10-7-2017

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CONVERSATION STARTERS - NORTHEASTERN REGION

"Yes, and…" Exploring the Future of Learning Analytics in Medical Education

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Key words: learning analytics, radiology, e-learning

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Abstract

This Conversations Starter article presents a selected research abstract from the 2017 Association of American Medical Colleges (AAMC) Northeastern Region Group on Educational Affairs (NEGEA) annual spring meeting. The abstract is paired with the integrative commentary of three experts who shared their thoughts stimulated by the study. Commentators brainstormed "what's next" with learning analytics in medical education, including advancements in interaction metrics and the use of interactivity analysis to deepen understanding of perceptual, cognitive, and social learning and transfer processes.

Commentary

The adoption of technology-enhanced learning in medical education dramatically expands the toolbox for investigating learning process. Learning analytics is a multidisciplinary endeavor that uses data collected from learner interactions with technology to make inferences about the mechanisms giving rise to improved knowledge and understanding.[1] Uncovering the relation between learner activity online and subsequent performance is thought to reveal important information about effective learning and study approaches, which presumably can be taught or fostered to improve academic achievement.[1] The learning analytics approach implicitly recognizes the importance of learner engagement[2-3] and adds a new dimension of data to offline engagement measures, such as active participation with teachers and peers, time on task, and emotional affinity to assignments.

In their study (see abstract below), Cirigliano, Guthrie, and Pusic used learning analytics to investigate the relation between medical student exploratory activities in a popular online radiology course module and subsequent performance on a multiple-choice test. Although there is extensive work in advertising and other industries to measure user engagement with online ads and subsequent behavior, [4] there is surprisingly little work in education to elucidate the measures of student online engagement that predict performance on subsequent learning tasks. Cirigliano et al.'s pilot work is exciting, stimulating future-oriented, "Yes, and…" conversations about where this kind of exploration can go next.

Expanding Interaction Metrics in Radiology Instruction

By its inherent visual nature and reliance on digital and computerized images, radiology is particularly well-suited to technology-enhanced learning, which can exercise the navigation and manipulation activities involved in image interpretation.[5] Indeed, in recent years, e-learning has found generalized acceptance amongst the radiology community for learners across the continuum, from medical students to practicing radiologists.[6] Much of what experienced radiologists know is procedural, or tacit, embodied in how they process the information in an image.[7-8] Click-level learning analytics offer interesting possibilities for representing and deconstructing the complex, iterative observational process by which medical images are interpreted. For example, one of the first steps of image interpretation is perceptual, in which normal findings are discriminated from abnormal.[9] Integrated into this perceptual process is employment of proper and efficient search strategies, pattern recognition, and ability to spatially translate two-dimensional images into three-dimensional anatomy.[7-9] As practicing radiologists are aware, the perceptual process is not a passive one in which an abnormality is always immediately obvious, but an active process in which the observer extracts information, searching for common pathology, especially in areas that are known to be overlooked. This requires active manipulation of images, not only through use of magnify buttons, as Cirigliano et al. studied, but also through window (contrast) and level (brightness), pan, black-white invert, and other buttons. These are additional interactions with imagery that are valued by learners[5] and also can be measured using mouse clicks.

Importantly, perceptual skills are only the first step in achieving mastery in radiologic interpretation.[7-9] Learners also must become proficient in higher order problem solving skills that might be termed “analysis” and “synthesis.”[9] In the analysis step, the radiologist must characterize the observed findings using appropriate terminology and compare the findings to prior images of the same or different modality (e.g. x-ray, MRI, or ultrasound). In the synthesis step, the radiologist must integrate the observed findings with knowledge of anatomy, pathology, and physiology and expected findings based on clinical history, in order to generate a diagnosis or differential diagnosis and recommendations for follow-up. Future exploration could address how mouse clicks or other interaction metrics can be applied to study the acquisition of these more complex cognitive skills.[8] So called “non-interpretive skills” in radiology,[10] including recommending appropriate imaging studies, communicating effectively with referring physicians and patients, and managing imaging safety and quality issues, may also prove to be fertile subjects for quantitative learning analysis. Interaction metrics from sophisticated online learning systems that use role-play and serious games to exercise interpersonal skills (see, for example, Johnson, Friedland, Schrider, Valente, & Sheridan[11]) could dramatically increase understanding of how such skills are acquired and demonstrated.

