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Abstract

In online learning, the most widely used model which outlines students' learning experience is the community of inquiry (CoI) model. Central to the CoI model is the construct of cognitive presence, which focuses on students' development of critical and deep thinking skills and is essential for the attainment of learning outcomes.

Given the latent nature of cognitive presence, there are significant challenges related to its assessment, which currently requires manual coding of online discussion transcripts or reliance on self-reported measures using survey instruments. In this paper, we present a novel model for assessing students' development of cognitive presence using automated learning analytics techniques. Building on the foundations of evidence-centered design, we developed a flexible model for assessing students' cognitive presence based on educational trace data that can be used in variety of learning contexts (e.g., traditional for-credit online courses, massive open online courses, and blended courses). We used the model to develop two analytics systems for real-time monitoring of cognitive presence development and for delivering valuable feedback for instructors, enabling them to use different instructional interventions during a course.

Introduction

Over the course of history, technology has been redefining almost all aspects of human life (Siemens, 2005). The development of communication technologies and the availability of large amounts of digital information have brought important changes to education. Modern education is becoming extensively reliant on digital technologies, with learning management systems (LMS) redefining on-campus learning in the last 15–20 years. Similarly, more and more K–12 institutions and corporations have adopted novel technologies as a way of enhancing the learning and training experience.

Whereas technology has dramatically changed on-campus course delivery, it has created a true revolution in online and distance education, which is becoming an increasingly important mode of education delivery (Vaughan, Cleveland-Innes, & Garrison, 2013). Recent reports (GSV Advisor, 2012) have shown that in the Fall 2010 term, 6.1 million US-based higher education students were enrolled in at least one online course, and those numbers have only been rising since then. The development of massive open online courses (MOOCs)—available free to millions of students—was a global phenomenon in education and attracted significant attention from business (Friedman, 2012), academia (Gaševi, Kovanovi, Joksimovi, & Siemens 2014), and the general public (Kovanovi, Joksimovi, Gaševi, Siemens, & Hatala, 2015d).

Along with the introduction of modern educational technologies has been an increased interest in the development of critical and deep thinking skills. Although critical thinking has long been considered as the primary goal of education by some (e.g., Dewey, 1910), it has been attracting more attention only since the 1980s. In more recent times, critical thinking has been recognized as one of the core 21st-century skills—alongside creativity, collaboration, and communication—necessary to work in the global economy (Trilling & Fadel, 2009).

One of the widely used approaches for the development of critical thinking skills is inquiry-based learning. Rather than presenting already established facts and information in a smooth path, inquiry-based learning begins with a question, problem, or scenario. Knowledge is built through the interaction between students and the learning materials as well as with other students and instructors. It is a foundational pedagogical tool behind social-constructivist approaches to learning (Anderson & Dron, 2010) which focus on knowledge (co)-construction between learners.

In the context of online learning, one pedagogical framework that focuses on the development of critical thinking skills is the Community of Inquiry (CoI) model (Garrison, Anderson, & Archer, 1999). This model outlines three main constructs—known as *presences*—that shape students' overall online learning in communities of inquiry. *Cognitive presence* is the central construct of the CoI model and represents the operationalization of critical thinking development within an inquiry-based learning context (Garrison,

Anderson, & Archer, 2001). Although cognitive presence has been recognized as important in student learning outcomes, assessing it is challenging, primarily because of its latent nature (Akyol & Garrison, 2011b). Also, the physical separation between course participants in online learning adds a layer of separation between observed behavior and the constructs of interest (Kearns, 2012). One potential approach for objective measuring of student learning and cognitive presence is through the use of fine-grained data collected by the educational technology (Shaffer et al., 2009). The field of learning analytics focuses on the utilization of this rich source of data for improvement of student learning outcomes and the learning experience (Baker & Siemens, 2013).

In this paper, we present a novel assessment model of students' cognitive presence based on the automated methods and techniques of learning analytics. The assessment model was built using the evidence-centered design framework (Mislevy, Almond, & Lukas, 2003) and was designed to collect, measure, and evaluate levels of student cognitive presence. We developed the model using several learning analytics methods, as explained in detail here.

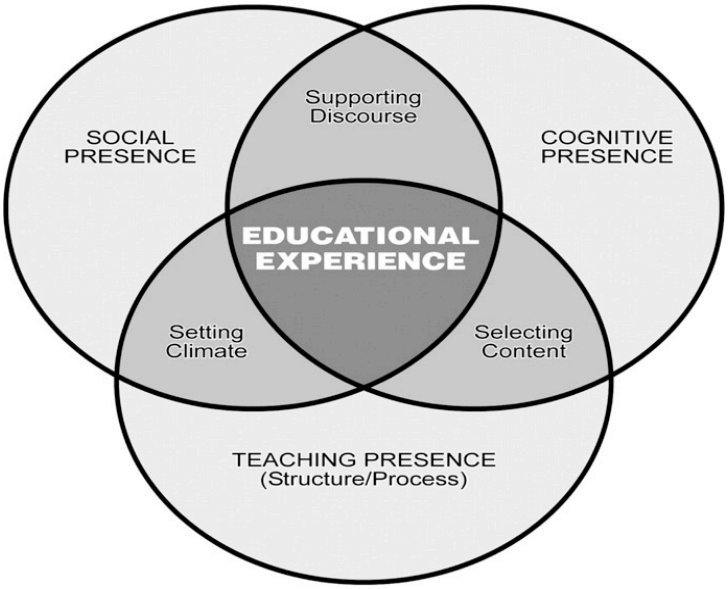
Community of Inquiry Model

Overview

Communities of inquiry is a theoretical model that describes different dimensions that form educational experience in online learning and defines a technique for assessing the quality of the educational experience. It is based on social-constructivist ideas and is best suited for learning in higher education (Garrison et al., 1999). The CoI model attracted much attention in the research community, resulting in a significant number of replication studies (Garrison, Anderson, & Archer, 2010).The model consists of three interdependent constructs (Figure 1) that together provide comprehensive coverage of distance learning phenomena:

- *Social presence* describes the relationships and social climate in a learning community that have a significant impact on success and quality of social learning (Rourke, Anderson, Garrison, & Archer, 1999).
- *Cognitive presence* describes the different phases of students' cognitive engagement and the process of knowledge construction and development of deep thinking (Garrison et al., 2001).
- *Teaching presence* explains the instructional role during the process of social learning (Anderson, Rourke, Garrison, & Archer, 2001).

