Master of Science in Biomedical Communications
Master's Research Proposal

An interactive learning tool for first-year medical students in the Health Science Research course at the University of Toronto

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KEYWORDS: e-learning, interactive media, knowledge construction/deep learning, cognitive theories of learning, constructivist theories of learning, biostatistics, quantitative medicine, undergraduate medical education, visualization

ABSTRACT: The undergraduate medical program of the University of Toronto has recently adapted an asynchronous "blended" classroom approach for its two-year, preclinical Health Science Research (HSR) course. This model requires students to learn course content outside of class via e-modules and dedicates class time to student-centred learning activities. Among the course's diverse subject matter, biostatistics is a topic for which students require more support; this suggests that the teaching strategy employed in the e-modules for this conceptually-abstract content may not be optimal for learning. Since a conceptual understanding of biostatistics is essential for critical appraisal of medical literature and the application of research to clinical scenarios, optimization of the learning environment for this material is desirable. This project aims to blend interactive media and case-based learning, and to harness their theoretical frameworks, to improve learning outcomes in biostatistics as taught within the context of the HSR course.

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INTRODUCTION

The Health Science Research (HSR) course is a two-year longitudinal component of the Foundations (pre-clerkship) curriculum in the University of Toronto's (U of T's) undergraduate medical program. A relatively new[1] addition to the curriculum, the course functions as an introduction to principles of research and aims to help students understand and use research to contribute to the improvement of individual and population health. More specifically, the course endeavours to develop students' understanding of qualitative and quantitative methodologies and techniques, engender appreciation of translational research, and facilitate understanding and application of critical appraisal criteria to clinical practice. In this way, the course may be considered a primer to evidence-based medicine (EBM), an approach to medical practice that entails the application of information from medical literature to day-to-day clinical problems (Guyatt & Rennie, 1993).

The course is taught using an asynchronous "blended," or "flipped," classroom model (Evans et al., 2016; Osguthorpe & Graham, 2003; Singh, Reed, & Centra Software, 2001), wherein students learn the course content independently, outside of class, and class time is dedicated to student-centred learning activities. Independent learning of course material is supported by e-modules and/or required readings; small-group tutorials and large-group sessions provide students the opportunity to discuss and apply the knowledge they've obtained through their independent learning.

The course is broken down into nine themes, or topics, each covered over a period of three to six weeks. One of these themes, "Quantitative Research Methods" (QRM), is an area in which students require more support in their learning. Preliminary observational research reveals that students have sought the most assistance in this area in previous academic years, and course developers have responded to this need by altering the course structure – i.e., by offering more formal opportunities to seek assistance—and by assembling an expert advisory team to provide support on this specific subject area.

The QRM theme provides an overview of quantitative research design and methodology, as well as a basic introduction to biostatistics. In this theme, students learn how to recognize and understand quantitative research methods --including quantitative research designs-- and how statistical analyses are applied in different quantitative research contexts. Based on the aforementioned observational research, the biostatistics component of this theme is the most challenging content for students. Importantly, conceptual understanding of biostatistics is emphasized in the QRM modules, rather than memorization

[1] The 2017/2018 academic year was the course's third iteration.

of the formulas and necessary calculations. This emphasis aligns with recent research suggesting that a conceptual approach to mathematics is beneficial for learning and achievement at the high school level; and that, conversely, teaching mathematics procedurally, as a series of steps to memorize and apply, is detrimental to students' learning and achievement (Boaler & Zoido, 2016).

QRM content is learned through non-interactive multimodal e-modules[2] and/or readings completed outside of class. Each e-module consists of a screencasted PowerPoint presentation, approximately fifteen to thirty-five minutes in length, given by a faculty member of the Stanford University School of Medicine. Stanford University uses these same modules to teach an equivalent course at their institution and employs them in a similar blended learning context; interestingly, this strategy has resulted in significantly higher course satisfaction while failing to significantly impact performance on the final exam, as compared to the years prior to implementation of this strategy (Evans et al., 2016). Similarly, Ilic and colleagues (2015) evaluated learning outcomes of first-year undergraduate medical students learning EBM in blended versus traditional environments. In their randomized controlled trial study, online learning materials for students in the experimental (blended learning) arm included online lectures, similar to Evans and colleagues (2016), and no significant differences were revealed between experimental and control (traditional learning) groups with respect to student learning outcomes. While no comparable evaluation has been performed regarding student learning outcomes in U of T's blended QRM course, similar findings may be anticipated due to the relatively high external validity of these studies.