Examining the Validity of Interaction Metrics

The task of interpreting interaction metrics as learner engagement can be difficult given the many factors that influence individuals’ interactivity with e-learning materials. Even in fields such as interactive marketing, where the association between user interactivity with online content and subsequent action is of longstanding interest, clearly defining engagement remains challenging.[12] There are intriguing complexities in the relationship between interaction metrics and subsequent academic performance that emerge when one considers interactivity as a proximal determinant, which is in turn affected by distal factors, such as ability, motivation, achievement orientation, self-efficacy, goal setting, and associated self-regulation.[13-16] For example, a confident learner motivated to achieve mastery and capable of self-regulation may approach the training system as an opportunity to explore and build knowledge. Interaction metrics reflecting this orientation might include longer dwell times and more diffuse connections among hyperlinks clicked. However, the learner may respond to formative assessment questions incorrectly as she self-tests in candid manner. Shorter dwell times might reflect a highly motivated learner who does not take the system seriously as a learning opportunity or who views it as an examination, with learning being something that happens elsewhere, such as the lecture hall or the clinic. In addition, properties of the training system, such as instructions and feedback, may interact with learner characteristics, such as level of training, affecting subsequent learner engagement (though see Lieberman, Abramson, Volkan, & McArdle[17]). In this light, the behavior captured by interaction metrics may be viewed as the tip of the iceberg, perhaps even a performance in and of themselves.

Use of very large log files to measure students' online behavior may be helpful to interpreting associations found between learner interactivity and subsequent performance. For example, Google analytics provides many interesting metrics, such as the bounce rate (time on page one without going further on the site), average time on site, number of page views per visit to the site, time on page (those who interacted with the site longer than the designated bounce time), and visitor recency (percentage of returning visitors). As large databases of online educational material accumulate, log analysis may help educators design strategies that promote optimal engagement. Online data also could be coupled with offline data that reflect learner intentions, including survey, interviews, focus groups, verbal protocols, and direct observation of pairs of students using the system together. Measures of personal characteristics might also be usefully included in a learning analytics study so as to examine the influence of distal factors and account for individual differences in engagement. The underlying objective is to build confidence that interaction metrics reflect what they are thought to (i.e., to ensure valid inferences about learner engagement) and that using them to design instruction will address learning (i.e., improving knowledge) versus performance (i.e., improving metrics). Defining engagement metrics also would expand theoretical understanding of how personal characteristics and motivational processes interact with learning environments to produce individual differences in learning strategies and academic outcomes. Delving into the various types and sources of motivation and how they correspond to performance in academic medicine would extend Cirigliano et al.'s work and contribute to a body of knowledge outside of, but integral to, medical education.

Context and Interaction

Cirigliano et al.'s study also raises interesting questions about how the larger educational context affects interaction metrics, their interpretation, and their relation to learning outcomes.[18] For example, how is the degree and nature of interaction affected by the use of e-learning delivered in isolation or together with other content delivery methods (e.g., lecture, small-group learning, clinical instruction)? How does the association between usage and learning outcomes differ when learners are individuals, pairs, or small groups? How might the use of mobile technologies in workplace learning environments affect the timing and purpose of interaction with e-learning? Bringing technology-enhanced learning into clinical and community-based settings could extend Cirigliano et al.'s work into contexts where learning outcomes can be measured as real-time knowledge acquisition and comprehension of content for immediate practical application. Evaluating the association among interaction metrics, training performance, and practical application in medically underserved areas could reveal the impact of significant environmental factors—limited socioeconomic means, rural living, exposure to multiple adverse events, lack of access to resources, language differences, and diverse cultural traditions—on the relevance and effectiveness of interactions exercised by technology-enhanced learning and associated formative assessment.

