Structural Framework for Interactions Between Community of Inquiry Presences, Cognitive Load, Demographics, and Grades

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Abstract: Active learning and sense of community in online classrooms have been linked to persistence, performance, and course satisfaction. A widely applied theoretical framework to describe community-building through discourse and creation of meaningful learning in a classroom is the Community of Inquiry framework, which outlines relationships between social presence, teaching presence, and cognitive presence. Speaking specifically to cognitive presence, learning demands working memory resources to process information, referred to as cognitive load. Using Structural Equation Modeling, this study proposes a structural relationship between Community of Inquiry presences, cognitive load, and learner performance in asynchronous online discussions in undergraduate STEM courses. Data collected over 9 terms with over 2000 students validate the proposed structural model. By constructing a unifying model, instructors can estimate these mental constructs that cannot be directly quantified and can lead to improved outcomes for students. Future work will include developing machine learning classification techniques to further validate the model by examining presences as they occurred in the course rather than relying on students' perception of presences.

Keywords: Community of Inquiry, Cognitive Load, Structural Equation Modeling

1. Introduction

1.1 Active Learning Online

Recent years have seen continued growth in online undergraduate course offerings, including the asynchronous online modality (*National Center for Education Statistics*, n.d.). While not all teaching strategies are transferable to the asynchronous online modality, the online learning environment offers unique options for actively engaging students. For example, active learning, which is grounded in the constructivist theories of learning, is well-established as an andragogical strategy to promote active participation in the knowledge construction. Active learning activities include group discussions, case studies, problem-based learning, role-playing, peer review, and hands-on activities. Active learning has broad support in both the traditional learning environment (Theobald et al., 2020) and the online learning environment (Berssanette & de Francisco, 2021). However, some active learning tasks are better suited for synchronous engagement while others can be modified for the asynchronous modality, typically using technology tools.

In online learning, active learning has been shown to have multiple positive impacts on students, including increased course satisfaction, stronger motivation, improved mastery of learning outcomes, and development of transferable skills like critical thinking (Berssanette & de Francisco, 2021; Rossi et al., 2021). Students report positive views regarding the use of active learning in online courses (Cole et al., 2021; Koohang et al., 2016). Active learning strategies that build community by engaging students with their peers and instructor can also help combat isolation that occurs in asynchronous online courses (Croft et al., 2010).

1.2 Online Learning Community

In the traditional classroom, active learning has been linked to improved persistence, particularly for non-traditional students (Braxton et al., 2008; Ellis, 2020; Yu et al., 2020). Similarly, active learning and community in online classrooms have been linked to persistence, performance, and course satisfaction (Armah et al., 2023; Burch, 2018; Jaggars & Xu, 2016; Joksimović et al., 2015; Moore, 2014; Sinclair, 2017; Yu et al., 2020). A widely applied theoretical framework to describe community-building through discourse and creation of meaningful learning in a classroom is the Community of Inquiry (CoI) framework, which outlines relationships between social presence, teaching presence, and cognitive presence (Garrison & Arbaugh, 2007). The CoI framework encourages socialization (peer-to-peer and student-to-instructor) and collaborative construction of meaning through asking and answering questions, applying knowledge, defending conclusions, and more. The CoI framework has been used to promote engagement and active learning in online courses (Irani & Denaro, 2020).

Social presence is the projection of the personality of learners and instructors into the community, with dimensions of affective responses (e.g. humor, expression of emotion, and use of paralanguage), interactive communication (e.g. reply to a peer or instructor), and cohesive responses (e.g. starting a new line of conversation and inviting a response) (Swan & Shih, 2005). Teaching presence spans the design, direction, and facilitation of interactions (peer-to-peer and instructor-to-learner) in a course by the instructor (Garrison & Arbaugh, 2007). Cognitive presence is the collaborative construction of meaning through discourse. Garrison contextualized the concept by describing cognitive presence as a "self-correcting process where members of the community challenge beliefs, suggest alternative perspectives for exploration, and negotiate understanding." (Garrison, 2016). Cognitive presence is operationalized through the practical inquiry model, described in four phases, with the lowest cognitive presence being triggering event (e.g. curiosity or seeking clarification), followed by exploration (e.g. stating unsubstantiated agreement/disagreement and sharing information or a content-relevant personal story) (Garrison & Arbaugh, 2007). Next is integration, which includes building onto arguments of others, drawing conclusions, presenting justified hypotheses, or presenting a supported agreement/disagreement, followed by the highest level of cognitive presence of resolution (e.g. synthesizing, thought experiment, or application and testing of a new thought) (Garrison & Arbaugh, 2007). In studies exploring cognitive presence in online discussions, students tend to demonstrate lower levels of cognitive presence (Chen et al., 2019; Faulconer, Chamberlain Jr., & Wood, 2022). The presences are positively related to each other, with each presence affecting the other (Kozan & Richardson, 2014; Lee, 2014; Zhu, 2018). Specifically, teaching presence and cognitive presence have shown strong correlations (Alharbi, 2022; Li, 2022; Maranna et al., 2022). Even the teaching presence of instructors who are not course designers correlate to learner cognitive presence (Silva, 2018).

1.3 Drawbacks of Active Learning Online

While active learning, particularly activities grounded in CoI, may improve certain learner outcomes, this influence is not universal. Active learning in online classrooms may cause anxiety in some students (England et al., 2017; Pilkington, 2018). Anxiety in higher education is modified by external factors (e.g. status as an international students), internal factors (e.g. self-esteem, social anxiety and motivation), institutional factors (e.g. teaching methodology and classroom procedures) (Eddy et al., 2015; Khoshlessan & Das, 2017; Russell & Topham, 2012). Students with higher anxiety may be less likely to persist in a course and a major (England et al., 2017). However, the anxiety induced in some students when engaging in collaborative active learning online may be more facilitative than debilitative and anxiety may decrease over time (Hilliard et al., 2020).

In online active learning activities, learning demands working memory resources to process information, referred to as cognitive load. Cognitive load can be described as intrinsic, extraneous, or germane. Intrinsic cognitive load is a result of the mental processing needed to understand a task, influenced by task complexity, interactivity, and the learning environment (Kalyuga, 2011; Mills, 2016). Extraneous cognitive load is a result of how material is presented, not the learning process, and occurs when there are distractions (Kalyuga, 2011; Mills, 2016). Germane cognitive load is the result of the intentional cognitive processing necessary for incorporating new information into schemata and transferring to long-term memory. 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).Germane cognitive load is considered "good" cognitive load. Intrinsic cognitive load is expected for learning tasks, but could be "bad" if the task complexity results in cognitive overload. Extraneous cognitive load is "bad" cognitive load and should be eliminated (or at least reduced) wherever possible (Kalyuga, 2011). Recent research suggests that teaching presence directly enhances learners' affective engagement, but also indirectly through a reduced extraneous cognitive load (Zhang et al., 2023).

Active learning has higher cognitive load, which may impact motivation, engagement, and self-regulation of learning (Deslauriers et al., 2019). 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). Cognitive load may also influence performance in online courses (Stachel et al., 2013), though this relationship is complex (Chang et al., 2017; Wang et al., 2020).Teaching presence may reduce extraneous cognitive load (Kozan, 2015). There is some evidence of a positive relationship between cognitive presence and cognitive load (Kozan, 2015), though this relationship is not reported in all studies (Mills, 2016). No studies reported a connection between learner/instructor social presence and cognitive load. Further research is needed to investigate possible relationships.

1.4 Purpose

Asynchronous online courses often use online discussions to both build community and promote active learning and can be evaluated through the lens of Community of Inquiry, with each presence as distinct but interrelated (Cho & Kim, 2013; Delaney & Betts, 2022; deNoyelles et al., 2014; Garrison, Anderson, et al., 2010; Hamann et al., 2009; Kozan & Richardson, 2014). However, some researchers have reported that student interactions in online collaborations may be superficial even when mastery of course outcomes is achieved (Chen et al., 2019; Vuopala et al., 2016). Students do value interactions with the instructor and their peers in the online classroom (Joyner et al., 2014) but may not be engaging in the discussions with socialization as a primary reason (Bolliger & Halupa, 2018).

This study focuses on the relationship between extraneous cognitive load and community of inquiry on learner performance in asynchronous online discussions in undergraduate STEM courses. A hypothesized graph of the relations between these mental constructs, along with grades and persistence, are provided in Figure 1. However, these concepts are not discipline-specific and future work will explore these correlations in additional disciplines. Understanding these relationships allows us to more effectively design and evaluate interventions. This study seeks to answer the following research questions:

1. How does the *Community of Inquiry* framework model social, cognitive, and teaching presence in our data?
    a. Does our data align with SEM models for Community of Inquiry as presented in the literature?
    b. What is the relationship between subscales in the Community of Inquiry framework?
    c. How well does our final SEM model for Community of Inquiry fit our survey data?
2. How does the *Cognitive Load* framework model various mental efforts associated with a discussion task?
    a. Does our data align with SEM models for Cognitive Load as presented in the literature?
    b. What is the relationship between subscales in the Cognitive Load framework?
    c. How well does our final SEM model for Cognitive Load fit our survey data?
3. How do Community of Inquiry, Cognitive Load, and Grades relate with one another in our data?
    a. What aspects of demographics and grades describe variances in our data?
    b. What is the relationship between Community of Inquiry, Cognitive Load, and Grades?
    c. What is the relationship between subscales of each?
    d. How well does our final SEM model fit our survey data?

