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New exploratory and confirmatory factor analysis insights into the community of inquiry survey

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ABSTRACT

This study has the aim of investigating the factor structure of an adapted version of the Community of Inquiry survey developed by Arbaugh et al. (2008). For this purpose, both exploratory and confirmatory analyses were employed in addition to a parallel analysis using two different samples. The results indicated a three-factor structure as well as high reliability indices for each subpart of the survey. More specifically, the three factors identified appear to correspond to three presences: teaching, cognitive, and social presences. Moreover, results of the study did not reveal any substantial changes that need to be made to any survey items. All these align completely with the theoretical assumptions of the Community of Inquiry Framework (e.g., Garrison & Akyol, 2013a, b), and call for further factor analytic studies on the survey.

1. Introduction

Given the increasing number of enrollments in at least one online course in recent years in the US (e.g., Allen & Seaman, 2010, 2011, 2013), and the highly growing preference for online higher education (Lloyd, Byrne, & McCoy, 2012), it has become important to evaluate online higher education programs (Kozan & Richardson, 2014). Online learning or education theoretical frameworks are important to such evaluation attempts (Kozan & Richardson, 2014). In this respect, originating in higher education computer conferencing or asynchronous textual group discussions (Garrison, Anderson, & Archer, 2010), Community of Inquiry (CoI) Framework (Garrison & Akyol, 2013a,b; Garrison, Anderson, & Archer, 2000, 2001; Garrison & Arbaugh, 2007) may be helpful greatly for formative evaluation attempts to ensure quality of online education and learner retention (Boston et al., 2009). Additionally, a common instrument has been developed by Arbaugh et al. (2008) for use with online learning environments that allows for the collection of empirical data regarding the process of learning.

What is as important as the development of such an instrument is validation and refinement studies using different learner groups and learning contexts. Given the dynamic and process-oriented nature of the CoI Framework which may be highly dependent on learner profile and learning context to a certain extent (Kozan & Richardson, 2014), validating and refining the CoI survey carries great importance in terms of increasing the validity and reliability of evaluation of online learning experiences. Therefore, it is not surprising that, in their pioneering work, Arbaugh et al. (2008) highlighted the importance of refinement studies. To serve this purpose to a certain extent, the current paper reports a multiphase exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) study using data collected from the CoI instrument.

1.1. The CoI Framework

Focusing on a socio-cognitive side of learning (Shea et al., 2011), the CoI Framework is primarily concerned about the learning process (Akyol et al., 2009; Swan, Garrison, & Richardson, 2009), which aligns with its social-constructivist approach to learning (Akyol & Garrison, 2011; Akyol, Ice, Garrison, & Mitchell, 2010; Akyol et al., 2009; Shea et al., 2011; Swan & Ice, 2010; Swan et al., 2009). The CoI Framework presumes three types of presence: (a) teaching presence, (b) cognitive presence, and (c) social presence. These presences are assumed to be closely related to each other and it is argued that educational experience happens within the intersection of the three (e.g., Arbaugh et al., 2008; Garrison et al., 2000).

Teaching presence comprises design and organization, facilitating discourse and direct instruction (Akyol & Garrison, 2008; Anderson, Rourke, Garrison, & Archer, 2001; Garrison, 2013). Anderson et al. (2001) described design and organization as designing "the process, structure, evaluation and interaction" (p. 5) and "providing guidelines and tips and modeling" (p. 6). As for facilitating discourse, it is the encouragement of reflective and sustained discourse including learners' engagement, and evaluation of the effectiveness (Anderson et al., 2001). Such a discourse consists of a critical and reflective dialogue purporting to collaboratively resolve cognitive conflicts (Garrison, 2013). Finally, direct instruction is the integration of subject matter

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and pedagogy knowledge as well as working out technical problems and guiding students towards further resources (Anderson et al., 2001).

Moreover, Garrison et al. (2000) stated that, through designing instruction and facilitating learning, teaching presence serves fostering cognitive and social presence. Likewise, Garrison and Akyol (2013a) claimed that teaching presence is essential regarding both learning consequences and alignment of social and cognitive presence. Additionally, Garrison (2011) asserted that teaching presence is the building block of a community of inquiry and aligns with learning outcomes, learner needs and capabilities of learners.

Cognitive presence is learners' capability of constructing and validating meaning through critical and continuous communication and thinking (Garrison et al., 2000, 2001). More specifically, cognitive presence is deliberately and iteratively progressing through triggering event, exploration, integration and resolution phases (Garrison & Arbaugh, 2007). Achieving these also corresponds with accomplishing a high level of learning through (a) starting with a problem to solve, (b) exploring ideas, (c) integrating them to the extent possible, and (d) choosing and applying the best solution. As a result, according to Vaughan and Garrison (2005), cognitive presence provides insights into what is accomplished through a learning experience. Kozan and Richardson (2014) further suggested that cognitive presence can mediate the relationship between teaching and social presences depending on learner priorities. For instance, what matters for learners outmost would be learning results and they might be inclined to employ social interactions to serve enhancement of learning (Kozan & Richardson, 2014).

Social presence includes not only social interaction but also encouragement of critical thinking and higher level learning (Garrison & Akyol, 2013a), thus being "an element central to learning in an online community of inquiry" (Garrison, Cleveland-Innes, & Fung, 2010, p. 32). Arguing that the original definition of social presence was not inclusive enough, Garrison (2009) described it as "the ability of participants to identify with the community (e.g., course of study), communicate purposefully in a trusting environment, and develop inter-personal relationships by way of projecting their individual personalities."(p. 352). Then, it is reasonable to assume that under the facilitative guidance of teaching presence, social presence can establish the social context in which cognitive presence can flourish. This concurs with Garrison and Arbaugh's (2007) idea that "social presence in a community of inquiry must create personal but purposeful relationships" (p. 160).