Closing Remarks

Learning analytics offer a rich opportunity to explore learning processes, and the contextual factors that influence them, in a way that conventional educational outcomes studies do not.[19] Analyses of this nature have the potential to improve theoretical understanding of knowledge and skill acquisition by elucidating the mechanisms of action whereby learning occurs. The sophistication of interaction metrics and performance assessment measures is limited only by the creativity (and budget) of those who design and develop technology-enhanced learning. Deriving deeper understanding from learning analytics requires equally sophisticated data collection strategies that enable investigation of context, validation of interaction metrics, and evaluation of practical application.

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AAMC NEGEA 2017 ABSTRACT

Click-Level Learning Analytics in an Online Medical Education Learning Platform

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Phenomenon: Students engaged with virtual patients and expository multimedia can interact with educational content in a number of ways. The nature of these interactions can reveal important information about both the media and the learning, particularly when documented in the detail provided by digital environments.[1] Through big data and learning analytics approaches we can now explore the click-level tendencies and handling methods employed by a large population of medical students using online learning platforms like MedU, an online suite of modules teaching patient-centered approaches to clinical problem-solving skills.[2]

Approach: Using measures of student interaction, we sought to identify patterns that predict downstream assessment performance in a linear online module.[3] We selected a MedU expository online module on the topic of musculoskeletal radiology. The module consisted of 6 sections, each of which had a set of 4-5 screens, with a variety of engagement activities, followed by a multiple-choice question (MCQ). We convened a multidisciplinary focus group of experts to identify potential learning analytic measures within the MedU system. These included: hyperlinks clicked on a page (yes/no), magnify buttons clicked (yes/no), expert advice links clicked (yes/no), and time on page (seconds). Each unit's engagement activity data was correlated with the (single) succeeding, relevant MCQ. These correlations were later compared with a single expert's ratings for relevance of content to the subsequent MCQ (rating dichotomously expressed as "fully relevant: yes/no").

Findings: We obtained click-level data describing usage of the module from July 1st, 2014 to May 5th, 2015 encompassing the experiences of 2,806 North American medical students. All six MCQ items showed acceptable item-total correlations. A number of the interaction behaviors were significantly correlated with likelihood that a student correctly answered the subsequent MCQ. Clicking hyperlinks (OR 1.21, 95% CI: 1.12, 1.31), magnifying images (OR 1.20, 95% CI: 1.11, 1.31), referring to the expert's answers (OR 1.21, 95% CI: 1.05, 1.39), and spending >100s seconds on each instructional page (OR 1.38, 95% CI: 1.27, 1.51) all were correlated with correct MCQ answers. Rushing through the pages (<20 seconds) was inversely correlated (OR 0.74, 95% CI 0.66, 0.83). For each assessment question, a unique logistic regression model could be constructed to indicate which activities/interactions would result in correctly answering the MCQ. For the five hyperlinks judged "completely relevant" by the expert, only one was in fact statistically significantly related to the subsequent MCQ. Similar ratios for the magnify (3/7) and time (5/8) interaction measures were observed.

Insights: Our intention was to demonstrate the merits of learning analytics within the online context, giving educators a new tool for improving experiences in online learning environments. Results of this analysis, where the data from thousands of learners are summarized, can serve as feedback to instructional designers as to which interaction elements are effective. It may also be useful to show students evidence that there is a statistically significant relationship between engaging with the material and performing well on assessments.

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Expert Commentator Biographies

Anna T. Cianciolo, Ph.D., is Associate Professor, Department of Medical Education at Southern Illinois University School of Medicine and Editor of *Teaching and Learning in Medicine*. Her research focuses on understanding and improving the performance of individuals, teams, and groups as they seek to solve the complex problems of academic health care, including diagnosis, collaborative learning, and clinical teaching and supervision.

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Valerie Terry, MPAff, Ph.D., is at the University of Texas-Rio Grande Valley School of Medicine with roles and responsibilities in a number of areas involving undergraduate and graduate curriculum design and implementation, instructional delivery and evaluation, including the use of educational technology, and faculty instruction and development. Her educational and research interests encompass the discipline of Communication, health care public policy and health literacy, with an emphasis on rhetorical theories as they inform symbolic constructions of social and political contexts. Dr. Terry is currently designing, developing and teaching comprehensive undergraduate and graduate Communication curriculum, partnering with a child psychiatrist faculty colleague.