Investigating the reliability and validity of the Community of Inquiry framework: an analysis of categories within each presence

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HIGHLIGHTS

- Categories within presences of the CoI framework are reliable and valid.
- A ten-factor CoI structure is valid despite high correlations between categories.
- Other CoI structures with less than 10 factors are valid but yield inferior fits.
- A second-order CoI structure with both presences and categories shows a very good fit.
- CoI structures are partially invariant across independent sample groups.

ABSTRACT

In online or blended environments, the Community of Inquiry (CoI) framework sets that a meaningful educational experience derives from the interrelation of teaching, social and cognitive presences. Each presence is subdivided, resulting in a structure in ten categories at the basis for the CoI survey instrument. Although the survey structure in three presences was repeatedly validated in the literature, the categories within presences were not and were consequently investigated in this study. High internal consistencies between items of each category demonstrated that the structure is reliable. Its convergent and discriminant validity were confirmed using multi-group confirmatory factor analyses, that further allowed to reinforce the construct validation by evaluating its factorial invariance across independent samples collected in two universities and varying in gender and age (n_1 = 343; n_2 = 420). To assess its discriminant validity and because high estimated correlations between categories were observed, alternative structures in eight, seven and six factors were also compared to the original ten-category structure. They were all valid despite yielding inferior fits. The partial structural invariance of CoI structures in categories were also confirmed across groups. Next, a CoI structure in three presences resulted in an insufficient fit to data across independent groups. Much more conclusively, a second-order structure including both presences and categories demonstrated a very good fit to the data, highlighting the importance of categories to reflect students' perceptions. This paper, although presented at a conceptual level, enlightens the potential of studying the influence of categories on each other, learning outcomes, or to identify areas of improvement in online and blended courses by relying on meaningful and trustful categories that further characterize the well-known presences.

1. Introduction

Information and communication technologies have transformed educational experiences and brought new opportunities in teaching and learning (Siemens, Gašević, & Dawson, 2015; Veletsianos, 2016). Higher education has also faced a diversification of its students, who increasingly demand time and/or space flexibility to balance their academic, personal and professional responsibilities (Lopez, Ayuela, Gonzalez-Burgos, Serrano-Gil, & Lalatsa, 2018; McDonald, 2014; Taylor, Vaughan, Ghani, Atas, & Fairbrother, 2018).

Therefore, online and blended environments have rapidly grown in higher education, offering flexibility to students while enhancing active learning thanks to the benefits of interactive technologies (Seaman, Allen, & Seaman, 2018; Siemens et al., 2015; Vaughan, Cleveland-Innes, & Garrison, 2013). In a socio-constructivist perspective, one of the most known and promising framework to guide research and practice is the Community of Inquiry (CoI) (Garrison, Anderson, & Archer, 2000; Redstone, Stefaniak, & Luo, 2018). Designed to improve teaching and learning, it proposes to engage students in critical reflection and collaborative discussions to foster higher-order learning (Garrison, Cleveland-Innes, & Fung, 2010). At its core, the CoI framework sets three main and interrelated presences for a deep and meaningful educational experience, namely teaching, social and cognitive (Garrison & Vaughan, 2008).

Further, each presence is subdivided to represent its multidimensional aspect resulting in a CoI structure in ten categories, which are associated to indicators (Akyol & Garrison, 2008) and to items of a survey instrument (Arbaugh et al., 2008). Allowing studies across disciplines and institutions (Arbaugh et al., 2008), the CoI instrument enables to evaluate students' perceptions of online and blended courses (Akyol, Garrison, & Ozden, 2009; Stenbom, 2018). While various studies examined its reliability and validity with a three-factor structure corresponding to presences (e.g., Arbaugh et al., 2008; Díaz, Swan, Ice, & Kupczynski, 2010; Kozan, & Richardson, 2014), the CoI structure in ten categories has not been investigated (Stenborn, 2018). Therefore, while analyzing and referring to presences is reliable and valid either from quantitative or qualitative data since students' perceptions reflect these (Çakıroğlu & Kılıç, 2018), the same is not true for categories since these have not been verified (Akyol & Garrison, 2008; Breivik, 2016; Kreijns, Van Acker, Vermeulen, & Van Buuren, 2014).

Despite this, several publications use the categories as a starting point for studying online and blended courses (e.g., Gutiérrez-Santiuste & Gallego-Arrufat, 2017; Hilliard & Stewart, 2019; Nazir & Brouwer, 2019; Rolim, Ferreira, Lins, & Găsević, 2019; Saadatmand, Uhlin, Hedberg, Åbjörnsson, & Kvarnström, 2017; Stenbom, Jansson, & Hulkko, 2016; Szeto, 2015; Tirado Morueta, Maraver López, Hernando Gómez, & Harris, 2016). Based on quantitative data collected through the CoI instrument, publications analyzed means and standard deviations of categories (e.g., Hilliard & Stewart, 2019; Nazir & Brouwer, 2019; Saadatmand et al., 2017) or even correlations between categories (e.g., Saadatmand et al., 2017). Based on qualitative data collected from students' communications, categories were used for deductive coding and analysis (e.g., Gutiérrez-Santiuste & Gallego-Arrufat, 2017; Nazir & Brouwer, 2019; Stenbom et al., 2016; Tirado Morueta et al., 2016), or even for analyzing their co-occurrence (e.g., Gutiérrez-Santiuste & Gallego-Arrufat, 2017). While the results in these publications enlighten dynamics between presences in online or blended environments, explicitly referring and discussing categories is disputable since there is not enough evidence that these are distinct from the students' perspective. To fill this knowledge gap, this study aims to assess the reliability and validity of the categories within the CoI framework.

