The Design of Learning Analytics to Support a Knowledge Community and Inquiry Approach to Secondary Science

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ABSTRACT

This paper describes a design-based research project that investigates how learning analytics tools and approaches, applied within the context of a technology-enhanced, blended learning environment, can support a Knowledge Community and Inquiry (KCI) approach to secondary science. Acknowledging that many learning analytic tools and designs emerged from online courseware environments, which maintain a focus on individual performance and accountability, this work seeks to contribute learning analytics designs that foster more collaborative learning approaches. The proposed designs are intended for use by students and teachers to inform their orchestrational moves within the classroom, necessitating real-time data capture, intuitive user interfaces, and visual representations that can be readily interpreted and acted upon. Following an overview of existing approaches within the field, I present the design of *CKBiology*; a platform and corresponding curriculum that have been specifically designed to support a KCI approach within two sections of a Grade 12 Biology course.

Keywords

Learning analytics; computer-supported collaborative learning; secondary education; science education; biology education

1. PROJECT BACKGROUND

There is a recognized need for new forms of learning and instruction to help prepare students for a 21st century "knowledge economy" [51]. In a departure from traditional forms of instruction, which maintain an emphasis on individual achievement, several research programs have investigated a form of learning in which students work together collaboratively as a "knowledge community" to create and advance knowledge [5, 45]. Knowledge Community and Inquiry (KCI) is a pedagogical model developed in the late 2000s by Jim Slotta from the University of Toronto. The KCI model seeks to blend aspects of two theoretical traditions: *Knowledge building communities* [45], and *learning communities* [8]. In keeping with the tradition of knowledge building communities, KCI curriculum designs enable students explore big ideas and work together to create and advance knowledge within a persistent community knowledge base. However, consistent with the tradition of learning communities, KCI curricula have specific targeted learning goals, including assessable outcomes, that can be mapped to specific curricular content expectations. By blending these two theoretical perspectives, KCI curriculum designs seek to simultaneously advance knowledge at both the community level and individual level by distributing expertise within the community and establishing important "needful" collaborative relationships amongst students.

In contrast to traditional educational approaches, wherein the teacher has sole authority over the assessment of students' work, knowledge communities provide students with a greater level of agency, allowing them to "develop ways to assess their own progress and work with others to assess the community's progress" [6]. In such contexts, activity designs must include a means of "making learning processes visible and articulated" [6].

Because knowledge communities focus on both individual and collective aspects of knowledge production, learning analytics in these contexts must serve the dual function of both *measuring* and *scaffolding* learning, producing a "feedforward effect" that serves to catalyze the development of new knowledge [1, 45].

1.1 Research Problem

While several learning analytic tools and approaches have begun to emerge within K-12 blended learning environments (e.g. Blackboard Analytics, Desire2Learn Insights), these applications tend to be teacher-centric, focusing on individual student achievement and accountability rather than knowledge advancement at the collective or community level. While some researchers have begun to apply learning analytics to more social learning designs [17, 39, 47], these studies have typically developed tools and approaches that are customized for researchers, often entailing time-consuming data coding/formatting requirements, and complex visual outputs, making them impractical for classroom use by students and teachers [55]. Moreover, little work has been done to advance *formative, concurrent* and *embedded* forms of assessment [30, 53] —i.e. tools that foster agency in students by providing *real-time* support and recommendations as they engage in collaborative inquiry.

2. RESEARCH GOALS

The purpose of my doctoral research project is to investigate how the use of learning analytics within a technology-enhanced, blended learning environment can serve to inform teachers and guide students in a Knowledge Community and Inquiry (KCI) approach to secondary science. Specific research questions are:

1. How can learning analytics techniques be employed to support progress along each orchestrational plane (i.e. at the

level of the individual, small group, and whole knowledge community)?
2. What are the orchestrational demands of a KCI script and how can these be successfully accommodated within the activity system of the classroom?
3. What forms of information and visualizations allow the students and teacher to perceive a sense of progress (or gaps in progress) within the knowledge community?

3. CURRENT KNOWLEDGE AND EXISTING APPROACHES

Because of its early applications in online courseware environments, which typically embrace a knowledge-transmission model of pedagogy, initial LA research maintained a focus on assessment at the level of individual learners, emphasizing individual achievement [2, 28]. However, recent advances in computer-supported collaborative learning (CSCL) have given rise to a subset of LA, sometimes referred to as *social learning analytics*, that is more closely aligned with constructivist and social-constructivist paradigms. Two examples of social LA approaches—*social network analysis (SNA)* and *discourse analysis*—are elaborated below. It should be noted that both of these approaches have long traditions of research that began well before the emergence of LA [37, 50]. However, the rise of online learning environments and electronic data mining techniques have made the processes of data collection and analysis substantially less arduous compared to previous methods (e.g. post-hoc interviews, ethnographic observations, video content analysis).

