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Exploring Communities of Inquiry in Massive Open Online Courses

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Abstract

This study presents an evaluation of the Community of Inquiry (CoI) survey instrument developed by Arbaugh et al. (2008) within the context of Massive Open Online Courses (MOOCs). The study reports the results of a reliability analysis and exploratory factor analysis of the CoI survey instrument using the data of 1,487 students from five MOOC courses. The findings confirmed the reliability and validity of the CoI survey instrument for the assessment of the key dimensions of the CoI model: teaching presence, social presence, and cognitive presence. Although the CoI survey instrument captured the same latent constructs within the MOOC context as in the Garrison's three-factor model (Garrison et al., 1999), analyses suggested a six-factor model with additional three factors as a better fit to the data. These additional factors were 1) course organization and design (a sub-component of teaching presence), 2) group affectivity (a sub-component of social presence), and 3) resolution phase of inquiry learning (a sub-component of cognitive presence). The emergence of these additional factors revealed that the discrepancies between the dynamics of the traditional online courses and MOOCs affect the student perceptions of the three CoI presences. Based on the results of our analysis, we provide an update to the famous CoI model which captures the distinctive characteristics of the CoI model within the MOOC setting. The results of the study and their implications are further discussed.

Keywords: Community of inquiry model, Massive open online courses, Online learning, Exploratory factor analysis

1. Introduction

The growing interest in MOOCs and online education more broadly has been fueled by various social, economic, and political factors that have converged to emphasize the growing societal need for an accessible and sustainable higher education. Some of the factors include concerns surrounding student debt (Matthews, 2013), increasing requirements for lifelong learning to sustain future employment opportunities (Fini, 2009), and an overall need to provide more accessible and democratized models of higher education (Siemens, 2013). While MOOCs have brought online learning to the center of public interest (Kovanović et al., 2015b; Gašević et al., 2014), their development has not been without its challenges.

A particularly significant challenge associated with the MOOC development relates to the present state of MOOC pedagogical designs and the disconnect with the current state of research in online and distance education. MOOCs were originally developed by researchers in online education as an experimentation platform for novel online pedagogical approaches based on the connectivist learning theory (Siemens, 2005), that emphasized the distributed course organization and self-directed student learning. As indicated by Rodriguez (2012), this form of MOOCs is now commonly known as connectivist MOOCs or cMOOCs. A prevalent group of current MOOCs, also known as xMOOCs (Rodriguez, 2012), have tended to adopt a learning design structured around the pre-recorded video lectures, automated assignments, and quizzes with limited direct teaching interaction undertaken by the instructor. This model of design and teaching is selected for its capacity to scale content and learning activities to a large number of students while diminishing the constraints associated with the need for instructors to engage with individual learners (Ng and Widom, 2014).

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The present models of MOOC pedagogical design are essentially focused on the transmission of content. This approach represents a radical departure from contemporary distance education practice that is grounded in social constructivist models of learning (Anderson and Dron, 2010). These models assume that students – rather than assimilating predefined knowledge – actively *construct their knowledge* through a series of interactions with learning content, instructors, and other students. This knowledge construction process is dependent also on their existing knowledge and experiences, meta-cognitive processes, and a particular learning context. By following the behaviorist notion of learning, the dominating MOOC design arguably represents a step back in the quality and richness of online instruction (Stacey, 2013; Bali, 2014). A plausible rationale for this disconnect lies in the multidisciplinary nature of MOOC and online learning research and the strong fragmentation of the MOOC research community to researchers from the field of education and researchers from the field of computer science (Gašević et al., 2014). With researchers from computer science and engineering fields often following a theory-agnostic philosophy of data analysis (Chris et al., 2008), the departure from the contemporary learning theories is not surprising. The disconnect with the previous line of research in online and distance education may also explain the enthusiasm of the early xMOOCs proponents. Although being dubbed a "revolution" (Friedman, 2012) and "tsunami" (Hennessy, 2012) in the field of education, they represent a logical "evolutionary" step in the development of online and distance learning (Bali, 2014; Daniel, 2014).

This paper presents the results of a study examining the use of the contemporary social constructivist models of online and distance education within the MOOC context. The focus of the analysis is on the Community of Inquiry (CoI) model (Garrison et al., 1999), a well-known and one of the most widely-adopted models of distance education (Garrison and Arbaugh, 2007). The CoI model outlines critical dimensions which shape students' online learning experience and also provides a survey instrument used for their assessment (Arbaugh et al., 2008). This paper examines if the CoI survey instrument can be used to evaluate the interactions in MOOC courses. Given the many pedagogical differences between MOOCs and "traditional," small-scale online-courses, a re-validation of the existing CoI survey instrument and its factor structure was conducted using the data of 1,487 students from five MOOC courses. By examining the CoI model of online learning within the MOOC context, we aim to bridge the gap between research in online learning and current MOOC pedagogical practices and to enable its use for assessment of the quality of MOOC learning experience. The results of our analyses and the broader theoretical and practical implications are further discussed.

2. Background work

2.1. Overview of the Community of Inquiry model

The Community of Inquiry (CoI) (Garrison et al., 1999) framework is a widely adopted pedagogical model that outlines the critical dimensions that shape a students' online learning experience. Rooted in the constructivist notions of learning Dewey (1933) and the work of Lipman (1991), the CoI model (Fig. 1) focuses on the development of higher-order thinking through inquiry-based learning in a learning community. In this context, learning community is defined as *"a group of individuals who collaboratively engage in purposeful critical discourse and reflection to construct personal meaning and confirm mutual understanding"* (Garrison, 2011, p. 2). The model defines three central dimensions of online learning, known as presences:

1) *Cognitive presence* is a central component in the model which describes phases of inquiry-based learning, including problem conceptualization, knowledge exploration, synthesis, and eventual solution (Garrison et al., 2001).

2) *Social presence* focuses on the important aspects that shape social climate in the course learning community, including student interactivity, group cohesion, and affectivity (Rourke et al., 1999).

3) *Teaching presence* describes different instructional activities before and during the course, which include course organization and design, direct instruction, and facilitation (Anderson et al., 2001).

To evaluate the levels of the three CoI presences, researchers typically employ a self-reported survey instrument (Arbaugh et al., 2008) used to measure the perceived levels of the three presences among the cohort of learners. The CoI model and its survey instrument have been widely used in practice (Garrison et al., 2010a), and have been validated in several research studies (e.g., Arbaugh et al., 2008; Gorsky et al., 2011; Rourke and Anderson, 2004). Although originally focused on inquiry-based learning in fully online environments, the generalizability of the CoI model resulted in its wider adoption in the online and blended learning contexts (Garrison et al., 2010a). As such, it has been used as a general framework for assessing students' learning experience within a broad range of learning settings (Anderson and Dron, 2010; Swan and Ice, 2010).

