Association of Learning Styles with Research Self-Efficacy: Study of Short-Term Research Training Program for Medical Students

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Abstract

Purpose: With a growing need for developing future physician scientists, identifying characteristics of medical students who are likely to benefit from research training programs is important. This study assessed if specific learning styles of medical students, participating in federally funded short-term research training programs, were associated with research self-efficacy, a potential predictor of research career success.
Method: Seventy-five first-year medical students from 28 medical schools, selected to participate in two competitive NIH-supported summer programs for research training in aging, completed rating scales to evaluate learning styles at baseline, and research self-efficacy before and after training. We examined associations of individual learning styles (visual-verbal, sequential-global, sensing-intuitive, and active-reflective) with students' gender, ranking of medical school, and research self-efficacy.
Results: Research self-efficacy improved significantly following the training programs. Students with a verbal learning style reported significantly greater research self-efficacy at baseline, while visual, sequential, and intuitive learners demonstrated significantly greater increases in research self-efficacy from baseline to posttraining. No significant relationships were found between learning styles and students' gender or ranking of their medical school.
Conclusions: Assessments of learning styles may provide useful information to guide future training endeavors aimed at developing the next generation of physician-scientists. Clin Trans Sci 2014; Volume 7: 489–492

Keywords: research training, medical education, physician scientist, learning styles, research self-efficacy

Introduction

The declining number of physician-researchers has been a concerning trend over the past two decades.[1] As of 2005, only 13% of medical students had reported a strong interest in pursuing a research career.[2] The National Institutes of Health (NIH) and other agencies have funded medical schools to implement research training initiatives. To maximize this investment, there is a need for evaluation strategies to gauge the success of such early-career programs in fomenting research trajectories, and understanding student characteristics that predict short- and long-term outcomes of these programs. One means of judging short-term success of these programs is to assess change in self-efficacy in the tasks of research.[3] Self-efficacy refers to the level of confidence in carrying out a task, and can be assessed through standardized self-report measures.

We previously reported that research self-efficacy improved significantly after participation in an intensive research training program for first-year medical students.[4] As a next step, we sought to determine whether students' learning styles predict a change in research self-efficacy following the training. Keefe[5] defined learning styles as specific "cognitive, affective, and psychological behaviors that serve as relatively stable indicators of how learners perceive, interact with, and respond to the learning environment." While they have clear limitations,[6] learning styles are potentially important predictors of short-term outcomes in training programs that offer individually tailored instruction such as mentored research experiences.[7] Commonly used learning style models have been used successfully to help teachers develop effective instruction methods (http://www.oncourseworkshop.com/Learning046.htm). Serious mismatches between learning styles and training programs may result in worse scholastic outcomes.[8] Although learning styles do not necessarily predict an individual's propensity for success in a given field,[9] several studies have reported relationships between learning styles and outcomes such as approaches to learning and response to specific teaching techniques.[10–12] To our knowledge, the use of learning styles to inform medical students' research training has not been reported, nor has learning style been evaluated as a possible predictor of change in trainees' self-efficacy. We hypothesized that research self-efficacy would improve as a result of training of medical students, and that learning styles would be significantly associated with variation in baseline self-efficacy as well as change in self-efficacy. We also explored the association of specific learning styles with trainees' gender and research ranking of their medical school. There is inconsistent evidence in the literature about gender differences in learning styles.[6,13] There also is a possibility that trainees coming from schools with high research ranking may have greater research self-efficacy at baseline and/or may benefit more from a summer research training program than their peers from lower ranked medical schools.

Methods

The study was approved by the University of California, San Diego (UCSD) Institutional Review Board. Participants were 75 medical students from 28 medical schools across the United States, who had applied for and were accepted into two competitive NIH-funded summer research training programs held in 2011 and 2012 at the UCSD. Detailed aspects of these programs have been described in an earlier study of changes in research self-efficacy among trainees.[14] Briefly, the Medical Student Training in Aging Research (MSTAR) and Medical student Sustained Training and Research Experience in Mental Health (M-STREAM) programs, funded by the National Institute on Aging and the National Institute of Mental Health, respectively, spotlight training in aging-related research. First-year students from any US medical

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school can apply to these programs, which take place during the summer between the first and second years of medical school training. Students are selected based on demonstrated academic excellence, interest in geriatrics or geriatric mental health, and potential for academic career advancement. The participants receive NIH stipends, hands-on research experience (clinical, basic, or translational), and individual mentoring. Both programs center on mentored research and experiential learning in which trainees are matched with senior researchers at NIH-approved centers. While most aspects of training are individualized to the students' research interests, some elements including workshops and a few didactic group sessions are common to all trainees.