2. Background work

2.1 The CoI framework: presences and categories

Teaching presence refers to "the design, facilitation and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile learning outcomes" (Anderson, Rourke, Garrison, & Archer, 2001, p. 5). Presences are subdivided into three categories: design and organization, facilitation, and direct instruction. The design and organization category relates to instruction parameters, i.e. the communication of course content, learning goals and all course-related directives, including due dates and timetables for assessment and learning activities. Facilitation corresponds to the means by which students' reflections, discussions and learning can be eased, as well as the development support of a sense of community. Finally, direct instruction refers to retroactions to students, through both focusing of discussions and feedback. It is important to note that in a community of inquiry, both students and the instructor facilitate, support and direct learning when appropriate (Vaughan et al., 2013).

Next, social presence corresponds to “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” (Garrison, 2009, p. 352). It is divided into three categories: affective expression, open communication and group cohesion. Affective expression concerns students’ sense of knowing each other, interacting socially, and belonging to the course. Open communication refers to students’ purposeful and trustful interactions with other students and course discussions in the online environment. Group cohesion targets students’ sense of collaboration within a learning community, where they can acknowledge different perspectives.

Finally, cognitive presence represents “the extent to which the participants in any particular configuration of a community of inquiry are able to construct meaning through sustained communication” (Garrison et al., 2000, p. 89), and is divided into four categories: triggering event, exploration, integration and resolution. The triggering event corresponds to a learning activity or any other course event that stimulates students’ interest and curiosity. Exploration concerns students’ building upon different information sources and perspectives through both individual and collaborative learning activities. Then integration refers to students’ development of solutions to or explanations of problems. Lastly, resolution corresponds to students’ ability to describe applications or to apply learnings in real settings.

According to Vaughan and Garrison (2005), cognitive presence is “the element within a community of inquiry which reflects the focus and success of the learning experience” (p. 8). While it represents the overarching goal of a collaborative meaningful educational experience, cognitive presence is mediated by teaching and social presences (Stenborn, 2018). Several authors (e.g., Garrison & Cleveland-Innes, 2005; Garrison et al., 2010; Shea, Li, & Pickett, 2006) have also highlighted the central role of teaching presence, which creates and sustains both social and cognitive presences in an online or blended learning environment. Still, both internal dynamics and interdependence of presences should be explored (Alin, 2010; Garrison et al., 2010) as a way to help understand areas of improvement to teaching and learning (Redstone et al., 2018). Several publications have also suggested to revise the CoI framework by adding a new presence or modifying the existing ones (Kozan & Caskurlu, 2018). However, since such modifications are still exploratory, the original framework has been used in this study. While studying presences highlights general course strengths and weaknesses, understanding the dynamics of categories inside the presences would provide more details on how to improve learning and teaching, provided of course that the categories are reliable and valid.

2.2 Presences validation through principal component and exploratory factor analyses

Factor analyses are the most common and powerful methods to evaluate the validity of a multi-dimensional construct (Clark & Watson, 1995; Thompson, & Daniel, 1996) such as the CoI instrument. Principal component and exploratory factor analyses (PCA and EFA) aim "to uncover complex patterns by exploring the dataset" (Yong, & Pearce, 2013, p. 79), particularly in contexts where the relationships are unknown or uncertain (Byrne, 2006). First validations of the CoI instrument (Arbaugh et al., 2008; Swan et al., 2008) confirmed the reliability and validity of the three presences using a single sample of 287 students across four institutions. The Keyzer-Meyer-Olkin (KMO) measure of sample adequacy was 0.96, with Cronbach's α above 0.90 for each presence. While these values assessed the high internal consistency of presences (Tabachnick & Fidell, 2007), PCA resulted in an additional fourth factor (eigenvalue > 1.0) associated with the design and organization category. Several authors (Bangert, 2009; Carlon et al., 2012; Díaz et al., 2010; Kozan, & Richardson, 2014; Shea, & Bidjerano, 2009) later confirmed the reliability and validity of presences with larger samples (ranging from 330 to 2159 students) in various disciplines, with similar methods and results. Among these results, some also suggested a potential fourth factor (e.g., Bangert, 2009; Díaz et al., 2010; Kozan, & Richardson, 2014). Very recently, Kovanović et al. (2018) extended this in Massive Open Online Courses (MOOC). With a slightly adapted CoI instrument and a sample of 1487 students, they obtained a KMO of 0.95, and Cronbach's α of 0.89 or higher. A PCA analysis also indicated a six-factor model composed of (i) the course organization and design category, (ii) the two first items of social presences "related to the level of affective expression between students" (p. 51), (iii) the resolution category, and the remaining items of (iv) teaching, (v) social and (vi) cognitive presences.