2.2. Community of Inquiry instrument

The CoI survey instrument, originally developed by Arbaugh et al. (2008), consists of thirty-four 5-point Likert scale items designed to measure student perceived levels of teaching (questions 1-13), social (questions 14-22), and cognitive (questions 23-34) presence. As with any survey instrument, the first two issues are whether it is reliable and valid (Field et al., 2012). Reliability concerns whether the instrument provides stable and consistent results (e.g., would similar participants produce similar responses) while validity examines whether the instrument measures what it was designed to measure (Tabachnick and Fidell, 2007). Reliability of the instrument is usually evaluated through Cronbach's α measure (Cronbach, 1951), whereas validity is typically assessed using principal component analysis (PCA) and exploratory factor analysis (EFA) (Field et al., 2012). Both PCA and EFA extract (usually a small) set of latent factors, also called components, which are associated with individual survey questions (Field et al., 2012). If the instrument used to measure N constructs is valid, then PCA or EFA should also reveal N latent factors, which are correctly associated with survey questions (i.e., questions used to measure each construct are all associated with the same factor). With this in mind, several studies examined the reliability and validity of the CoI survey instrument (e.g., Arbaugh et al., 2008; Swan et al., 2008; Díaz et al., 2010; Shea and Bidjerano, 2009; Garrison et al., 2010b; Kozan and Richardson, 2014b).

In their seminal study, Arbaugh et al. (2008) conducted a PCA analysis on the data ($N = 287$) from graduate-level courses from four institutions in the USA and Canada. The results of the Arbaugh et al. (2008) study indicated the valid three-factor solution of the CoI survey instrument. An examination of the same dataset by Swan et al. (2008) revealed a strong internal consistency of the CoI survey instrument, with Cronbach's α of .94, .91, and .95 for teaching, social, and cognitive presences, respectively. The PCA analysis was also used by Díaz et al. (2010) for analysis of the data from a both graduate and undergraduate courses at four different institutions ($N = 412$), which provided further confirmation of the CoI instrument reliability and three-factor structure. The only departure from the hypothesized factor structure was related to item #22 (measuring group cohesion in social presence) which loaded almost identically to both social and teaching presence factors (the absolute difference between factor loadings was .004). The reliability and three-factor structure were also confirmed by Shea and Bidjerano (2009), who used EFA on a large dataset ($N = 2,159$) from a multi-institutional fully-online learning program. Similar results using EFA are presented by Garrison et al. (2010b), who analyzed the data from fourteen courses in two study programs ($N = 205$), and by Kozan and Richardson (2014b) who analyzed data ($N = 219$) from students enrolled in a fully online graduate degree program. Similar to the Díaz et al. (2010) study, Kozan and Richardson (2014b) also reported item #22 loading on both the social presence and cognitive presence factors.

It should be noted that studies by Arbaugh et al. (2008) and Díaz et al. (2010) suggested the existence of a potential fourth factor which encompasses survey items related to the course organization and design, a sub-component of the teaching presence. As indicated by Arbaugh et al. (2008), the presence of the fourth factor does not invalidate the theoretical foundations on which the CoI model was developed, as the CoI model theorizes that each of the presences comprises a number of sub-components. For example, teaching presence is defined as consisting of course organization and design, facilitation, and direct instruction, while social presence consists of an affective expression, open communication, and group cohesion (Garrison et al., 1999). The existing literature (Arbaugh, 2007; Shea et al., 2006) also points out to the possibility that teaching presence activities before (i.e., course organization and design) and during the course (i.e., facilitation and direct instruction) might be driven by different dynamics and thus be reflected in the separate factor loadings.

Although the CoI instrument has been used extensively for evaluation of traditional for-credit online and blended learning settings, its adoption in the MOOC context has been limited. To the best of our knowledge, only the study by Damm (2016) used the CoI survey instrument to evaluate the learning experience of students from eight "MOOC-like" non-credit courses offered by a respected U.S. book publisher. However, unlike most MOOCs, these courses had a \$175-\$200 course registration fee, and as a result, were much smaller (around 400 students each). Likewise, it is reasonable to assume that students in these courses had commitments more similar to the traditional for-credit online courses than typical MOOCs which do not charge a registration fee. Although Damm (2016) used the CoI survey instrument to measure the course experience of course participants, they did not

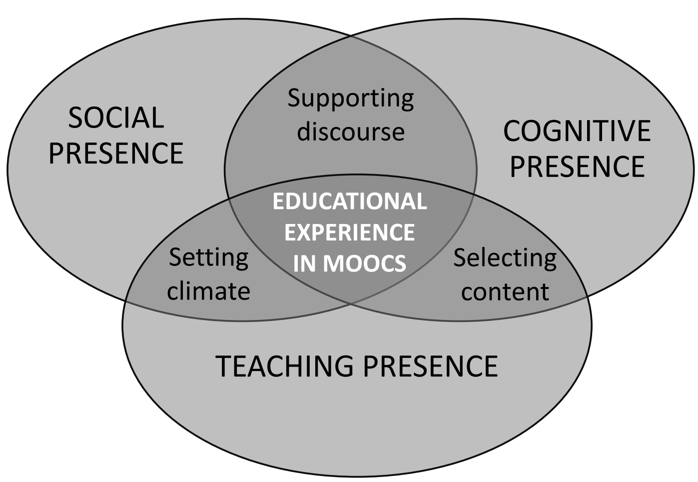

Fig. 1. The original CoI model by Garrison et al. (1999), showing the interconnected nature of the three presences in shaping students' online learning experience.

evaluate the factor structure of the CoI instrument and instead used in-depth interviews with the students to validate survey results. Overall, their findings suggest that the CoI survey can be used to assess the level of student course engagement and three CoI presences (Damm, 2016).

3. Research questions

While there has been substantial work on the validation of the CoI instrument, the primary context was traditional, formal education, with data coming from the small-scale, for-credit online courses. However, to our knowledge, the use of CoI model and validation of its survey instrument have not been examined within the MOOC context. Given the rapidly emerging MOOC research, as well the broad adoption of the CoI model within traditional online settings, the goal of the present study is to examine whether the CoI survey instrument can be used for examination of student learning experiences within MOOC courses. As the CoI instrument has not been validated in the MOOC context, we focused our investigation on examining its reliability and validity within the MOOC setting. Hence, we focused on the following research questions:

RQ 1: What is the reliability of the Community of Inquiry survey instrument in the MOOC context?

Given that CoI survey instrument has been originally designed for small-scale online learning environments, we first want to examine the reliability of the existing instrument on measuring the levels of the three CoI presences. With many differences between MOOCs and small-scale online courses (e.g., course cohort sizes and learner demographics and motivation), it might be that the reliability of the existing instrument is not sufficiently high to reliably measure the three key constructs of the CoI model.

RQ 2: What is the factor structure of the CoI survey in a MOOC setting? Is the factor structure of the CoI instrument in MOOCs different from ones observed in traditional online courses?

While reliability analyses provide an indication of the internal consistency of the instrument, it is also important to examine the relationship between survey items and the underlying factors which they are supposed to measure. As such, the focus of this question is to examine if the pedagogical differences between traditional online courses and MOOCs impact the validity of the CoI survey instrument and if so, to what extent. For example, it might be that due to specifics of MOOCs, certain questions are not interpreted as originally intended, and thus, reflect different latent constructs than originally theorized.