Figure 1. Community of inquiry (CoI) model

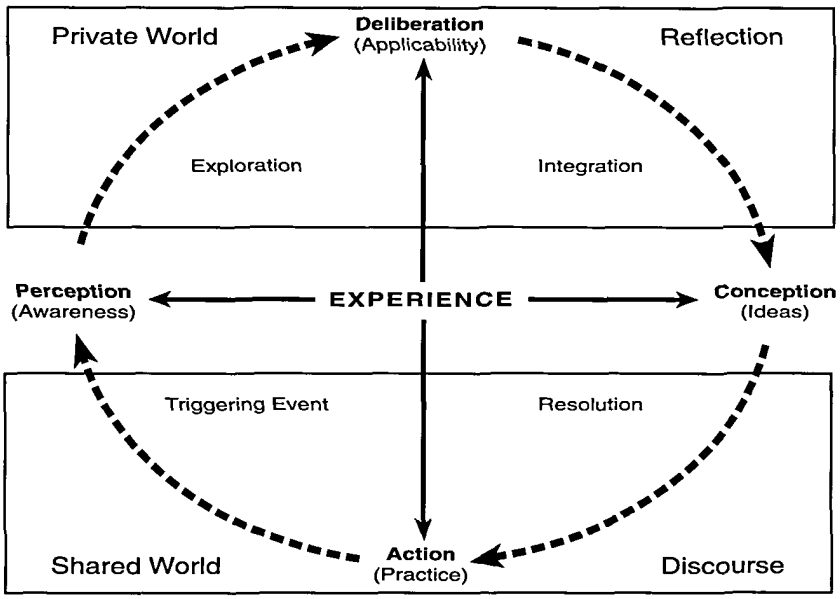


With its broad adoption in online learning, the CoI model has been used in a variety of settings that do not necessarily fall under the category of inquiry based (Garrison et al., 2010). Because the CoI model defines critical dimensions of the online learning experience, it can be used to understand and research a range of settings, including blended, lifelong, and workplace learning (Garrison et al., 2010). Likewise, the model was used as a framework for the evaluation of the different pedagogical approaches in distance and online education (Anderson & Dron, 2010).

Cognitive Presence

Cognitive presence, as defined by Garrison et al. (1999), is the “extent to which the participants in any particular configuration of a community of inquiry are able to construct meaning through sustained communication” (p. 89). It is grounded in the critical-thinking literature, most notably in the works of John Dewey and his idea that education has two sides, psychological and social, and that education is, in essence, a collaborative reconstruction of experience (Garrison et al., 1999). Cognitive presence in the CoI model is operationalized by the practical inquiry model (Garrison et al., 2001).

Figure 2. Practical inquiry model of cognitive presence



In the model, there is a clear distinction between the private (individual) world of reflective thinking and the shared (social) world of discourse and discussion, both of which are required for the development of critical thinking skills. Through dimensions of *action-deliberation* and *perception-conception*, the model defines four phases of cognitive presence:

- **Triggering event** in which an issue, dilemma, or problem is identified. In formal education, such triggers are often explicitly defined by the instructors, but any student who participates in the discussion can also do so (Garrison et al., 2001). This phase is called triggering event as it "triggers" the cycle of learning when a problem or issue regarding the practical application of knowledge is identified, which leads to the dilemma and awareness of that problem. For the quality of the learning process, the instructor has a major role in initiating or modifying triggering events and sometimes even discarding distracting ones to lead students to the desired learning outcomes. The discourse is occurring in the shared world and is the main way that students develop awareness of the dilemma or problem.
- **Exploration**, in which students are constantly moving between the private world of critical reflection and the shared world of discourse (Garrison et al., 2001). At the start of the phase, students should understand the basic nature of the problem and then move to a fuller exploration of the relevant information. As the students gain more knowledgeable at the end of this phase,

they also become more selective about the ideas that are relevant, which leads them to synthesis and integration of the explored ideas.

- **Integration**, characterized by the synthesis of the ideas that were generated in the exploration phase and ultimately by the construction of meaning (Garrison et al., 2001). This phase is, unfortunately, the hardest one to detect from the content of discourse transcripts. In general, students will tend to stay in the more "comfortable" phase of exploration, so a strong teacher presence is essential to guide critical thinking into more advanced stages through probing questions, comments, and diagnosis of misconceptions (Garrison et al., 2001).
- **Resolution**, in which the dilemma or problem is resolved by the means of direct or vicarious action (Garrison et al., 2001). In general, this is accomplished through hypothesis testing and implementation of the proposed solution. In the typical learning context, however, resolution usually involves vicarious testing through thought experiments or through building a consensus in the community as practical implementation is not feasible. The outcome of this phase is the knowledge that students are assumed to have acquired that will enable them to move to the next cycle with the triggering of the new issue, dilemma, or problem.