The CoI instrument was also validated through PCA and EFA in other languages. For instance, Moreira, Ferreira and Almeida (2013) confirmed the three-factor structure of a Portuguese version of the instrument (*n*=510). The KMO of 0.97 demonstrated the sample adequacy with high internal consistencies of 0.89 or higher. A Turkish version of the instrument was tested by Olpak and Kiliç Çakmak (2018). They obtained (*n*=575) a KMO of 0.98 and high internal consistencies above 0.95. Finally, Yu and Richardson (2015) validated the three-factor structure of a Korean version of the instrument. They performed an EFA (*n*=498) yielding to the suppression of two survey items due to cross-loadings on multiple factors. The KMO was then 0.97, with high internal consistencies above 0.90.

2.3 Presences validation through confirmatory factor analyses

Confirmatory factor analyses (CFA) test models establishing relationships between observed and latent variables, by comparing a hypothesized covariance structure to the covariance structure of empirical data (Schreiber, Nora, Stage, Barlow, & King, 2006). If a model converges successfully, its fit is evaluated throughout various fit indices and statistics (Jackson, Gillaspy, & Purc-Stephenson, 2009). The literature suggests relying on several goodness-of-fit indices that have different measurement properties (Byrne, 2006; Schreiber et al., 2006) such as the non-normed fit index (NNFI), the comparative fit index (CFI) and the incremental fit index (IFI). All these are considered as acceptable if as high as 0.9 (Bentler, & Bonett, 1980; McDonald, & Ho, 2002) and a good fit at 0.95 (Hu, & Bentler, 1999; Schreiber et al., 2006). In what concerns residual-based fit, the most common index is the root-mean-square error of approximation (RMSEA), which is acceptable below 0.08 (McDonald, & Ho, 2002), and a good fit below 0.06 (Schreiber et al., 2006).

To assess the construct validity of a CoI structure with three latent factors corresponding to presences, several authors performed CFA either with the original English-speaking version of the instrument or in other languages. Bangert (2009) performed a CFA (*n*=587) and concluded to a reasonable model fit with $\chi^2(524) = 4426$ and RMSEA = 0.068. However, the global chi-square value was very large with a ratio χ^2/df above 8, the literature recommending a ratio below 3 for model acceptance (Jöreskog, 1993; Schreiber et al., 2006). No other fit index was provided to confirm the results. All factor loadings were significant, and estimated correlations were 0.70 between teaching and social presences, 0.83 between social and cognitive presences, and 0.83 between teaching and cognitive presences. More conclusively, Kozan and Richardson (2014) used two separate samples (*n*=219 and *n*=178) and obtained acceptable fits to data with chi-square ratios χ^2/df below 3 when including eight error covariance parameters in their models. Goodness-of-fit indices CFI, IFI, NNFI were 0.97, while RMSEA was 0.08. All factor loadings were significant. Estimated correlations were 0.48-0.50 between teaching and social presences, 0.72-0.79 between social and cognitive presences, and 0.77-0.77 between teaching and cognitive presences (for first-second sample, respectively).

In other languages, Horzum (2015) tested the three-factor CoI structure of a Turkish version of the instrument through CFA (*n*=277). He obtained a good model fit with a chi-square ratio χ^2/df below 2, RMSEA = 0.071, and CFI = 0.98 = NNFI. More recently, Olpak and Kiliç Çakmak (2018) tested another Turkish version of the instrument (*n*=575) and obtained an acceptable model fit (χ^2/df = 4.86, CFI = 0.99 = NNFI, RMSEA = 0.08) with the inclusion of two error covariance parameters. Estimated correlations were 0.85 between teaching and social presences, 0.91 between social and cognitive presences, and 0.84 between teaching and cognitive presences. Ma et al. (2017) tested a Chinese version of the instrument through CFA (*n*=325), although they included 14 additional items related to learning presence (self-efficacy and effort regulation, see Shea & Bidjerano, 2010). They concluded to an excellent fit to the data with a chi-square ratio χ^2/df below 3, RMSEA = 0.07 and CFI = 0.93 = NNFI. Yu and Richardson (2015) also performed CFA (*n*=497) with a Korean version of the instrument, removing two items that yielded to cross-loadings in previous EFA. They obtained a global chi-square $\chi^2(461) = 1926$ (ratio χ^2/df = 4.18), RMSEA = 0.084 and IFI = 0.98 = CFI. The authors concluded to an excellent model fit despite both RMSEA and the chi-square statistic were quite high. All factor loadings were significant. Estimated correlations were 0.73 between teaching and social presences, 0.82 between social and cognitive presences, and 0.87 between teaching and cognitive presences. Note that the high estimated correlations between presences, confirmed by multiple authors in English or other languages, highlight their interdependence and therefore that of their categories.