4. Material and methods

4.1. Study data

The data for this study was collected from five different MOOCs offered by the Delft University of Technology in the Netherlands on edX platform during the Fall 2014 term (Table 1). The courses included a range of learning activities such as recorded video materials, reading materials, short multiple-choice quizzes, homework assignments, and online forum discussions (see Hennis et al., 2016). Students who successfully completed a course were issued a course completion certificate.

Before the course commencement, all registered students were invited to complete a voluntary pre-course questionnaire. The questionnaire consisted of items related to a student's reasons for enrolling in the course, anticipated level of course commitment, previous domain knowledge, and their perceived importance of the different course resources and tools[1]. After the course end, all enrolled students were again invited to complete a post-course survey which also included the 34 items of the original Community of Inquiry questionnaire by Arbaugh et al. (2008). The wording of the CoI survey was the same as in the original study by Arbaugh et al. (2008), with few limited changes to the text of the questions (e.g., term "instructor" was changed to "teaching team").

The study data consisted of the de-identified answers to pre- and post-course surveys. The collection of course data and its use for the research purposes was approved by the Delft University ethics board. In both pre- and post-course surveys, students were shown a message that their data will be used solely for research and evaluation purposes and improving the course experience. In total, 2,446 students completed the post-course survey, with a subset of 1,887 students completing the CoI survey questions (Table 1). While the CoI survey response rate was low (2.6%-0.5%), it is primarily caused by the large number of students who did not take active participation in the course, as common in most MOOCs (Liyanagunawardena et al., 2014).

[1] The list of pre- and post-course survey questions, summary statistics, and a sample of responses available upon request.

Table 1
Basic statistics for courses included in the study.

Course	Number of weeks	Certificate threshold	Enrolled students	Certified students	CoI survey responses	Median age	Top countries	Gender		Highest degree		
								Male	Female	High school or less	College (Bachelors or Associate)	Advanced (Masters or Doctorate)
Introduction to Functional Programming	8	60%	38,029	1,968 (5.2%)	992 (2.6%)	31	USA (28.6%) India (8.4%) UK (5.3%)	90.0%	9.6%	21.8%	42.5%	33.1%
Solving Complex Problems	5	60%	32,424	1,396 (4.3%)	463 (1.4%)	33	USA (21.5%) India (8.2%) UK (4.6%)	75.2%	24.4%	18.7%	38.9%	40.3%
Delft Design Approach	10	60%	13,503	136 (1.0%)	69 (0.5%)	31	USA (19.8%) India (10.9%) Netherlands (5.7%)	68.6%	31.0%	19.0%	42.0%	36.8%
Introduction to Drinking Water Treatment	10	60%	10,543	281 (2.7%)	114 (1.0%)	31	USA (17.3%) India (9.8%) Netherlands (3.5%)	29.6%	70.0%	17.2%	44.8%	35.5%
Technology for Biobased Products	7	55%	9,606	347 (3.6%)	249 (2.6%)	30	USA (16.1%) India (11.2%) Netherlands (6.0%)	36.0%	63.6%	21.2%	36.8%	39.5%
		Total	104,105	4,128 (4.0%)	1,887 (45.7%)							

4.2. *Data preparation*

As the first step of our data preparation we coded Likert-scale responses to 1–5 scale (1: strongly disagree, 5: strongly agree). Next, following the work of Shea and Bidjerano (2009), we pre-processed the data to remove the data points not suitable for the factor analysis procedure. We removed all incomplete survey responses (7%) and multivariate outliers with Mahalanobis distance larger than 65.25 ($p < .001$) (9%), as done by Shea and Bidjerano (2009). Finally, we removed all cases with standardized Z-scores above 3.29 on any of the 34 CoI survey items (5%). The final dataset consisted of 1,487 cases, which is a 21% reduction of the original dataset. The mean and standard deviation for the 34 items of the CoI survey instrument are shown on Table 2.

4.3. *Analysis procedure*

To evaluate the use of the CoI survey instrument in the MOOC context, we first conducted a scale reliability analysis using Cronbach's alpha and item-rest correlation analysis (Field et al., 2012). In cases where an instrument is used to measure several related constructs, Cronbach (1951) suggested that an analysis should also be conducted for each of the subscales. Thus, we conducted three separate analyses, one for each of the three presences. We also used item-rest correlation to examine whether the reliability of an instrument can be improved by the exclusion of particular survey items (Field et al., 2012).

Post the reliability analysis, we followed with the analysis of the latent factors of the CoI survey instrument. As both PCA (Swan et al., 2008; Díaz et al., 2010; Arbaugh et al., 2008) and EFA (Garrison et al., 2010b; Shea and Bidjerano, 2009; Kozan and Richardson, 2014b) have been used for the study of the CoI survey instrument, we first evaluated the advantages and disadvantages of both methods. Based on our investigation, we eventually decided to use EFA for several reasons.

While both PCA and EFA share many similarities and often produce similar results (Velicer, 1974; Velicer et al., 1982; Jensen, 1983), they fundamentally differ in the way in which they model the relationship between latent and manifest variables (Field et al., 2012). PCA considers all variance among the manifest variables to be a shared variance (known as communality) arising from a set of common latent factors (Winter and Dodou, 2016). In contrast, EFA assumes that – aside from the common factors – each manifest variable has a unique latent factor contributing to the unique portion of its variance (the random or unique portion of variance) (Winter and Dodou, 2016). In practice, the PCA procedure derives a lower-rank representation of the manifest variable covariance matrix, while EFA provides a more sound modeling of the relationship between a set of variables (Field et al., 2012). As such, it is often considered to be the only procedure that can be used to estimate the underlying structure of latent factors (Field et al., 2012). In cases where a unique portion of variance is small and manifest variables strongly load on a single factor, both methods produce similar results (Winter and Dodou, 2016; Guadagnoli and Velicer, 1988). However, in cases with smaller communality, the differences can be more significant as pointed out by Snook and Gorsuch (1989), and Widaman (1990, 1993). Finally, while results of both PCA and EFA depend on the number of extracted factors, they differ in ways in which they respond to over- and under-extraction of latent factors (Winter and Dodou, 2016). Although in both methods under-extraction is a more serious

Table 2
Results of reliability and sampling adequacy analysis. Overall KMO score: .95. Overall Cronbach's α: 0.95.