Overall, the cognitive presence model allows for assessment of the development of critical thinking over time within the group dynamics of communities of inquiry. The focus is on the evaluation of the *process*, and not the *product* of critical thinking, as this is much more important from the standpoint of cognitive development within communities of inquiry (Garrison et al., 2001). Instead of looking at the correctness, logic, depth, and other aspects of the products of critical thinking, the quality of the process is judged through participants' interactions. As summarized by Garrison et al. (2001), the essential characteristic of communities of inquiry is that "members question one another, demand reasons for beliefs, and point out consequences of each other's ideas—thus creating a self-judging community when adequate levels of social, cognitive, and teacher presence are evident" (p. 12).

Assessment of Cognitive Presence

Quantitative Content Analysis Approach

In the CoI model, the primary approach for assessing the three presences is qualitative content analysis, which is *"*a research technique for making replicable and valid inferences from texts (or other meaningful matter) to the contexts of their use*"* (Krippendorff, 2003, p. 18). Qualitative content analysis is a well-established research technique often used in social science research. It usually involves using a particular coding scheme for annotation of a vast number of text documents. Before starting content analysis, researchers first define *unit of analysis* (e.g., message, paragraph, sentence, clause), which is the smallest unit of text that can be annotated, and then a code is manually assigned to each unit (De Wever, Schellens, Valcke, & Van Keer, 2006; Fahy, 2001; Strijbos, Martens, Prins, & Jochems, 2006).

For assessing the levels of cognitive presence, the CoI model has a defined coding scheme with a list of descriptors and indicators of the four phases of cognitive presence (Appendix B). Also, a list of associated socio-cognitive processes for each indicator provides a broader description of the indicators. The coding scheme has been used in a significant number of studies (c.f. Garrison et al., 2010), and in most cases sufficiently high interrater agreement was obtained (i.e., Cohen's Kappa > 0.7 which represents nearly perfect agreement).

The coding scheme was successfully used in many studies of the process of development of critical thinking in distance education. However, there are many aspects of critical thinking in general, and cognitive presence in particular, that are not addressed by this coding scheme.

Survey Instrument Approach

Besides the coding instrument, the CoI self-reported instrument for measuring the levels of the three presences is also available (Arbaugh et al., 2008). The instrument enables instructors to gather data that reflect the different presences within a course. The survey consists of 34 items on a 5-point Likert scale, with items 1–13 measuring teaching presence, items 14–22 social presence, and items 23–34 cognitive presence (Appendix C).

Evidence-Centered Design and Learning Analytics

Overview of Educational Assessment

Educational assessment deals with the measurement of student learning. Gipps (1994) defined educational assessment as "a wide range of methods for evaluating pupil performance and attainment including formal testing and examinations, practical and oral assessment, classroom-based assessment carried out by teachers and portfolios" (p. vii). Assessment represents one of the central components of education and a well-established domain of educational research and practice with roots in psychology and psychometrics. Distinctions exist between different types of assessment depending on their purposes. The purpose of *formative assessment* is to provide students and instructors feedback on learning progress so as to improve the learning outcomes (Gipps, 1994). In contrast, the goal of *summative assessment* is to examine the outcomes of the learning processes and the overall level of student learning. For example, asking a student to submit an outline of a paper is a form of formative assessment, whereas assigning a final grade to the student is a form of summative assessment.

Attention to formative assessment has grown over time, with calls for more assessment *for learning* rather than assessment *of learning* for accountability and measurement purposes. The provision of timely formative feedback has been shown to be one of the best approaches for improving student learning outcomes (Yeh, 2009). According to Shute (2008), formative feedback should be "nonevaluative, supportive, timely, and specific" (p. 153). Nicol and Macfarlane-Dick (2006) listed seven guidelines defining good formative feedback:

1. "Helps clarify what good performance is (goals, criteria, expected standards),
2. Facilitates the development of self-assessment (reflection) in learning,
3. Delivers high-quality information to students about their learning,
4. Encourages teacher and peer dialogue around learning,
5. Encourages positive motivational beliefs and self-esteem,
6. Provides opportunities to close the gap between current and desired performance, and
7. Provides information to teachers that can be used to help shape teaching" (p. 205).

In the context of online and blended learning, educational technology enables development of different systems for the provision of relevant, timely formative self-, peer-, and instructor-led feedback, which in turn helps students develop their metacognitive skills and strategies (Vaughan et al., 2013). For example, quizzes, tutoring systems, practice exams, and blogging systems are often used to help students in their self-assessment of learning. Similarly, discussion boards, collaborative writing tools, and wikis are often used for peer feedback as they allow for easy asynchronous communication among the students. Finally, instructor-led feedback—aside from rubrics and summative feedback in the form of midterm and final

grades—is supported through collaborative writing tools and video conferencing, which enable instructors to provide students with comments on the quality of their learning products (Vaughan et al., 2013).

Evidence-Centered Design (ECD) Framework

Several models that outline the dimensions and elements of successful assessment have been developed (Kane & Bejar, 2014), with evidence-centered design (ECD) (Mislevy et al., 2003) being one of the more prominent and more researched. ECD is "an approach to constructing educational assessments through an evidentiary arguments" (Mislevy et al., 2003, p. i). Developed by Educational Testing Service, it is a conceptual framework designed to enhance the design and implementation of various forms of assessment, in particular, large-scale assessment (Snow, Haertel, Fulkerson, Feng, & Nichols, 2010). ECD is designed to be flexible enough to support a variety of assessment types, to be useful as a form of development checklist, and to be a tool for improving the overall quality of student assessment (Bond, 2014). According to Mislevy et al. (2003), the three fundamental premises behind ECD are:

1. "An assessment must build around the important knowledge in the domain of interest and an understanding of how that knowledge is acquired and put to use.
2. The chain of reasoning from what participants say and do in assessments to inferences about what they know, can do, or should do next, must be based on the principles of evidentiary reasoning.
3. The purpose must be the driving force behind design decisions, which reflect constraints, resources, and conditions of use" (p. 20).