All the students complete two rating scales listed below, a few days before starting the program. The research self-efficacy scale is repeated a few days after completion of the summer training.

Research Self-Efficacy Scale (RSES): We used a generalized self-efficacy scale,[15] modified by adding specific items to address targeted research skills in medical students, and then tested for internal consistency. [4]

Index of Learning Styles (ILS)[8]: This measure of learning styles has been widely used because of ease of access, administration, and analysis, as well as limited question burden on test-takers.[16] Reliability and validity of the ILS have been demonstrated among undergraduate students in engineering, liberal arts, education, management, medical students, and medical and orthodontic residents.[13,16–18] Several studies have reported relationships between learning styles and approaches to learning and response to specific teaching techniques.[10–12]

The ILS model classifies students' learning preferences according to four dimensions[8]: *Visual-Verbal* (visual learners do better with pictures, diagrams, films, and demonstrations, whereas verbal learners get more out of words—written or spoken), *Sequential-Global* (sequential learners tend to learn incrementally in linear, logical steps whereas global learners understand larger conceptual themes before individual steps but may have difficulty explaining how they did it), *Sensing-Intuitive* (sensing learners work carefully learning facts, memorizing data, and using well-established methods whereas intuitive learners tend to work faster, and prefer abstractions, theories, and innovation), and *Active-Reflective* (active learners process information by doing something active with it such as experimentation, whereas reflective learners prefer to first think it through quietly and introspectively). The ILS consists of 11 self-report forced-choice items for each of the four dimensions. While there are several different methods of computing aggregate ILS scores for a group, we used a two-point scale, in which having a score of 1 to 11 on either side of the dimension indicates a preference for a particular learning style. This method has been employed in a number of studies.[9,11,18–22]

Statistical Analysis: All the variables were checked for normality of distribution and appropriateness for parametric statistics. We then examined associations of baseline characteristics (gender, MSTAR vs. M-STREAM program and year of study) with the four learning styles using independent t-tests. Based on the most recent U.S. News and World Report on Medical School Research rankings, medical schools were divided into top-20 versus lower-tier schools, and this categorization was used as a potential covariate of baseline research self-efficacy. Next, we contrasted the four learning styles with baseline RSES scores employing independent t-tests. We then calculated the baseline to posttraining change in RSES scores within each learning style category and performed paired t-tests to examine change in RSES scores from baseline to follow up. Finally, we performed a hierarchical regression, with baseline RSES scores and covariates (if significant at the alpha = 0.05 level) entered in the first block and the four learning style scores entered simultaneously in the second block, predicting RSES change scores. This use of baseline score as a covariate mitigates problems in analysis of change scores due to regression to the mean of high baseline scores.[23] We computed the change in R^2 for each block of the regression, and assessed the significance of this change. We employed a significance level of $p < 0.05$.

Results

Of the 79 eligible trainees, 75 agreed to participate, and completed all the baseline assessments. There were no significant differences in learning style scores of MSTAR ($n = 33$) versus M-STREAM ($n = 42$) students or those trained in 2011 ($n = 33$) versus 2012 ($n = 42$); therefore, we combined all the participants into a single group for further analyses. The students came from 28 different medical schools in the United States. Forty-two participants (55.3%) were female, and 46 (60.5%) came from top-20 medical schools based on the most recent U.S. News and World Report research rankings.

Table 1 provides the mean baseline and post-training RSES values for each ILS dimension. Overall, there was a mean improvement of 3.3 points (SD = 4.5) from a baseline mean RSES score of 27.7 (SD = 3.8) paired $t(75) = 6.5$, $p < 0.001$). Of the 75 participants, majorities had visual (84%), global (64%), sensing (61%), and active (54%) learning styles. There were no significant differences between genders or between students from top-20 versus lower-tier medical schools in learning style preferences. At baseline, respondents with a verbal (vs. visual) learning preference had greater RSES Scores (F (1,65) = 6.9, $p = 0.011$), but no other learning styles were associated with baseline RSES scores. With regard to the association of learning styles with changes in RSES scores, significantly greater change was evident among students with visual (vs. verbal), sequential (vs. global), and intuitive (vs. sensing) learning styles. In terms of the magnitude of these associations, the second block of the regression containing all four ILS categories accounted for 11% of the variance in RSES change ($F(4,69) = 3.6$, $p = 0.011$), with the full model accounting (baseline RSES scores + ILS categories) for 55% of variance in RSES change.