In this respect, affective or emotional expressions, a part of social presence, constitute interpersonal communications (Garrison & Akyol, 2013a). Furthermore, open communication is reciprocal and respectful communication (Garrison et al., 2000). The third component, group cohesion, establishes and maintains a feeling or sense of a community fueled by a feeling of belongingness (Garrison et al., 2000). Given that teaching presence should encourage both social and cognitive presences (Garrison, 2011; Garrison & Akyol, 2013a; Garrison et al., 2000), and that social presence should go beyond social communications thus enhancing cognitive presence (Garrison & Akyol, 2013a), it becomes essential to test these assumptions through a measurement instrument.

1.2. The CoI instrument

Arbaugh et al. (2008) developed a 34-item survey (the CoI survey) in order to measure the presences within online learning environments based on a single instrument. The survey consists of three subparts (corresponding to the three presences) each of which includes a different number of items that purport to measure each presence type. There has been some previous research aimed at establishing the validity and reliability of this survey. For instance, through a principal component analysis, Arbaugh et al. (2008) claimed that their results point to the construct validity of the presences as measured by the CoI survey.

Specifically speaking, Arbaugh et al. (2008) implemented a principal component analysis (PCA) using a multi institutional graduate student sample ($N = 287$). The results yielded four factors with eigenvalues bigger than 1. It is noteworthy to state here that while the first factor (teaching presence) had an eigenvalue bigger than 17, the eigenvalues of the other three factors fanged from 1.18 to 1.92, which was depicted in the scree plot as well. The researchers reported a total of 61.3% with the first factor explaining 51.1% of it. A 3-component solution reached in the study accompanied factor loadings that are equal to or bigger than .425. Consequently, Arbaugh et al. (2008) claimed that their results align with the theoretical assumptions of a 3-component CoI Framework accepting that there might be a fourth factor, or that it would be possible that the teaching presence part of the survey could be divided into further subscales.

Similarly, Swan et al.'s (2008) CFA produced the triple structure suggested by the CoI Framework. Swan et al. (2008) also reported high reliability indexes (Cronbach's Alpha) for each part of the CoI survey focusing on teaching, social and cognitive presence respectively: (a) teaching presence = 0.94; (b) social presence = 0.91; (c) cognitive presence = 0.95. Further, the authors stated that "As such, confirmatory factor analysis, using principal component analysis with obliminal rotation was utilized." (p. 6). Swan et al. (2008) concluded that their results confirmed the three-part structure of the CoI Framework.

Another study, Diaz, Swan, Ice, and Kupczynski (2010), employed a PCA on multiplicative scores that are ratings on the CoI survey multiplied by the importance ratings of the CoI survey items. Results with no specific number of components set before suggested existence of four components with eigenvalues larger than 1. The first of these (cognitive presence) had an eigenvalue of 15.02 while the eigenvalues for the other two were 2.45 and 3.59. In line with Arbaugh et al. (2008), the authors asserted that the fourth component may be a subpart of teaching presence without constituting an independent component on its own.

Additionally, studies by Garrison, et al. (2010), and Shea and Bidjerano (2009) both ran factor analyses and structural equation model analysis (SEM) using the CoI survey. According to authors of both studies, SEM analyses suggested a mediating effect of social presence between teaching presence and cognitive presence, and teaching presence has both direct and total effects on cognitive presence. Shea and Bidjerano (2009) also employed an EFA (using principal axis factoring) with oblimin rotation. Claiming that a three-factor structure worked better, the researchers also tried a four-factor solution. Overall, the results produced three factors with eigenvalues bigger than 1. The first factor (i.e., cognitive presence) had an eigenvalue of 17.02 while the other two eigenvalues were 1.33 and 3.27. These explained 63% of the total variance with reliability indexes bigger than .91. Garrison, et al (2010) also ran a PCA with oblimin rotation on the CoI survey data resulting in a three-component structure. Teaching presence had an eigenvalue of 13.08 while social presence had 2.09 and cognitive presence had 3.06. The total variance explained was 53.6% with reliability scores above .86 for each subpart.

Given the differences between EFA and PCA in terms of their purposes and models tested (e.g., Bandalos & Boehm-Kaufman, 2009; Schmitt, 2011) or possible differences regarding solutions (e.g., Field, 2009), it may be worthwhile to further the research on this instrument. For instance, while Shea and Bidjerano (2009) and Diaz et al. (2010) reported cognitive presence with the highest eigenvalue, Arbaugh et al. (2008) and Garrison et al. (2010) stated that teaching presence had the highest. Moreover, exploratory analysis depends on the shared variances among the items only while PCA works on the total variance in the items (Gaskin & Happell, 2014). Likewise, Mertler and Vannatta (2002) stated that while factor analysis focuses on shared variance among the variables, PCA deals with unique, shared and error variances. Therefore, it seems statistically appropriate to run an EFA while determining the factor structure of an instrument since factors would be determined based on the intercorrelations among the items not the total variance. After all, Field (2009) stated that "only factor analysis can estimate the underlying factors" while PCA deals with "which linear components exist within the data" and item contributions to them (p. 638).

Moreover, most of the previous research did not employ a CFA except for Swan et al. (2008) and this study will allow a verification or comparison point for the previous CFA findings. Additionally, in light of previously mixed findings, it appears prudent to run additional EFA studies on the CoI survey in different learning contexts to increase the ecological validity of the instrument. In this regard, the present paper first reports results of an EFA and then CFA run on the CoI survey data collected in a fully online graduate program at a large Midwestern university in the USA. Particularly, the current study addresses the following question: Does the CoI survey have an interpretable factor structure that is in line with theoretical assumptions emanating from the CoI Framework?