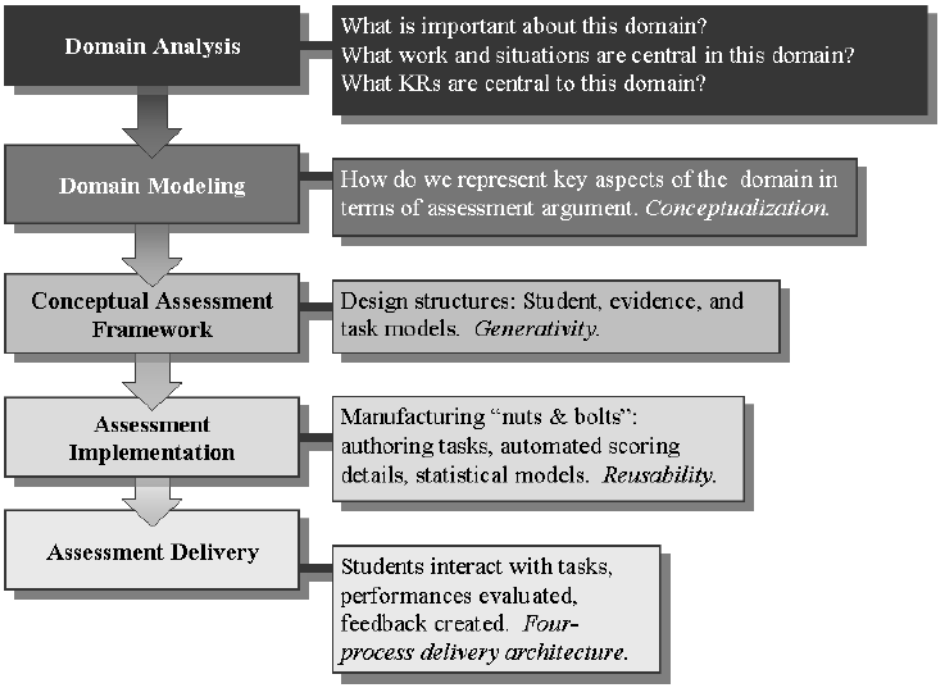
Although ECD was primarily developed for standardized test development, its generalizability and flexibility make ECD useful for a variety of assessment types, such as assessment of argumentative reading and writing skills (Deane & Song, 2014), and the solid foundation for formative feedback (Snow et al., 2010).

The ECD framework consists of five layers (Figure 3) (Mislevy, Behrens, DiCerbo, & Levy, 2012). The focus of *domain analysis* is building the understanding of a domain necessary to identify relevant constructs (e.g., knowledge, skills, tasks, activities, scenarios). *Domain modeling* builds on the identified constructs, resulting in a developed structure and identification of dependencies among them. Tangible products of domain modeling often are one or more *design patterns*, which provide the basis for specifying tangible elements of assessment design (Kane & Bejar, 2014). The third layer, *conceptual assessment framework* (CAF), outlines the critical operational elements (models) of the assessment that together coherently implement the goals of the assessment. The three core elements of the CAF framework are the

1. *Student model* (i.e., "what we measure"), which defines variables that are the target of the assessment. In our study, these were student cognitive presence and metacognition.
2. *Evidence model* (i.e., "how we measure"), which defines how we should measure the variables specified in the student model. It has two parts:
    a. *The evaluation component* provides definitions and specifications for identification and evaluation of observed variables (Mislevy et al., 2003).
    b. *Measurement model*, which provides a link between variables in student model and observed variables and their values. In the simplest form, measures of observed variables can be plain summed scores, but more complex models using Bayesian statistics or item-response theory can be defined (Mislevy et al., 2012).
3. *Task model* (i.e., "when we measure"), defines the structure of activities so that the evidence of student performance related to variables of interest can be adequately acquired (Mislevy et al., 2003).

The last two layers concern practical issues of assessment implementation and delivery. The *assessment implementation layer* focuses on the authoring of assessment tasks (or development of automated systems for their production), the specification of scoring, statistical models, model testing, estimation of model parameters, and other implementation details. Finally, *assessment delivery* defines the *four-process delivery architecture* for the actual assessment orchestration and its practical use.

Figure 3. Evidence-centered design framework (Mislevy et al., 2012)



Assessment Through Automated Learning Analytics

According to Siemens, Long, Gaševi, and Conole (2011), learning analytics is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (para. 4). It is a multidisciplinary research area that draws heavily from machine learning and data mining (Cooper, 2012) with the intention to build systems and tools that can "inform and empower instructors and learners, such as informing instructors about ways that specific students are struggling, so that the instructor can contact the learner" (Baker & Siemens, 2013, p. 4).

Although learning analytics is still a very young research field, its potential to impact educational practice and research through student assessment has been recognized (Ellis, 2013). As summarized by Ellis (2013), "Assessment analytics offers the potential for student attainment to be measured across time, in comparison with individual students' starting points (ipsative development), with their peers and/or against benchmarks or standards" (p. 663). Indeed, over time a large number of studies have investigated the use of automated analytical systems for assessment of student learning, including assessment of student essays (Dikli, 2006; Duwairi, 2006; Foltz et al., 1999), reading comprehension (Allen, Snow, & McNamara, 2015; Mintz, Stefanescu, Feng, D'Mello, & Graesser, 2014), digital literacies (Dawson & Siemens, 2014), programming skills (Blikstein, 2011), self-assigned grades (Fuentes, Romero, & Ventura, 2014), and social capital (Joksimovi, et al., 2016; Joksimovi, Gaševi, Kovanovi, Riecke, & Hatala, 2015a). Learning analytics is also used extensively to predict students' final course outcomes and to identify "at-risk" students (Ferguson, 2012).

