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A Case Study of Community of Inquiry Presences and Cognitive Load in Asynchronous Online STEM Courses

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Abstract
The design and facilitation of asynchronous online courses can have notable impacts on students related to persistence, performance, and perspectives. This case study presents current conditions for cognitive load and Community of Inquiry (CoI) presences in an asynchronous online introductory undergraduate STEM course. Researchers present the novel use of Python script to clean and organize data and a simplification of the instructional efficiency calculation for use of anonymous data. Key relationships between cognitive load and CoI presences are found through validated use of NASA-TLX instrument and transcript analysis of discussion posts. The data show that student presences are not consistent throughout a course but are consistent across sections. Instructor presences are not consistent throughout a course or across sections. The study also explored predominant factors within each presence, confirming previous reports of low cognitive presence in discussions. The highest extraneous cognitive load was reported for understanding expectations and preparing an initial post. These results provide support for improvements to course design and instructor professional development to promote Community of Inquiry and reduce extraneous cognitive load.

Keywords: Cognitive load, online courses, instructional design, community of inquiry, cognitive presence, teaching presence

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The rise in online course offerings in higher education already underway was accelerated by the COVID-19 pandemic. Withdrawal rates in online STEM courses tend to be higher than traditional courses (Wladis et al., 2012). Dimensions of persistence revealed in the literature include learner characteristics, institutional characteristics, external and environmental factors, student expectations and satisfaction, and internal personal factors (including engagement and psychological attributes) (Cochran et al., 2014; Hachey et al., 2015; Harrell & Bower, 2011; Hart, 2012; McKinney et al., 2018).

Some factors linked to persistence are within the realm of control for course designers and instructors. Specifically, attrition has been correlated to cognitive load, especially when cognitive overload (often the result of extraneous and intrinsic load) occurs early in the online course (Tyler-Smith, 2006). Extraneous cognitive load is the working memory required to interact with learning materials while intrinsic cognitive load results from the inherent difficulty of the learning task. Course designers can address elements of cognitive load when developing online course templates, including design of instructions, rubrics, and other course materials. In order to do this, though, course designers must understand where students perceive the highest extraneous load. Measuring cognitive load in asynchronous online courses is an emerging research topic.

Instructors can directly influence student persistence in online STEM courses through careful course design and strategic selection of pedagogical methods employed (Lou et al., 2006). Instructors can work to reduce cognitive load in their online courses, though their level of control over course materials may be limited based on institutional policy such as using course templates and centralizing course edits through an instructional design team. The Community of Inquiry (CoI) framework may also support persistence. The CoI framework, which encompasses teaching, social, and cognitive presences, is a well-known and widely applied theoretical framework that centers on the creation of meaningful learning through collaboration and discourse (Garrison & Arbaugh, 2007). CoI presences can be evaluated directly through transcript analysis or indirectly through self-reported perspectives. While there are understandable benefits to the direct measure, transcript analysis is time-consuming, and thus many studies rely on indirect measures. Currently, uncertain relationships exist between CoI presences and cognitive load.

Because of persistence issues in online STEM courses, it is important to investigate and establish course design and facilitation best practices. Cognitive load mitigation strategies and the Community of Inquiry framework are not discipline-specific pedagogical approaches, making them transferable across STEM courses in online learning. Careful course design can strengthen the Community of Inquiry presences while mitigating impacts to cognitive load, thus promoting persistence, performance, and satisfaction. This case study presents a picture of current conditions for cognitive load and Community of Inquiry presences in an asynchronous online introductory undergraduate STEM course. Importantly, this study seeks to establish key relationships between cognitive load and CoI presences to answer the following exploratory research questions:

1. Are student social and cognitive presences and instructor social and teaching presences consistent throughout a course (module to module) and across sections?
2. What factors predominate within each presence?
3. What tasks in asynchronous online discussions influenced cognitive load?

This study presents important information to both researchers and practitioners. As previously mentioned, transcript collection and analysis are time-intensive, complex activities. This study presents methods for the novel use of Python script to clean and organize raw discussion transcript data used in this type of analysis. Furthermore, this study presents a simplification of the instructional efficiency calculation to be used with anonymous data. Important to practitioners, researchers, and administrators, this study reports on predominant CoI presence factors and cognitive load in asynchronous discussions. The unexpected results justify further investigation regarding students' self-reported cognitive load. By understanding the classroom ecosystem through the lenses of CoI and cognitive load, we can design effective interventions aimed at improving persistence in online STEM courses.

Literature Review

Community of Inquiry

Many asynchronous online courses implement an online discussion to promote peer interactivity, nurture communication skill, and develop a sense of community. This community can be evaluated through the lens of Community of Inquiry (CoI), specifically teaching presence, social presence, and cognitive presence (deNoyelles et al., 2014). This model presents each of these presences as distinct but interrelated, whose synergy promotes an effective learning environment (Garrison & Arbaugh, 2007).

Learners and instructors project their personality into the community through social presence, with the dimensions of affective responses, interactive communication, and cohesive responses. In affective responses, learners express emotions, humor, and feelings, including the use of paralanguage like emojis, punctuation, and conspicuous capitalization (Swan & Shih, 2005). In interactive communication, learners respond to and engage with others while cohesive responses speak to the group and invite interaction (Swan & Shih, 2005). As postulated in the peer support hypothesis, strong peer connections limit isolation in e-learning and therefore may address persistence in online STEM students (E. K. Faulconer et al., 2018; Sinclair, 2017). It is important to note that the influence of social presence on persistence is debated within online education (Hart, 2012; Pattison, 2017).

Teaching presence includes design, direction, and facilitation of social and cognitive interactions in an online course, including formative and summative feedback. Furthermore, students report perceived value of strong instructor presence in online courses (Joyner et al., 2014), with studies correlating teaching presence to learner satisfaction and perceived learning (Shea & Bidjerano, 2009). Elements of teaching presence in non-STEM (Gaytan, 2015) and STEM (Hegeman, 2015) online courses have been correlated to persistence.