2. Methods

2.1. Research context

The research data were collected from graduate students pursuing a fully online Learning, Design, and Technology Master of Science Program in a College of Education. At the time of data collection, which occurred over seven 8-week consecutive semesters (Summer 2012–Summer 2013), the participants were registered in eleven graduate level online courses (3 credits each). These courses were of both required and elective type and aimed at providing both fundamental area knowledge and practical application of that knowledge through various projects and assignments. There were twenty instructors teaching these courses. Six of these courses were the same even though they were offered in different sections within several semesters. It is important to note here that these numbers cover both the first and second data sets used for the following EFAs and CFAs.

2.2. Participants

Students enrolling in the aforementioned online program are generally professionals working full time. They are generally employed in instructional design, e-learning or human performance-related positions. Originally there were 643 survey responses received. The data set was randomly divided into two smaller sets by assigning a relatively higher number of participants to EFAs (N = 352) than CFAs (N = 291). The odds were that some of the participants enrolled in more than one online course thereby constituting duplicate cases in each data set. In an effort to eliminate such cases, the data were screened and reduced first by participants' name or student identity number, and then by computer internet protocol numbers in each data set separately. In other words, only one of the cases with the same name, identity number, or internet protocol number was kept while the others were eliminated and not used in further analyses. For the first data set used for the EFAs, data elimination resulted in a total of 219 participants. As for the second data set serving the CFAs, there were 178 participants left after eliminating the duplicate cases.

Claiming that sample size would not matter greatly especially when the communalities are high (with a mean level of ≥.7), and there are a small number of factors well-determined by high loadings of at least three variables, MacCallum, Widaman, Zhang, and Hong (1999) pointed out that "common rules of thumb regarding sample size in factor analysis are not valid or useful" (p. 96). The authors further stated that a sample size of 100–200 is adequate given communalities with a level of ≥.5 and well-determined factors. In the present study, the mean communality was .712 (ranging from .548 to .862) for the EFA data and .748 for the CFA data (ranging from .497 to .900). Additionally, both data sets produced better solutions with three factors and high factor loadings ranging from .428 to .939, and at least eight indicators loading on a factor. These suggest that sample sizes of both data sets were suitable for factor analytic purposes.

2.3. Measure

An adapted version of the CoI survey developed by Arbaugh et al. (2008) with 34 items was used for data collection purposes: (a) While the original scale ranged from 0 (strongly disagree) to 4 (strongly agree), the scale employed here ranged from 1 (strongly disagree) to 5 (strongly agree), (b) the original twelfth teaching presence item (The instructor provided feedback that helped me understand my strengths and weaknesses relative to the course's goals and objectives) was shortened by removing the "relative to the course's goals and objectives" part (i.e., The instructor provided feedback that helped me understand my strengths and weaknesses) based on the Community of Inquiry Survey Instrument (draft v14) (n.d.) taken from "The Community of Inquiry" website, and (c) the twenty eighth cognitive presence item used in the present study (Discussing course content with my classmates was valuable in helping me appreciate different perspectives) was a transformed version of Arbaugh et al.'s (2008) item (Online discussions were valuable in helping me appreciate different perspectives) by another version of the survey (J. Richardson, personal communication, n.d.).

2.4. Procedures

An online version of the survey was created using Qualtrics, an online survey system. The link to the survey was delivered to the participants through the online course management system. Data collection occurred in tandem with the end of course evaluation process. For data matching purposes, participants were asked to provide the last five digits of their university identification numbers while submitting their responses. In other words, participants were not required to provide their identification numbers, which let some participants respond anonymously.

2.4.1. Data preparation

All data were first checked for univariate and multivariate cases eliminating 37 cases in the first data set and 30 cases in the second data set. Including these, less than 5% of the data was missing in each data set, which allows application of nearly any procedures to deal with missing data points leading to comparable consequences (Tabachnick & Fidell, 2013). Following Gerolimatos, Gould, and Edelstein (2012, p. 606), mean imputation or the mean of each variable was used to replace missing data points. Based on a cut-off point of .90 or above (Tabachnick & Fidell, 2013, p. 88), correlation statistics produced no multicollinearity or singularity problems existing in both data sets (r's ≤ .87). Exceeding Tabachnick and Fidell's (2013) benchmark of ">.30", these mostly medium-to-large, positive, and significant correlations among the variables suggest a reasonable factorability level of the data.

Finally, both data sets were checked for the normality assumption. Most of the variables did not a have a normal distribution of the data points. Relevant transformations were conducted on these without any significant improvements. Therefore, the data pertaining to these variables were left as they were. Given that the larger the sample size, the closer the data distribution to normality (Field, 2009), violation of normality may not impact the results dramatically in the present study. Further, Tabachnick and Fidell (2013) stated that when factor analysis is used for descriptive purposes, assumptions related to distribution of scores are not operative. The authors added that even though violating the normality assumption weakens the solution, it "may still be worthwhile" (p. 618).

3. Results and discussion

3.1. Exploratory factor analyses

219 cases were used for the EFAs. Out of this total: (a) 207 (94.5%) were fully online Masters students in the main program; (b) 6 (2.7%) were face-to-face Masters students who also take online courses in the same program; (c) 4 (1.8%) were doctoral students who take both online and face-to-face classes in the same program; (d) 2 (1%) were graduate students from another program. The number of online courses taken before current data collection ranged from zero (30 participants: 13.7%) to five or more than five (122 participants: 55.7%).

3.1.1. Preliminary analyses

Table 1 depicts the minimum–maximum range, means and standard deviations for each subpart of the CoI survey corresponding to each presence type, and the total scale.