In a similar manner, the generalizability of the ECD makes it possible to include automated elements in the assessment design (Mislevy et al., 2012), as already demonstrated by several studies (Behrens, Mislevy, Bauer, Williamson, & Levy, 2004; Rupp et al., 2012; Shaffer et al., 2009). Although ECD was originally developed for traditional multiple-choice questions, it can be used in more complex scenarios (Behrens et al., 2004) where automated data mining and learning analytics can provide richer data for more complex assessment that moves beyond traditional item scoring. Learning analytics and educational data mining can serve to identify variables indicative of the latent constructs of interest and improve the quality of the evidence used for student assessment (Mislevy et al., 2012). Finally, studies have indicated the utility of the ECD framework in developing models of formative assessment (Shute, 2004; Shute, Ventura, Bauer, & Zapata-Rivera, 2009; Snow et al., 2010).

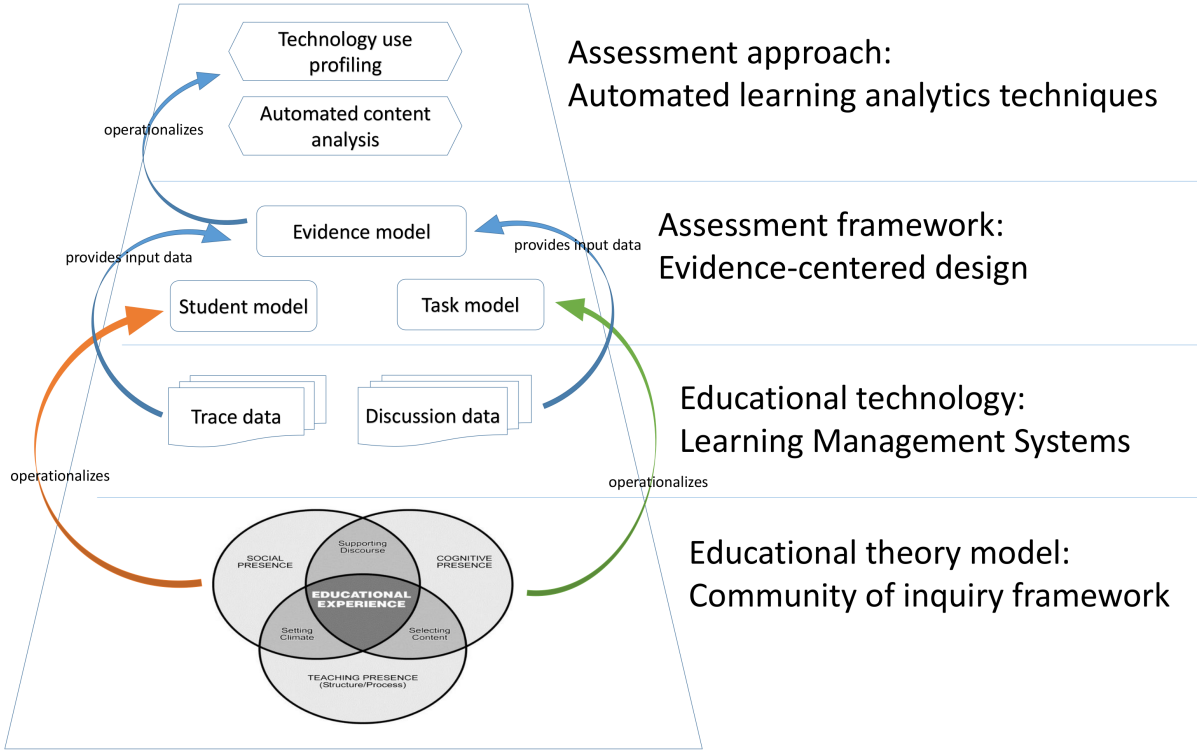
Cognitive Presence Assessment Model

Here, we describe the integral parts of the ECD-based assessment model. The model is conceptually outlined in Figure 4. The theoretical foundations of social-constructivist learning operationalized by the CoI model are at the bottom of the pyramid. Next is the technological layer, which provides input data for the particular assessment. Building on these foundations is ECD-based assessment framework layer, with student model, task model, and evidence model being the three key components. Finally, from these three models, we developed two analytical approaches, as an implementation of the described assessment model.

Student Model

The goal of student model in the ECD framework is to operationalize the knowledge, skills, or other attributes (KSAs) that are the target of the assessment (Mislevy et al., 2003). In our study, the central construct that was evaluated was student cognitive presence. Besides cognitive presence, important KSAs were students' prior domain knowledge, self-efficacy (Bandura, 1977; Shea & Bidjerano, 2010), self-regulation of learning (Butler & Winne, 1995), metacognition (Akyol & Garrison, 2011a; Azevedo & Aleven, 2013; Flavell, 1979), goal orientation (Meece, Blumenfeld, & Hoyle, 1988; Senko, Hulleman, & Harackiewicz, 2011), motivation (Ames, 1992; Deci, Vallerand, Pelletier, & Ryan, 1991; Hartnett, George, & Dron, 2011; Kizilcec & Schneider, 2015), digital literacy (Gilster, 1997), and familiarity with the available technological tools. It might be the case, for example, that a student who exhibits lower cognitive presence is facing challenges with a particular study domain or adopted learning technology. Similarly, individual differences in goal orientation and motivation will most likely be reflected in their study approaches and regulation of their learning activities (Biggs, Kember, & Leung, 2001).