2.4 Steps towards categories validation

In a study that aimed at modeling structural relationships between presences (n=338), Kozan (2016) confirmed the internal reliability of categories with Cronbach's α ranging from 0.79 to 0.94 for categories within teaching presence, from 0.76 to 0.93 for categories within social presence, and from 0.83 to 0.89 for categories within cognitive presence. Next and for each category, the items responses were summed to obtain a single observed variable value, using a controversial technique of items parceling (Little, Cunningham, Shahar, & Widaman, 2002). A CFA was performed on the resulting model with three latent factors (for presences) and ten observed variables (for categories). The global chi-square was $\chi^2(32) = 93$ (ratio below 3), with CFI = IFI = NNFI = 0.99 and RMSEA = 0.07 suggesting a good model fit. All factor loadings were significant, and correlations between categories (here, observed variables) ranged from 0.41 to 0.84, suggesting high interdependence. Parceling items however reduced the CoI instrument to ten observed variables corresponding to categories. Little, Cunningham, Shahar and Widaman (2002) explained that "when constructs are not unidimensional, and when it is unclear what dimensions may underlie a construct, espousing item parceling may be particularly problematic […] only under conditions of unidimensionality should parceling be considered" (p. 163). Since items parceling should not be recommended given the multidimensionality of the CoI structure, and would not provide any information about the validation of categories, the above results only confirmed the reliability of categories and their potential high interdependence.

Very recently, Caskurlu (2018) took a step towards the construct validation of categories. Isolating each presence as a model, she performed three independent separate CFA (*n*=310) to confirm corresponding categories (one model per presence). With the inclusion of seven error covariance parameters suggested by modification indices in initial outputs, she obtained good fitting models. For teaching presence, the model resulted in a global chi-square $\chi^2(60) = 127$, NNFI = 0.96 and CFI = 0.98 = IFI. The residual-based fit index RMSEA was 0.06. For social presence, she obtained a global chi-square $\chi^2(22) = 56$, NNFI = 0.96, CFI = 0.98 = IFI, and RMSEA = 0.08. For cognitive presence, fit indices and statistics were $\chi^2(45) = 120$, NNFI = 0.95, CFI = 0.95, IFI = 0.98, and RMSEA = 0.08. All chi-square ratios χ^2/df were below 3, and goodness-of-fit or residual-based fit indices indicated good fitting models. All factor loadings were also significant. However, standardized covariance values between categories were quite high ranging from 0.74 to 1.01 (the highest values were obtained for facilitation with direct instruction and for affective expression with group cohesion), and the author also tested alternative models by grouping categories inside each presence. As these did not provide better results, they were consequently not retained and the author concluded to the validity of categories inside each presence. However, she mentioned that “factor structure of the three presences should be examined with the data obtained from multiple institutions and different level of participants” (p. 10), since her data were collected in a single program.

2.5 Research questions

The previous subsections have shown that the three presences of the CoI framework are reliable and valid despite several publications suggesting a potential fourth presence (e.g., Arbaugh et al., 2008; Kozan, & Richardson, 2014; Moreira et al., 2013). Furthermore, the multidimensional aspect of presences is not clear. In particular, while Arbaugh and Hwang (2006) provided evidence of three distinct factors within teaching presence, other authors (Shea & Bidjerano, 2008; Shea, Li, & Pickett, 2006) found a two-factor solution consisting of (i) design and organization and (ii) direct facilitation (thus a single factor for both facilitation and direct instruction). As for Arbaugh (2007), he showed that design and organization items loaded both on teaching presence and a fourth factor. Regarding the social presence, Lowenthal and Dunlap (2014) expressed doubts about the formulation of items and suggested that it should be investigated.

While Garrison and Arbaugh (2007) pointed out “the need for conceptual refinement of the relationships and interactions between/among the elements” (p. 165) of the whole CoI framework, Garrison (2016) and Swan (2019) both cautioned about preserving its integrity. Recently, Caskurlu (2018) investigated the multidimensional aspect of presences by performing three independent separate CFA (one per presence) and provided evidence of categories despite high covariances between several categories (i.e., facilitation with direct instruction and affective expression with group cohesion). However, the high correlations between presences, confirmed by multiple other authors (e.g., Bangert, 2009; Kozan & Richardson, 2014; Yu & Richardson, 2015), have emphasized the need to validate the CoI structure in ten categories as a whole. Such a validation would allow to study the internal dynamics between categories of the CoI framework, and thus provide more details on strengths and weaknesses of online or blended environments. Further, all previous studies validated the instrument using a single sample (e.g., Bangert, 2009; Caskurly, 2018; Horzum, 2015; Kozan, & Richardson, 2014; Ma et al., 2017; Yu, & Richardson, 2015). More recently, several authors emphasized the importance of obtaining robust and generalized results across multiple samples and institutions (Caskurlu, 2018; Kozan & Caskurlu, 2018; Stenborn, 2018). The sample of Arbaugh et al. (2008) included participants from four universities, but it was not large enough to perform multi-group tests. To fill these gaps, this study assesses the reliability and validity of the CoI structure in ten categories by performing multi-group evaluations across two independent universities (i.e., groups). The following specific research questions are addressed:

Q1. Can the reliability of a CoI structure in ten categories be confirmed?

Q2. Can the convergent validity of a CoI structure in ten categories be confirmed, across two independent groups?

Q3. Can the discriminant validity of a CoI structure in ten categories be confirmed, across two independent groups?