Table 1 shows that for the sample used in the present study, the level of presences were quite high given that even means are close to possible total maximum scores for each presence part. Previous research on the CoI Framework assumed that all the studied contexts were real learning communities or communities of inquiries (Garrison, n.d.). Moreover, Matthews, Bogle, Boles, Day, and Swan (2013) diagnosed CoI survey items that were rated "less than 3.75, or slightly less than "agree" (4)" on average as problematic (p. 493). Average individual item ratings ranged from (a) 4.17 (SD = 1.05) to 4.56 (SD = .66) for teaching presence; (b) 4.19 (SD = .76) to 4.57 (SD = .54) for social presence; and (c) 4.26 (SD = .76) to 4.54 (SD = .57) for cognitive presence in the present study. These suggest that, overall, the online learning environment studied may have comprised an effective learning community based on learner perceptions.

Finally, an initial EFA without any number of factors extracted was run in order to check sampling and data adequacy. The correlation matrix showed that the data were suitable for factor analysis with large correlation values mostly bigger than .30. Bartlett's test of sphericity, χ^2 (561) = 6623. 84, $p < .001$, also indicated that correlations among the variables were large enough for an EFA. The Kaiser–Meyer–Olkin (KMO) referred to the suitability of the sampling for the present analyses, KMO = .94 which is bigger than the suggested minimum values of .5 (Field, 2009) and .6 (Tabachnick & Fidell, 2013). Further, all KMO values for each item were higher than .89 as well.

3.1.2. Factor solutions

The aforementioned initial EFA with oblimin rotation run to check the preliminary analyses also served the purpose of obtaining eigenvalues for each possible factor while checking the factor correlations. The factors had significant correlations bigger than .390 except for the correlation between the second and fourth factors with a value of .244. Four factors had eigenvalues higher than 1, explaining 68.51% of the variance together. The scree plot produced somehow ambiguous results suggesting 2–4 factors to extract from the data. Similarly, the pattern matrix of the initial EFA also pointed to 4 possible factors.

In addition, parallel analysis indicated the existence of three factors whose measured eigenvalues are bigger than possible random eigenvalues (1.83, 1.72, 1.63 respectively). The eigenvalues for these three factors were 16.39, 3.61, and 2.03, and they managed to explain a substantial amount of variance (64.83%). The fourth potential factor had a random eigenvalue of 1.57 which is bigger than its measured eigenvalue of 1.25. Further, an examination of the Pattern Matrix showed that all of the items strongly loading on the fourth factor were cognitive presence items with the thirty-first cognitive presence item cross-loading on the third and fourth factors.

Consequently, two EFAs with oblimin and promax rotations were run consecutively with three factors extracted. Both produced positive loadings on the teaching and social presence factors; however, only the promax rotation led to positive loadings on the cognitive presence factor. Moreover, it was the promax rotation that resulted in positive factor correlations only, which aligns more fully with the theory. Therefore, the promax rotation was employed in further analyses. Compared to the initial EFA which resulted in a four-factor structure, the pattern matrix of the EFA with promax rotation revealed one single cross-loading on the second and third factors. Specifically, this item (item #22: Online discussions help me develop a sense of collaboration) had a stronger loading on the social presence factor (.546) than the cognitive presence factor (.379). When three factors were extracted, items loading on the fourth factor switched to the second factor. This may suggest that the fourth factor (conceptually cognitive presence within the survey) might have been a subpart of the cognitive presence section of the survey.

Furthermore, the resultant pattern matrix produced a clearer factor solution showing that (a) all items loaded on their corresponding factor; and (b) none of the items loaded on the wrong factor. The first factor accounted for the largest amount of variance (48.21%), followed by the second factor (10.64%) and the third factor (5.98%). These three factors were named as teaching presence (TP), cognitive presence (CP), and social presence (SP) respectively, which concurs with the CoI Framework completely.

Finally, since the twenty-second item (Online discussions help me develop a sense of collaboration) cross-loaded on social presence and cognitive presence factors, a fourth EFA with three factors extracted was conducted eliminating this item. Because (a) this did not lead to a clearer factor solution; (b) the item itself is conceptually relevant to the construct of social presence; and (c) it distinctively loaded on the social presence factor; the following sections reporting the solution structure include this item. Table 2 presents the factor loadings for each of the survey items.

As Table 2 shows, under the condition of a cut-point of .32 (Comrey & Lee, 1992, as cited in Tabachnick & Fidell, 2013, p. 654) the TP factor included thirteen items that commonly focus on an online instructor's efforts invested in creating an online learning community or community of inquiry. Items loaded strongly (>.32) on the TP factor having values ranging from .939 to .557. The second factor or CP factor included twelve items that showed strong loadings on the factor itself with values going from .832 to .441. These items provided insights into how cognitively active learners were during instruction. Finally, the SP factor consisted of nine items with strong loadings ranging from .937 to .546. These items reflected the extent to which learners engaged in the learning community socially in a way that facilitates cognitive presence further. Overall, item loadings on these factors pictured a clear loading profile that included no bad or wrong loadings.

Moreover, the CP factor had large and positive correlations with the TP factor (r = .694) and the SP factor (r = .596). The TP and SP factors

Table 1
Descriptive statistics (N = 219).

	Possible minimum	Minimum	Possible maximum	Maximum	Mean	SD
Teaching presence (13 items)	13	20	65	65	56.84	9
Social presence (9 items)	9	29	45	45	39.80	4.43
Cognitive presence (12 items)	12	29.35	60	60	52.63	6.17
Total presence	34	98	170	170	149.25	17.05

Table 2
Factor loadings.