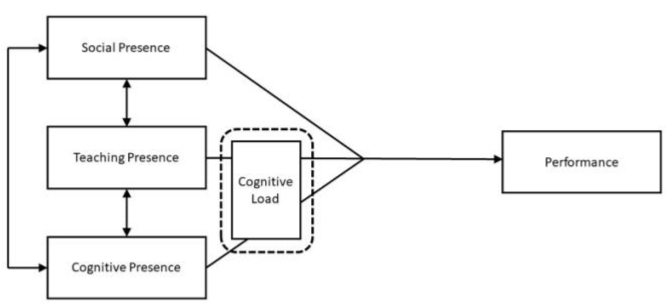

Figure 1 *Simple Hypothesized Conceptual Framework for the Relationship between CoI Presences and Cognitive Load on Student Outcomes*

2. Methods

2.1 Research Site and Course Context

The population for this study consisted of students enrolled in introductory undergraduate physics and pre-calculus courses. The courses were offered at a United States medium-sized, private (not-for-profit) university with majority undergraduate enrollment, primarily nonresidential (geographically dispersed).

The courses studied were offered asynchronously online in a 9-week term, administered using a learning management system (LMS). Course templates were used, ensuring consistency across sections including course description, learning outcomes, learning objectives, textbook, multi-media resources, and student assignments and activities. This means that the primary distinction between sections of a course are human-centered, including the instructor of record and the student cohorts. Course instructors teaching the sections used in this study were both full-time faculty (of varying ranks) and contingent (adjunct) faculty.

In both courses, the discussion activities tasked students with crafting an initial post and providing thoughtful reply posts to two or more posts (instructor or student). Student participation in this course activity were graded using a rubric. In physics, 20 of 100 points were allocated to timeliness and participation, with the initial post worth 35 points and the reply posts earning 30 points. The final 15 points addressed professionalism, including spelling, grammar, organization, ethics, and netiquette. In math, 20 of 100 points were allocated to timeliness of the initial post, content of the post earns up to 40 points, at least two replies to classmates earns up to 30 points, and the remaining 10 points are for the professional writing, including the use of the Canvas equation editor for typing mathematics. In the physics course, the nine discussion activities in the course were worth 12% of the total course grade (1.33% each) while in the math course, the nine discussion activities were worth 30% of the total course grade (3.33% each).

Participants

From the total population of students enrolled in the courses during the study time frame, the sample for survey data was determined through non-probability self-selection (Table 1). Survey participants were recruited through LMS announcements. Participation was incentivized through a $5 e-card to a common online retailer. Census data (rather than self-selection) was used for LMS data (e.g. performance).

All data was collected confidentially, with anonymization prior to analysis through de-identification and assignment of a numeric identifier. All data were reported in aggregate with no individually identifying information. The study was reviewed by the Institutional Review Board and deemed “exempt” (#21-058).

Table 1: Study Population and Sample Data.

Term	Enrollment (#)	Survey Responses (#)	Response Rate (%)
AUG 2021	274	53	19
SEP 2021	258	11	4
OCT 2021	312	41	13
NOV 2021	206	17	8
JAN 2022	331	57	17
MAY 2022	263	27	10
JUL 2022	154	8	5
AUG 2022	256	37	14
SEP 2022	148	27	18
TOTAL	**2202**	**278**	**13**

2.2 Measures

This study used a quantitative methods approach, collecting survey data using two validated surveys as well as grade data from the Learning Management System. The first survey included 33[1] of

[1] One item was missed when administering the survey due to human error.

the 34-item Community of Inquiry (CoI) instrument, which has three subscales: social, teaching, and cognitive presence (Garrison et al., 1999). Garrison's CoI instrument has been validated, demonstrating high internal consistency and reliability (Carlon et al., 2012; Garrison, Cleveland-Innes, et al., 2010; Garrison et al., 1999; Shea & Bidjerano, 2009). Shea and Bidjerano (2009) presented a Structural Equation Modeling using the 34-item CoI instrument and showing their data aligned to the three-subscale model as shown in Figure 2.

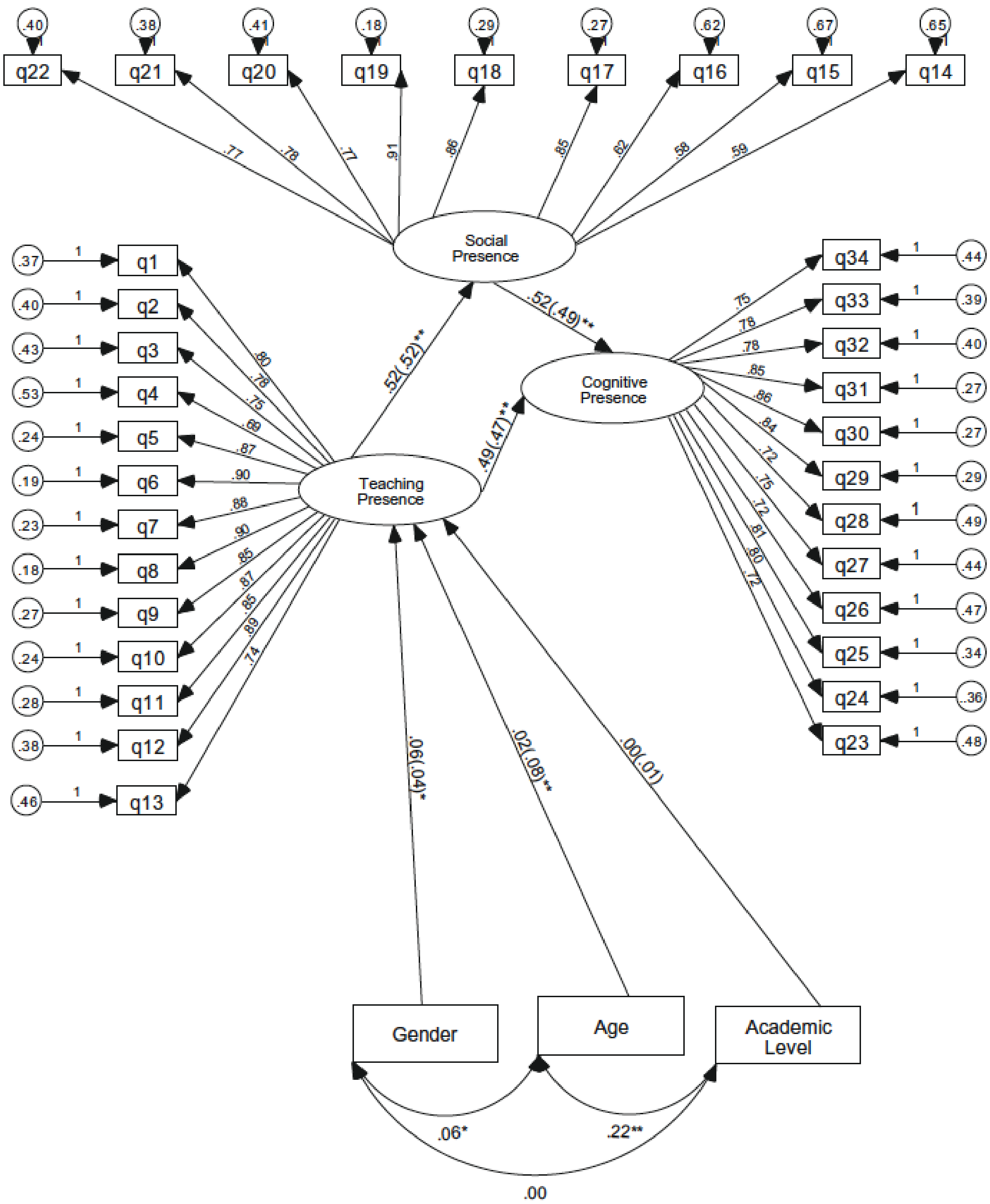

Figure 2: Structural Equation Modeling of 34-item Community of Inquiry survey instrument from Shea and Bidjerano (2009).

The second survey was the NASA Task Load Index instrument (Faulconer, Bolch, et al., 2022). The validated model for this instrument used five discrete tasks associated with engaging in asynchronous online discussions: understanding expectations, crafting an initial post, reading posts from instructors and peers, creating reply posts, and integrating instructor feedback. For each task, respondents were queried on cognitive load related to mental activity, time pressure, effort, and frustration. As illustrated in Figure 3, Confirmatory Factor Analysis (CFA) was used to verify the five discrete tasks could be considered as causal values on associated survey items about Mental Demand (MnA), Temporal Demand (TmP), Effort (Eff), and Frustration (Frs).