Derived from the potential convergent and discriminant validity of a CoI structure in ten categories, two subquestions arise. First, we wonder if it would demonstrate factorial invariance across two independent groups, which would enlarge and reinforce the construct validation. Second, we would like to compare the CoI structure in ten categories to a more classical structure in three presences across groups. Specifically, the following research subquestions are addressed assuming the validity of a CoI structure in ten categories:

Sub1. Does a CoI structure in ten categories demonstrate factorial invariance across two independent groups?

Sub2. Would the CoI framework be best represented by presences or categories across two independent groups?

3. Methodology

3.1. Sample and procedure

The participants were French-speaking students enrolled in online courses at one medium and one large size universities in Quebec, Canada. During Winter 2016, 763 students completed an online survey on a purposeful basis. As a survey could be submitted only if all questions were answered, it avoided any missing data. Sample sizes are n_1=343 in university 1 (U1) and n_2=420 in university 2 (U2). The distribution of students according to gender and age is presented in Table 1.

		Age (years)										
Gender		≤20	21-25	26-30	31-35	36-40	41-45	46-50	51-55	56-60	≥61	Total
M	U1	1	15	15	20	21	19	9	9	3	5	117
	U2	8	35	19	13	12	4	5	1	0	0	97
	Total	9	50	34	33	33	23	14	10	3	5	214
F	U1	2	53	42	40	30	24	19	11	3	2	226
	U2	50	140	48	27	24	15	10	7	1	1	323
	Total	52	193	90	67	54	39	29	18	4	3	549

Table 1: Frequency distributions for gender and age in U1 and U2

3.2. Measure

The CoI survey is a 34-item instrument consisting of three parts (one per presence) subdivided in a total of ten categories. Teaching presence is assessed by 4 items related to the design and organization category (TP1 to TP4), 6 items for facilitation (TP5 to TP10), and 3 items for direct instruction (TP11 to TP13). Next, social presence is measured through 3 items related to the affective expression category (SP14 to SP16), 3 items for open communication (SP17 to SP19), and 3 items for group cohesion (SP20 to SP22). Finally, cognitive presence is evaluated through 3 items related to a triggering event (CP23 to CP25), 3 items for exploration (CP26 to CP28), 3 items for integration (CP29 to CP31), and 3 items for resolution (CP32 to CP34).

For this study, we used the latest version of the CoI instrument as freely translated in French by Nadeau (2012). The English-speaking version can be found on CoI interactive website (labelled v14, see CoI, n.d.), while the French-speaking version is provided in Appendix A. For validation purposes, back-translations were obtained from two independent professional translators. Experienced educational researchers performed comparisons of meaning between original and back-translated items as well as between original and translated items, which supported the equivalency of both instruments (Prieto, 1992). Note that, while the original instrument employed a 5-point Likert scale (e.g., Arbaugh et al., 2008; Caskurlu, 2018; Kozan, & Richardson, 2014; Swan et al., 2008), except for Bangert (2009) using a 6-point scale, a 7-point Likert scale was used in this study to allow more variability in the students' answers. It was coded from 1 = ‘‘strongly disagree’’ to 7 = ‘‘Strongly agree’’.

3.3. Data analysis

Commonly used for scale validation, construct validation and factorial invariance evaluation of a measurement instrument (Gallagher, & Brown, 2013), CFA were performed in this study. EQS 6.2 (Bentler, 2006) was used with the default maximum likehood method. Although this method assumes that observed variables are continuous, categorical data are commonly treated as such in literature (Byrne, 2006). Bentler and Chou (1987) indicated that categorical data relying on at least four categories can be treated as continuous if they are normally distributed. A robust option can also be invoked in EQS when the normality distribution assumption does not hold. It computes a Satorra and Bentler (1988) chi-square statistic, which has been shown to be reliable for various distributions and sample sizes (Byrne, 2006). It also displays valid and robust versions of fit and misfit indexes like the NNFI, CFI, IFI, RMSEA and corresponding 90% confidence interval. In addition to overall fit and misfit reviews, standardized residual matrices and related frequency distributions were inspected to detect any sign of model misspecification as recommended in the literature (e.g., Byrne, 2006; Gallagher, & Brown, 2013; Schermelleh-engel, Moosbrugger, & Müller, 2003; Schreiber et al., 2006).

Multi-group models were designed in EQS. First, configural invariance assessed the overall models fits across groups (Byrne, 2006; Putnick, & Bornstein, 2016). Accordingly, chi-square statistics and fit indices were provided for the overall multi-group models. Then equality constraints were imposed on each factor loading between observed and latent variables to test the measurement invariance. Equality constraints were later imposed between covariance parameters of latent factors, allowing to evaluate structural invariance across groups. When (i) results demonstrate an acceptable fit to data and (ii) the CFI difference (ΔCFI) between unconstrained and constrained models is 0.01 or smaller (Byrne, 2006; Cheung, & Rensvold, 2002), it provides evidence of the measurement or structural invariance of an instrument across groups. In that case, all estimated regression coefficients are valid across groups thanks to the imposed constraints. As such, results presented in the next section are stronger than single-group evaluations since they demonstrate the factorial invariance of the CoI instrument. For more details about conducting multi-group analyses, we refer the reader to Byrne (2006) or Putnick and Bornstein (2016).