The construction of meaning through communication is referred to as cognitive presence. Cognitive presence is grounded in the Practical Inquiry Model (Garrison et al., 2001). The four phases of cognitive presence are triggering event (curiosity, puzzlement, or seeking clarification), exploration (stating unsubstantiated agreement/disagreement, sharing information, sharing a content-relevant personal story, or stating an opinion), integration (building onto arguments of others, drawing conclusions, presenting justified hypotheses, or presenting a supported agreement/disagreement), and resolution (synthesizing, thought experiment, or application and testing of a new thought) (Garrison & Arbaugh, 2007). Cognitive presence in asynchronous discussions tends to occur at the lower levels (triggering event or exploration) rather than at the higher levels (integration or resolution) (Y. Chen et al., 2019). Both course design and instructor facilitation of discussions can promote strong cognitive presence in asynchronous online discussions. Cognitive presence in online courses can be predicted by both social and teaching presence (Lee, 2014; Zhu, 2018). Even the teaching presence of instructors who are not course designers correlates to learner cognitive presence (Silva, 2018). Design and facilitation to promote cognitive presence has been shown to improve persistence and performance in non-STEM online courses (Ice et al., 2011; Jaggars & Xu, 2016).

Cognitive Load

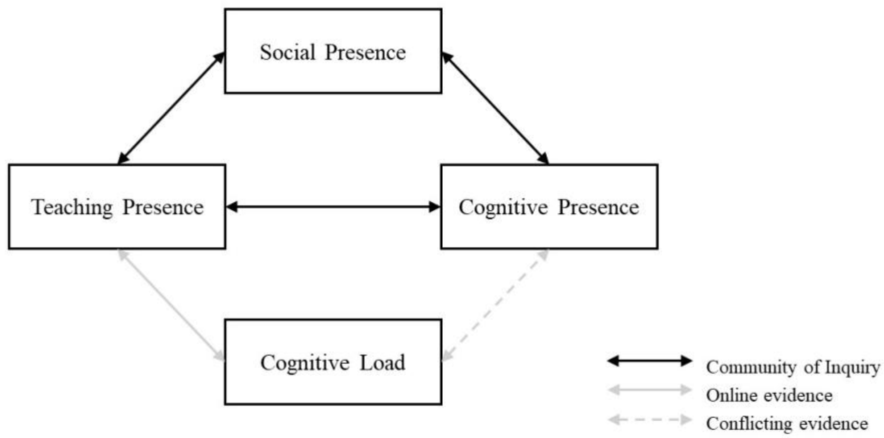
In online learning environments, as with all learning environments, tasks and activities demand working memory resources to process information. Intrinsic cognitive load is a product of mental processing necessary to understand a task and transfer new information to long-term memory. This can be due to task complexity, interactivity, and the learning environment in which the task takes place (Kalyuga, 2011; Mills, 2016). Extraneous cognitive load results from how material is presented and is not related to the learning process; extraneous cognitive load occurs when there are distractions (Kalyuga, 2011; Mills, 2016). Germane cognitive load is due to the intentional cognitive processing necessary for learning. Increasing germane load can enhance learning (Kalyuga, 2011). Intrinsic cognitive load may be expected for certain learning tasks, especially if the task or learning environment is new to the student, but it could be considered “bad” cognitive load if the task complexity results in too high of cognitive load. Germane cognitive load is “good” cognitive load as it is the effort to integrate and connect new knowledge with existing knowledge. Extraneous cognitive load is “bad” cognitive load and should be eliminated (or at least reduced) wherever possible (Kalyuga, 2011).

High cognitive load, referred to as cognitive overload, can inhibit learning by reducing the processing of new information. Cognitive overload is typically the result of extraneous and intrinsic load (Stiller & Koster, 2016). In online learning environments, cognitive overload has been correlated to attrition (Tyler-Smith, 2006) and reduced learner satisfaction (Bradford, 2011; Kozan, 2015). While the evidence is more robust in traditional STEM courses (Gillmore et al., 2015), there is preliminary evidence to support the influence of cognitive load on academic performance in online STEM courses (Stachel et al., 2013).

Relationship Between CoI and Cognitive Load

Careful course design can strengthen CoI presences while mitigating extraneous cognitive load. There is some tentative evidence of relationships between CoI presences and cognitive load. In a study of a graduate-level non-STEM online course, teaching presence reduced extraneous load (Kozan, 2015). The relationship between cognitive presence and cognitive load is uncertain, with a study in a non-STEM graduate course reporting a positive correlation (Kozan, 2015) while a study of an online STEM course reported no relationship (Mills, 2016). Further research is needed to investigate this possible relationship. No studies reported a connection between learner or instructor social presence and cognitive load. In summary, while the relationships between the Community of Inquiry presences are well explored in the literature, much less attention is given to the relationships between the CoI presences and cognitive load. A summary of the evidence for relationships between CoI Presences and Cognitive Load is provided in Figure 1.

Figure 1
Conceptual Framework for the Relationship Between CoI Presences and Cognitive Load



Material and Methods

Research Site and Course Context

The study population consists of students enrolled in an introductory undergraduate physics course and their instructors. The courses were held at a medium-sized private university located within the United States. Due to the online nature of the degree programs, students are geographically dispersed across the world.

The course was offered asynchronously online over a nine-week term, administered via Canvas, the learning management system. The institution used course templates, ensuring that across sections, students were presented with the same learning objectives, course materials, and assignments. The course template was developed via collaboration between a content expert and an instructional designer. The primary differences between sections of a course in each semester are the cohorts of learners engaged in each section and the instructor. Course instructors for this study were all contingent (adjunct) faculty.

The physics course was a survey course including topics in mechanics, heat, light, sound, electricity and magnetism, and modern physics. Topics were arranged into nine modules, one per week. Typical activities in each module were textbook reading, short problem solving and lecture videos, homework exercises (completed through the textbook publisher's platform), freely available online simulations (accessed through the same platform), discussion, two chapter quizzes, and two summative exams. There were nine discussion activities in the course, one in each module. The discussions accounted for 12% of the total course grade (1.33% each).
The discussion board activities required students to make an initial post providing a thoughtful, 500-word maximum, real-world application based on a topic from the current module. Posts that described a student's own experiences were welcomed and encouraged. Students also were required to post substantive responses to at least two peer or instructor posts. Initial discussion posts require an embedded graphic, image, video URL, or other resource.

Discussion post scoring used a rubric. Out of 100 points, 20 points were allocated to timeliness and participation, the initial post secured 35 points, the quality of the two peer responses earned 30 points, and general spelling, grammar, organization, ethics, and netiquette were addressed with the final 15 points.