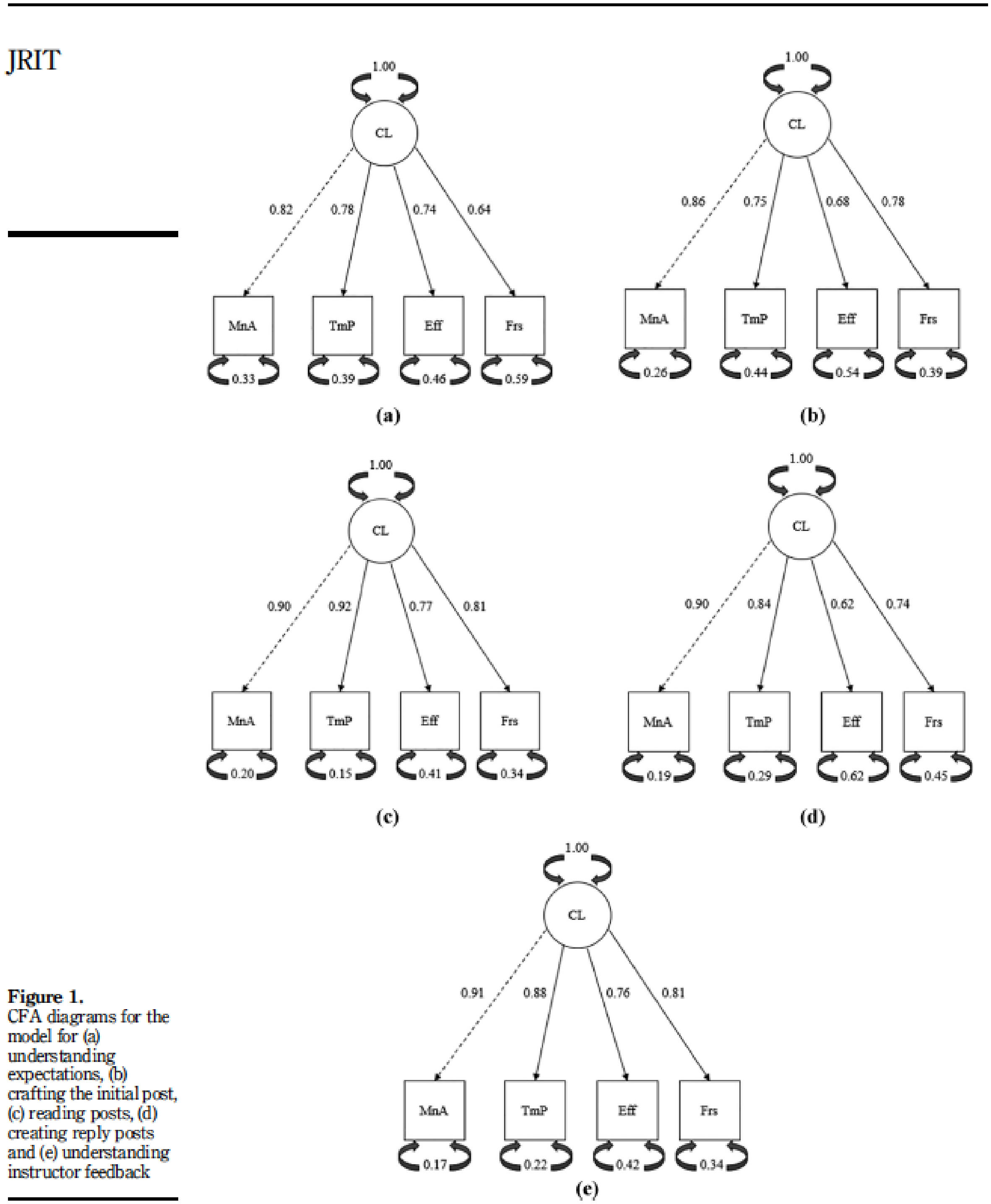

Figure 3: CFA diagrams for NASA TLX instrument from Faulconer, Bolch, and Wood (2022).

Surveys were administered through Qualtrics. Academic performance data was collected from the LMS, including final course grade and individual performance on each of the nine discussions in a course.

2.3 Data Cleaning

After combining all 9 solicitations of the combined survey instrument, we had 292 respondents. We then removed all students who:

- Declined to have their data included for the study;
- Did not provide their name for anonymous linking of their survey with course grades;
- Completed less than 75% of the survey questions; and
- Completed the survey but withdrew from the course and thus we did not have course grade data available.

The remaining 278 participants were then linked with their course grades and then anonymized. All cleaning was performed in Python and scripts can be found in the GitHub (link not provided for blind review) associated with this project.

Survey response columns were then renamed for descriptive clarity when visualizing the SEM models. Columns associated to the Community of Inquiry instrument were formatted as "*X*P_n", where *X* was either C (cognitive), S (social), or T (teaching) and the n represented the nth question of that presence type. For example, questions 14-22 in the Community of Inquiry instrument are theoretically caused by Social Presence and thus were written as SP_1 – SP_9. For the Cognitive Load instrument, abbreviations were formatted as "CL_XXX_n", where XXX was the cognitive load subscale abbreviated as: UE – Understanding Expectations, IP – Initial Post, RP – Reading Posts, RtP – Replying to Posts, and IF – Integrating Feedback, while the "n" represented a specific mental efforts: 1 – Mental Demand, 2 – Temporal Demand, 3 – Effort, 4 – Frustration. A full table for all abbreviations can be found in the Appendix.

3. Data Analysis

3.1 Structural Equation Modeling

The researchers used Structural Equation Modeling to further validate the structures of the individual instruments (Community of Inquiry instrument and the NASA-TLX). This was performed using the semopy (**S**tructural **E**quation **M**odeling **O**ptimization in **PY**thon) Python package (Meshcheryakov et al., 2021). Consider Figure 2 again. The rectangular boxes are *measurable values* related to either the survey itself (questions 1-34) or measurable aspects about each participant (gender, age, academic level). These measurable values are assumed to be caused by the *latent value* – a value that cannot be measured directly. The numbers seen on arrows from the latent value (oval) to measurable values (rectangle) are the linear regression coefficient estimates. The circles are measurement errors related to each question, which is why they are perfectly correlated to each measurable value with a regression coefficient of 1. The goal of SEM is to create a linear mixed model of regression equations that can be used to estimate latent values. Thus, for each latent value, a linear regression is developed of the form:

$$latent\ value = (m_1x_1 + e_1) + (m_2x_2 + e_2) + \cdots (m_nx_n + e_n)$$

$x_1, x_2, \ldots x_n$ are the measurable values assumed to be caused by the $latent\ value$
m_k is the estimated coefficient for measurable value x_k
e_k is the estimated error for measurable value x_k

An SEM model constructs a linear regression for each latent value based on the *researcher-supplied* assumptions on which measurable values are assumed to be caused by each latent value. These assumed relations form the *structural model* of linear regression equations. If a structural model is not known from the research literature, *Exploratory Factor Analysis* (EFA) can be performed to statistically extract the smallest number of latent values (also known as *factors*) that explain the covariance observed among the measurable values. Structural models can then be statistically tested to consider how well the model fits the data.

To evaluate the statistical fit of any SEM model, we use the evaluation metrics found in Table 2 as they are calculated through semopy and are commonly used in the literature to evaluate the statistical fit of an SEM model (Hoyle, 2012). The exact meaning and calculation of each evaluation metric is beyond the scope of this paper. However, it is important to note that numerous authors caution against hard cutoffs for evaluation metrics as model and data characteristics can affect evaluation metrics (Hoyle, 2012). For example, the number of factors, when holding all else constant, tends to decrease CFI and TLI (Kenny & McCoach, 2003). Therefore, we are willing to accept evaluation values slightly below target when the model provides a theoretically-sound structure, such as mirroring validated structural models in the literature using the same survey instrument to collect data.

Evaluation Metric	Abbreviation	Target	Literature
Root Mean Square Error of Approximation	RMSEA	< 0.10	(MacCallum et al., 1996)
Comparative Fit Index	CFI	> 0.90	(Bentler & Bonett, 1980)
Goodness of Fit Index	GFI	> 0.90	(Bentler & Bonett, 1980)
Tucker Lewis Index	TLI	> 0.95	(Tucker & Lewis, 1973)

Table 2: Soft targets for SEM evaluation metrics.

4. Results

To thoroughly investigate the Community of Inquiry and Cognitive Load frameworks within the context of our data, we systematically construct and test SEM structural models for each framework separately (Subsections 4.1 Structural Equation Modeling for Community of Inquiry, 4.2 Structural Equation Modeling for Cognitive Load, 4.3 Structural Equation Modeling for Grades), then investigate potential combinations (Subsection 4.4 Structural Equation Modeling for Community of Inquiry, Cognitive Load, and Grades) to form a unified structural model relating Community of Inquiry, Cognitive Load, and student performance.

4.1 Structural Equation Modeling for Community of Inquiry

An SEM model for Community of Inquiry was presented by Shea and Bidjerano (2009) in Figure 2. We first replicated the same structure with our own data as seen in Figure 4. Evaluative metrics for the Figure 4 model are:

- RMSEA=0.15 (target <0.1)
- CFI=0.67 (target >0.9)
- GFI=0.64 (target >0.9)
- TLI=0.65 (target >0.95)

By all metrics, this was a poor structural model for our data. To determine a more appropriate structural model that fit our data, we conducted an Exploratory Factor Analysis which suggested intermediate latent factors as presented in Figure 5. Evaluative metrics for the model are:

- RMSEA=0.08 (target <0.1)
- CFI=0.92 (target >0.9)
- GFI=0.88 (target >0.9)
- TLI=0.91 (target >0.95)

Noting the soft nature of our evaluation targets and that GFI and TLI in particular can be negatively influenced by number of factors (which we increased by adding intermediate latent factors), we find this model adequately fits our data. Of note are the regression coefficients for the intermediate teaching latent factors. While one latent factor is always fixed to 1, the others have negative regression coefficients. The intermediate factor *latent_tp1* loads onto questions about instructor communication (e.g., clearly communicated course topics, goals, instructions on how to participate, and important due dates), *latent_tp2* loads onto questions involving course participants in general (e.g., guiding class towards understanding, keeping course participants engaged and on task, and reinforcing sense of community), and *latent_tp3* loads onto questions involving instructor feedback (e.g., feedback for understanding and in a timely fashion). Descriptive statistics provide some reasoning for the change in regression coefficient signs: *latent_tp1* questions had mean scores of about 2.9 and standard deviation of about 1.6 while the other teaching presence questions had averages of at least 4 and standard deviation of about 1.2. Since the average scores that *latent_tp2* and *latent_tp3* were far higher than those of *latent_tp1*, the regression coefficients were negative to compensate for this difference.