Knowledge of quantitative research design, methodology, and biostatistics are essential for the practice of evidence based-medicine, as they permit interpretation of medical literature and enable patient care based on the best evidence currently available (Barratt et al., 2004; Freeman, Collier, Staniforth, & Smith, 2008; Guyatt et al., 1995; Montori et al., 2004). Development of a tool that will enhance students' independent learning of this subject matter in the asynchronous blended learning environment of the HSR course is therefore desirable.

The presently proposed project is motivated by the hypothesis that the design of HSR's biostatistics e-modules plays a critical role in students' learning outcomes—particularly, their ability to gain a conceptual understanding of the subject matter. Interactive multimodal learning environments[3] are thought to

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[2] These e-modules are multimedia explanations, or linear presentations, of the content to be learned, which include both verbal and visual representations of the material. 'Multimodal' refers to the dual verbal and visual representation of the content, whereas 'non-interactive' refers to a lack of responsiveness to the learner's actions during learning.
[3] learning environments that represent the content to be learned using verbal (semantic) and non-verbal (visual) modes, and in which presentation of verbal and corresponding visual representations is dependent on the learner's actions

promote meaningful learning of any subject matter (Moreno & Mayer, 2007), and exposure to real-world problems and hands-on experiences are recommended for teaching undergraduate-level statistics (Dinov, Sanchez, & Christou, 2008). This project will therefore endeavour to develop an interactive visual tool to enhance the independent learning of biostatistics by first-year undergraduate medical students in the HSR course. The tool will be created through an iterative design process guided by extensive formative evaluation. Summative evaluation of student learning outcomes resulting from implementation of these tools is outside the temporal scope of this project; such an evaluation is encouraged in the future.

Before reviewing the literature on use of interactive visual tools in teaching and learning biostatistics, we must first clarify the meanings of a few key terms: 'interactive' and 'learning.' Within the context of teaching and learning, 'interactive' can refer to the capacity to elicit cognitive (mental) engagement alone. In this sense of the term, interactivity refers to an intellectual interaction with a subject matter under study in order to construct meaning, relate it to personal knowledge, and apply it to problem solving (Bernard et al., 2009). However, 'interactive' can also refer to the capacity to elicit a two-way action, or multidirectional communication. In this sense of the term, interactivity refers to a responsiveness to, or dependency on, a learner's actions during learning (Moreno & Mayer, 2007). The tool to be developed in this project will be interactive in this latter sense; that is, the tool will be responsive to, and dependent upon, the learner's actions during learning.

'Learning,' on the other hand, may simply refer to information acquisition, a process which involves adding information to a learner's memory. In this case, the learner simply receives information. However, 'learning' may also refer to knowledge construction, a process which involves building a mental representation. In this case, the learner actively works to select relevant information from a lesson, mentally organize it into a coherent structure, and integrate it with existing knowledge (Moreno & Mayer, 2007). Deep cognitive processing underlies this type of learning, often deemed in the literature 'deep learning' (Marton, 1976; Moreno & Mayer, 2007; Richardson, 2015). It is this latter type of learning which the present project endeavours to support.

BACKGROUND

Many international pedagogical resources in probability and statistics suggest that undergraduate students studying statistics should be exposed to real-world problems and be given hands-on experiences in generating, collecting, and displaying data (Dinov, Sanchez, & Christou, 2008). Recommendations for teaching statistics to non-statisticians further highlight the importance of using of real-world situations in effective statistics education (Mustafa & Yilmaz, 1996). These collective recommendations allude to problem- or case-based learning, visualization, and interactivity as ideal candidates for teaching tools.

Problem- and case-based learning

Problem-based learning (PBL) is an open inquiry instructional approach that situates learning in a meaningful task, i.e. the investigation, explanation, and resolution of meaningful problems. Facilitators provide minimal guidance to students during the problem-solving process. Learning is thought to be achieved through this problem-solving process and through reflection on the problem-solving experience (Hmelo-Silver, 2004; Srinivasan, Wilkes, Stevenson, Nguyen, & Slavin, 2007). Case-based learning (CBL) is a similar instructional approach, though it differs in the level of guidance provided by facilitators and in the amount of preparation the students have before the learning sessions; it is therefore considered a *guided* inquiry approach (Srinivasan et al., 2007). Both PBL and CBL emphasize active construction of knowledge and aim to help students become active learners, blending cognitive[4] and constructivist[5] models of learning to achieve deep learning (Hmelo-Silver, 2004; Thistlethwaite et al., 2012). For this reason, they are both attractive candidates for a biostatistics learning tool that promotes deep learning.