3.1 Social Network Analysis

A social network consists of *actors* (e.g. individual students) and a set of dyadic *ties* between these actors, such as communicative interactions. The ties between actors can be classified as *strong* or *weak*, depending on their frequency, quality, or importance [23]. A visual representation of a social network, called a *sociograph*, provides an opportunity to identify potential relational patterns among actors and groups of actors within the network [20]. Such patterns can be used to understand things such as group cohesion and effectiveness [26], or how students' communication behaviour changes over time [21]. The position of an actor within a social network is also of interest to researchers. For example, the position a student occupies within a social network may be used to identify his/her role in co-constructing knowledge as well as his/her perceived sense of belonging within a community [14].

Positions within a social network are described by measures of *centrality*, which illustrate "how well positioned an individual is to receive and disseminate information" [21]. For example, *betweenness centrality* is a measure of the frequency of shortest paths that exist between pairs of actors [39]. Those with high betweenness centrality are referred to as *brokers* because they have a high degree of control over the flow of information and resources to other actors in the network [14, 32]. Brokers serve to bridge knowledge across groups (or *clusters*), engage diverse information, and are responsible for the spread of new ideas and behaviours within the community [9]. *Closeness centrality* refers to how close an actor is to all other actors in a network using the shortest possible paths [39]. Actors with high closeness centrality are considered *specialists*, who strengthen connections and foster relationships within a cluster, gaining advantage through improved expertise [9]. Finally, *degree centrality* refers to the number of direct connections an actor has with other actors in the network. Because of their many connections, actors with high degree centrality are considered "popular" within a network, serving the role of information *hubs* [42]. Caroline Haythornthwaite has identified five principles that serve to guide researchers in their examination of social networks [22]:

1. *Cohesion*, which groups actors according to strong common relationships with each other
2. *Structural equivalence*, which groups actors according to similarity in relations with others
3. *Prominence*, which identifies actors that are considered "in charge"
4. *Range*, which indicates the extent of an actor's network, and
5. *Brokerage*, which indicates connections that bridge an actor to other clusters within a network

Using these principles, SNA researchers can explore various properties of social networks, including *relational* properties (e.g. how cohesive the group is, or what subgroups of interconnected actors exist), and *positional* properties (e.g. the roles and positions actors occupy within a network) [22].

3.2 Discourse Analysis

Within a knowledge community, language serves as critical mediator of knowledge construction and is a fundamental component of inquiry [18, 25]. Discourse analysis refers to the language that occurs in specific contexts, including the connections among and across sentences that follow one another [19]. Research has shown that students can achieve greater levels of understanding when they engage in complex discourse activities, such as asking thought-provoking questions [27], elaborating on content [56], providing explanations of concepts [12], negotiating discrepancies in knowledge [41], and modeling the cognitive states of others [44].

Discourse analytic approaches draw upon work in *exploratory dialogue* [35], *latent semantic analysis* [29], and *computer-supported argumentation* [46]. These methods can be employed to study which aspects of a topic learners are focusing on, which viewpoints they adopt, how topics are distributed within a community, and how students react to varying ideas and contributions [17]. Discourse analytic approaches have been used to generate models that can predict students' final course grades based on the content of online discussion posts [36], to design automated agents capable of scaffolding more effective collaboration [34], and to develop tools for instructors to help facilitate collaborative interactions [33].

3.3 Learning Analytics in Knowledge Building Environments

One of the theoretical perspectives upon which the KCI model was founded is *Knowledge Building* (KB) [45]. A *Knowledge Building Community* is one in which the shared aim of the community is to collectively advance its knowledge [45]. Here, members share collective responsibility for knowledge advancement and are honoured more for the contributions they make to towards advancing the state of knowledge within the community than for the knowledge that they keep within their own heads [58]. Scardamalia and Bereiter have developed a software environment called Knowledge Forum (KF) with the specific aim to support the underlying principles of knowledge building [45].

Research on learning analytics within knowledge building environments began in the late 1990s with the development of the Knowledge Forum Analytic Toolkit [10] and Vocabulary Analyzer tool [24]. The Analytic Toolkit provided a basic description of Knowledge Forum database usage, including metrics such as the number of notes written and read, the number of revisions made, and the number and type of scaffolds used [10]. The Vocabulary Analyzer tool tracked vocabulary development over time by identifying when new words were introduced into a KF database, and traced the uptake of these words within the KB community [24]. Other analytic tools that have been developed to assess KB activities include the Knowledge Building Discourse Explorer (KBDeX) [40], the Knowledge Space Visualizer (KSV) [52], the Promising Ideas tool [11], the Epistemic Discourse Moves Tool [42], and the Comparative Word Cloud tool [42]. These recent advances have emphasized the importance of assessments that provide *concurrent*, *embedded* and *transformative* supports for KB [53]. My dissertation research builds upon this work, situating similar forms of analytics within a more scripted KCI approach.

4. NEW SOLUTIONS

A central challenge in LA research is to incorporate the process of interpreting and responding to analytic information within the flow of curricular activities. Wise & Vytasek have defined a *learning analytics implementation design* as "the purposeful framing of the human processes involved in taking up and using analytic tools, data, and reports as part of an educational endeavor" [57]. LA implementation designs are concerned with questions such as: (1) At what points, and with what frequency, during the learning process should LA be consulted? (2) Who should have access to particular kinds of LA? (3) *Why* are these LA being consulted (i.e. what kinds of questions do they serve to answer?) and (4) What is the context for interpreting and acting upon the information provided by the LA? [57].