SEM models also provide covariation between latent values (seen as dotted bi-directional arrows) as well as a hypothesis test p-value on whether the two latent values covary independently (null hypothesis) or jointly (alternatively hypothesis). Correlation is a normalized version of covariance. Like correlation, covariance near 0 means that the two latent factors do not relate to one another. Covariation and p-values for latent values of the model are:

- *teaching* and *social*: covariance = -0.127, p-value = 0.00
- *teaching* and *cognitive*: covariance = -0.186, p-value = 0.00
- *social* and *cognitive*: covariance = 0.498, p-value = 0.00

At all significance levels, we have statistically significant evidence to reject that each pair of latent values covary independently. For *teaching* and *social/cognitive* latent values, as *teaching* presence increases, *social/cognitive* presence decreases. Both covariances are near 0 though, so this would be described as a weak negative covariance. For *social* and *cognitive* latent values, we found a moderate positive covariance.

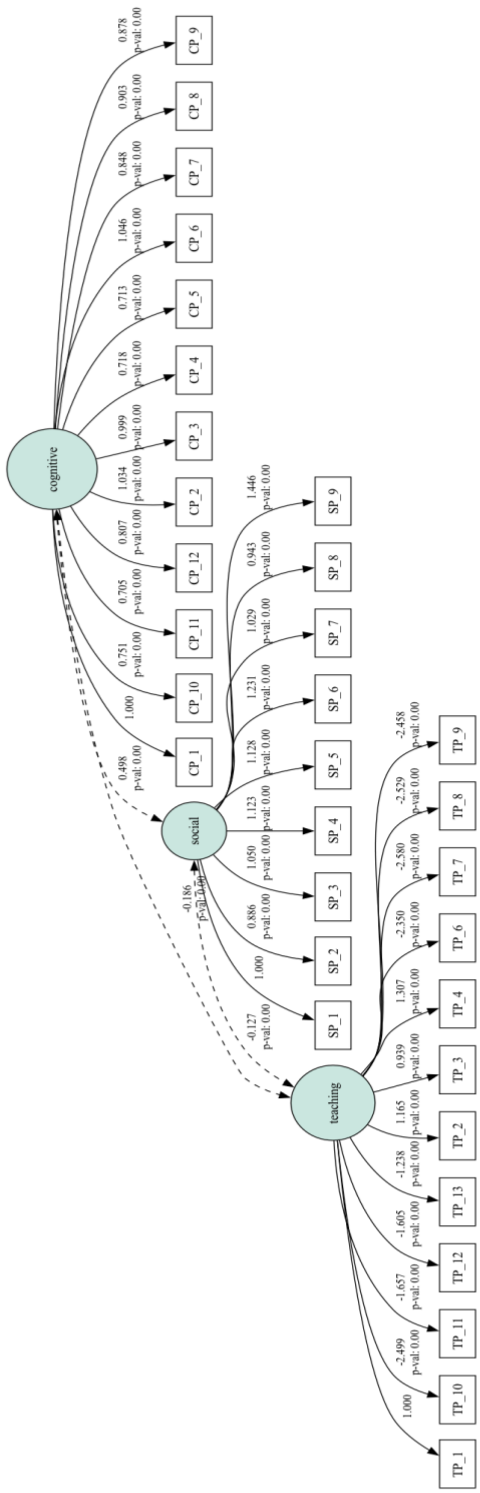

Figure 4: Initial SEM Model for Community of Inquiry Instrument.

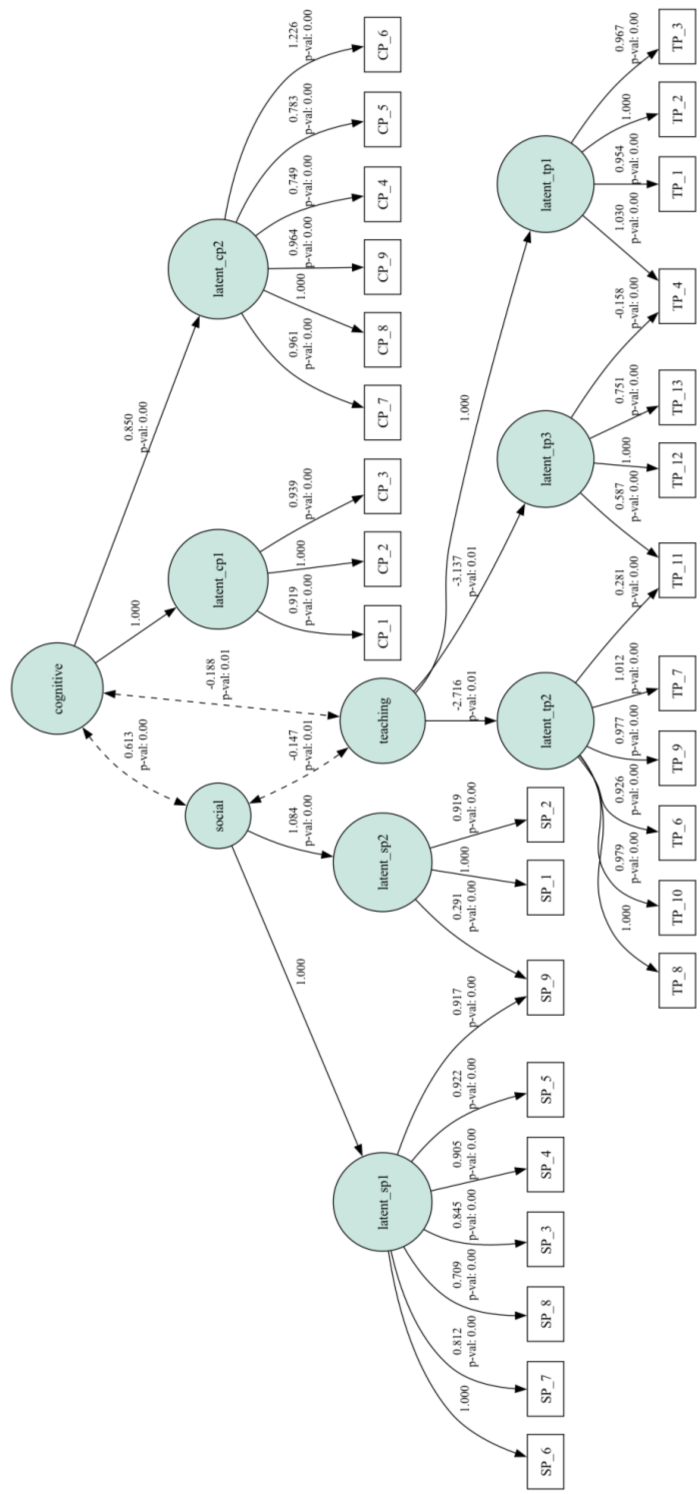

Figure 5: SEM Model for Community of Inquiry with Intermediate Latent Variables.

4.2 Structural Equation Modeling for Cognitive Load

To begin the SEM model for Cognitive Load, we let the five subscales act as intermediate latent factors that are theoretically caused by Cognitive Load as presented in Figure 6. Evaluative metrics for the Figure 6 model are:

- RMSEA=0.13 (target <0.1)
- CFI=0.86 (target >0.9)
- GFI=0.84 (target >0.9)
- TLI=0.84 (target >0.95)

While the evaluative metrics are not ideal, they suggest the model somewhat fits the data we have. Again, we employed an Exploratory Factor Analysis to determine if a more appropriate structural model existed for our data. Unlike the Community of Inquiry structural model, the Cognitive Load exploratory factor analysis suggested a mixed loading for the same five latent factors, as seen in Figure 7. Evaluative metrics for the Figure 7 model are:

- RMSEA=0.13 (target <0.1)
- CFI=0.87 (target >0.9)
- GFI=0.84 (target >0.9)
- TLI=0.84 (target >0.95)

The factor analysis provides a marginal improvement to the CFI metric (+0.01) and otherwise no change in the evaluative metrics. Thus, we find this model best describes our data and is close enough to the evaluation metric targets to consider as adequately fitting our data. Reading the arrows in Figure 7 to determine which additional measurable values the latent factors are loading onto can be difficult and so a written equation version is provided in Table 3. This is the exact format semopy uses to construct the SEM model visualizations.

```
replying_to_posts =~ CL_RtP_1 + CL_RtP_3 + CL_RtP_2 + CL_RtP_4

understanding_expectations =~ CL_UE_3 + CL_UE_1 + CL_UE_2 + CL_UE_4

integrate_feedback =~ CL_IF_4 + CL_IF_2 + CL_IF_1 + CL_IF_3 + CL_RP_4 + CL_RtP_4 + CL_IP_4

reading_posts =~ CL_RP_2 + CL_RP_3 + CL_RP_1 + CL_RP_4 + CL_RtP_2

initial_post =~ CL_IP_1 + CL_IP_4 + CL_IP_2 + CL_IP_3 + CL_UE_2

cognitive_load =~ understanding_expectations + initial_post + reading_posts + replying_to_posts + integrate_feedback
```

Table 3: Results from Exploratory Factor Analysis for Cognitive Load

Note the latent factor *integrate_feedback* has three additional questions it loads to from three different subscales but from the same type of question: frustration. This suggests frustration plays an important role in students' evaluation of their own cognitive load when it comes to integrating feedback from the instructor. The other two overloaded questions (CL_RtP_2 and CL_UE_2) relate to Temporal Demands, suggesting the time it takes to reply to other posts plays a role in reading posts and that the time it takes to understand expectations plays a role in their initial post – both reasonable inclusions to their respective latent value. We highlight these inclusions as they are statistically-driven additions that make theoretical sense to the model.