No	Items	Factor 1	Factor 2	Factor 3
TP7	The instructor helped to keep course participants engaged and participating in productive dialogue.	.939		
TP3	The instructor provided clear instructions on how to participate in course learning activities.	.910		
TP2	The instructor clearly communicated important course goals.	.884		
TP8	The instructor helped keep the course participants on task in a way that helped me to learn.	.881		
TP13	The instructor provided feedback in a timely manner.	.844		
TP1	The instructor clearly communicated important course topics.	.827		
TP6	The instructor was helpful in guiding the class towards understanding course topics in a way that helped me clarify my thinking.	.818		
TP10	Instructor actions reinforced the development of a sense of community among course participants.	.769		
TP5	The instructor was helpful in identifying areas of agreement and disagreement on course topics that helped me to learn.	.750		
TP4	The instructor clearly communicated important due dates/time frames for learning activities.	.686		
TP11	The instructor helped to focus discussion on relevant issues in a way that helped me to learn.	.676		
TP9	The instructor encouraged course participants to explore new concepts in this course.	.660		
TP12	The instructor provided feedback that helped me understand my strengths and weaknesses.	.557		
CP29	Combining new information helped me answer questions raised in course activities.		.832	
CP25	I felt motivated to explore content related questions.		.807	
CP23	Problems posed increased my interest in course issues.		.762	
CP31	Reflection on course content and discussions helped me understand fundamental concepts in this class.		.760	
CP26	I utilized a variety of information sources to explore problems posed in this course.		.754	
CP24	Course activities piqued my curiosity.		.743	
CP33	I have developed solutions to course problems that can be applied in practice.		.732	
CP30	Learning activities helped me construct explanations/solutions.		.662	
CP28	Discussing course content with my classmates was valuable in helping me appreciate different perspectives.		.648	
CP34	I can apply the knowledge created in this course to my work or other non-class related activities.		.616	
CP32	I can describe ways to test and apply the knowledge created in this course.		.615	
CP27	Brainstorming and finding relevant information helped me resolve content related questions.		.441	
SP19	I felt comfortable interacting with other course participants.			.937
SP17	I felt comfortable conversing through the online medium.			.893
SP18	I felt comfortable participating in the course discussions.			.765
SP21	I felt that my point of view was acknowledged by other course participants.			.704
SP16	Online or web-based communication is an excellent medium for social interaction.			.701
SP20	I felt comfortable disagreeing with other course participants while still maintaining a sense of trust.			.697
SP15	I was able to form distinct impressions of some course participants.			.586
SP14	Getting to know other course participants gave me a sense of belonging in the course.			.549
SP22	Online discussions help me to develop a sense of collaboration.		.379	.546

had a positive and medium correlation ($r = .450$). These also suggested that the three factors extracted were different enough from each other. Finally, Cronbach's Alpha or internal consistency value turned out to be .963 for TP, .911 for SP, and .938 for CP.

3.2. Confirmatory factor analyses

This section reports two separate CFA procedures conducted on (a) the same data set used for earlier EFAs; and (b) the second separate data set. Analyses were done using Lisrel 8.80 (Jöreskog & Sörbom, 2007). Based on the results of our parallel analysis rejecting a fourth factor, CFAs included three factors specified.

3.2.1. Analyses conducted on the previously used EFA data set

The first CFA conducted on the same data used for earlier EFAs referred to a relatively adequate fit due to some high indices ($\chi^2 = 1500.97$; df = 524; $p = .00$); non-normed fit index [NNFI] = 0.96; comparative fit index [CFI] = 0.96; incremental fit index [IFI] = 0.96; root mean square error of approximation [RMSEA] = 0.096; goodness of fit index [GFI] = 0.70).

According to Levesque, Stanek, Zuehlke, and Ryan (2004), GFI, CFI, and IFI indices are generally considered to be acceptable when they are equal to or above .90. As for RMSEA, Levesque et al. (2004) stated that an index of .05 or smaller reflects a very good fit, and an index between .08 and .05 refers to a reasonable fit while a value bigger than .10 points to a poor fit. Given these guidelines, the first CFA revealed a relatively high RMSEA and a poor GFI while the other indices refer to an acceptable model. Finally, all t values were bigger than 1.96 showing that factor loadings were significant.

Consequently, we conducted five more CFAs with three factors until the Root Mean Square Error of Approximation (RMSEA) became lower than .08. In other words, six models were tested. We stopped when RMSEA reached 0.079. The other fit indices of the final model used for evaluation purposes were as follows (See Table 3).

Table 3
Fit indices for the final model based on the first data set.

Index	Value
GFI	0.75
Expected Cross-Validation Index (ECVI)	6.31
NNFI	0.97
CFI	0.98
IFI	0.98

All these suggest that the final model exhibited a reasonably good fit ($\chi^2 = 1201.36$; df = 519; $p = .00$). Moreover, it also showed that all items loaded very strongly on their corresponding presence factor (t values were bigger than the absolute value of 1.96). The cross-loading item in earlier EFAs (i.e., item #22 = Online discussions help me to develop a sense of collaboration) was no exception in this regard. There were no cross-loadings in this model; however, it included five correlated error variances. This is not surprising given the mostly medium-to-large positive correlations existing among them. Consequently, these CFA results align with the EFA results gained earlier in that (a) there are three presence types that can be identified; and (b) items seem to measure what they are intended to measure. These further concur with the CoI Framework.

3.2.2. Analyses conducted on the new data set

One would argue that using the same data set, it would be easier to confirm or get closer to confirm a factorial model. Therefore, a second series of CFAs were conducted using the second data set including 178 participants. Among these were (a) 168 (94.4%) online Masters students in the target program; (b) 4 (2.2.%) face-to-face Masters students