Consideration for these questions can be incorporated into a curricular *script,* which specifies how and when to constrain particular interactions, the sequence in which activities take place, and the roles and responsibilities of individuals within the knowledge community [16, 54]. Scripting can also support "designed moments" of student reflection as well as opportunities for collaboration and communication with others in the knowledge community [31, 38, 54].

Whereas scripting refers to the structuring of activities before they are run, *orchestration* refers to the process of executing a curricular script once an activity has already begun [49, 54]. As described previously, the efforts of a knowledge community require assessment procedures that consider individual (I), small group (G) and whole class (C) achievements. Therefore, of importance to this work is Dillenbourg's notion of *orchestrational planes*, which refers to the activities that occur at each IGC level [15]. Because information generated from each orchestrational plane will influence the activities, materials, and interactions that occur in another, it will be important to consider the design of technology supports to facilitate these transitions.

5. METHODOLOGY

This project employs a design-based research (DBR) methodology—an approach that has been widely used in the learning sciences to support the creation and development of innovative learning environments through the parallel processes of design, evaluation, and theory-building [7, 13]. DBR is a suitable methodology for my research because it will support the iterative design and improvement of both the learning analytics technology elements and curriculum materials while also contributing to the testing and refinement of the underlying Knowledge Community and Inquiry theoretical model. Beyond merely understanding the usability or feasibility of new educational technologies, DBR researchers seek to understand *how* these technologies can be productively embedded into educational systems (e.g., curriculum designs, activity structures, pedagogical practices) [3] as well as the relative *improvability* of these designs within such systems [4]. Accordingly, the specific methods employed by DBR researchers are, by necessity, quite diverse [3].

5.1 Research Context and Participants

The effectiveness of any research that is situated within a real classroom context is critically dependent upon the classroom teacher's understanding and enactment of the designed approaches and materials [48]. As such, researchers in the learning sciences have developed a collaborative approach to the design of educational innovations that "fit" within the context of real-world classrooms [43]. The co-design approach engages teachers as active participants in the design process, positioning them as professional contributors to an interdisciplinary co-design team [13]. Roschelle, Penuel, and Shechtman define co-design as "a highly-facilitated, team-based process in which teachers, researchers, and developers work together in defined roles to design an educational innovation, realize the design in one or more prototypes, and evaluate each prototype's significance for addressing a concrete educational need" [43].

My research is being conducted within a university laboratory school in a large urban area, where I have established a co-design partnership a high school biology teacher who is a veteran of collaborative inquiry approaches and has participated in prior KCI studies. Data collection will take place within two sections of a Grade 12 Biology course during the 2016-2017 academic year (n=29). There will be a total of five design iterations—one per curricular unit—each lasting approximately 4-6 weeks in duration.

5.2 Data sources

Sources of data will consist of the following:

- Co-design meeting minutes and lesson planning documents
- Researcher field notes of classroom observations
- Audio and video recordings of classroom enactment
- Data log files
- Surveys (e.g. group efficacy and cohesiveness questionnaire)
- Semi-structured interviews with the teacher and student participants

5.3 Approach to Analysis

For each design cycle, findings from the above-mentioned data sources will be synthesized into design recommendations to be incorporated into subsequent iterations of the KCI curriculum and related analytic tools/processes. For example, researcher field notes and the audio/video footage collected at the time of enactment may reveal moments in the script where students are "stuck," suggesting potential opportunities for an analytic process to intervene. The student and teacher interviews may reveal changes in experience/satisfaction from one design iteration to the next, suggesting design features that are productive in this context or, conversely, design features that are in need of revision. Data from the technology log files may reveal moments in the script when analytic tools are not referenced or used, indicating features that may be extraneous to the design or which may require additional training or pedagogical support. The outcome of this research will be a KCI curriculum script with embedded analytic tools/processes, as well as a corresponding set of design principles and recommendations for future design iterations.

6. CURRENT STATUS OF THE DESIGN

At the time of writing, students are using the first iteration of our *CKBiology* platform design, and we are currently preparing the second design iteration which will be run in the classroom at the end of November. Screenshots of the current design are provided in Appendix A.

In essence, students work together to populate a shared community knowledge base over the course of the unit. After each lesson within the unit, students are assigned three types of tasks to complete for homework: (1) Explaining a term or concept, (2) identifying the relationship between two terms or concepts, and (3) vetting explanations that others in the knowledge community have submitted. For each of these lessons, students are shown two progress bars; one representing their own progress on their assigned tasks, and another representing the progress of the whole knowledge community.

At the end of every unit, students complete an in-class review activity wherein they contribute knowledge individually, negotiate this knowledge in small groups, and improve upon this knowledge as a whole class. I am currently exploring potential group-level processes that may best be supported by learning analytic interventions, and considering the ways to best represent these processes to students and the teacher. I am also in the process of designing a teacher dashboard to facilitate orchestrational moves within the classroom (e.g. forming student groups and distributing resources).

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