Study Population and Sampling

The self-selected sample was drawn from the population (see Table 1). Census data (rather than self-selection) was used for learning management system (LMS) and institutional data. LMS data were collected confidentially, with data anonymized prior to analysis. Individual students and instructors were de-identified and given a numeric identifier. The sample for the survey data was drawn through a non-probability, self-selective sampling. Participants were recruited through initial and reminder announcements in the LMS. Survey participation was not incentivized. Survey data were collected anonymously. All data were reported in aggregate, with no individually identifying information. This study was reviewed by the Institutional Review Board and deemed “exempt” (Approval #20-114).

Table 1

Population and Sample Information

Term - Section	Enrollment (#)	Survey Respondents (#)	Response Rate (%)
June 2020	39	16*	14.0
July 2020	75		
August 2020	186	20	10.8
October 2020	181	25	13.8
November 2020	101	15	14.9
December 2020	17	2	11.8
January 2021	182	22	12.1

Note. *Survey for June/July 2020 ran simultaneously, and respondents were not distinguished.

Data Collection

This was a mixed methods study, using qualitative data (discussion transcripts) and quantitative data (survey and academic performance data). Discussion transcript collection, organization, and deidentification evolved over the first six months of the project. Initially, a research member manually copied every discussion post to a Word file, parsed each post into sentences, reviewed sentences to remove identifiers, and copied deidentified sentences into an Excel sheet. This process was extremely time-intensive and thus an expert in large-scale data analysis was brought on to the project.

The refined process used a plugin to extract the webpage discussion into a PDF file, used PDF to Word conversion software, and ran a Python script to parse the webpage conversion into sentences, deidentify the sentences, and correlate each sentence to the speaker in an Excel file. The Python script and example files are available in GitHub at https://github.com/Darryl-Chamberlain-Jr/CoI_Python_Database_Analysis. Figure 2 presents an example of a discussion transcript before and after automated cleaning is provided.

Figure 2
Example of Raw Discussion Data (a) and Outcome of Automated Cleaning (b)

Collapse Subdiscussion Full Name 1

Full Name 1
Oct 17, 2020 Oct 17, 2021 at 9:30pm

Class, Most of the material covered in Chapter 1 of the textbook was a welcome refresher from my high school physics class. The only topic that was new to me or I straight up don't remember was the information on centripetal acceleration. According to our textbook, centripetal acceleration is the acceleration of an object moving in a circular path and is always perpendicular to the object's instantaneous velocity. (Bord & Ostdiek, 2018) My favorite example is whenever I am driving my car by myself or on a roller coaster, I enjoy the feeling and force of taking turns at a good speed.

...

Reply Reply to Comment   Collapse Subdiscussion Full Name 2

Full Name 2
Oct 18, 2020 Oct 18, 2021 at 4:37pm

	A	B	C	D	E	F	G	H	I
1	Speaker ID	Analysis Unit							
2	KX5T8	Class,							
3	KX5T8	Most of the material covered in Chapter 1 of the textbook was a welcome refresher from my high school p							
4	KX5T8	The only topic that was new to me or I straight up don't remember was the information on centripetal acc							
5	KX5T8	According to our textbook, centripetal acceleration is the acceleration of an object moving in a circular path							
6	KX5T8	My favorite example is whenever I am driving my car by myself or on a roller coaster, I enjoy the feeling an							
7									

Survey data were collected using the NASA Task Load Index (NASA-TLX) instrument to measure cognitive load. This instrument is a subjective workload assessment tool. This use of the survey instrument was previously validated by the authors (Faulconer et al., 2022). The validated model established five discrete tasks involved in asynchronous online discussions: understanding expectations, crafting an initial post, reading posts from instructors and peers, creating *reply to* posts, and integrating instructor feedback. For each task, the validated model reported cognitive load associated with mental activity, time pressure, effort, and frustration. Because the subscales are independent and thus can be dropped, the validation of the model did not include the subscales of physical ability and perceived success. The surveys were administered online through Qualtrics. Academic performance was measured as final course grades as well as scores for each discussion assignment, graded through a rubric. The rubric categories include timeliness and participation, initial post, peer responses, and general requirements. Grades were reported as a percent mark from 0% to 100%. Final course grades were weighted, with discussions accounting for 12% of the overall course grade.

Data Analysis

Discussion Transcript Analysis. Discussion content generated by participants (instructors and learners) was analyzed for community of inquiry presences. To measure social presence of instructors and learners, posts were coded based on factors of affective responses (e.g. expression of emotion), interactive responses (e.g. quoting other messages), and cohesive responses (e.g. vocatives) using operational definitions for each (Hughes et al., 2007; Rourke et al., 1999). These presences were analyzed in two ways: by Presence Density and Correlation Coefficients.

Presence Density. Presence density is a common variable in measuring CoI in discussions (Baisley-Nodine et al., 2018; Darabi et al., 2011; Hughes et al., 2007; Lee, 2014; Rourke et al., 1999). Raw number of instances of a presence is skewed by the length of a message (Rourke et al., 1999). Thus, the results were analyzed by Presence Density (Equation (1) which represents the number of instances a code appears per 1000 words and is calculated by

$$PD = \frac{Subpresence(\#\ of\ sentences)}{Discussion(\#\ of\ words)} * 1000 \tag{1}$$

where the number of words in a discussion refers to the number of either student words or instructor words written in response to a particular discussion topic. Social presence density (SPD) calculated the number of instances a social code appeared per 1000 student words and has been used to report results in the literature (e.g, Hughes et al., 2007). Similarly, teaching presence of instructors and cognitive presence of learners was coded using previously reported categories (Darabi et al., 2011), with results reported as teaching presence density (TPD) and cognitive presence density (CPD). Very infrequently, learner posts were identified by instructors and researchers as having been plagiarized. Because these posts cannot accurately represent the learner's social and cognitive presence, they have been removed from the study.
Each analysis unit (sentence) from the transcripts were evaluated by 2 trained raters who received the analysis units in a spreadsheet file where they documented their codes independently, then compared codes and discussed differences. Sometimes consensus was reached while other times separate codes were logged. Table 2 displays an example of the coding. Frequency of individual and categories of codes were examined.