4. Results

4.1. Preliminary analyses

The normality of both samples (U1 and U2) was first evaluated. Variables demonstrated significant nonzero univariate kurtosis with Mardia's normalized estimates of 130 for U1 and 99 for U2. This indicated that data are non-normally distributed (Mardia's normalized estimates >5.00), which was also confirmed by displaying distribution frequencies in SPSS. Therefore, the robust option was invoked for all following tests in EQS to obtain corrected standard errors, fit indices and statistics.

Next, the reliability of presences and categories was examined. Cronbach's α ranged from 0.80 to 0.94 (see Table 2), thus implying a high internal consistency among items for each presence and category (Tabachnick & Fidell, 2007).

Presences	Categories	Internal reliability (Cronbach's Alpha)	
Teaching presence	Design and organization	0.95	0.88
	Facilitation		0.94
	Direct instruction		0.87
Social presence	Affective expression	0.93	0.86
	Open communication		0.94
	Group cohesion		0.87
Cognitive presence	Triggering event	0.95	0.89
	Exploration		0.80
	Integration		0.87
	Resolution		0.89

Table 2: Internal reliability of presences and categories (for the whole sample U1+U2)

Correlations were also computed for presences and categories. They are 0.52 between teaching and social presences, 0.71 between teaching and cognitive presences, and 0.69 between social and cognitive presences for the whole sample (U1+U2). For categories, correlations ranged from 0.30 to 0.82 (see Table 3), which confirmed their interdependence with medium to high correlations. No sign of multicollinearity was detected as all correlations were <0.90 and variance inflation factors <10 (Alin, 2010; Tabachnick & Fidell, 2007). The KMO index was 0.96 (p=0.000) for the whole sample (U1+U2), which confirmed the sample adequacy for factor analysis (sample adequacy was also tested for each sample; it resulted in KMO of 0.96 and 0.90 for U1 and U2, respectively).

Correlations		Teaching presence: Design and organization	Teaching presence: Facilitation	Teaching presence: Direct instruction	Social presence: Affective expression	Social presence: Open communi-cation	Social presence: Group cohesion	Cognitive presence: Triggering event	Cognitive presence: Exploration	Cognitive presence: Integration
Teaching presence	Facilitation	0,72								
	Direct instruction	0,63	0,80							
Social presence	Affective expression	0,30	0,52	0,51						
	Open communication	0,36	0,44	0,39	0,61					
	Group cohesion	0,33	0,45	0,41	0,68	0,82				
Cognitive Presence	Triggering event	0,44	0,63	0,59	0,58	0,55	0,60			
	Exploration	0,42	0,61	0,59	0,61	0,57	0,65	0,76		
	Integration	0,52	0,68	0,64	0,57	0,57	0,59	0,79	0,79	
	Resolution	0,52	0,61	0,59	0,45	0,47	0,45	0,71	0,66	0,77

Table 3: Correlations between categories (for the whole sample U1+U2)

4.2. Assessing the convergent validity of a CoI structure in ten categories

A configural model with ten latent factors corresponding to categories of the CoI framework (Model 1) was tested. Since medium to high correlations were observed between categories, covariance parameters between all latent factors were also included. Average off-diagonal standardized residuals were 0.04 for U1 and U2, with 93.11% and 90.42% (U1 and U2, respectively) of residuals between -0.1 and 0.1. Although the frequency distributions of residuals for U1 and U2 showed a small positive asymmetry, with 4.37% (resp. 7.06%) of residuals between 0.1 and 0.2 against 1.68% (resp. 0.84%) between -0.1 and -0.2, the residual inspection did not provide any sign of misspecification as all standardized residuals were very small and below 1.96 (Schermelleh-Engel et al., 2003). Model 1 converged after 12 iterations with a Satorra-Bentler chi-square of $\chi^2(964) = 2277$, indicating a good fit with a ratio of 2.36<3 (Jöreskog, 1993; Schreiber et al., 2006). Goodness-of-fit indices were NNFI = 0.89 and CFI = 0.91 = IFI, around the acceptance level of 0.9 (Bentler, & Bonett, 1980; McDonald, & Ho, 2002). Further, the residual-based fit index RMSEA was 0.060 with a 90% confidence interval of [0.057; 0.063], implying a good model fit (Schreiber et al., 2006).

Since a goodness-of-fit index (NNFI) obtained with Model 1 was below the acceptance level of 0.90, several error covariance parameters suggested by Kozan and Richardson (2014) and Caskurlu (2018) were included in a new version of the model (Model 2). These all sounded theoretically grounded (Byrne, 2006; Schreiber et al., 2006) and were between:

- Facilitation items (TP5 and TP6) related to the instructor's helpfulness towards students' understanding of course topics,
- Direct instruction items (TP12 and TP13) related to the instructor's feedback,
- Affective expression items (SP14 and SP15) related to the development of relationships between students,
- Affective expression and group cohesion items (SP14 and SP22) related to a sense of belonging and collaboration in the course,

- Affective expression and open communication items (SP16 and SP17) related to social interactions through online communications,
- Open communication and group cohesion items (SP19 and SP20) related to interactions and trust between students,
- Resolution items (CP32 and CP34) related to applications of acquired course knowledge.