Figure 4. Conceptual diagram of the framework for assessment of cognitive presence using learning analytics



Task Model

The task model defines the activities and tasks to be used to provide evidence about the constructs specified in the student model. For cognitive presence assessment—given the social-constructivist underpinning of the learning with the CoI model—there are two broad groups of activities: private-world self-reflective learning tasks and shared-world social learning tasks.

The first group consists of activities that are indicative of students' individual learning. Those include accessing course resources, taking practice exams, watching lecture recordings, and producing essays, video presentations, wiki pages, blog posts, and other types of text/video content. The list of activities in the first group will depend on the design and organization of a particular course (Gaševi, Dawson, Rogers, & Gasevic, 2016). For example, in a traditional online course, it is very unlikely that students would write blog posts, whereas in a connectivist MOOC (cMOOC) that would be a very common activity (Joksimović et al., 2015b). The particular course design choices will have an impact on the design

elements that will be included in the evidence model and subsequently provide evidence of student learning.

The second group of activities consists of students' discourse within online discussion forums. Those involve reading other students' messages and posting new messages and message replies. Given that the use of online discussions is essential for the social-constructivist pedagogies and the foundation of inquiry-based learning, online discussions and their use are the primary targets of the current content analysis approaches. The course design also plays a major role in creating rules and setting up students' expectations of their participation (Gaševi, Adesope, Joksimovi, & Kovanovi, 2015), as the mere provision of the technological affordances for online discussions in most cases is not sufficient.

Evidence Model

The evidence model provides instructions on how to gather the information about the variables described in student model from the execution of the tasks and activities defined in the task model (Mislevy et al., 2003). The *evaluation component* (also called *evaluation rules*) of the evidence model defines how identification and evaluation of the observed variables should be conducted, whereas the *measurement model* specifies the connection between student model variables and the observed variables (Mislevy et al., 2003).

In our context, the evaluation component consists of the list of observed variables extracted from the LMS trace data and online discussion data. From the LMS trace data, the primary observed variables are individual event records of student actions defined in the task model. Those include trace records of student course logins, discussion views, viewing of course resources, quiz attempts, and other events prescribed by the course design. From discussion data, the primary variables that are indicative of student model variables are discussion post contents and discussion post metadata (i.e., date and time of posting, discussion topic name, the list of previous topic messages). The evaluation component simply accumulates the list of events for a particular student, which are then used in the measurement model to define appropriate measures of student model variables.

Based on the evidence rules, the measurement model for trace data consists of two types of measures: (1) *count measures*, which provide an indication of how many times a particular action occurred for a given student, and (2) *time-on-task measures* (Kovanovi et al. 2015a, 2015b), which indicate how much *time* a student spent on a particular type of activity. Count measures included variables such as the number of logins, the number of course page views, the number of resource downloads/views, the number of discussions, and other measures related to different parts of the LMS. Most of the extracted count measures have corresponding time-on-task measures (e.g., time spent viewing course pages, time spent viewing resources). As indicated by Kovanovi et al. (2015a, 2015b), there are a small number of "instantaneous" measures that do not have a meaningful corresponding time-on-task measure (e.g.,

logging into the LMS system, running a search on the discussion data, marking a discussion as read, subscribing to the discussion updates). From online discussion data, the measurement model consisted of the different text classification features, which were extracted from the list of student online postings and its metadata. Those included (1) measures of message context and position within threaded discussion (e.g., message ordinal number in the thread, 0-1 indicator [whether the message was the first or last in the thread], similarity with the previous message), (2) large number of different linguistic measures (i.e., text cohesion, count of words in the various psychological categories), and (3) message content features (e.g., length, number of content concepts).

Empirical Validation of the Framework

The model was used in several studies to develop two different learning analytics assessments of student learning within the community of inquiry model. The study by Kovanović, Gašević, Joksimović, Hatala, and Adesope (2015c) built on the proposed model to define a student-clustering model that provided insights into students' use of the available LMS tools as an indicator of their learning regulation. The student model consisted of student cognitive presence, and the task model consisted of (1) viewing and posting to online discussions, (2) using online quizzes, (3) submitting assessments, and (4) using online course resources. The evaluation model consisted of thirteen variables from the two groups of activities, private-world and shared-world activities:

A. Private-world self-learning activities
    1. `UserLoginCount`: the number of times student logged into the system.
    2. `CourseViewCount`: the number of times student opened course information pages
    3. `AssignmentViewTime`: the time spent on course assignments
    4. `AssignmentViewCount`: the number of times student opened assignment pages
    5. `ResourceViewTime`: the time spent reading online resources
    6. `ResourceViewCount`: the number of times student opened one of the course resources
B. Shared-world discussion-related measures
    7. `ForumSearchCount`: the number of times student searched in online discussions
    8. `DiscussionViewTime`: the time spent viewing online discussions
    9. `DiscussionViewCount`: the number of times student opened online discussions
    10. `AddPostTime`: the time spent posting discussion messages
    11. `AddPostCount`: the number of discussion board messages posted by the student
    12. `UpdatePostTime`: the time spent updating discussion messages

13. `UpdatePostCount`: the number of times student updated one of his or her discussion messages.

Using the defined student, task, and evaluation model, Kovanovi et al. (2015c) developed an automated clustering system that can be used to detect study strategies indicative of student cognitive presence development. The study identified six different study strategies that differed in levels of cognitive presence development, with studies that included an online discussion component showing higher cognitive presence development than studies that focused primarily on individual learning activities.