PBL has received criticism as an instructional approach in the context of undergraduate medical education due to its lack of structure and the direct ramifications of this fact, e.g. time inefficiency, likelihood to lead learners to erroneous conclusions, and little guarantee that students learn how to apply the material necessary for clinical practice (Srinivasan et al., 2007). CBL, due to its structured nature, addresses these weaknesses of PBL and consequently tends to be preferred by students in medical education settings (Srinivasan et al., 2007; Thistlethwaite et al., 2012). Therefore, CBL is an optimal instructional approach for the tool to be developed in the present project.

To my knowledge, little research has been conducted on the use of CBL to promote deep learning of biostatistics in undergraduate medical education. One relevant study (Marantz, Burton, & Steiner-Grossman, 2003) investigated the effects of incorporating CBL into a compulsory epidemiology and biostatistics course in the Albert Einstein College of Medicine's first-year undergraduate medical curriculum. Student ratings of their learning in this class after incorporation of CBL were consistently higher over the five-year period during which they were evaluated, as compared to their ratings in the

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[4] cognitivism posits that knowledge acquisition is a mental activity that entails internal coding and structuring by the learner. According to this theory, learning occurs through the transfer of knowledge from the external world into internal frameworks, such as memory. (Ertmer & Newby, 2008)

[5] constructivism posits that knowledge is actively built up by the subject; it cannot be passively received through the senses or by way of communication (von Glasersfeld, 1990). According to this theory, learning involves a personal construction of knowledge through experiences and interactions. (Ertmer & Newby, 2008)

class before CBL incorporation. However, multiple-choice exam scores of students in the CBL-incorporated course were comparable to those of students in the course before CBL was implemented. Interestingly, following incorporation of CBL into the course, the school's highest score on the U.S. Medical Licensing Examinations was in epidemiology and biostatistics.

It is not clear the extent to which the findings of Marantz and colleagues (2003) are relevant for the present project, as the CBL-incorporated course they described did not employ a blended learning approach, as does U of T's HSR course. Importantly, these findings do not preclude implementation of CBL into a blended learning approach for the same subject matter.

Interactive multimodal learning environments

Multimodal learning environments (MLEs) are learning environments that represent the content to be learned using verbal (semantic) and non-verbal (visual) modes. In interactive multimodal learning environments (IMLEs), presentation of verbal and corresponding visual representations of content is dependent on the learner's actions (Moreno & Mayer, 2007). MLEs are thought to be the most effective learning environments as they can enable comprehension and memory and enhance learning and problem-solving (Moreno & Mayer, 2007; Romero, Berger, Healy, & Aberson, 2000). IMLEs, if carefully designed, may promote deep cognitive processing (Moreno & Mayer, 2007) and ultimately lead to deep learning.

A potential challenge when designing IMLEs is exceeding the cognitive processing capacity of learners with the demands of the learning environment, a phenomenon known as cognitive overload. Moreno and Mayer (2007) provide a set of five empirically-based design principles from the cognitive-affective theory of learning with media (CATLM) to guide the creation of IMLEs that optimize learning and reduce the likelihood of cognitive overload. Together, these principles reduce extraneous processing, or cognitive processing that is not necessary for making sense of new information, so that the learner's available cognitive resources can be used to engage in essential[6] and generative[7] processing activities, which together result in the creation of a meaningful learning outcome.

The first principle, guided activity, enables interaction with a pedagogical agent that helps guide cognitive processing during learning. This guided activity promotes essential and generative processing by prompting students to actively engage in the selection, organization, and integration of new information.

[6] entails selection of new information represented in working memory

[7] entails making sense of new information, e.g. mentally organizing it into a coherent structure and integrating the new knowledge representations with prior knowledge

The second principle, reflection—and reflection upon correct answers during the process of meaning-making, in particular—also promotes essential and generative processing, as it encourages active organization and integration of new information. The third principle, feedback—more specifically, explanatory feedback that consists of a principle-based explanation as to why students' answers are correct or incorrect—reduces extraneous processing by providing students with proper schemas to repair their misconceptions. The fourth principle, pacing-- or the ability to control the pace of presentation of the content to be learned-- reduces representational holding[8] by allowing students to process smaller chunks of information in their working memory. The fifth and final principle, pretraining, provides or activates relevant prior knowledge. This helps guide learners' generative processing by showing them into which prior knowledge they should integrate new information.

To my knowledge, there are no published studies on multimodal interactive learning tools aimed at promoting deep learning of biostatistics in undergraduate medical education. However, such tools have been developed for use in general statistics courses for a variety of educated audiences.