Teaching presence					Social presence					Cognitive presence				
Item	Mean (SD)	Cronbach's α	Item-rest r	KMO	Item	Mean (SD)	Cronbach's α	Item-rest r	KMO	Item	Mean (SD)	Cronbach's α	Item-rest r	KMO
TP1	4.08 (0.74)	.94	.69	.94	SP1	2.96 (0.75)	.89	.58	.86	CP1	3.91 (0.74)	.90	.66	.95
TP2	4.12 (0.72)	.94	.71	.94	SP2	2.96 (0.79)	.90	.52	.86	CP2	4.00 (0.71)	.90	.68	.93
TP3	4.03 (0.75)	.93	.71	.96	SP3	3.42 (0.83)	.90	.54	.94	CP3	4.03 (0.71)	.90	.72	.94
TP4	4.01 (0.82)	.94	.59	.96	SP4	3.40 (0.78)	.88	.71	.94	CP4	3.93 (0.80)	.91	.61	.92
TP5	3.72 (0.81)	.93	.76	.97	SP5	3.31 (0.75)	.88	.77	.88	CP5	3.67 (0.81)	.91	.63	.96
TP6	3.91 (0.83)	.93	.77	.96	SP6	3.27 (0.71)	.87	.81	.89	CP6	3.41 (0.82)	.91	.47	.97
TP7	3.80 (0.83)	.93	.77	.96	SP7	3.21 (0.63)	.88	.72	.93	CP7	3.73 (0.72)	.90	.70	.95
TP8	3.77 (0.80)	.93	.80	.97	SP8	3.19 (0.56)	.89	.66	.94	CP8	3.85 (0.71)	.90	.73	.96
TP9	4.16 (0.78)	.94	.60	.97	SP9	3.24 (0.72)	.88	.70	.96	CP9	3.84 (0.74)	.90	.70	.97
TP10	3.62 (0.86)	.93	.75	.97						CP10	3.84 (0.71)	.90	.68	.95
TP11	3.71 (0.83)	.93	.78	.97						CP11	3.67 (0.82)	.91	.61	.95
TP12	3.39 (0.92)	.94	.69	.94						CP12	3.91 (0.77)	.91	.62	.94
TP13	3.60 (0.88)	.94	.68	.94										
TP	3.84 (0.81)	.94[1]	.71[2]	.96[3]	SP	3.22 (0.72)	.90[1]	.67[2]	.91[3]	CP	3.82 (0.75)	.91[1]	.65[2]	.95[3]

[1] Overall Chronbach's α for a subscale.
[2] Average item-rest r for subscale items.
[3] Average KMO for subscale items.

problem than over extraction (Fava and Velicer, 1996), it is shown that results of PCA are more severely distorted due to the over-extraction (Lawrence and Hancock, 1999). Given the unexplored nature of the CoI survey instrument in the MOOC context, this is another reason to favor EFA over PCA.

Following the approach by Shea and Bidjerano (2009), we conducted EFA of the student responses to the CoI survey instrument. Specifically, we performed a principal axis factoring (PAF) with oblimin rotation and Kaiser normalization to examine the factor structure arising from student completion of the CoI instrument in the MOOC context. The use of oblimin rotation – instead of orthogonal rotation – was warranted based on the interconnected nature of three CoI presences. The adequacy of the analysis procedure was also further evaluated using Bartlett's test of sphericity and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy.

With 34 manifest variables, the sample of 1,487 cases more than satisfied the popular sample size criteria. For instance, Tinsley and Kass (1979) suggested 5-10 participants per variable (up to 300 participants). Similarly, Tabachnick and Fidell (2007) suggested the inclusion of a sample size of at least 300 cases, while Comrey (1973) defined samples above 1,000 as excellent. Finally, a more comprehensive framework for determining the required sample size is given by MacCallum et al. (1999) which takes into the account the level of item communalities and the number of extracted factors. With all communalities (i.e., above .6) and few factors, even the small samples (i.e., less than 100) may be satisfactory (MacCallum et al., 1999). In contrast, with low communalities (i.e., well below .5) and a larger number of factors, MacCallum et al. (1999) suggest sample sizes of at least 500.

The prior research has largely demonstrated a stable three-factor structure (Swan et al., 2008; Díaz et al., 2010; Garrison et al., 2010b; Shea and Bidjerano, 2009; Arbaugh et al., 2008; Kozan and Richardson, 2014b) associated with the CoI survey instrument. Hence, for the first validation of the CoI survey instrument, we extracted the three factors using principal axis factoring (PAF). However, we also evaluated the best factor structure that emerged from the collected data set. To select the number of factors for extraction, we evaluated the scree plot (Cattell, 1966) for the inflection point and Kaiser's criterion of eigenvalues larger than one (Kaiser, 1960), as commonly undertaken in EFA/PCA analysis.

5. Results

5.1. RQ1: Reliability analysis results

To validate the CoI survey instrument in the MOOC context, we examined the reliability of the CoI instrument using Cronbach's alpha measure (Cronbach, 1951). All three subscales obtained overall reliability scores of .89 or above (Table 2) which indicates a reliable measurement instrument (Kline, 1999). We can also see that none of the items on all three subscales had an alpha value higher than the overall alpha value, indicating that none of the items negatively affects instrument reliability. Likewise, the correlations of all item with the rest of their respective scale items were sufficiently high, i.e., significantly above the threshold of .3 used in the literature (Field et al., 2012; Everitt, 2002).

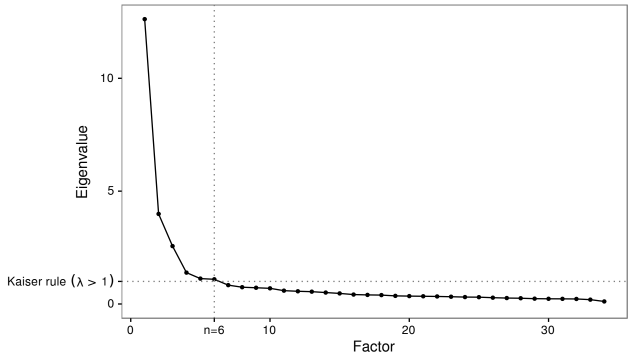

Fig. 2. Principal component analysis scree plot.

Component	Initial eigenvalues		
	Total	Percentage of variance	Cumulative percentage
1	12.62	.37	.37
2	3.99	.12	.49
3	2.56	.07	.56
4	1.39	.04	.60
5	1.12	.03	.64
6	1.09	.03	.67

Table 3. Eigenvalues from principal component analysis.

5.2. RQ2: Exploratory factor analysis results

An exploratory factor analysis (EFA) using the principal axis factoring was conducted on the 34 items of the community of inquiry survey instrument collected from 1,487 MOOC participants. The Kaiser-Meyer-Olkin (KMO) measure confirmed the adequacy of our sample, KMO=0.95 ("superb" according to Kaiser (1974)), with all individual KMO scores at or above 0.86 (Table 2) which is higher than the accepted threshold of 0.5 (Kaiser, 1974). The results of Bartlett's test were highly significant $\chi^2(561) = 34,045.36, p < .00001$. The results of these analyses, together with the satisfaction of the popular sample size criteria (Tinsley and Kass, 1979; Tabachnick and Fidell, 2007; Comrey, 1973), provide sufficient validation of the adequacy of our sample.

To select the optimal number of factors for extraction, we first plotted the eigenvalues from the PCA analysis (Fig. 2 and Table 3). The scree plot gave inconclusive results with either five or six factors[2] being an optimal solution. However, Kaiser rule (Kaiser, 1960) of eigenvalues larger than one indicated an optimal the six-factor model. In the rest of the analysis, we focused on the original three-factor model and the discovered six-factor model.

5.2.1. Three factor model results

To confirm the original structure of the CoI survey instrument, we first examined the three-factor solution of the principal axis factoring with oblimin rotation and Kaiser normalization. Overall, the model accounted for 52% of the variance (Table 4), with the average item communality of 0.52. The fit based on the off-diagonal values was 0.99, and the root mean square of the residuals (RMSR) was 0.05. These results are indicators of an overall good model fit (Field et al., 2012).