As with the Community of Inquiry SEM model, we consider the covariance between cognitive load latent factors. All covariances are provided in Table 4. We see moderate positive covariance (about 0.4 or more) between six of the possible ten pairs of latent factors, suggesting a complex interrelated relationship between the cognitive load subscales. A graphical representation of the relationships between latent factors is presented in Figure 8.

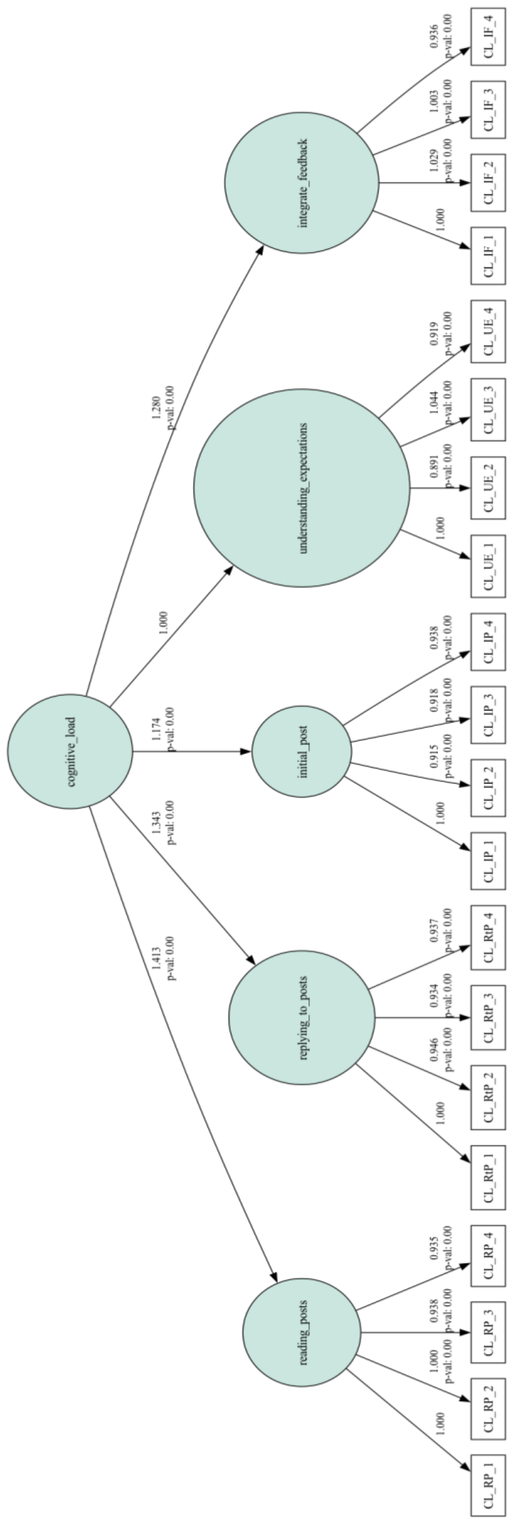

Figure 6: Initial SEM model for Cognitive Load based on Faulconer, Bolch, and Wood (2022).

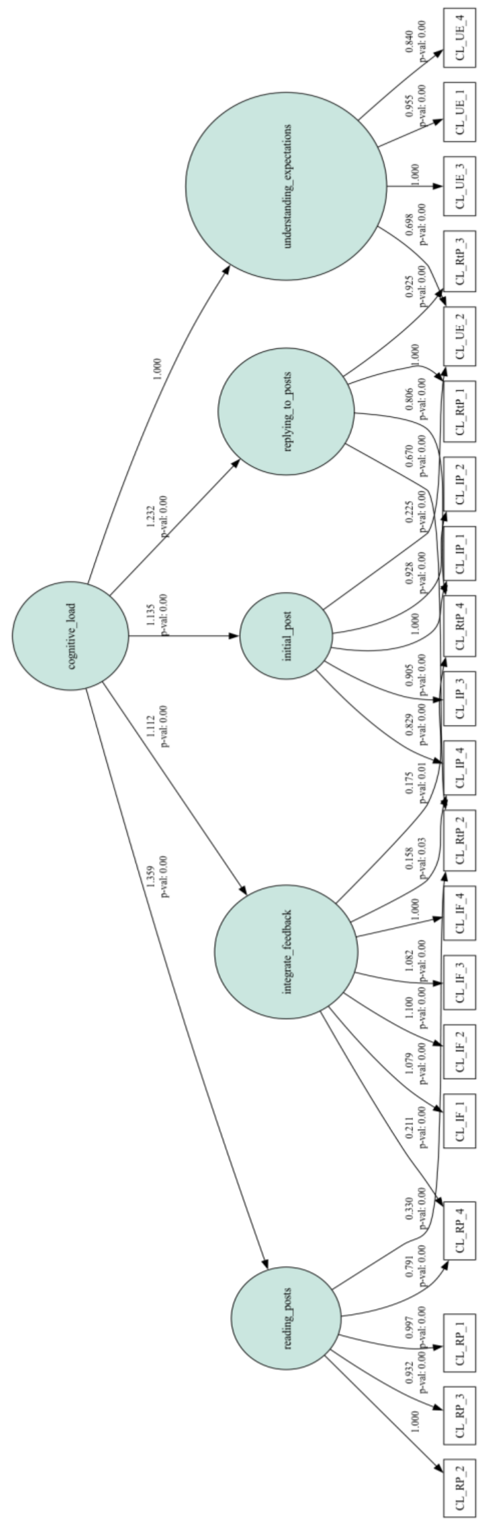

Figure 7: SEM model for Cognitive Load by applying a mixed loading to the five latent factors.

	Understanding Expectations	*Initial Post*	*Reading Posts*	*Replying to Posts*	*Integrate Feedback*
Understanding Expectations		0.850 (0.00)	0.013 (0.94)	-0.018 (0.93)	0.386 (0.01)
Initial Post	0.850 (0.00)		0.297 (0.02)	0.503 (0.00)	-0.088 (0.51)
Reading Posts	0.013 (0.94)	0.297 (0.02)		0.713 (0.00)	0.426 (0.00)
Replying to Posts	-0.018 (0.93)	0.503 (0.00)	0.713 (0.00)		0.481 (0.00)
Integrate Feedback	0.386 (0.01)	-0.088 (0.51)	0.426 (0.00)	0.481 (0.00)	

Table 4: Covariance matrix for latent factors associated to Cognitive Load with p-values in parentheses. Grayed-out cells do not provide evidence that the two latent values covary with one another.

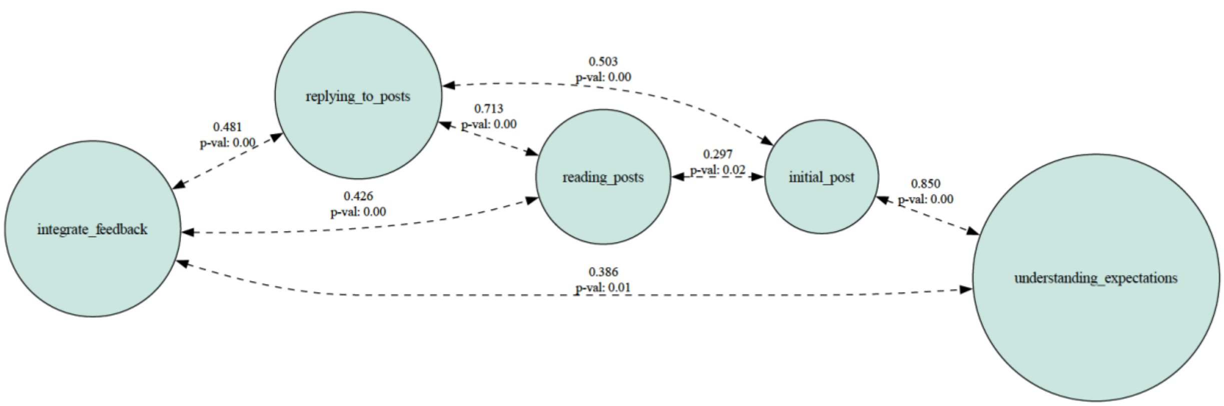

Figure 8: Graphical representation of covariance between latent factors related to Cognitive Load.