Table 2

Example Coding of Analysis Units from the Introductory Undergraduate Physics Course

	Coder #1		**Coder #2**	
Analysis Unit	Type of Presence	Sub-category	Type of Presence	Sub-category
For this week's discussion, I would like to talk about acceleration.	Social	SS	Social	SS
Acceleration is the rate of change of velocity.	Cognitive	IS	Cognitive	IS
The quicker we turn the corner, the greater we accelerate.	Cognitive	CL	Cognitive	CL
In aviation, the acceleration is described in unit of "Gs."	Cognitive	IS	Cognitive	IS

Cohen's kappa (Equation(2) measures the agreement between two raters for multiple categories and is calculated by

$$\kappa = \frac{n_a - n_e}{n - n_e} \qquad (2)$$

where n_a is the number of agreements between the coders, n_e is the number of agreements if codes were randomly applied, and n is the total number of items coded (Cohen, 1960). Our kappa for the October 2020 discussion transcripts is $\kappa = 0.992$, which suggests extremely high reliability between the two coders (Landis & Koch, 1977).

Correlation Coefficient. A correlation coefficient measures the strength of a relationship between two variables. To identify the trends in presence densities across modules and between sections of the discussion activities, we calculated correlation coefficients using the Excel function CORREL. We categorized correlation strengths according to (Dancey & Reidy, 2007) as presented below:
None: $|r| = 0$
Weak: $0 < |r| < 0.4$
Moderate: $0.4 \leq |r| < 0.7$
Strong: $|r| \geq 0.7$
Note the sign of the correlation corresponds to direction of the relation and does not affect the strength of the relation. If a correlation coefficient is negative, it means as one variable increases the other decreases. A positive value indicates that as one variable increases, so does the other.

Survey and Performance Data Analysis. Results from the survey measuring students' perceived cognitive load were paired with students' performance in discussions to analyze the effects of various parts of a discussion on students' perceived cognitive load through the calculation of Instructional Efficiency.

Instructional Efficiency. Instructional efficiency (Equation (3) is a measure of the effects of instructional conditions on student learning and is calculated by

$$E = \frac{1}{n}\sum_{i=1}^{n} \frac{Z_i(P_{test}) - Z_i(E_{test})}{\sqrt{2}} \qquad (3)$$

where n is the number of participants in each group, $Z_i(P_{test})$ is the standardized test performance for student i, and $Z_i(E_{test})$ is the standardized test mental effort of each cognitive factor for student i (van Gog & Paas, 2008). Essentially, Instructional Efficiency standardizes the performance and mental efforts for each student, then calculates the difference between the standardized performance and each mental effort score. In our study, $Z_i(P_{test})$ is the discussion grade per student and $Z_i(E_{test})$ is the survey responses per student. Since our data were anonymous rather than confidential, we cannot match a specific discussion grade to a survey response and thus sum all standardized discussion grades in the calculation.

As this sum is 0, the term falls out of the equation, and we are left with the Anonymous Instructional Efficiency equation (Equation (4) calculated as

$$AE = \frac{1}{n}\sum_{i=1}^{n}\frac{-Z_i(E_{test})}{\sqrt{2}} \tag{4}$$

Note the $Z_i(E_{test})$ does not sum to zero as we standardized across a task and sum for each factor within a task. A negative anonymous instructional efficiency suggests the extraneous cognitive load is higher for this item compared to others.

Results

The results section will present data addressing our research questions. The first section summarizes Community of Inquiry presence densities and corresponding correlation coefficient strengths to describe the consistency of each category of presence either between cohorts or across the modules. The second section summarizes aggregated presence densities for each category to address the identification of predominant factors within each presence. The final section presents the anonymous Instructional Efficiencies among the four tasks to address which tasks influenced cognitive load.

Consistency of Community of Inquiry Presences

Student Social Presence Density. Student interactive and cohesive subpresence densities commonly were between 10 and 15 throughout the nine modules for all four cohorts while affective subpresence density was relatively constant between 0 and 2 (see Figure 3). These patterns were weak, however, based on the weak correlation both between cohorts and between modules.

Student social presence density weakly correlates between cohorts, as seen by 67% of the Student SPD having weak correlation (see Table 3). Affective subpresence has the lowest correlation between cohorts with 100% of correlations being weak. Cohesive subpresence has the highest correlation between cohorts with 83% of cohesive subpresences being moderate. Student social presence densities weakly correlate across modules. Affective, interactive, and cohesive subpresences were weakly correlated across modules (-0.13, -0.17, and -0.38, respectively). Note the negative correlation coefficient for each subprence suggests such instances decrease as the term goes on and suggests early discussions may Have been designed to ellicit social responses from students.

Figure 3
Student Social Presence Density Throughout the Course (Cohorts 1 through 4)

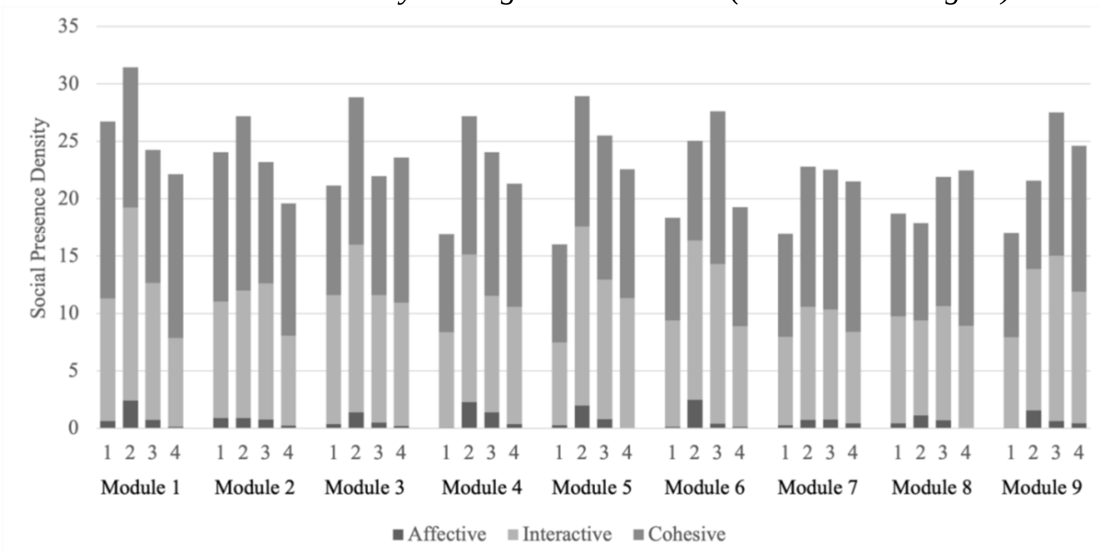


Table 3
Correlation Coefficients for Student Social Presence Density between cohorts.