The three factors explained 21%, 17%, and 14% of the variability, respectively (Table 4). All survey items loaded with 0.3 or more at only one factor, and only two items (item #9, and #28) loaded on two factors with 0.2 or more (Table 4). The item clustering suggests that the first factor represents teaching presence (`TP`), the second factor cognitive presence (`CP`), and the third factor social presence (`SP`). Correlation analyses among the three extracted factors (Table 5a) revealed a strong correlation between cognitive and teaching presences (0.61), while social presence correlated moderately with both teaching presence (0.33) and cognitive presence (0.34). The individual item loadings unveiled that all but one item (question #28) loaded significantly only on their hypothesized factors. Question #28, related to the exploration phase of cognitive presence, had a standardized loading of .37 with the factor representing social presence, and .25 to the factor representing cognitive presence.

Following the initial three-factor analysis of the CoI survey instrument, we conducted an additional analysis without item #28 which was shown to load on a factor representing social presence (Table 4). Although loadings in an EFA analysis are more resistant to additions and removals of survey items than PCA (Widaman, 2007), we wanted to confirm whether there were any significant changes in the factor structure. The changes in item loadings and the overall model statistics were minor (on the second decimal point), indicating that the exclusion of the particular survey item did not negatively affect the results of our factor analysis.

5.2.2. Six factor model results

In addition to the original three-factor model, we also examined the six-factor model which was shown to provide the best fit for our data. The six-factor model accounted for 61% of the variance, 9% more than the original three-factor solution (Table 4) with the average item communality of .61. The fit based on the off-diagonal values was higher than .99, and the root mean square of the residuals (RMSR) was .02, indicating an excellent model fit (Field et al., 2012).

[2]When discussing PCA and EFA results, we ignored the minor technical differences between principal components and latent factors and used the term 'factor' to keep the writing more coherent and consistent. This approach is often used in factor analysis literature, for example by Field et al. (2012)

Table 4
Factor loading matrix for the three- and six-factor models. For every model, the largest loading for each item is shown boldface.

		Three factor model			Modified three factor model			Six-factor model					
#	Question	TP	CP	SP	TP	CP	SP	TP	CP	SP	Res.	Org.	Aff.
1.	TP1: The teaching team clearly communicated important course topics.	**.63**	.15	-.12	**.63**	.15	-.11	.07	-.03	-.01	.06	**.64**	.03
2.	TP2: The teaching team clearly communicated important course goals.	**.62**	.17	-.10	**.62**	.17	-.09	.01	.002	.02	.02	**.70**	.03
3.	TP3: The teaching team provided clear instructions on how to participate in course learning activities.	**.67**	.08	-.06	**.66**	.08	-.06	.17	.002	.01	-.02	**.56**	.04
4.	TP4: The teaching team clearly communicated important due dates/time frames for learning activities.	**.53**	.10	-.02	**.52**	.11	-.02	.20	.08	.03	-.04	**.36**	-.01
5.	TP5: The teaching team was helpful in identifying areas of agreement and disagreement in course discussions.	**.80**	-.09	.02	**.80**	-.08	.02	**.58**	-.01	-.001	-.03	.22	.01
6.	TP6: The teaching team was helpful in guiding the class towards understanding course topics	**.77**	.02	-.05	**.76**	.03	-.05	**.42**	-.03	.02	.03	.39	-.04
7.	TP7:The teaching team helped to keep course participants engaged and participating in productive dialogue.	**.82**	-.09	.02	**.82**	-.09	.02	**.71**	.02	.01	-.04	.11	-.06
8.	TP8:The teaching team helped keep the course participants on task in a way that helped me to learn.	**.85**	-.08	.01	**.85**	-.08	.004	**.66**	.05	-.03	-.08	.20	-.005
9.	TP9:The teaching team encouraged course participants to explore new concepts in this course.	**.50**	.20	-.10	**.50**	.20	-.09	**.38**	.26	-.01	-.08	.15	-.16
10.	TP10:The teaching team reinforced the development of a sense of community among course participants.	**.79**	-.13	.10	**.80**	-.12	.10	**.80**	-.09	-.0001	.11	-.01	.02
11.	TP11:The teaching team helped to focus discussion on relevant issues in a way that helped me to learn.	**.77**	-.03	.07	**.78**	-.03	.07	**.73**	-.01	.01	.10	.04	-.01
12.	TP12:The teaching team provided feedback that helped me understand my strengths and weaknesses.	**.75**	-.15	.12	**.75**	-.14	.12	**.77**	-.05	-.06	.05	-.05	.11
13.	TP13: The teaching team provided feedback in a timely fashion.	**.71**	-.13	.13	**.71**	-.13	.13	**.78**	.02	.03	-.04	-.08	-.01
14.	SP1: Getting to know other course participants gave me a sense of belonging in the course.	.15	-.10	**.55**	.16	-.08	**.54**	-.03	-.04	-.04	.01	.08	**.91**
15.	SP2: I was able to form distinct impressions of some course participants.	.09	-.07	**.51**	.10	-.06	**.50**	.001	.03	-.01	-.02	.01	**.74**
16.	SP3: Online or web-based communication is an excellent medium for social interaction.	.06	.06	**.50**	.06	.07	**.49**	-.03	.05	**.34**	-.01	.10	.22
17.	SP4: I felt comfortable conversing through the online medium.	-.10	.09	**.73**	-.10	.11	**.73**	-.10	.03	**.81**	-.03	.08	-.10
18.	SP5: I felt comfortable participating in the course discussions.	-.11	.04	**.84**	-.11	.07	**.84**	-.08	-.05	**.94**	.02	.06	-.13
19.	SP6: I felt comfortable interacting with other course participants.	-.11	.02	**.88**	-.11	.05	**.89**	-.08	-.06	**.95**	.01	.05	-.09
20.	SP7: I felt comfortable disagreeing with other course participants while still maintaining a sense of trust.	-.08	-.001	**.80**	-.08	.02	**.80**	.07	-.03	**.81**	.02	-.10	-.09
21.	SP8: I felt that my point of view was acknowledged by other course participants.	-.02	-.02	**.71**	-.01	-.002	**.71**	.06	-.03	**.60**	.02	-.05	.09
22.	SP9: Online discussions help me to develop a sense of collaboration.	-.01	.0002	**.72**	.003	.02	**.72**	.07	.03	**.54**	.002	-.06	.17
23.	CP1: Problems posed increased my interest in course issues.	.03	**.68**	-.04	.03	**.68**	-.03	-.17	**.56**	-.002	.03	.24	.01
24.	CP2: Course activities piqued my curiosity.	.001	**.75**	-.08	-.001	**.75**	-.07	-.23	**.63**	-.05	.01	.27	.02
25.	CP3: I felt motivated to explore content related questions.	-.07	**.82**	-.03	-.07	**.82**	-.02	-.18	**.69**	-.01	.03	.15	-.01
26.	CP4: I utilized a variety of information sources to explore problems posed in this course.	-.12	**.69**	.01	-.11	**.69**	.02	-.01	**.75**	.01	-.08	-.11	-.08
27.	CP5: Brainstorming and finding relevant information helped me resolve content related questions.	.02	**.57**	.07	.03	**.56**	.07	.15	**.63**	-.08	-.004	-.17	.09
28.	CP6: Online discussions were valuable in helping me appreciate different perspectives.	.08	.25	**.37**	-	-	-	.23	**.40**	.19	-.10	-.17	.11
29.	CP7: Combining new information helped me answer questions raised in course activities.	-.03	**.67**	.08	-.01	**.66**	.07	.08	**.71**	-.02	-.02	-.12	.03
30.	CP8: Learning activities helped me construct explanations/solutions.	.05	**.70**	.03	.06	**.69**	.03	.03	**.59**	.01	.09	.04	-.003
31.	CP9: Reflection on course content and discussions helped me understand fundamental concepts in this class.	.03	**.66**	.05	.03	**.66**	.05	.08	**.49**	.05	.19	-.03	-.05
32.	CP10: I can describe ways to test and apply the knowledge created in this course.	.004	**.69**	-.005	.002	**.69**	.005	.01	.10	.04	**.75**	-.004	-.05
33.	CP11: I have developed solutions to course problems that can be applied in practice.	.04	**.58**	.02	.04	**.58**	.03	.10	.01	-.01	**.77**	-.07	.02
34.	CP12: I can apply the knowledge created in this course to my work or other non-class related activities.	.03	**.62**	-.02	.02	**.63**	-.01	-.05	-.01	-.002	**.80**	.08	.03
	Eigenvalue	7.17	5.79	4.88	7.12	5.67	4.69	5.47	4.28	4.17	2.5	2.34	1.83
	Percentage of variance	.21	.17	.14	.22	.17	.14	.16	.13	.12	.07	.07	.05
	Total variance	.21	.38	.52	.22	.39	.53	.16	.41	.28	.48	.55	.61
	Alpha	.93	.88	.9	.93	.89	.9	.92	.88	.88	.78	.82	.6
	Correlation	.72	.65	.67	.72	.67	.65	.74	.66	.72	.71	.71	.7