4.3 Structural Equation Modeling for Grades

Without a theoretical model to begin our SEM structural model for a grade-related latent value, we start by performing an Exploratory Factor Analysis using discussion grade average, final grade in course, and all collected demographics (gender, age category, ethnicity, GPA group, major, and employment status). Results of the EFA are provided in Table 5.

grades =~ Total_Course_Score + Discussion_Score + gpa_group + ethnicity

Table 5: Results of Exploratory Factor Analysis for a grade-related latent value

Of the collected demographics, the EFA identified *gpa_group* and *ethnicity* being impacted by a grade-related latent factor. Ethnicity being related to achievement has been well-documented in the literature (e.g., Whitcomb et al., 2021) and it should be no surprise that GPA is related to a latent factor for grades. The SEM model for the *grades* latent factor is presented in Figure 9.

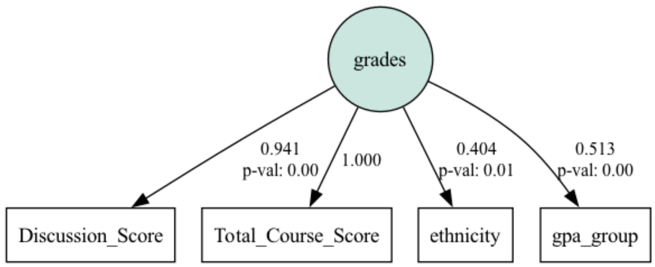

Figure 9: SEM model for grade-related latent factor as identified by Exploratory Factor Analysis.

Evaluative metrics for the model are:

- RMSEA=0.07 (target <0.1)
- CFI=0.98 (target >0.9)
- GFI=0.97 (target >0.9)
- TLI=0.95 (target >0.95)

By all evaluative metrics, the *grades* latent factor SEM model fits our data well.

4.4 Structural Equation Modeling for Community of Inquiry, Cognitive Load, and Grades

Now, we consider structural models that accommodate the Community of Inquiry and Cognitive Load structural models while including additional measurables such as grades and demographic information such as gender, age category, ethnicity, GPA category, major, and employment status (full/part/retired/none).

SEM Attempt 1: *Exploratory Factor Analysis with all Measurable Values*

As a baseline, we perform an Exploratory Factor Analysis including all measurable values to identify if a mix of Community of Inquiry and Cognitive Load measurable items are caused by a single latent value. The result of the EFA is provided in Table 6.

```
eta1 =~ CL_RtP_1 + CL_RtP_2 + CL_RtP_3 + CL_RtP_4
eta2 =~ CP_8 + CP_2 + CP_7 + CP_3 + CP_9 + CP_1 + CP_6 + SP_9 + CP_12 + CP_11 + CP_10 + SP_8 + CP_4 + CP_5 +
TP_11 + SP_2 + TP_12 + TP_13 + CL_RtP_1
eta3 =~ CL_UE_3 + CL_UE_4
eta4 =~ TP_2 + TP_1 + TP_3 + TP_4
eta6 =~ CL_IF_2 + CL_IF_1 + CL_IF_3 + CL_IF_4
eta8 =~ CL_IP_1 + CL_IP_3 + CL_IP_2 + CL_IP_4
eta9 =~ CL_RP_4 + CL_RtP_4 + CL_RP_3 + CL_IF_4
eta10 =~ TP_10 + TP_7 + TP_8 + TP_9 + TP_6 + TP_11 + TP_12 + SP_1 + TP_13 + SP_2 + CL_UE_4
eta11 =~ SP_1 + SP_2 + CL_UE_2
eta14 =~ SP_6 + SP_9 + SP_5 + SP_4 + SP_8 + SP_7 + CP_6 + SP_3 + CL_RtP_4
eta15 =~ CL_IP_4 + CL_UE_4 + CL_IF_3
```

Table 6: Results from Exploratory Factor Analysis for all measurable values.

As a quick review of the identified latent factors:

- **eta1** – Cognitive Load latent factor *replying_to_posts*
- **eta2** – Almost all *cognitive_presence* along with *latent_tp3*
- **eta3** – Partial Cognitive Load latent factor *understanding_expectations*
- **eta4** – Community of Inquiry intermediate latent factor *latent_tp1*

- **eta6** – Cognitive Load latent factor *integrate_feedback*
- **eta8** – Cognitive Load latent factor *initial_post*
- **eta9** – Some Cognitive Load *frustration* questions
- **eta10** – Almost all *teaching_presence* with some additional measurable values
- **eta11** – Community of Inquiry intermediate latent factor *latent_sp1*
- **eta14** – Community of Inquiry intermediate latent factor *latent_sp2*
- **eta15** – Some Cognitive Load *frustration* questions

First, note that **no additional measurable values** from grades nor demographics have been added to the latent factors. These values did not improve the statistical fit of the linear regressions. Also note the inclusion of intermediate latent factors from both the Community of Inquiry and Cognitive Load structural models. This is additional confirmation our previous two structural models provide a theoretically-sound fit for the data and that these latent factors are distinct mental constructs. Evaluative metrics for the SEM model provided in Figure 10 are:

- RMSEA=0.13 (target <0.1)
- CFI=0.87 (target >0.9)
- GFI=0.84 (target >0.9)
- TLI=0.84 (target >0.95)

The evaluative metrics match the metrics for the Cognitive Load SEM model separately, which suggests it fits our data adequately. However, we recognize that Exploratory Factor Analysis does not provide layers of latent factors in its analysis. By combining the SEM models we identified separately for *presence*, *cognitive_load*, and *grades*, we may arrive at an SEM model that better fits our data.

Attempt 2: *Exploratory Factor Analysis with Prior Structural Models*

Utilizing the SEM models provided in (Community of Inquiry with intermediate latent factors), Figure 7 (Cognitive Load with mixed factor loading), and Figure 9 (Grade-related latent factor), we can examine a unified SEM model and identify the covariance between the three top-layer latent factors. Evaluative metrics for the SEM model provided in Figure 11 are:

- RMSEA=0.07 (target <0.1)
- CFI=0.87 (target >0.9)
- GFI=0.79 (target >0.9)
- TLI=0.86 (target >0.95)

Unlike previous models, the GFI differs drastically from CFI and TLI. GFI (Goodness of Fit Index) is an *absolute index*, which describes the fit of data as compared to population covariance and assumes that the best-fit model accounts for all variance of factors. GFI is sensitive to variance in a small number of factors. In contrast, CFI and TLI are *comparative indices*, which describe the fit of variances in the data and compares the data fit to the assumption that there is no relationship among variables. The lower absolute index suggests there is covariance we are not accounting for with our model, but that the model does describe the variance of individual measurable values and latent factors well.

As covariation and p-values in Figure 11 are impossible to read, they are provided in Table 7.

	presence	*cognitive_load*	*grades*
teaching	-0.038 (0.05)	-0.087 (0.04)	0.043 (0.07)
social	0.167 (0.00)	0.255 (0.00)	-0.152 (0.00)
cognitive	0.851 (0.00)	-0.316 (0.00)	0.229 (0.00)
presence		-0.320 (0.00)	0.209 (0.00)
cognitive_load	-0.320 (0.00)		-0.227 (0.01)
grades	0.209 (0.00)	-0.227 (0.01)	

Table 7: Covariation and p-value among top-level latent factors as well as intermediate Community of Inquiry factors.