Liu, Lin, and Kinshuk (2010) developed a simulation-based tool ("Simulation-Assisted Learning Statistics" [SALS]) intended to correct misconceptions about, and improve understanding of, topics in statistics at the secondary (high school) level. The development of SALS was motivated by research suggesting that students often hold misconceptions about statistical concepts, which obstruct comprehension and application of statistics. The central mechanism of this interactive multimodal learning tool was dynamically-linked multiple representations (DLMRs), which allowed learner actions performed on one visual (graphical) representation to automatically show in other (graphical) representations. The cognitive conflict theory of learning[9] guided the design of this tool, including its four phases: externalization, reflection, construction, and application. In the externalization stage, learners were prompted to answer questions about a target concept presented to them in a relatable context and then received feedback on their responses. This phase encouraged awareness of the learners' implicit understandings and misconceptions. In the reflection stage, learners were guided to explore and reflect on the answers they provided during the externalization phase through manipulation of DLMRs. This phase allowed learners to compare their existing ideas about statistical concepts with correct ones obtained on the basis of their own manipulation and experimentation. In the construction phase, the learners were guided to construct their own understanding of target concepts through manipulation of

[8] cognitive processes aimed at holding a mental representation in working memory during the meaning-making process; a special subclass of extraneous processing.
[9] posits that conceptual change (learning) can be elicited through cognitive conflict, or a situation in which new knowledge is incompatible with prior knowledge

DLMRs. This phase was intended to help learners to develop correct statistical concepts through a process of manipulation and discovery. Finally, in the application phase, learners were prompted to answer multiple choice questions and complete hands-on problem-solving activities involving the DLMRs. This final phase allowed learners to elaborate on their newly constructed concepts and evaluated their ability to transfer them. In an experimental setting, this tool more effectively corrected misconceptions than lecture-based learning (control group) and was associated with increased understanding of target concepts in comparison to lecture-based learning.

Another group, the WISE (Web Interface for Statistics Education) team at Claremont Graduate University, has developed a suite of publicly-accessible interactive statistics tutorials designed to support teaching and learning in post-secondary social sciences domains. These tutorials, which are primarily realized through Java applets, provide guided interactive exercises on a variety of topics in statistics. Centred around graphical DLMRs, they are intended to provide students with the experiences they need to develop a conceptual understanding of statistics (Ransdell, Aberson, Berger, Emerson, & Romero, 1997). Principles of cognitive learning theory guided the applets' designs. In particular, the applets work to elicit elaborative processing, enable confrontation of misconceptions, and facilitate association of new material with familiar concepts. Elaborative processing is known to aid in comprehension and retention of conceptual material and is promoted by concluding tutorials with questions that require explanation of newly acquired concepts. This encourages deep processing of the content and integration of the new concepts with students' existing knowledge of statistics. Confrontation of misconceptions allows students to become aware of their misunderstandings and to correct them. When learners use the applets, they are posed questions that purposefully elicit incorrect answers, which allows direction of their attention to *why* their answers were incorrect and *which* concepts they misunderstood. Finally, integration of new material with familiar concepts is thought to support learning of new material. The tutorials begin with a series of questions that reinforce pre-requisite concepts, thereby priming relevant material in learners' minds so that they may interpret the tutorial in the context of what they already know (Romero et al., 2000). Use of these interactive tutorials in introductory and intermediate statistics courses for psychology undergraduate and graduate students are as effective or more effective in fostering learning of target concepts when compared to traditional lecture-based teaching methods (Aberson, Berger, Healy, Kyle, & Romero, 2000; Aberson, Berger, Healy, & Romero, 2003; Aberson, Berger, Healy, Romero, & Berger, 2002).

The theoretical frameworks that guided Liu and colleagues' and the WISE team's designs, as well as the instantiation of interactivity in their respective tools, can be informative for the design and development of my interactive multimodal tool for undergraduate medical biostatistics education. However, the graphical visualizations used in all these tools may not be appropriate for learning contexts outside a statistics or mathematics course where graph interpretation might be taught. The ability to comprehend and interpret graphs is influenced by an individual's familiarity with the content being graphed and their prior knowledge of mathematics and/statistics, amongst other factors (Del Puy Pérez-Echeverría, Postigo, & Marín, 2018; Glazer, 2011); this can result in variable comprehension and interpretation of the visualization and weak conceptual relation of the material when there is no formal instruction for reading a particular graphical representation (Del Puy Pérez-Echeverría et al., 2018). Addressing the challenges of graphical literacy is outside the scope of the current project; therefore, alternative visual representations will be explored.