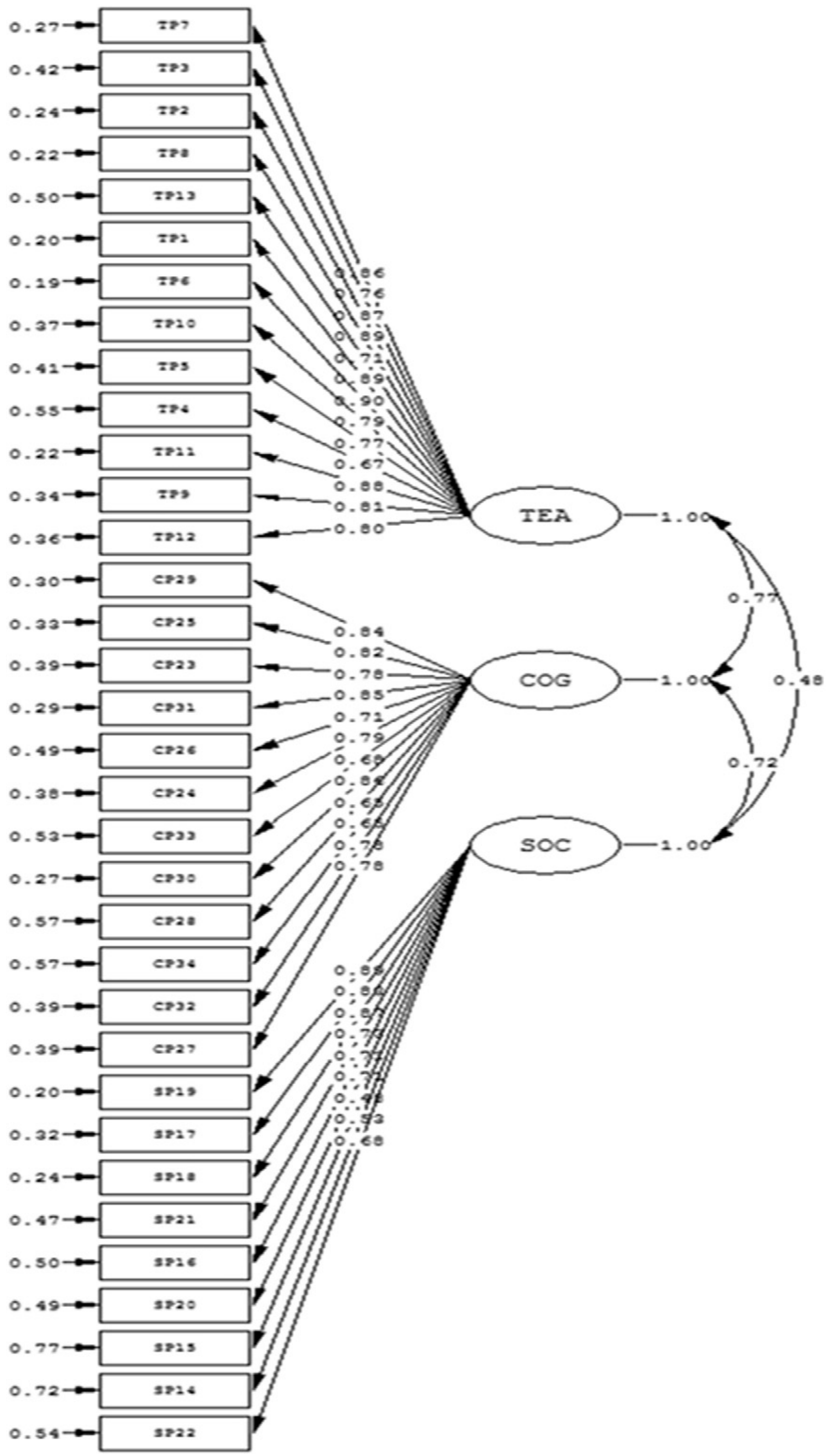

Fig. 1. Initial model (SP = Social presence; CP = Cognitive presence; TP = Teaching presence; TEA = TP factor; COG = CP factor; SOC = SP factor).

in the same program; (c) 5 (2.8%) doctoral students in the same program; and (d) 1 in another graduate program (.6%). The number of online courses the participants had taken ranged from zero (13 participants: 7.3%) to five or more than five (118 participants: 66.3%). Cronbach's alpha values were (a) .961 for TP; (b) .900 for SP; and (c) .944 for CP. Further, mean ratings ranged from (a) 4.28 (SD = .86) to 4.52 (SD = .71) for TP; (b) 4.19 (SD = .77) to 4.57 (SD = .54) for SP; and (c) 4.34 (SD = .66) to 4.59 (SD = .53). As for overall means for each presence: (a) 57 for TP (SD = 8.80; min. = 28.33; max. = 65); (b) 39.60 for SP (SD = 4.52; min. = 27; max. = 45); and (c) 53.15 for CP (SD = 6.27; min. = 35; max. = 60).

The first model, which was based on the results of the earlier EFAs, did not result in a reasonably good fit especially due to a high RMSEA value of 0.11 ($\chi^2 = 1587.11$; df = 524; $p = .00$) and low GFI of 0.64. On the other hand, an IFI of 0.96, a CFI of 0.96, and a NNFI of 0.95 indicated an acceptably good fit. Fig. 1 presents the initial model.

As a result, further maximum modifications were employed to come up with a better fit. It was the eleventh model that provided the lowest

Table 4
Fit indices for the final model based on the second new data set.

Index	Value
GFI	0.73
ECVI	7.28
NNFI	0.97
CFI	0.97
IFI	0.97

RMSEA value of 0.082 ($\chi^2 = 1193.71$; df $= 514$; $p = .00$). Moreover, all items strongly loaded on their corresponding presence based on this model (t values were bigger than 1.96). The rest of fit indices used for evaluation purposes are given in Table 4.

NNFI, CFI, and IFI values above suggest a very good fit in addition to a reasonable level of RMSEA whereas the GFI value does not. Additionally, the final model chosen depicts eight correlated error variances. These correlated errors are normal to observe since their corresponding items load on the same factor. These results concur with previous EFAs conducted, CFA conducted on the first data set, and the CoI Framework largely. Fig. 2 presents the final model.