Thanks to these parameters inclusion, average off-diagonal standardized residuals showed a small decrease (especially for U2), with 94.10% and 95.96% (U1 and U2, respectively) of residuals between -0.1 and 0.1. Model 2 converged after 8 iterations. The Satorra-Bentler statistic was $\chi^2(950) = 1855$, corresponding to a very good ratio of 1.95<3. Goodness-of-fit indices were NNFI = 0.93, CFI = 0.94 = IFI, all indicating an acceptable model fit. The residual-based fit index RMSEA = 0.050 [0.047; 0.053], implicating a very good model fit. A two-stage search with multivariate Wald tests was also performed to remove any unnecessary parameter (Green, Thompson, & Poirier, 1999). Error covariance parameters included in Model 2 were all statistically significant. Further, all items loaded strongly (>0.50) on corresponding latent factors, which provided evidence of the convergent validity of a ten-factor CoI structure (Costello, & Osborne, 2005).

All covariance parameters between latent factors were statistically significant in Model 2, with all estimated correlations (r) above 0.34. However, several factors were highly correlated, especially r(facilitation, direct instruction) = 0.99(U1)/0.96(U2), r(open communication, group cohesion) = 0.92(U1)/0.89(U2), r(triggering event, exploration) = 0.94(U1)/0.84(U2), and r(exploration, integration) = 0.98(U1)/0.92(U2), which indicated that discriminant validity between these categories could not hold. For this reason, alternative models with less than ten latent factors were compared to Model 2 to assess the discriminant validity of a ten-factor CoI structure.

4.3. Assessing the discriminant validity of a CoI structure in ten categories

Several alternative models with less than ten latent factors were investigated by grouping categories together. First, a configural eight-factor model was tested by considering a single factor for both exploration and integration and another for both facilitation and direct instruction (Model 3). The error covariance parameters mentioned above were also included in Model 3 (as well as in all following alternative models). Fit statistics and indices showed a little decrease compared to Model 2; they are displayed in Table 4. Further, several latent factors were still highly correlated: *r*(open communication, group cohesion) = 0.92(U1)/0.89(U2) and *r*(triggering event, exploration) = 0.91(U1)/0.88(U2). Based on Model 3 and grouping open communication with group cohesion, a seven-factor model was also tested (Model 4). Again, its fit showed a decrease compared to Model 3. Finally, a six-factor model was tested by further grouping triggering event with exploration and integration (Model 5). Table 4 presents a summary of fit indices and statistics for Model 2 to Model 5.

	Satorra-Bentler	χ^2/df	NNFI	CFI	IFI	RMSEA
Model 2	**$\chi^2(950) = 1855$**	**1.95**	**0.93**	**0.94**	**0.94**	**0.050 [0.047; 0.053]**
	Ten-factor configural model (with seven error covariance parameters)					
Model 3	$\chi^2(984) = 1971$	2.00	0.92	0.93	0.93	0.051 [0.048; 0.055]
	grouping (exploration + integration) and (facilitation + direct instruction)					
Model 4	$\chi^2(1000) = 2146$	2.15	0.91	0.92	0.92	0.055 [0.052; 0.058]
	by further grouping (open communication + group cohesion)					
Model 5	$\chi^2(1012) = 2264$	2.24	0.90	0.91	0.91	0.057 [0.054; 0.060]
	by further grouping (triggering event + exploration + integration)					

Table 4: Comparison of fits for ten, eight, seven and six-factor configural models

All alternative configural models (Model 3 to Model 5) showed acceptable fits to the data, and covariance parameters between latent factors were all significant. For instance, estimated correlations for a six-factor model (Model 5) ranged between 0.34 and 0.87, suggesting that the structure is valuable. However, results showed that grouping categories decrease models fits. A comparison of standardized residuals for Model 2 through Model 5 also suggested that Model 2 was a better fit to the data. Further, all chi-square difference tests between alternative models (Models 3 to 5) and Model 2 were significant ($p<0.001$). Therefore, such results confirmed the discriminant validity of a ten-factor CoI structure.

Next, as our data set was composed of two independent samples, we wondered if the construct validation of the CoI structure could be reinforced by demonstrating its factorial invariance across groups.

4.4. Examining the factorial invariance of a CoI structure in ten categories

To assess the measurement invariance of a ten-factor CoI structure, constraints were included in Model 2 to force equality of factor loadings and error covariance parameters across groups. The model converged after 8 iterations with $\chi^2(991) = 1922$, resulting in a very good ratio of $1.94<3$. Goodness-of-fit and residual-based fit indices were the same as for Model 2 and indicate a good fit with data. Following the procedure described by Byrne (2006), three factor loadings and one error covariance constraints that did not operate equivalently across groups were iteratively removed using a Lagrangian Multiplier test. The corresponding released model (Model 6) converged after 8 iterations with $\chi^2(987) = 1894$, improving the previous ratio to 1.92 and decreasing RMSEA to 0.049 [0.046; 0.052]. Goodness-of-fit indices were the same as for Model 2. As Model 6 resulted in a good fit to data and $\Delta CFI \leq 0.01$ between configural and constrained models, it provided evidence of the partial measurement invariance of a ten-factor CoI structure across groups (Byrne, 2006).