Table 5
Correlation between factors in two examined models.

(a)
Correlation between factors for the three-factor solution

	TP	CP	SP
TP	1.00	0.61	0.33
CP		1.00	0.34
SP			1.00

(b)
Correlation between factors for the six-factor solution

	TP	CP	SP	Res.	Org.	Aff.
TP	1.00	0.47	0.29	0.45	0.46	0.34
CP		1.00	0.32	0.64	0.34	0.23
SP			1.00	0.29	0.07	0.50
Res.				1.00	0.35	0.21
Org.					1.00	0.02
Aff.						1.00

The six factors accounted for 16%, 13%, 12%, 7%, 7%, and 5% of the variance, respectively (Table 4). The grouping of survey items suggests that the first factor related primarily to teaching presence (TP), except the course organization and design which was captured by the fifth factor (Org.). The second factor primarily related to the cognitive presence (CP), except for the resolution phase which was captured by the sixth factor (Res.). Finally, the third factor related to the social presence (SP), except for the first two social presence items which were related to the level of affective expression between students (Aff.). The correlations between the extracted factors are shown in Table 5b. As expected, the three new factors most significantly correlated with the factor representing the rest of their respective subscales (i.e., course organization and design with the teaching presence, group affectivity with the social presence, and resolution phase with the cognitive presence).

Although factors with less than three items are typically not retained (Tabachnick and Fidell, 2007), we opted to retain all six factors suggested by the Kaiser rule, given their meaningful interpretation and the large sample size in our study. As indicated by Worthington and Whittaker (2006) and Yong and Pearce (2013), two-item factors can be retained in cases when they highly correlate with each other (i.e., .7) and are relatively uncorrelated with other items which was the case in our study. In our case, the correlation between the two questions (SP1 and SP2) was .7 while the correlations with other social presence items were in the .34–.48 range and with the rest of the CoI instrument in the .09–.35 range. Finally, as indicated by Worthington and Whittaker (2006), the decision on the number of factors should be driven by theory and the interpretability of the extracted factors.

6. Discussion

6.1. RQ1: Reliability of the CoI instrument in the MOOC context

The results from the reliability analysis confirmed that the use of the CoI survey instrument within the MOOC context is internally consistent. The obtained Cronbach's α values for the three subscales were just slightly lower than the ones in the existing research (Swan et al., 2008) and still sufficiently above the .8 level which is often used in the literature (Kline, 1999). Similar to the previous studies (Swan et al., 2008; Díaz et al., 2010; Garrison et al., 2010b; Shea and Bidjerano, 2009), the lowest level of internal consistency was achieved for social presence (.89) and the highest for the teaching presence (.93).

6.2. RQ2: Validation of the CoI factor structure in the MOOC context

6.2.1. Validation of the original three-factor model

To identify whether the factor structure of the CoI survey instrument was influenced by the MOOC pedagogical design and learning context, we examined the original three-factor structure and compared it with the existing literature (Swan et al., 2008; Díaz et al., 2010; Garrison et al., 2010b; Shea and Bidjerano, 2009; Arbaugh et al., 2008; Kozan and Richardson, 2014b). The results of the previously published studies and the present study are summarized in Table 6. Our results indicate that the factor structure of the CoI survey instrument still holds in the MOOC context and is aligned with the existing literature (Garrison et al., 2010b; Kozan and Richardson, 2014b). Similarly, our results indicate a strong correlation between teaching and cognitive presences, and a moderate correlation of social presence with both teaching and cognitive presences (Table 5a), which is also aligned with the published studies (Arbaugh et al., 2008; Shea and Bidjerano, 2009; Kozan and Richardson, 2014a)

Overall, the three-factor model explained 52% of variance which is very similar to the results reported by Garrison et al. (2010b) (54%), and slightly lower than reported in other studies in non-MOOC context, which typically reported between 60-65% of the explained variance (Table 5a). However, the percentage of variance explained is highly dependent on the adopted analysis procedure and particular study details. In our case, the results of PCA analysis (Table 3), which we conducted for the purpose of scree-plot analysis, show higher percentages of variance explained than for the EFA analysis (Table 4). The solution with three principal components accounted for 56% of the variance, while the solution with six principal components accounted for 67% of the variance (Table 3). The higher percentage of variance explained for PCA is because it focuses on maximizing variance explained by each subsequent factor (the latent model relations are essentially a side-product), whereas EFA directly models relationships between latent and manifest variables. Similarly, using six latent variables, which was suggested as optimal, could explain more variability in the collected data, than in the cases when only three factors were used. However, it is important to also take into the account the parsimony and clarity of the factor structure and their theoretical justifications.

This study found that one survey item (i.e., question #28 measuring cognitive presence: *"Online discussions were valuable in helping me appreciate different perspectives"*) loaded on the "wrong" factor, i.e., loaded onto social presence. The differences in factor loadings between traditional for-credit online courses and MOOCs suggest a specific relationship between social and cognitive presence within MOOC contexts. These differences in factor loadings are likely a result of the differences in course designs between MOOCs and small-scale online courses which put more emphasis on discussion participation. In addition to pedagogical differences, there are also substantial differences in the basic demographics of students enrolling in MOOCs and traditional, small scale, for-credit online courses (Hennis et al., 2016). These differences can have a strong influence on the use of the available technologies and tools such as online discussions (Kovanović et al., 2015a). As such, students in MOOCs are likely perceiving discussion participation as more social, rather than a cognitive activity which is likely reflected on the loading of the abovementioned (cognitive presence) item (#28) to be more related to the social than the cognitive presence factor.