Finally, because NNFI, CFI, and IFI values that pertain to the final model above refer to a very good fit including a reasonable RMSEA while GFI does not, we tried to improve this model by letting item 22 (SP22: Online discussions help me to develop a sense of collaboration) cross-load on both SP and CP. Allowing such a cross-loading decreased the RMSEA from 0.082 to 0.081, and the ECVI from 7.28 to 7.21. In other words, this did not improve the fit dramatically. Further, relevant statistics showed that item 22 (Online discussions help me to develop a sense of collaboration) was able to load on both SP and CP strongly;

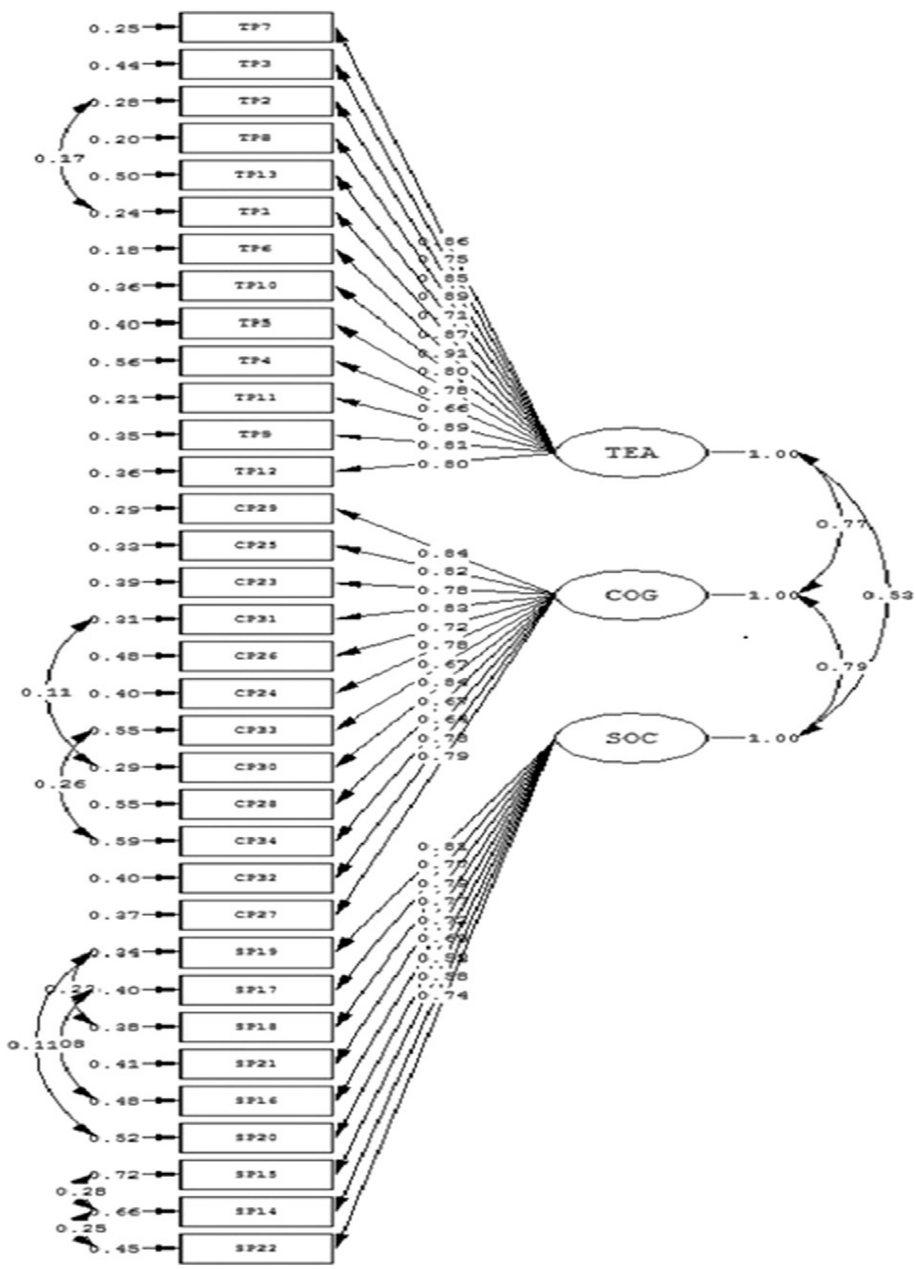

Fig. 2. Final model (SP = Social presence; CP = Cognitive presence; TP = Teaching presence; TEA = TP factor; COG = CP factor; SOC = SP factor).

however, the statistics were higher for its loading on SP. This is also in line with the CoI Framework.

4. Conclusions

The present study examined whether the CoI survey used to measure levels of presences as suggested by the CoI Framework shows a clear factor structure corresponding to each presence: cognitive presence, social presence and teaching presence. To this end, we first employed EFAs (exploratory factor analyses) in order to specify the prototype model that we further examined through CFAs (confirmatory factor analyses). During the EFAs we also used promax rotation not oblimin since only promax created positive correlations among the factors or presences. This is different from some earlier research that implemented PCA (principal component analysis) and oblimin rotation (e.g., Arbaugh et al., 2008; Shea & Bidjerano, 2009). The present EFAs with promax rotation consisted of all positive factor loadings indicating that higher ratings for each item related to higher levels of presence it aimed at measuring, which aligns with the CoI Framework.

It is interesting to observe that studies reviewed here reported negative loadings for a presence type except for Garrison et al. (2010) which also implemented oblimin rotation. These may suggest that increasing levels of some items were negatively associated with the presence it was intended to measure, the reasons for which warrants further research probably through qualitative inquiries. One possible reason would be what Garrison (n.d.) warned us about: Not all learning contexts may be real learning communities. In the case of the program being studied here the students do move through the program as a "loose" cohort, meaning if they keep on track they stay together and have shared courses throughout the program. Moreover, in this regard, based on Matthews et al.'s (2013) suggestion that items rated less than 3.75 or 4.00 may be problematic, some of the earlier research has low mean ratings for items individually or for each presence collectively. Therefore, similar to the current study, future validation studies might focus on data collected from a learning community based on Matthews et al.'s (2013) criteria above. It is important to state that Matthews et al. (2013) implemented the CoI Framework survey using a scale ranging from 1 (strongly disagree) to 5 (strongly agree).