Correlation Strength	Affective %	Interactive %	Cohesive %	Student SPD %
None	0%	0%	0%	0%
Weak	100%	83%	17%	67%
Moderate	0%	17%	83%	33%
Strong	0%	0%	0%	0%

Student Cognitive Presence Density. Student exploration subpresence densities showed a linear increase from 20-30 in early discussions to 30-40 in later discussions. All other cognitive subpresences had relatively constant densities between 0-10 (see Figure 4). These patterns are confirmed with the strong correlations between cohorts and especially strong correlations for the exploration subpresence. Note more than half of the correlation coefficients for all cognitive presences combined are in the moderate to strong correlation range (see Table 4). Resolution subpresence has the lowest correlation between cohorts with 83% of correlations being weak. Exploration subpresence has the highest correlation between cohorts with 83% of correlations being strong. Moreover, correlations for the subpresences across modules were strong for the exploration subpresence (0.70) and weak for triggering event, integration, and resolution subpresences ($-0.32, 0.27$ and -0.27, respectively).

Figure 4
Student Cognitive Presence Density Throughout the Course (Cohorts 1- 4)

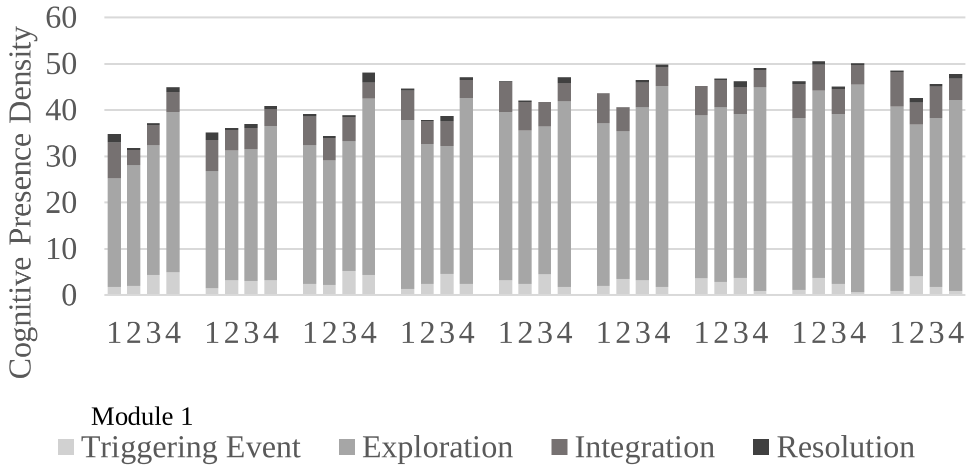


Table 4
Correlation Coefficients for Student Cognitive Presence Density

Correlation Strength	Triggering Event %	Exploration %	Integration %	Resolution %	Student CPD %
None	0%	0%	0%	0%	0%
Weak	17%	0%	33%	83%	33%
Moderate	50%	17%	50%	17%	33%
Strong	33%	83%	17%	0%	33%

Instructor Social Presence Density. In contrast to student social presence densities, instructor social presence densities do not appear correlated in any way, as each instructor had vastly different teaching densities (see Figure 5).Note 88% of the correlation coefficients for all instructor social presence combined are in the weak to no correlation range (Table 5). As with the students, affective subpresence has the lowest correlation between cohorts with 83% showing no correlation due to some instructors not illustrating any affective subpresence. Again, similar to the students, cohesive subpresence has the highest correlation between cohorts, though 83% of these correlations are weak. Correlations across modules were also weak for affective, interactive, and cohesive subpresences (0.24, −0.07, and 0.14, respectively). Note that the affective subpresence is relatively uncommon, making the rare occurrences hard to discern in the graphical representation of the data (as denoted with the asterisk*).

Figure 5
Instructor Social Presence Density Throughout the Course (Cohorts 1 – 4)

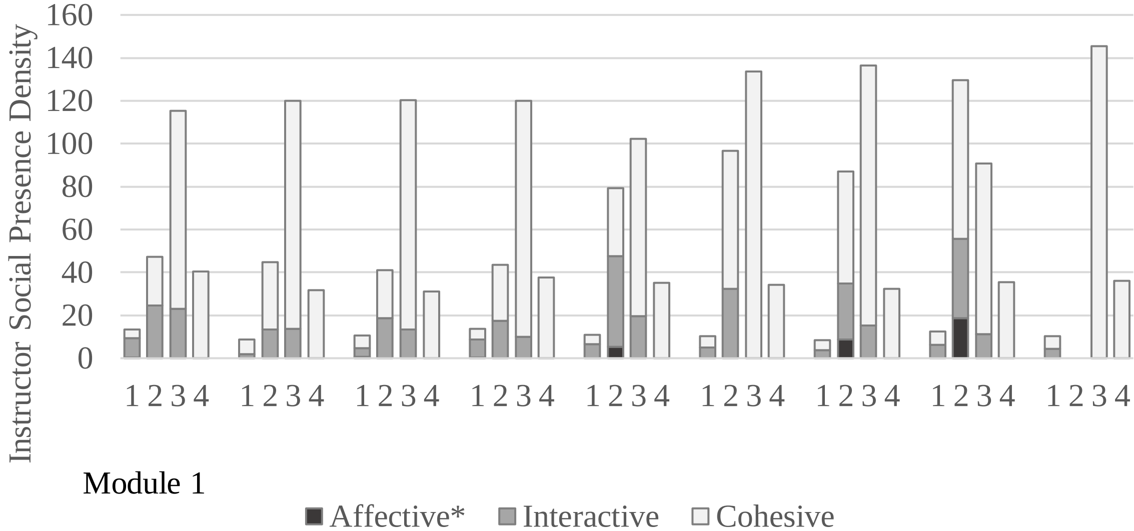


Table 5
Correlation Coefficients for Instructor Social Presence Density

Correlation Strength	Affective %	Interactive %	Cohesive %	Instructor SPD %
None	83%	50%	0%	44%
Weak	0%	50%	83%	44%
Moderate	17%	0%	17%	11%
Strong	0%	0%	0%	0%

Instructor Teaching Presence Density. Instructor teaching presence density also appears weakly correlated between cohorts and across modules (see Figure 6). Approximately three-quarters of the correlation coefficients for all teaching presences combined are in the weak to no correlation range (see Table 6). Instructor Design & Organization subpresence has the lowest correlation between cohorts with 50% showing no correlation and the other 50% showing weak correlation. Facilitating Discourse subpresence has the highest correlation between cohorts with 50% of correlations being moderate to strong. Correlation across modules is weak for Facilitating Discourse, Instructional Design & Organization, and Direct Instruction (0.23, 0.01, −0.07, respectively).