Discussion and Conclusions

This study extends our prior report indicating that research self-efficacy improves among medical students engaged in NIH-funded intensive summer research training programs. We found that the increase in the trainees' research self-efficacy was more strongly related to their learning styles than to their baseline research self-efficacy scores. Whereas the baseline RSES scores were significantly associated only with verbal (vs. visual) learning styles, improvement in research self-efficacy was associated with visual, intuitive, and sequential learning preferences. No significant associations were found between the learning style and students' gender or ranking of their medical school.

This study has several limitations. The study sample comprised medical students interested in acquiring research experience in aging. Thus, our results may not be representative of medical students in general, or even those pursuing research careers in non–aging-related specialties. We are also limited by our sample size. Another limitation is the reliance on subjective measures (ILS

	Baseline RSES Score	Follow-Up RSES Score	Test of Pre-Post Change in RSES Scores		Test of Moderation of Learning Style on Change in RSES Scores[a]	
	Mean (SD)	Mean (SD)	Paired *t*-test value	*p* Value	*t*-test value	*p* Value
Visual-Verbal					-2.457	.017
Visual (*n* = 64)	27.2 (3.8)	31.2 (3.4)	7.6	<0.001		
Verbal (*n* = 12)	30.2 (2.7)	29.5 (3.1)	–0.5	0.613		
Sequential-Global					2.705	.009
Sequential (*n* = 27)	27.4 (3.6)	32.0 (2.9)	5.6	<0.001		
Global (*n* = 49)	27.9 (3.9)	30.35 (3.6)	3.8	<0.001		
Sensing-Intuitive					–.2110	.039
Sensing (*n* = 46)	28.1 (4.2)	31.1 (3.3)	4.2	<0.001		
Intuitive (*n* = 30)	27.1 (3.2)	30.7 (3.7)	4.9	<0.001		
Active-Reflective					.426	.671
Active (*n* = 41)	27.5 (4.2)	31.0 (3.7)	4.0	<0.001		
Reflective (*n* = 35)	27.9 (3.4)	31.0 (3.2)	5.9	<0.001		

[a]Hierarchical regression adjusting for baseline RSES values with all four learning styles entered simultaneously; *t*-values represent statistical tests of regression coefficients of learning style predicting RSES change scores.
RSES = Research Self-Efficacy Scale.

Table 1. Change in research self-efficacy with the summer training program, by learning style preferences.

and RSES). Also, students' ability to engage in scholarly research (self-efficacy) may represent an attitudinal (rather than behavioral) outcome. Learning styles may change somewhat over time.[24] Some students might have sought additional information or instruction through online or other sources; we did not collect those data. Nearly half (45%) of the variance in the change in research self-efficacy remained unexplained, after accounting for baseline variation in self-efficacy and ILS styles. Other factors such as students' motivation, aptitude, research focus, and work habits may play a critical role in that respect. Similarly, mentorship experience and institutional resources may also influence success of training programs. Finally, this study is based on a short-term training outcome (increase in research self-efficacy as a marker for improvement), which may or may not predict longer-term career trajectory.

Notwithstanding the above-mentioned limitations, learning styles may provide useful aid in determining characteristics of the students as well as of the training programs that are associated with success of early-stage research training programs. We view the present investigation as an initial step in improving our understanding of and eventually enhancing the process of individualized research training. Our results associating specific learning styles with a training outcome are consistent with some prior observational research. For example, Cook et al.[12] reported associations between preferences on the visual-verbal scale and case-based learning of internal medicine residents, following a web-based learning module. We speculate that learning style preferences may be important in understanding the active ingredients of short-term mentored research training, a common model among medical student research training programs. However, at the present time, there is only limited understanding of which elements of research training (e.g., individual mentoring, conducting a research project, didactics) are directly related to positive outcomes. Of note, neither gender nor the national research ranking of a student's medical school appeared to predict greater increase in research self-efficacy in our summer research training programs.

In future research, it would be useful to determine the "active ingredients" of non–classroom-based training, such as the quality of mentoring relationship, in order to help advance efforts to individualize programs that capitalize on students' and mentors' strengths. Prospective programs of this kind, guided by the trainees' individual learning preferences, may provide an opportunity for to enhance clinical and translational research training.

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