Another study in which the proposed conceptual framework was used was the one by Kovanovi et al. (2016) on the social component of the cognitive presence development. In that case, the task model was only online discussion posting and viewing. The evaluation portion of the evidence model consisted of discussion message contents and associated metadata, whereas the measurement model consisted of 205 measures extracted from the discussion message content and metadata. Those measures included

- 108 LIWC (Linguistic Inquiry and Word Count) features (Tausczik & Pennebaker, 2010), which is a set of word counts in different linguistic categories (e.g., positive/negative emotional words, cognitive words, pronouns, social words, perceptual words)
- 205 Coh-Metrix (McNamara, Graesser, McCarthy, & Cai, 2014), which is a set of measures related to the cohesion of the written text.
- Six discussion context features—number of replies, message depth (i.e., thread ordinal position), cosine similarity with previous/next message, indicator of first/last message in the discussion thread
- Message content features—number of named entities extracted using DBPedia Spotlight (Mendes, Jakob, García-Silva, & Bizer, 2011), message length, and average Latent Semantic Analysis (LSA) similarity of message paragraphs (i.e., how similar paragraphs of a message are).

Using the set of measures, Kovanovi et al. (2016) developed a learning analytics system that can automatically detect the level of cognitive presence in each discussion message. Through automated text mining techniques, Kovanovi and colleagues developed a system that classifies each message to one of the four phases of cognitive presence, which is then used to assess the student's development of cognitive presence.

Summary and Contributions

In this paper, we presented a novel model for assessing levels of cognitive presence in communities of inquiry based on automated learning analytics techniques. Using evidence-centered design as the theoretical foundation, we developed an assessment model and a set of automated learning analytics tools that can be used to provide rich and holistic forms of assessment of students' cognitive presence development. The flexibility of the assessment model and the automated nature of the analytics tools are significant improvements over current approaches for cognitive presence assessment, and this study contributed to advancements in research on and practice with the CoI model.

Although the development of critical thinking involves both individual learning (i.e., private-world learning) and social learning (i.e., shared-world learning), the current models of assessment based on content analysis look only at cognitive presence development as expressed in transcripts of online discussions. As students' use of online learning systems involves more than just the use of online discussions, examining the LMS trace data records can provide insights into individual learning activities and learning self-regulation, which can be then used to explain the observed levels of critical thinking in the discussion transcripts.

The use of automated analytics techniques for assessment enables continuous monitoring of cognitive presence development, which instructors can use to alter their instructional approaches during a course and in turn improve student learning outcomes. Current content analysis and self-reported instruments do not allow for this type of feedback, primarily because of their high costs and invasiveness, respectively. Automation of cognitive presence assessment also opens the door for more personalized learning experiences and individually tailored instructional interventions. For example, a student's cognitive presence can be monitored with regard to different course topics or learning objectives, which can give instructors cues for what parts of the curriculum students may require additional instructional support on. At present, this is not commonly done as the existing assessment instruments are almost exclusively administered post-course and examine cognitive presence at the whole-course level.

The use of learning analytics for the assessment of cognitive presence eases adoption of the CoI model by practitioners and researchers and in a wider set of learning contexts. The existing content analysis methods are very time-consuming, expensive, and require—aside from knowledge of the CoI model—special training in the CoI coding scheme before acceptable levels of interrater agreement are reached. The use of automated methods allows for much simpler, easier, and richer monitoring of student cognitive presence development, which improves the potential adoption of CoI model by the researchers and practitioners. Automation is particularly important for settings such as MOOCs, where the particularly large number of students makes it very hard to assess cognitive presence using existing instruments. Finally, by being automated and based on tracked evidence of student activities, learning analytics

assessment models provide more objective validation of student learning, unlike transcript coding or self-reporting.

From a theoretical perspective, the developed assessment models provide further insights into the CoI model. Given the data-driven nature of developed assessment models, they provide evidence-based operationalization of the CoI constructs with data available in discussion transcripts and other types of digital traces such as clickstream data in LMSs. As the CoI model and its instruments provide very high-level conceptual descriptions of the phases of cognitive presence, automated models can be used to provide more precise data-driven operationalization of the cognitive presence construct. For example, how is a sense of puzzlement (indicative of triggering even phase) shown in discussion transcripts or trace data? Similarly, how is divergence (in a message or community), which is indicative of the exploration phase, expressed on the linguistic level? These and similar questions are implicitly answered by developing automated data-driven learning analytics assessment techniques.

Developing assessment models for constructs such as cognitive presence is a significant step toward more comprehensive models for student assessment. For a long time, there have been calls for shifting the focus of assessment from final grades and item-based testing to assessment for learning. This is especially important given the recent developments in online education, MOOCs, and the overall rise of not-for-credit learning, where there are no final grades for learners and no summative assessment in the traditional sense. Nonetheless, it is still important to provide instructors and students with (formative and summative) feedback that would improve both learning outcomes and learning experience. By means of learning analytics and assessment of cognitive presence, we made one step toward this important goal.

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Appendix A: ECD Design Pattern

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Overview	
Summary	• Cognitive presence is a central construct in the Community of Inquiry (CoI) model (Garrison et al., 1999) concerning students' development of critical thinking and deep thinking skills. • Cognitive presence is specifically related to online and distance learning, especially to the traditional learning management systems (LMS)-driven for-credit online courses. However, cognitive presence can be applied more broadly to any online learning experience. • Data sources include (1) traces collected by learning management systems and include records of the different activities that students performed as well as (2) online discussions (the content of discussion messages and their metadata).
	• Community of Inquiry model is introduced by Garrison et al. (1999), while cognitive presence is operationalized by Garrison et al. (2001)
Rationale	• Cognitive presence is the key construct in the widely used community of inquiry model of online learning, and is therefore, of a direct importance for student learning through social knowledge construction. By developing cognitive presence, students develop critical thinking and deep thinking skills, which are the key graduate skills identified by many higher education institutions and are part of the larger group of so-called "21st-century skills" that are deemed essential for success in the modern global economy.
	• The primary purpose of assessing levels of cognitive presence is to provide formative feedback to both instructors and students. From the instructor's perspective, insights into students' development of cognitive presence are crucial as they guide them in modifying and altering their instructional approach. From the students' perspective, the feedback related to the development of cognitive presence could be used to provide them with actionable real-time recommendations about how to improve their study approach. The feedback is of particular importance in massive open online courses, where a large number of students makes it hard for the instructors to intervene on the individual-student level.