METHODS

Materials and Measures

Based on current understanding of the literature and of the problem space this project addresses, I propose to create an interactive simulation tool that is centred on DLMRs and that contextualizes biostatistics within the CBL framework cases used for teaching other components of the undergraduate medical curriculum. However, the precise nature of the interactive multimodal tool to be designed will ultimately depend on the results of formative evaluation (see next section). The tool will be tailored to those topics in biostatistics identified as most challenging to students, to feedback provided through formative evaluation, and in consultation with the literature and existing media.

The design of the tool will be guided by both cognitive and constructivist theories of learning (Ertmer & Newby, 2008), as well as the cognitive-affective theory of learning with media (Moreno & Mayer, 2007). If deemed appropriate through initial formative assessment, the cognitive conflict theory of learning (Liu et al., 2010) may also guide design.

Target Audience

The end users of my proposed tool are first year undergraduate medical students at U of T. These students have diverse academic backgrounds and exposures to research methods and statistics. Approximately seventy-five percent of each cohort has no prior research experience, with the remaining twenty-five percent holding Master's or Doctorate degrees.

Evaluation

Thorough and extensive formative evaluations will be conducted to guide the design of this tool, including needs assessments, rapid prototyping, and usability testing.

Needs Assessments

Formal needs assessments will be conducted with the target audience and/or their proxies to determine the content to be covered by the interactive learning tool, to identify strengths and weaknesses of the current e-modules, and to gain a preliminary understanding of target audience preferences.

Needs assessments of the MD program classes of 2T0 and 2T1 will first be performed via their proxies, the 2T0 and 2T1 HSR course representatives, beginning in August 2018. Informal informational interviews will be conducted with these individuals to identify areas about which students have voiced concern, including content and teaching/learning strategies. First-year HSR course evaluation data from the 2015-2016, 2016-2017, and 2017-2018 academic years will also be reviewed and analyzed to better understand any teaching or learning challenges students have faced in the course since its introduction into the curriculum.

In addition, an exit survey completed by the MD class of 1T9 (first cohort to take HSR) will also be reviewed and analyzed to understand student perception of HSR utility following course completion (i.e., during clerkship). This data will be used to construct user personas for rapid prototyping.

If the data collected from HSR class representatives and course evaluations are insufficient, a focus group will be conducted with 10-12 consenting volunteers from the MD program class of 2T1, i.e. students who took the first year of HSR during the 2017/2018 academic year. Participants will be asked to provide feedback on any learning challenges they faced in the QRM theme of HSR, on their preferred visual representations in mathematics and statistics, and on the following aspects of the QRM biostatistics modules currently in use:

- Presentation
- Effectiveness
- Engagement
- Capacity to stimulate interest in subject matter
- Capacity to foster active learning

Rapid prototyping

Prototypes of multiple candidate tools will be created based on needs assessment and literature and media research. These prototypes will be tested, beginning in winter 2019, to determine which candidates best address the project's visual and design problems. 2T1 and 2T2 MD students will be engaged for prototype testing. Feedback obtained from the testing sessions will be used to guide the continued development of prototypes, in conjunction with the previously discussed learning and designs theories. Multiple rounds of prototype development/revision and testing/feedback will be conducted during winter 2019, enabling an iterative design process centred around the needs of the end user.

Usability testing

Advanced prototype(s) or full mock-up(s) emerging from the iterative design process will be evaluated by 2T1 and 2T2 MD students in the winter 2019. Feedback obtained from this testing will be incorporated during creation of the final products.

Procedure

The final product is intended for use within the context of U of T's HSR course and will be available in the HSR course portal hosted by the university. Upon completion, the tool will be accessible to students currently enrolled in the HSR course and to those who will enrol in the course in the future. It may also be accessible to those who have already completed the course, if they retain access to the course in the portal following course completion.

Scope

The tool will encompass either one large e-module with many parts and covering one (1) topic, i.e. the entire contents of one of the seven QRM biostatistics topics; or several smaller e-modules covering multiple disparate sub-topics from several of the seven QRM biostatistics topics. The precise content of the e-module(s) will be determined based on findings from the needs assessment.

Anticipated significance

The tool resulting from this project will provide students the opportunity for contextualized active learning, with the intended result of improved interest in, and understanding of, biostatistics; however, evaluation of these outcomes is outside the scope of the present project. Ultimately, the tool will support

U of T MD students' ability to critically assess medical literature and to appropriately apply research to real clinical scenarios.

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