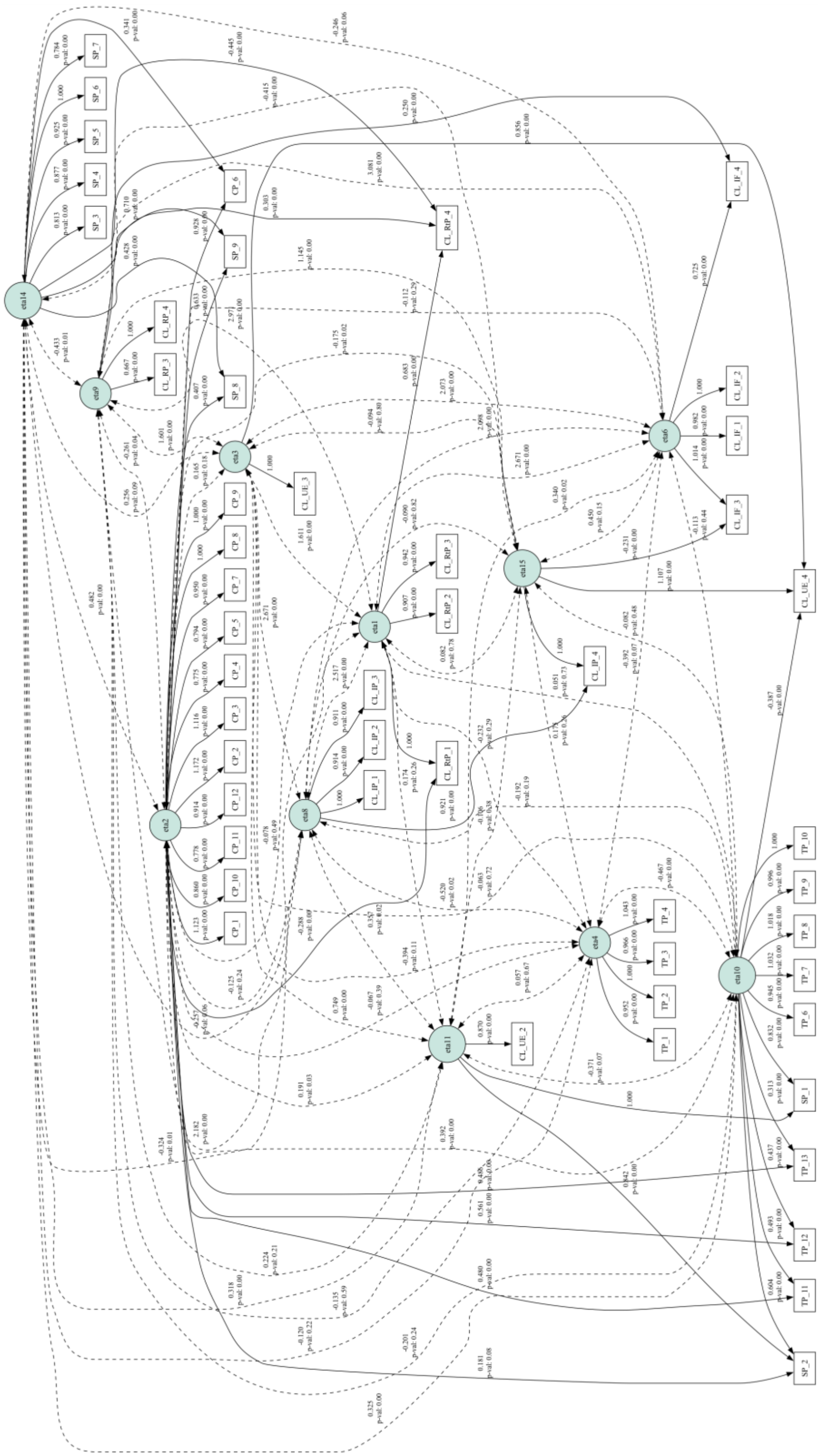

Figure 10: SEM model from Exploratory Factor Analysis with all measurable values.

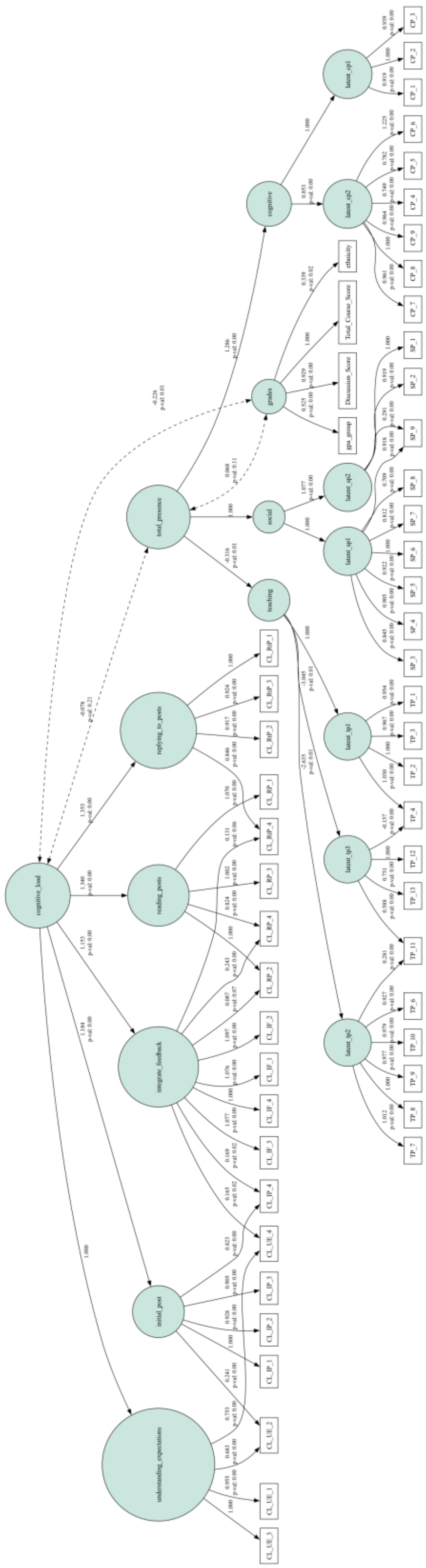

Figure 11: SEM Model based on best-fit SEM Models for Community of Inquiry, Cognitive Load, and Grades individually.

Note that *teaching* does not provide statistically significant results to suggest it varies with total Community of Inquiry *presence* as well as *grades*. The *teaching* factor has low covariation with *cognitive-_load* as well. While *teaching* may influence other latent factors (as we saw when examining the Community of Inquiry SEM model separately), it does not covary with the other latent factors. This is not too surprising as *teaching* is the only latent factor related to the instructor directly and all other factors relate to the student directly. Cognitive load appears to have a mild negative relationship with all latent factors expect social presence. Social presence and cognitive load also have a mild negative relationship with *grades* while cognitive presence and total presence have a positive relationship with *grades*. We hypothesize why social presence may have a negative covariance with *cognitive_load* and *grades* in the Discussion.

To simplify the SEM model visualization, we use the estimates for intermediate latent values to act as measurable values for the top-layer latent factors *presence*, *cognitive_load*, and *grades*. Evaluative metrics for the SEM model provided in Figure 11 are:

- RMSEA=0.09 (target <0.1)
- CFI=0.94 (target >0.9)
- GFI=0.92 (target >0.9)
- TLI=0.93 (target >0.95)

As mentioned previously, a higher number of factors reduces CFI and TLI. Thus, by reducing the number of latent factors, we expected CFI and TLI to increase. Moreover, by decreasing the number of factors, we reduce the sensitivity of variance for the GFI and so expected GFI to increase. The reduced SEM model fits our data well.

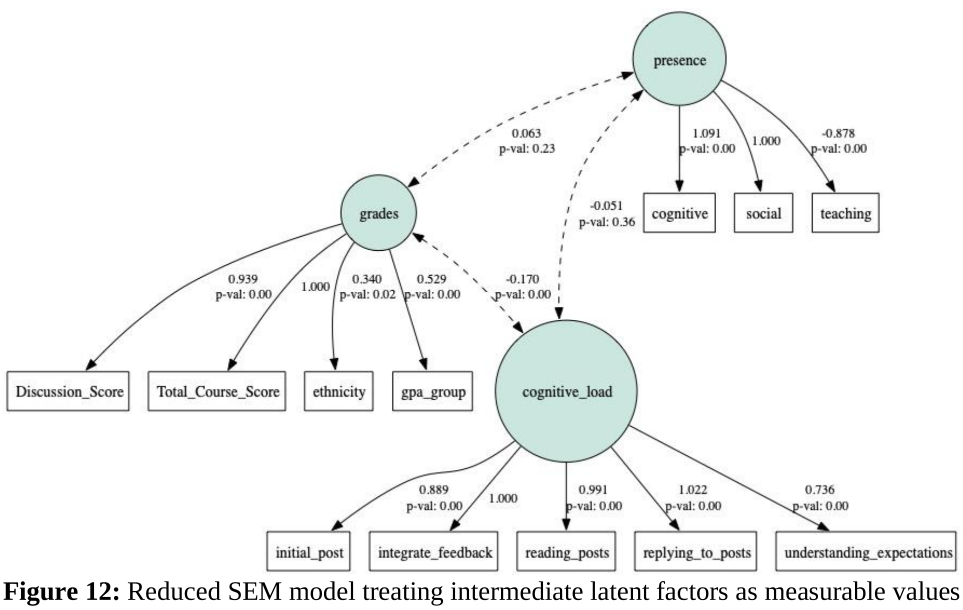

Figure 12: Reduced SEM model treating intermediate latent factors as measurable values using model estimates.

Note that unlike our full SEM model, the reduced SEM model does not provide statistically significant evidence that total presence covaries with *grades* and *cognitive_load*. Thus, we should consider this as an oversimplified model for generally describing the overall SEM model and not for accurately estimating latent factors. It also further emphasizes that SEM structural models should have a theoretically-sound structure that comes close to certain metric thresholds rather than searching for the highest-metric model.

Discussion

As we were able to create a unified SEM model that fit our data far better than using Exploratory Factor Analysis on all measurable data collected, we provide a brief summary of our method so that others may replicate it.

- Create SEM Model for 3-factor (teaching, social, cognitive presences) structural model with Community of Inquiry data.
- Perform Exploratory Factor Analysis to check if an intermediate latent factor model emerges from the data and create the associated SEM Model to evaluate fit.
- Create SEM Model for 5-factor (understanding expectations, crafting an initial post, reading posts from instructors and peers, creating reply posts, and integrating instructor feedback) structural model with Cognitive Load data.
- Perform Exploratory Factor Analysis to check if a mixed loading model emerges from the data and create the associated SEM Model to evaluate fit.
- Perform Exploratory Factor Analysis to see what 1-factor (grade-related latent factor) structural model emerges with course grades and demographic values, and create the associated SEM Model to evaluate fit.
- Combine the best structural models for each latent factor and evaluate fit.
- For visualization sake, use the final SEM Model to estimate intermediate latent factors and treat them as measurable values to create a final SEM Model visualization.