Figure 6

Instructor Teaching Presence Density Throughout the Course (Cohorts 1 – 4)

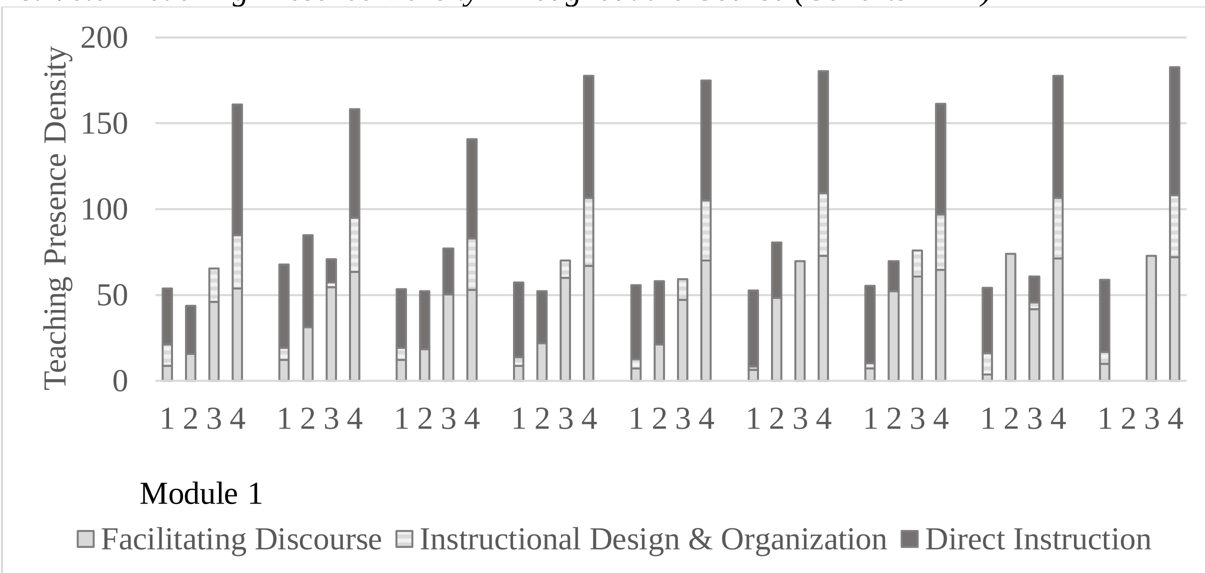


Table 6

Correlation Coefficients for Instructor Teaching Presence Density

Correlation Strength	Facilitating Discourse %	Design & Organization %	Direct Instruction %	Instructor TPD %
None	0%	50%	0%	17%
Weak	50%	50%	67%	56%
Moderate	33%	0%	17%	17%
Strong	17%	0%	17%	11%

Predominant Community of Inquiry Presence Results

Average presence density of the aggregated data for each student and instructor subpresence is presented in Table 7. Within the student presences, Information Sharing (24.98) dominates all other subpresences and is almost five times more frequent than the next two highest subpresences: Natural Expression (5.38) and Vocatives (5.10). No other social subpresences were higher than 5 instances per 1000 words. Within the instructor presences, Encouraging (21.31), Vocatives (16.01), and Clarification (13.26) predominate. Of special note is the fact that no other instructor social subpresence density beyond encouragement has density above 3 while the top five teaching subpresence densities are above 6.

Table 1
Emergence of Predominant Community of Inquiry Categories in Each Presence

Student Social Presence Density		**Instructor Social Presence Density**	
Natural Expression	5.38	Vocatives	16.01
Vocatives	5.10	Greetings and Salutation	2.72
Social Sharing	4.15	Expressing Appreciation	1.95
Expressing Appreciation	3.60	Natural Expression	1.74
Greetings and Salutation	1.11	Information Exchange	1.46

Student Cognitive Presence Density		**Instructor Teaching Presence Density**	
Information Sharing	24.98	Encouraging	21.31
Personal Narrative	3.92	Clarification	13.26
Opinion	3.91	Resource Sharing	9.78
Building On	2.77	Expectation Setting	9.09
Clarification	2.40	Questioning	6.96

Anonymous Instructional Efficiency Results

Anonymous Instructional Efficiency by cognitive factor and task are presented in Table 8. Recall that a negative anonymous instructional efficiency suggests the extraneous cognitive load is higher for this item compared to others. High extraneous cognitive load was found across all four cognitive factor subscales for the tasks "Understanding what is expected" and "Crafting your initial discussion post." Low extraneous cognitive load was found across the four cognitive factors for the tasks "Critically reading posts from your instructor and peers" and "Integrating instructor feedback into future discussion posts." Extraneous cognitive load appeared relatively neutral for the task "Creating reply to posts."

Table 8
Anonymous Instructional Efficiency by Cognitive Factor and Task

	Mental Demand	**Temporal Demand**	**Effort**	**Frustration**
Understanding what is expected	-0.169	-0.170	-0.253	-0.119
Crafting your initial discussion post	-0.263	-0.226	-0.164	-0.111
Critically reading posts from your instructor and peers	0.159	0.112	0.157	0.079
Creating reply to posts	0.052	0.058	0.045	0.001
Integrating instructor feedback into future discussion posts	0.221	0.227	0.215	0.149

Discussion

We organize the discussion around interpreting the results presented to answer our research questions sequentially. Limitations and implications are also explored in this section.

Consistency of Community of Inquiry Presences

A summary of the previously presented correlation coefficients between cohorts and across modules are presented in Table 9. Student Community of Inquiry presences (social and cognitive presences) moderately to strongly correlated across the four cohorts. This suggests future research can analyze discussion transcripts of some cohorts to understand how presences are distributed for all sections of the course in each time frame. However, student presences overall were weakly correlated across modules. This result is intuitive as the presences may be reliant on the types of tasks assigned for the discussion (i.e., the discussion prompt). Therefore, future studies should include transcript analysis for Student CoI presences in all modules within the course in the analysis, but census sampling of cohorts may not be necessary.