Student Model	

Focal Construct	• Cognitive presence, which is defined as the "extent to which the participants in any particular configuration of a community of inquiry are able to construct meaning through sustained communication" (Garrison et al., 1999, p. 89).
	• Cognitive presence is theorized to develop through four distinct phases:
	  ○ *Triggering event*—The cycle of learning is triggered by a problem, issue, or dilemma.
	  ○ *Exploration*—Students explore, brainstorm, and collect potentially relevant information on the given problem.
	  ○ *Integration*—Students synthesize the relevant information and start building solutions.
	  ○ *Resolution*—The developed solutions are applied or tested on the original problem. This phase often triggers a new learning cycle.

Additional Knowledge, Skills, and Abilities	• Prior-knowledge • Self-efficacy • Self-regulation of learning • Metacognition • Motivation • Goal orientation • Familiarity with educational technology • Digital literacy

Task Model	

Characteristic Features of the Task	• The course should be fully online or blended/hybrid.
	• Students should be using an LMS that is recording data about their activities within the system.
	  ○ The trace data about the different learning activities (e.g., logins, page views, online quizzes)
	  ○ The content of their online discussions and associated metadata (i.e., date and time of posting, author, discussion name, whether a message is a reply or not, a "source" message if the message is a reply)

Variable Features of the Task	• Variables extracted from the tools available in learning management systems, as specified by the course design:
	  ○ Use of online quizzes
	  ○ Use of video lecture recordings
	  ○ Use of blogs/wikis
	  ○ Use of course assignment submissions
	  ○ Use of text recourses
	  ○ Use of online discussions
	  ○ The design of online discussions
	  ○ The overall course grading rubric

Potential Task Products	• Student online discussions
	  ○ Content of all messages (i.e., message text)
	  ○ Context of all messages (i.e., message position within discussions, time, date, and author information)
	• Trace data recordings of the learning management system use
	  ○ Count measures
	  ○ Time-on-task measures

Evidence Model	

Potential Observations	• The total number of times each type of activity (e.g., system log-in, course view, quiz attempt, discussion view) was executed by each student. Also, the total time spent on each type of activity available in the course.
	• The content and metadata of all student discussion messages
	  ○ Text cohesiveness metrics (i.e., Co-Metrix variables)
	  ○ Number of content-related words
	  ○ Average paragraph similarity based on latent semantic analysis
	  ○ Number of words in different psychological categories (i.e., variables of the Linguistic Inquiry and Word Count framework)
	  ○ Discussion context features (position within the thread, similarity with previous/next message, first/last message)

Potential Frameworks	• Develop an automated learning analytics system that can detect students' levels of cognitive presence based on the data gathered by LMSs.

Appendix B: Cognitive Presence Coding Scheme

The cognitive presence coding scheme, as defined by Garrison et al. (2001).

Phase	Descriptor	Indicator	Socio-cognitive process
Triggering Event	Evocative	Recognizing the problem	Presenting background information that culminates in a question
		Sense of puzzlement	Asking questions Messages that take discussion in new direction
Exploration	Inquisitive	Divergence—within the community	Unsubstantiated contradiction of previous ideas
		Divergence—within a single message	Many different ideas/themes presented in one message
		Information exchange	Personal narratives/descriptions/facts (not used as evidence to support a conclusion)
		Suggestions for consideration	Author explicitly characterizes message as exploration—e.g., “Does that seem about right?” or “Am I way off the mark?”
		Brainstorming	Adds to established points but does not systematically defend/justify/develop addition
		Leaps to conclusions	Offers unsupported opinions
Integration	Tentative	Convergence—among group members	Reference to previous message followed by substantiated agreement, e.g., “I agree because...”
		Convergence—within a single message	Justified, developed, defensible, yet tentative hypotheses
		Connecting ideas, synthesis	Integrating information from various sources—textbook, articles, personal experience
		Creating solutions	Explicit characterization of message as a solution by participant
Resolution	Committed	Vicarious application to real world	None
		Testing solutions	Coded
		Defending solutions	

Appendix C: Cognitive Presence Survey Instrument

The survey items related to cognitive presence, as defined by Arbaugh et al., (2008) are:

A. Triggering event questions:
   1) Problems posed increased my interest in course issues.
   2) Course activities piqued my curiosity.
   3) I felt motivated to explore content related questions.

B. Exploration questions:
   1) I utilized a variety of information sources to explore problems posed in this course.
   2) Brainstorming and finding relevant information helped me resolve content related questions.
   3) Online discussions were valuable in helping me appreciate different perspectives.

C. Integration questions:
   1) Combining new information helped me answer questions raised in course activities.
   2) Learning activities helped me construct explanations/solutions.
   3) Reflection on course content and discussions helped me understand fundamental concepts in this class.

D. Resolution questions:
   1) I can describe ways to test and apply the knowledge created in this course.
   2) I have developed solutions to course problems that can be applied in practice.
   3) I can apply the knowledge created in this course to my work or other non-class- related activities.

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