To further summarize the results of our study, we provide short summaries according to each research question.

1. *How does the Community of Inquiry framework model social, cognitive, and teaching presence in our data?*

We tested SEM models using structural equations as present in the literature (Shea & Bidjerano, 2009). While the model presented in Shea and Bidjerano (2009) for Community of Inquiry was not a fit for our data, a modified version that introduced a layer of latent values for each presence was a fit for our data and was provided in Figure 5. This further validates the Community of Inquiry 34-question survey instrument. With this SEM model applied to our data, we found statistically significant evidence to reject that each pair of latent values covary independently. In other words, we found evidence that the three latent values covary with one another. For *teaching* and *social/cognitive* latent values, as *teaching* presence increases, *social/cognitive* presence decreases. Both covariances are near 0 though, so this would be described as a weak negative covariance. For *social* and *cognitive* latent values, we found a moderate positive covariance. Evaluative metrics for our Community of Inquiry SEM model suggested a strong fit, with RMSEA=0.08 (target <0.1), CFI=0.92 (target >0.9), GFI=0.88 (target >0.9), and TLI=0.91 (target >0.95).

2. *How does the Cognitive Load framework model various mental efforts associated with a discussion task?*

The structural equations that mirror the Confirmatory Factor Analysis performed in Faulconer et al (2022) were a fit for our data and an Exploratory Factor Analysis provided a small subset of overloaded measurable variables on the same latent cognitive load factors and was provided in Figure 7. This further validates the 20-question NASA-TLX instrument. With this SEM model applied to our data, we found statistically significant evidence to reject that six of the potential 10 pairs of latent cognitive load factors vary independently as presented in Table 4 and visualized in Figure 8. Evaluative metrics for our Cognitive Load SEM model suggested a fit, with RMSEA=0.13 (target <0.1), CFI=0.87 (target >0.9), GFI=0.84 (target >0.9), TLI=0.84 (target >0.95).

3. *How do Community of Inquiry, Cognitive Load, and Grades relate with one another in our data?*

After performing an Exploratory Factor Analysis on demographics collected as well as discussion and final course grades, an SEM model for the *grade* latent factor was developed that only included final course grade, discussion average grade, GPA category, and ethnicity as presented in Figure 9. Evaluative metrics for our Grades SEM model suggested a strong fit, with RMSEA=0.07 (target <0.1), CFI=0.98 (target >0.9), GFI=0.97 (target >0.9), TLI=0.95 (target >0.95).

Our final SEM model for Community of Inquiry, Cognitive Load, and Grades combined the best SEM models for each construct separately. We found statistically significant evidence that total Community of Inquiry presence, Cognitive Load, and grades showed mild covariance with one another. When we investigated Community of Inquiry teaching, social, and cognitive presences, we found that teaching presence did not provide evidence of covarying with total presence nor with grades and only showed low negative covariance with cognitive load which does not match results from the literature (Ice et al., 2011; Lee, 2014; Silva, 2018; Zhu, 2018). One potential explanation is that while the entire teaching presence does not covary with cognitive load, intermediate latent teaching factors may, such as instructor's social presence (Ratan et al., 2022). As expected from the literature (Jo et al., 2017; Stachel et al., 2013), cognitive presence showed a mild negative covariance with cognitive load and mild positive covariance with grades. However, social presence showed a mild positive covariance with cognitive load and mild negative covariance with grades, again not matching results from the literature (Hostetter, 2013), which will require further exploration to definitively explain. One potential explanation for the mild negative covariance between grades and social presence may involve instructors not valuing or including social moves with a grade. Evaluative metrics for our integrated SEM model suggested a strong fit, with RMSEA=0.07 (target <0.1), CFI=0.87 (target >0.9), GFI=0.79 (target >0.9), TLI=0.86 (target >0.95).

Implications

Numerous studies have explored and confirmed relationships between Community of Inquiry presences as well as between presences and learner outcomes such as performance (Maranna et al., 2022). However, these relationships did not consider the role of cognitive load in this relationship between CoI presences and learner performance. Our results suggest teaching and cognitive presences have a negative covariance with cognitive load (e.g., as cognitive presence increases, cognitive load decreases) while social presence has a positive covariance with cognitive load (e.g., as social presence increases, cognitive load increases). The overall Community of Inquiry presence, as perceived by the student, negatively covaries with cognitive load (e.g., as CoI presence increases, cognitive load decreases). These results combined confirm that there are different types of cognitive load (germane, extraneous), that presence can both increase some cognitive load (germane) while decreasing other cognitive load (extraneous), and that CoI presences covary in complex ways with cognitive load and student performance. Potentially surprisingly, teaching presence was the only Community of Inquiry presence without statistical evidence to suggest it covaried with student performance. This provides evidence to further encourage active learning where students are the center of the learning experience as their social and cognitive presences more closely relate to outcomes that the instructor's interventions.

Limitations and Future Directions

This study presents a structural model to estimate Community of Inquiry and Cognitive Load in a unified method. However, there are numerous limitations to accepting this structural model as universal. Data was collected from a single university that is not representative of all college-level education. Data consisted of students' perceptions of Community of Inquiry presences and Cognitive Load subscales rather than measures of students' actions in a course, which may differ (Ozogul, Zhu, & Phillips, 2022). The response rate for student participation was 13%, which was below our target rate of 20% and thus may not have been representative of our student population. Participation in the survey was voluntary, which may have introduced confirmation and other biases to the data. Participation in the survey was limited to two introductory-level courses in Physics and Mathematics, which may not be representative of all introductory-level STEM courses nor all undergraduate-level STEM courses. We acknowledge these limitations and plan to address them with future work. Specifically, we have two methods address the majority of these limitations: (1) qualitatively categorize discussion post sentences by students and instructors according to the Community of Inquiry framework as a direct measure of student actions to estimate Community of Inquiry presences and (2) conduct the same survey on an expanded participant poll in other introductory-level STEM courses both at the same institution and others to provide further evidence for the structural model. We also plan to employ machine learning classification methods, such as random decision forests, to scale-up the qualitative categorization of discussion post sentences for real-time estimates of Community of Inquiry presences that can be used to improve students' educational experiences.

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Appendix A

Community of Inquiry Instrument

Original Number	Abbreviation	Full Name
q1	TP_1	Teaching Presence 1
q2	TP_2	Teaching Presence 2
q3	TP_3	Teaching Presence 3
q4	TP_4	Teaching Presence 4
q5		
q6	TP_6	Teaching Presence 6
q7	TP_7	Teaching Presence 7
q8	TP_8	Teaching Presence 8
q9	TP_9	Teaching Presence 9
q10	TP_10	Teaching Presence 10
q11	TP_11	Teaching Presence 11
q12	TP_12	Teaching Presence 12
q13	TP_13	Teaching Presence 13
q14	SP_1	Social Presence 1
q15	SP_2	Social Presence 2
q16	SP_3	Social Presence 3
q17	SP_4	Social Presence 4
q18	SP_5	Social Presence 5
q19	SP_6	Social Presence 6
q20	SP_7	Social Presence 7
q21	SP_8	Social Presence 8
q22	SP_9	Social Presence 9
q23	CP_1	Cognitive Presence 1
q24	CP_2	Cognitive Presence 2
q25	CP_3	Cognitive Presence 3
q26	CP_4	Cognitive Presence 4
q27	CP_5	Cognitive Presence 5
q28	CP_6	Cognitive Presence 6
q29	CP_7	Cognitive Presence 7
q30	CP_8	Cognitive Presence 8
q31	CP_9	Cognitive Presence 9
q32	CP_10	Cognitive Presence 10

Cognitive Load Instrument

Original Number	Abbreviation	Full Name
MnA	CL_UE_1	Cognitive Load Understanding Expectations 1
TmP	CL_UE_2	Cognitive Load Understanding Expectations 2
Eff	CL_UE_3	Cognitive Load Understanding Expectations 3
Frs	CL_UE_4	Cognitive Load Understanding Expectations 4
MnA	CL_IP_1	Cognitive Load Initial Post 1
TmP	CL_IP_2	Cognitive Load Initial Post 2
Eff	CL_IP_3	Cognitive Load Initial Post 3
Frs	CL_IP_4	Cognitive Load Initial Post 4
MnA	CL_RP_1	Cognitive Load Reading Posts 1
TmP	CL_RP_2	Cognitive Load Reading Posts 2
Eff	CL_RP_3	Cognitive Load Reading Posts 3
Frs	CL_RP_4	Cognitive Load Reading Posts 4
MnA	CL_RtP_1	Cognitive Load Replying to Posts 1
TmP	CL_RtP_2	Cognitive Load Replying to Posts 2
Eff	CL_RtP_3	Cognitive Load Replying to Posts 3
Frs	CL_RtP_4	Cognitive Load Replying to Posts 4
MnA	CL_IF_1	Cognitive Load Integrate Feedback 1
TmP	CL_IF_2	Cognitive Load Integrate Feedback 2
Eff	CL_IF_3	Cognitive Load Integrate Feedback 3
Frs	CL_IF_4	Cognitive Load Integrate Feedback 4

q33	CP_11	Cognitive Presence 11
q34	CP_12	Cognitive Presence 12

Table 8: Abbreviations for Community of Inquiry and Cognitive Load Instruments. Note q5 was not included in our instrument due to human error.