Looking at the average scores of CoI survey items (Table 2), we see that students perceived level of social presence was much lower than their perceived level of teaching and cognitive presence (3.22, 3.84 and 3.82, respectively). According to Matthews et al. (2013), survey items with an average score below 3.75 represent aspects of students learning experience that need further inspection and improvement. With this criteria, all items from social presence subscale are well below the accepted level indicating significant obstacles in developing social presence in MOOC settings. While this warrants further examination, the previous research of online communities of inquiry (Garrison, 2011; Poquet et al., 2016; Akyol and Garrison, 2008; Akyol et al., 2011) indicate the critical importance of cohort size and course duration on the development of social presence, with students in shorter courses or larger cohorts having lower levels of social presence. Hence, it appears that the large-scale nature of MOOC enrollments and relatively short course duration represent significant challenges for social presence development in the MOOC context.

6.2.2. Examination of the optimal six-factor model

Interestingly, the model with six factors was suggested as optimal by Kaiser's rule and also partially by the scree plot analysis (Fig. 2). The model with six factors explained additional 9% of the variance and distinguished between different sub-components of the three presences. The three added factors were related to the resolution phase of cognitive presence, course organization and design within teaching presence, and affective communication within social presence (Table 4). The differences in the factor structure are likely resulting from the significant pedagogical differences between traditional online courses and MOOCs and emphasize the unique characteristics of MOOCs regarding the development of the communities of inquiry.

Building upon the original diagram of the CoI model by Garrison et al. (1999), we developed an updated visual representation of the CoI model which emphasizes the specifics of communities of inquiry within the MOOC context (Fig. 3). The three smaller inner circles are used to represent the three additional latent factors, and to emphasize the unique characteristics that these three sub-components have within the MOOC setting. While we initially intended to preserve the original Venn diagram notation of the CoI model (Fig. 1), given the precise semantics of Venn diagrams (in particular the meaning of circle overlapping), we decide for the model shown in Fig. 3. However, like in the previous work on the validation of the CoI survey instrument, it is important to point out that the identification of the six-factor model does not invalidate the theoretical foundation of the CoI model or the usability of the CoI survey instrument. While certain survey items (e.,g, Item #28) might require some changing and rephrasing in the context of MOOCs, the overall results indicate that the current CoI survey instrument can be used in the MOOC context without raising issues of the instrument's internal consistency or validity.

Table 6
Comparison of the present study findings with the existing studies of the CoI survey instrument.

Study	Method	Var.	Factor (var.)	Factor (var.)	Factor (var.)	Factor (var.)	Factor (var.)	Factor (var.)
Arbaugh et al. (2008) and	PCA	61.3%	TP (51%)	SP (5.6%)	CP (4.5%)			
Swan et al. (2008)		64.7%	TP' (51%)	SP (5.6%)	CP (4.5%)	TP" (3.5%)		
Garrison et al. (2010b)	EFA	53.6%	TP (38.5%)	CP (9%)	SP (6.1%)			
Kozan and Richardson (2014b)	EFA	64.8%	TP (48.2%)	CP (10.6%)	SP (6%)			
Shea and Bidjerano (2009)	EFA	64.2%	CP (50.6%)	TP (9.6%)	SP (3.9%)			
Díaz et al. (2010)	PCA	61.9%	CP (44.2%)	TP (10.6%)	SP (7.2%)			
		66.2%	CP (44.2%)	TP' (10.6%)	TP" (7.2%)	SP (4.3%)		
Present study	EFA	52%	TP (21%)	CP (17%)	SP (14%)			
		61%	TP' (16%)	CP' (13%)	SP' (12%)	Res. (7%)	Org. (7%)	Aff. (5%)

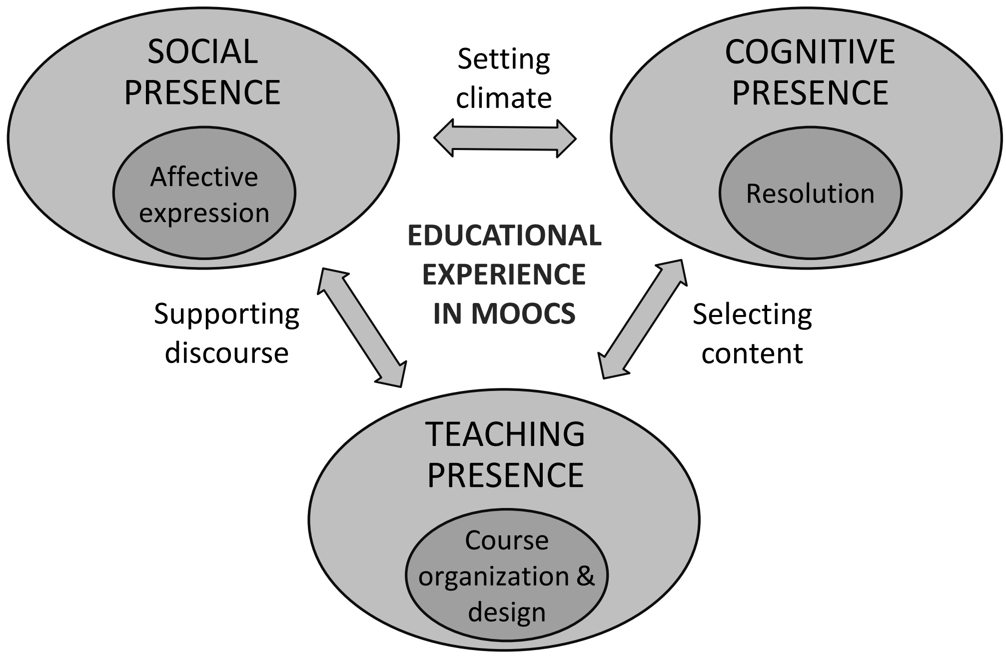

Fig. 3. Updated version of the CoI model by Garrison et al. (1999) which captures the distinct characteristics of the CoI model within the MOOC context. The smaller inner circles emphasize the specifics of course organization & design, affective expression, and resolution phase within the MOOC setting.