However, determining an effective learning community, which incorporates high levels of teaching, social and cognitive presence, based on mean ratings per item or presence may miss the individual cases in which some ratings may be well below the average. For instance, if we base our decisions on a cut-off rating of 4 per item, then, we should get a minimum total rating of 52 for TP, 36 for SP, and 48 for CP. It should be noted here that the total maximum rating is 65 for TP, 45 for SP, and 60 for CP (for a scale ranging from 1 to 5). Consequently, future research may need to eliminate cases below the minimum total ratings above for each presence or the participants for whom there was not an effective learning community despite the high group average pointing to the opposite inference. Such a stricter procedure may inevitably result in violation of the normality assumption further limiting the use of certain parametric tests, which would require larger sample sizes to compensate.

The present results provided further insights into the existence of a potential fourth factor too. Some previous research pointed to a possible fourth factor that would also serve as a subcomponent of TP (e.g., Arbaugh et al., 2008; Diaz et al., 2010). However, such decisions appear to be based on eigenvalues and scree plots mainly. The present study employed parallel analysis to test the three-factor versus four-factor solutions while running the EFAs. Results indicated lower measured eigenvalues compared to random eigenvalues that pertain to a potential fourth factor suggesting that three factors would fit the existing data better. This is in line with Shea and Bidjerano (2009) claim that a three-factor structure would fit the data better compared to a four-factor structure.

Such differences might have emanated from the implementation of different methodologies. We used principal axis factoring that was also used by Shea and Bidjerano (2009) while others used PCA. Brown (2006) claimed that quantitative approaches on which PCA depends do not relate to common factor model. Specifically, PCA is mainly concerned about explaining the variance of the variables not the intercorrelations among them on which EFA focuses (Brown, 2006). Therefore, given the differences between EFA and PCA (e.g., Bandalos & Boehm-Kaufman, 2009; Field, 2009; Schmitt, 2011) all future research should be sure to include a detailed rationale for following a certain statistical procedure. We also provided a detailed presentation of goodness of fit indices we used in order to encourage future research to compare theirs with these.

Moreover, previous research suggested some minor refinements to items on the CoI survey. For instance, Arbaugh et al. (2008) argued that item 1 (TP1: The instructor clearly communicated important course topics), and item 12 (TP12: The instructor provided feedback that helped me understand my strengths and weaknesses relative to the course's goals and objectives) "do not factor out" smoothly since their loadings were not very different from "the next highest loading as compared to other items" (p. 135). According to Arbaugh et al. (2008), this may stem from wording of the items or problems related to the underlying "theoretical assumptions" (p. 135). In this sense, some present loadings in each presence are not quite different from other loadings in magnitude as well. However, given the high correlations among the items, and reliability indexes this might be reasonable. After all, we did not identify any multicollinearity or singularity cases, and statistics referred to a good level of factorability.

Cross-loadings with low differences in magnitude would be more problematic though. In our study, only item 22 (SP22: Online discussions help me to develop a sense of collaboration) had cross-loadings with values of .379 on CP and .546 on SP. Even though this seems to be distinct enough in magnitude, given our cut-off point of .32 both of them are strong loadings. Given the clear loadings of other items, this might have originated from wording of this item to a certain extent. However, even when a slightly stricter cut-off point such as .40 is employed, its loading on CP would disappear. As a result, future research may need to watch for possible similar cross-loadings that may make it harder to decide which factor a specific item belongs to.

Moreover, EFAs conducted in the present study implied that item 22 (Online discussions help me to develop a sense of collaboration) may need to be revised or removed because it strongly loaded on both SP and CP factors. However, CFAs conducted on the original data set and the new data set did not confirm this implication. Specifically speaking, the latter showed that removing this item from the model did not contribute much to the fitness of it. Consequently, based on these results, this item should be kept on the survey until similar EFA and CFA studies conducted in different learning contexts provide promising counter evidence. Needless to say, keeping it aligns with the CoI Framework. This contrasts with recent suggestions regarding refinement of SP items (Kozan & Richardson, 2014; Lowenthal & Dunlap, 2014) to some extent.

In terms of practice it may be that as program administrators we find that students who go through a program together, as a cohort, will find a pre-formed learning community, one that extends beyond a single semester. While a learning community with peers would not have direct implications for the CoI survey results for teaching presence or cognitive presence it could certainly play an important role. Each of the presences overlaps and many of the research studies to date have found that social presence mediates teaching presence and/or cognitive presence. What if a strong social presence base was in place? Therefore, continuing pre-formed online learning communities may turn out to be an effective strategy that would increase levels of cognitive, teaching and social presence.

However, the current results should be approached carefully due to some limitations. First, the sampling method was convenience and it recruited participants from one single graduate program at one university.

Therefore, generalizability is an issue. This warrants further research in different fields as well thereby increasing the ecological validity. Second, we did not collect data on either the design of the courses used or instructors' online teaching of them. Such information would provide deeper insights into learners' perception of an online learning environment thereby contributing to further research. Finally, the courses were fully online and extending this research context to face-to-face or in-class and blended learning contexts may also provide more insights into how to make the best use of the CoI survey. This concurs with recent suggestions of applying the CoI Framework to larger learning contexts than online discussions (e.g., Archer, 2010) or more than one online course (Shea et al., 2010). All these call for future research in order to get deeper insights into the factor structure of the CoI Framework.

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