs.12196

Liddell, T. M., and Kruschke, J. K. (2014). Ostracism and fines in a public goods game with accidental contributions: The importance of punishment type. Judgment and Decision Making, 9(6), 523–547. http://journal.sjdm.org/14/14721a/jdm14721a.pdf

Breithaupt, F., Gardner, K. M., Kruschke, J. K., Liddell, T. M., and Zorowitz, S. (2013). The disappearance of moral choice in serially reproduced narratives. In: M. A. Finlayson, B. Fisseni, B. L¨owe, and J. C. Meister (Eds.), Workshop on Computational Models of Narrative, pp. 36–42. Germany: Dagstuhl Publishing.

Selected Grants:

Remak Distinguished Scholar Award, Indiana University, 2012–2013. Principal investigators: J. K. Kruschke and F. Breitfhaupt. Approx. $10,000 research funds.

NIH/NIDA R01-DA017924. P.I.: Peter Finn. Co-investigators: John Kruschke and Richard Viken. "Attention biases and hot cognition in drug dependence." April 2005 – 2010 .

National Science Foundation BCS-9910720. P.I.: John K. Kruschke. "Attention in associative learning." June 2000 – May 2004, extended to Dec. 2004. $337,186 total.

Australian Research Council Large Grant, 1999-2001, #A79941108. Chief Investigators: M. Kalish, S. Lewandowsky. Partner Investigator: J. Kruschke. Associate Investigator: R. Kliegl.
$124,000 (Australian) direct costs. Title: Knowledge partitioning: models of the limits of expertise.

National Institutes of Mental Health FIRST Award #R29-MH51572. P.I.: John K. Kruschke. "Explorations of a connectionist category learning model." April 1994 – March 1999. $343,405 total.

Selected Service:

Member, National Science Foundation Site Review Team, Pittsburgh Science of Learning Center, Spring 2010.

Member, Grant Proposal Review Panel, National Institutes of Health, Cognition and Perception Study Section. Spring 2009, San Francisco.

Member, Grant Proposal Review Panel, National Science Foundation, Human Cognition and Perception Program. Fall 1998 – Fall 2001. Reviewed approximately 18 proposals with meetings in Washington, D.C., twice each year.

Representative to The Science Coalition's signature event, "Science: Investing in the Future." Made presentations to members of Congress, Sept. 22, 1999, Washington, D.C.

Chair, Fourteenth Annual Conference of the Cognitive Science Society, Indiana University, Bloomington IN, July 29–August 1, 1992. Directed reviews of 284 submitted papers, organized Proceedings, directed the budget, etc.

Various IU departmental committees, including various terms on the Budgetary Advisory Committee, acting as Chair of that committee some years.

Action Editor for Bayesian Special Issue, Psychonomic Bulletin & Review, 2015 – 2016.
Editorial Board, Frontiers in Psychology: Cognition, 2015 – .
Editorial Board, Psychological Review, 2006 – .
Action Editor for Bayesian Special Issue, Perspectives on Psychological Science, 2011.
Action Editor, Journal of Mathematical Psychology, 2008 – 2013.
Consulting Editor, Journal of Experimental Psychology: General, 1996 – 2001, 2011 – 2013.
Editorial Board, Psychonomic Bulletin & Review, 2003 – 2010.
Editorial Board, Memory & Cognition, 2005 – 2008.
Editorial Board, (Journal of) Cognitive Science, 1999 – 2001.
Consulting Editor, Journal of Experimental Psychology: Learning, Memory, and Cognition, 1993 – 1997.

DEPARTMENT OF
PSYCHOLOGICAL AND
BRAIN SCIENCES
INDIANA UNIVERSITY
Bloomington

February 24, 2017

To the SOTL grant review committee,

I am writing to provide my strong and enthusiastic support for the proposal "Improving Teaching Through Enhanced Analysis of Teaching Evaluations" submitted by faculty members Rick Hullinger, John Kruschke, and Ben Motz. This proposal holds tremendous promise for enhancing the quality of the information instructors get from their teaching evaluations, increasing instructors' views of the worth of teaching evaluations, and in turn, improving the quality of undergraduate education. For these reasons and more, this proposal has my strong support. In fact, given that tens of thousands of students complete course evaluations at IU each year, thus providing feedback to thousands of instructors, I can't imagine any proposal with such extraordinary potential for impact on instruction.

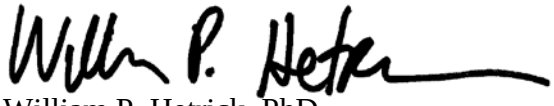
For the last year, Rick Hullinger and Ben Motz have been involved in our department's efforts to redesign our own course evaluations to make them both more effective and easier for our faculty to understand and respond to. As a result, they bring a full understanding of the potential benefits of course evaluation data, and well as the weaknesses, biases that can plague the data and its interpretation. Rick's background in software development and user interface design and his current role as our Director of Pedagogy make him a natural to lead a project focused on the analysis and visualization of teaching evaluation data. Ben Motz, our department's Director of Undergraduate Instruction and Online Instruction, is committed to our department's goals of excellence in undergraduate education. As you will see from his CV, he is also active in pedagogy research and is quite adept at analyzing large data sets. His outstanding previous work involving large data sets and student learning outcomes resulted in his being awarded the President's Award for Excellence in Teaching and Learning Technology in 2015. John Kruschke is a dedicated teacher and one of the nation's foremost experts in Bayesian data analysis. He brings an understanding of how to correctly analyze and compare data sets that are filled with non-linear, bimodal, and categorical data. His guidance will ensure that the approaches used generate meaningful and accurate statistics from the OCQ that can be used to make well-informed decisions about how our instructors can improve their teaching. I have no doubt that this is the correct team to make this project an unqualified success.

Because this work will focus on the analysis of the university-wide OCQ questions, the benefits of this project will far exceed our department, or even The College. The same tools could easily be used by any

IU instructor to provide insights into his/her teaching effectiveness. The generalizability of this work means that this small project has the potential to have a university-wide impact, and I cannot think of a better use of SOTL's grant funds.

In conclusion, this project has ***my strongest and most enthusiastic support***. If you have questions that I might be able to answer, please do not hesitate to email (whetrick@indiana.edu) or call (812-855-2620).

Sincerely,



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