The fourth factor found by our analysis was associated with the items assessing the levels of resolution within students' cognitive presence development. Despite the high internal reliability of cognitive presence scale (Table 2), the items relating to the resolution phase loaded on a separate factor than the items relating to the remaining three phases of cognitive presence. This suggestsl that cognitive presence items capture two distinct, yet related learning processes. There are several likely reasons contributing to the distinction between the resolution and other three phases. As we already know from the literature, students in traditional online courses often fail to reach higher levels of cognitive presence (i.e., integration and resolution) (Garrison et al., 2001). This failure is usually attributed (to a large extent) to the course design and expectations (Garrison et al., 2010a; Gašević et al., 2015). Secondly, the literature also showed the critical importance of teachers' role in reaching the resolution phase (Celentin, 2007; Garrison and Arbaugh, 2007). Finally, a significant impact of time and course duration on the development of three presences has also been suggested (Akyol and Garrison, 2008; Akyol et al., 2011). For instance, Akyol et al. (2011) showed that students in a shorter, six-week version of a course did not reach the integration and resolution to the same extent as the students in a longer, thirteen-week version of the same course. With this in mind, the open nature of MOOCs, their broad accessibility to a diverse student population, the limited direct instruction and facilitation, and the shorter course length than formal for-credit online courses all contribute to the resolution having different dynamics separate from other phases of cognitive presence. While future research is needed on understanding what the driving force behind reaching the resolution within MOOC context is, one possible explanation might be the different motivations for participation in MOOCs, in general, and for participation in online discussions, in particular. For example, it might be that reaching high levels of cognitive presence requires significantly more active forum participation which is not mandated by the course design. Hence, students who engage in active forum participation might be more likely to reach the higher levels of cognitive presence than students focused on the individual learning activities.

The items related to course organization and design loaded on a separate (fifth) factor while the rest of teaching presence items (i.e., facilitation and direct instruction) loaded on the first factor. Loading of teaching presence items onto two different factors is an indication of the unique characteristics and importance of course organization and design within MOOC contexts. Similar findings were already reported by Arbaugh et al. (2008) who noted the existence of two factors related to teaching presence, the first one representing course organization and design, and the second one representing facilitation and direct instruction. As suggested by Arbaugh et al. (2008), the separate factors capture the different times at which these teaching activities take place (i.e., organization and design pre-course, and facilitation and direct instruction during the course). In the MOOC context, the difference between teaching activities that happen before and during the course is even more emphasized, as most MOOCs follow a very structured and predefined course organization with almost no changes during the course. Given a massive number of students in a MOOC, even slightest changes are very challenging to implement during the course execution (Jaschik, 2013). Similarly, given the limited teaching staff involved, a majority of MOOCs employ pre-recorded videos for setting up course goals and objectives, and expectations of student course participation. As well, MOOCs frequently use automated methods for feedback and assessment (e.g., computer-graded quizzes and assignments). Although further research is necessary, it is likely that due to this "dehumanization" of the role of the teacher before and during the course manifests as two separate constructs.

Finally, the first two items related to the affectivity group of the social presence loaded on a separate (sixth) factor. This indicates different dynamics surrounding the development of affect in the group communication among the students in a MOOC. This is well aligned with the previous research (Garrison, 2011; Poquet et al., 2016; Akyol and Garrison, 2008; Akyol et al., 2011) that noted the importance of course duration and cohort size on the development of social presence in general, and affectivity in particular. For example, Akyol et al. (2011) showed that students in a shorter version of a course had significantly lower levels of affective expression than students in the longer version of the same course. Similarly, Poquet et al. (2016) also reported challenges of establishing affective expression in MOOCs, particularly in shorter courses with large student cohorts. Based on this, it seems likely that some of the unique pedagogical characteristics of MOOCs, namely larger student cohorts and shorter course duration, have a significant effect on the development of affectivity in MOOCs as a process separate from social presence.

6.3. Limitations

There are several limitations of the present study. First of all, the self-selection bias and a low survey response rate could have had a substantial effect on the results validity. If students who completed the questionnaire are more similar to students from traditional online courses, then the confirmation of the CoI model within MOOCs is not surprising. Similarly, the selection of the six-factor model as optimal could be challenged, as it is not entirely clear whether the model with six, five, or just three factors should be deemed optimal. Given that – aside from factor eigenvalues – model clarity and parsimony should be taken into account, there are several potential interpretations of the factor analysis results, which should be addressed in the future replication studies on additional datasets.

While the data used in the present study comes from five different courses from a range of disciplines, they are all collected at the single institution and single run of each course. As such, there is a chance that the obtained results pertain to a specific institution and not to the broader context of MOOCs. Another potential limitation of the present study is that there were different survey completion rates between the analyzed courses which might impact the broader validity of the results presented in this paper. Similarly, given the focus of our study on MOOCs in general, we did not analyze the data from selected courses separately, but rather in a combined manner. As such, it might be that the strength of the obtained relationships significantly varies between the courses analyzed and that the present results represent a broad average for the included courses. Next, since we used the anonymized data from multiple courses, it might be that several students were included more than once. However, given the diversity of subject domains of the courses analyzed, that seems highly unlikely.

6.4. Open Questions and Future Work

While the current study provided insights into the use of the CoI instrument in the MOOC context, there are some open questions. In particular, in the future work, we will examine the present study results in the additional datasets from different institutions to confirm their validity and examine the obtained factor structure. Finally, besides validation of the CoI survey instrument, it is also important to understand the effects of and relationships between the three CoI presences. Hence, in our future work, we will also investigate the relationships between the three presences, similarly to the work of Shea and Bidjerano (2009) and Garrison et al. (2010b). Given the specifics of learning in MOOCs, it is important to examine whether the existing relationships between the three presences still hold in the MOOC context and whether there are some particular differences in sustaining communities of inquiry within MOOC courses.

7. Conclusions

In this paper, we evaluated the use of the CoI survey instrument within the MOOC context. Through the exploratory factor analysis of the data ($N = 1,487$) from five MOOCs, we examined whether the differences between traditional small-scale online courses, for which the CoI survey was initially designed, and MOOCs affect the reliability and validity of the CoI survey instrument. First of all, our results indicate that *Community of Inquiry survey instrument is a reliable and valid tool for measuring the perceived levels of teaching, cognitive, and social presences within the context of Massive Open Online Courses*. The demonstrated validity and reliability of the CoI instrument are important from the practical perspective as the present instrument can be easily included in the default post-course evaluation surveys which are administered in many MOOCs today. The inclusion of the CoI survey instrument would then enable the examination of how the particular characteristics of the course (e..g, organization and design, subject domain, or student population) affect the levels of three presences. Through the analysis of the relationships between the three presences (Shea and Bidjerano, 2009), the CoI survey data can also provide an improved understanding of the MOOC learning processes. Most importantly, it would enable a pedagogically-sound evaluation and quality assurance of MOOCs.

In addition to the validation of the CoI instrument, the current study also revealed some specifics of the MOOC context which are summarized in the updated CoI model shown on Fig. 3. While our results validated the structure of the three-factor model, all model selection criteria (i.e., scree plot and Kaiser criterion) indicated a six-factor model as optimal. The three additional factors correspond to 1) course organization and design (sub-component of teaching presence), 2) resolution phase (sub-component of cognitive presence), and 3) affective expression (sub-component of social presence). These differences highlight the key areas in which the MOOC context is different from the traditional small-scale online course context. Firstly, the open nature of MOOCs, their shorter duration and limited instructor involvement negatively impact reaching the higher levels of cognitive presence. Secondly, given the large number of students and the limited interactions between students and instructors, course organization and design are of particular importance, and represent a construct separated from the rest of teaching presence. Finally, affective expression in student group communication seems especially challenging to develop, which is likely caused by the large student cohorts and shorter course duration (Garrison, 2011; Akyol and Garrison, 2008; Akyol et al., 2011).

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