In contrast, Instructor Community of Inquiry presences (social and teaching presences) were weakly correlated across the four cohorts and across modules. Future research will require that every instructor discussion transcript be analyzed as there is wide variation instructor to instructor and even module to module for the same instructor. However, with a larger sample size for instructors, this should be re-evaluated. This finding highlights unique instructor approaches to facilitating discussions. This finding also underlines the potential for targeted professional development to promote stronger community of inquiry presences and reduce cognitive load through strong facilitation of asynchronous online discussions.

Table 9

Summary of Correlation Coefficient Strengths both between Cohorts (left) and across Modules (right)

Cohort Correl. Strength	St. SPD %	St. CPD %	Inst. SPD %	Inst. TPD %
None	0%	0%	44%	17%
Weak	67%	33%	44%	56%
Moderate	33%	33%	11%	17%
Strong	6%	33%	0%	11%

Module Correl. Strength	St. Soc.	St. Cog.	Inst. Soc.	Inst. Teach.
None	0	0	0	0
Weak	3	3	3	3
Moderate	0	0	0	0
Strong	0	1	0	0

Predominant Community of Inquiry Presence Factors

Understanding the predominant factors for each CoI presence provides an important baseline, especially if an instructor or course designer wishes to execute an intervention to promote a specific factor or presence. Recall this is evaluated as Presence Density, which indicates the number of instances a CoI code appears per 1000 words. Regarding student social presence densities, the factors that predominated were natural expression (5.38), vocatives (5.10), and social sharing (4.15), representing both interactive and cohesive responses. For instructor social presences, the factors that predominated were vocatives (16.01) and greetings and salutations (2.72). This suggests the emphasis on cohesive responses and less interaction. This is supported by other studies evaluating social presence density, which have found vocatives to be a large component of student posts in online discussions (Baisley-Nodine et al., 2018; Lee, 2014). Interestingly, affective responses were much less common for both students and instructors. It would be interesting to explore how important affective responses are to student perceptions of community. There is some evidence that social presence correlates with performance (Hostetter, 2013). One study also reported a positive correlation between social presence and cognitive presence (Lee, 2014).

Student cognitive presence density was highest for information sharing (24.98), which occurred much more frequently than the next two most common codes of personal narrative (3.92) and opinion (3.91). These fall into the Exploration phase of cognitive presence, which is a lower level. This means that students are sharing information with little evaluation, analysis, synthesis, or resolution. These results reflect previous work that suggest Triggering Event and Exploration would be the most prevalent without an intervention (Kovanovic et al., 2016; Lee, 2014).

Instructor teaching presences were predominantly encouraging (21.31), clarification (13.26), and resources (9.78). Encouraging falls into the category of facilitating discourse while clarification and resources both are types of direct instruction. The exploration of teaching presence density in the existing literature is scant. A dated paper reported teaching presence density for two courses, with both courses showing well over three-quarters of teaching presence codes in the direct instruction category (Anderson et al., 2001). Multiple studies report that student cognitive presence is predicted by teaching presence (Ice et al., 2011; Lee, 2014; Silva, 2018; Zhu, 2018). Social presence has also been connected to critical thinking (Rovai, 2007), which could be viewed through the lens of cognitive presence. However, our results show student cognitive presence as moderately to strongly correlated across cohorts while teaching presence was weakly correlated across instructors, suggesting that cognitive presence and teaching presence were not correlated. More instructor data are required to examine the relationship between student cognitive presence and teaching presence.

The Foundation for Designing Interventions

From this data, we can identify specific discussion design (e.g., prompt, instructions, or rubric) implications. Small discussion groups can promote closer connections and less ambiguous roles in the discussion (Akcaoglu & Lee, 2016; Qiu et al., 2014). A significant weighting for discussions in the overall course grade can spur motivation and may increase the number of posts and self-reported sense of community (Rovai, 2003). Importantly, this study confirmed that students tend to only reach lower levels of cognitive presence. Design of discussion prompts that target the highest levels of thinking (e.g., analysis, synthesis, and evaluation), those that consider

divergent (open-ended) questions, and real-world scenarios can encourage strong cognitive presence (Darabi et al., 2011; Ertmer et al., 2011; Howell et al., 2017).
Furthermore, these data provide key implications for designing professional development to promote strong Community of Inquiry presences for both instructors and students. Instructor engagement occurs on a spectrum, ranging from “ghosting” to “swamping” the discussion. Informing instructors of the benefits of moderate engagement could be a critical piece to professional development. The research shows that instructor time on task is a stronger predictor of student grades on discussions than the number of instructor posts (Cranney et al., 2011), students report a preference for active instructor engagement in discussions (Hosler & Arend, 2012), and the research suggests that a moderate amount of instructor involvement results in stronger student engagement (Aloni & Harrington, 2018; Goode et al., 2018). With this knowledge, instructors can focus their efforts on providing a moderate number of meaningful contributions that further the conversation and encourage students to reach integration and resolution, the higher levels of cognitive presence.

Instructor actions like providing formative feedback within in the discussions followed by summative feedback post-discussion demonstrates strong teaching presence and can promote learner cognitive presence (Stein et al., 2013). Additionally, instructors can use strategies like Socratic questioning to promote conceptual learning and to push students to clarify their thinking and make judgements about their reasoning, which models how to ask probing questions and reduces their reliance on the instructor for furthering the conversation (Aloni & Harrington, 2018). Instructor emphasis on areas of disagreement or misconception promotes engagement (G. Chen & Chiu, 2008). If instructors identify the level of cognitive presence demonstrated by a student, they can engage with the student to promote student demonstration of more complex thinking skills (Giacumo & Savenye, 2019). Instructor facilitation can also encourage metacognition by asking reflective questions to increase student interaction with learning objectives (Faulconer, 2017). It is important to note that instructor posts with high cognitive presence may limit student demonstration of high levels of cognitive presence (Ice et al., 2011; Jaggars & Xu, 2016).

High Cognitive Load Tasks in Asynchronous Online Discussions

Based on the anonymous instructional efficiencies, the tasks “Understanding what is expected” and “Crafting your initial discussion post” posed the highest extraneous cognitive load for students. This result confirms previously published results by the authors using the same course during a preceding time frame (Faulconer et al, 2022). For these two tasks, the highest extraneous cognitive load was associated with effort for understanding what is expected while both temporal demand and mental demand were highest for crafting the initial discussion post. Aligned with the previous study, the lowest extraneous cognitive load was reported for integrating instructor feedback. This is a very interesting finding. It is unclear why students are not experiencing cognitive load here. One might hypothesize that students do not experience cognitive load from this because they are skilled at understanding and applying feedback, so that they do not need to exert much mental effort or time and therefore experience little frustration with the task. One might also hypothesize that students do not report cognitive load here because they do not effectively perform this task but are unaware of this and therefore do not experience the associated extraneous load. One might also hypothesize that students do not report cognitive load here simply because they do not do this task. Further qualitative and quantitative exploration is warranted.

The research consistently suggests that cognitive load is an important criterion in designing high-quality online courses (Bradford, 2011; Caskurlu et al., 2021). With the highest extraneous cognitive load reported in this study falling on the tasks of understanding expectations and crafting the initial post, discussion design efforts can be focused, keeping in mind that students perceive high load for both time and mental demand for these two tasks. As with any type of educational technology tool, there is an ever-growing selection of new platforms, both free and fee based. While it may be attractive to try new tools, course designers must consider the extraneous cognitive load placed on students in learning to navigate a new tool. Aimed at the highest cognitive load area of understanding expectations, course designers can use tabs and other design features to scaffold instructions in the learning management system (Darabi et al., 2011; Darabi & Jin, 2013; Gašević et al., 2015; Kanuka et al., 2007; Mayer & Moreno, 2003). For example, “Big Picture” instructions could establish the context of the discussion assignment in the course, academic career, or professional career by emphasizing transferable skills developed in the activity and the real-world relevance. This is an area where instructors could also emphasize expectations for social and cognitive presence as well as engagement. A “Summary” tab could provide main tasks without minutia, limiting cognitive load for students who have a strong understanding of the basic expectations but want to ensure their work meets all criteria. A “Detailed Instructions” tab could provide step-by-step, explicit, encouraging instructions. This level of support could help students who are less confident in the tasks required to engage in the discussions. In this area, instructors could provide example posts that demonstrate higher levels of cognitive load or creativity. In any instruction format, course designers should apply word economy and eliminate extraneous materials where possible (Mayer & Moreno, 2003). Textual and graphical signaling cues can be used to further address extraneous load (Mayer & Moreno, 2003; Schneider et al., 2018).

Rubric design is another aspect that can address extraneous load associated with understanding expectations, ensuring that expectations within the rubric align clearly and deliberately with community and engagement expectations communicated in the instructions (Alfauzan & Tarchouna, 2017). As with other aspects of discussion design, rubrics should be evaluated for word economy and clarity (Mayer & Moreno, 2003). When deciding expectations, research suggests that the best predictor of learning is not the number of posts a student makes but the number of posts read, the time spent reading, and the time delay before responding (Goggins & Xing, 2016). Furthermore, the actual discussion prompt itself can significantly influence student engagement and achievement of higher levels of cognitive presence, as seen by the module-to-module variability in this current study.

Instructors can implement strategies to address cognitive load when facilitating discussions. In discussions, students may focus on just a few posts and miss the bigger picture, connections, and corrections of misconceptions or inaccuracies (Kwon et al., 2018). Because graphic organizers reduce cognitive load (Stull & Mayer, 2007), providing one may increase cognitive presence in future discussion posts (Kwon et al., 2018). Another strategy to reduce extraneous cognitive load when facilitating discussions is to consistently use formatting for attention guidance (Eryilmaz et al., 2012, 2015), such as using bold font and/or highlighting when asking a question for anyone to respond to. The previous suggestion to provide both formative and summative discussion feedback discussed implications for teaching presence and cognitive presence, but this could also address the cognitive load for students uncertain of expectations.

Limitations

One of the predominant limitations of this study is nonresponse error for the cognitive load measure. The cognitive load survey was not incentivized and was voluntary, which may have reduced participation. Because this study measures cognitive load, among other variables, it is reasonable to think that some students opted out of participation based on the nature of the topic. Furthermore, those who experienced the highest cognitive load may have withdrawn from the course prior to completing the research survey, thus skewing results. Similarly, another limitation of this study is the few instructors evaluated and inherent instructor variability present in discussion facilitation, grading, and feedback. Thus, the small sample size may reduce generalizability.

Another limitation of this study is a result of anonymous versus confidential data for student perceptions of cognitive load. However, the purpose of this study is to explore instructional efficiency. Future research exploring learner-level correlations between cognitive load and CoI presences and their influence on outcomes including persistence, performance, and perspectives is warranted. Furthermore, more investigation into these variables and their potential relationships in other online STEM courses is suggested. It is unknown if the instructional efficiency and hypothesized relationships are consistent throughout introductory undergraduate STEM or are more discipline specific.

Conclusions

This study provides key insights for researchers and practitioners interested in cognitive load and the Community of Inquiry framework. Of importance to researchers, this study presented key methodology for measuring CoI presences and cognitive load. First, the methodology employed here supports the use of an author-generated, open-source Python script for efficient cleaning and organization of transcript data retrieved from the LMS. Second, the instructional efficiency calculation can be applied to anonymous survey data. Furthermore, a sampling of student CoI Presence Densities can be evaluated as representative of the population, though each module must be evaluated in the cohorts of the course included in the sample.

Preliminary results indicate the instructor's Presence Densities must be evaluated as census data as there is significant variability between instructors.

Of importance to researchers and practitioners, this study reaffirms the emerging trend in the literature for cognitive presence and cognitive load. The key takeaways from the results of this study are as follows:

1. Confirming previous reports, students tend to engage in discussions at lower levels of cognitive presence.
2. Confirming the authors' previous study, discussion tasks with the highest extraneous cognitive load are understanding expectations and crafting the initial post, with high mental and temporal demand.
3. Students reported the lowest extraneous cognitive load for the task of applying instructor feedback to future discussion engagement. These findings warrant further quantitative and qualitative investigation.
4. Collectively, these results support further investigation to address the unclear relationships between Community of Inquiry and Cognitive Load.

With methodological uncertainties addressed, future researchers can more effectively explore correlations between cognitive load, CoI presences and subpresences, performance, persistence, and perspectives.

Declarations

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