Finally, equality constraints between covariance parameters of latent factors were included across groups to test structural invariance. As before, a Lagrangian Multiplier test was performed to determine the covariance parameters that did not operate equivalently across groups. These were design and organization with either facilitation or direct instruction, direct instruction with exploration, affective expression with group cohesion, and triggering event with resolution. The corresponding released model (Model 7) converged after 8 iterations with $\chi^2(1026) = 1935$, thus a very good ratio of $1.89<3$. Again, goodness-of-fit indices were the same as for Model 2, while RMSEA was 0.048 [0.045; 0.051] indicating a very good model fit. Since ΔCFI $\leq$0.01 and with a good model fit, it provided evidence of the partial structural invariance of a ten-factor CoI structure across groups (Byrne, 2006). The corresponding standardized solution is presented in Figures 1a, 1b, 1c. Estimated correlations between latent factors for groups U1-U2 are presented in Table 5.

NOTE: FIGURES 1a, 1b, 1c SHOULD APPEAR NEARBY.

Figures 1a, 1b, 1c: Estimated standardized coefficients of the ten-factor model (Model 7). Coefficients are provided for U1-U2 (unless identical).

Estimated (U1-U2)	correlations	Teaching presence: Design and organization	Facilitation	Direct instruction	Social presence: Affective expression	Open communi-cation	Group cohesion	Cognitive presence: Triggering event	Exploration	Integration
Teaching presence	Facilitation	0.76-0.77								
	Direct instruction	0.73-0.82	*0.99*							
Social presence	Affective expression	0.35	0.57	0.63						
	Open communication	0.39	0.46	0.47	0.69					
	Group cohesion	0.38	0.49	0.51	0.87-0.78	*0.90*				
Cognitive Presence	Triggering event	0.49	0.65	0.72	0.65	0.56	0.65			
	Exploration	0.51	0.70	0.75-0.80	0.78	0.69	0.82	*0.89*		
	Integration	0.58	0.74	0.80	0.67	0.62	0.68	0.88	*0.97*	
	Resolution	0.56	0.65	0.70	0.50	0.50	0.50	0.83-0.74	0.76	0.87

Table 5: Estimated correlations for groups U1-U2 (unless identical), with a ten-factor CoI structure (Model 7)

As can be seen in Table 5, Model 7 showed several high estimated correlations similarly to Model 2. As for the configural invariance, alternative structural invariance models with eight, seven or six latent factors were tested. Based on highest estimated correlations in Table 5, a model with eight latent factors was built grouping facilitation with direct instruction and exploration with integration (Model 8). Further grouping open communication with group cohesion yielded a model with seven latent factors (Model 9). Finally, grouping triggering event with exploration and integration resulted in a six-factor model (Model 10). As before, equality constraints that did not operate equivalently across groups were iteratively removed. Table 6 displays fit statistics and indices that were obtained for the corresponding partial structural invariance models.

	Satorra-Bentler	χ^2/df	NNFI	CFI	IFI	RMSEA
Model 7	$\boldsymbol{\chi^2(1026) = 1935}$	**1.89**	**0.93**	**0.94**	**0.94**	**0.048 [0.045; 0.051]**
						Ten-factor partial structural invariance model
Model 8	$\chi^2(1045) = 2030$	1.94	0.93	0.93	0.93	0.050 [0.046; 0.053]
						grouping (exploration + integration) and (facilitation + direct instruction)
Model 9	$\chi^2(1053) = 2205$	2.09	0.91	0.92	0.92	0.054 [0.050; 0.057]
						by further grouping (open communication + group cohesion)
Model 10	$\chi^2(1057) = 2311$	2.19	0.91	0.91	0.91	0.056 [0.053; 0.059]
						by further grouping (triggering event + exploration + integration)

Table 6: Comparison of fits for ten, eight, seven and six-factor partial structural invariance models

All alternative partial structural invariance models resulted in acceptable fits with data, although fits slightly decreased compared to Model 7. CFI differences with corresponding configural invariance models (ΔCFI $\leq$0.01) also confirmed their validity. Estimated correlations between factors are provided in Appendix B. Further, chi-square difference tests between alternative partial structural invariance models (Models 8 to 10) and Model 7 were all significant ($p<0.001$). This confirmed the discriminant validity of a ten-factor partial structural invariance CoI structure.

Now that the validity of categories within the CoI structure have been assessed, the question of whether the data were better supported by presences or categories is addressed by comparing a ten-factor structure to a more classical three-factor structure.

4.5. Comparing representations of the CoI structure in presences or categories

A configural model with three latent factors corresponding to presences (Model 11) was tested. It included covariance parameters between all latent factors, as well as error covariance parameters mentioned in Section 4.2. Average off-diagonal standardized residuals were 0.05 for U1 and 0.06 for U2, with 89.74% and 82.69% (U1 and U2, respectively) of residuals between -0.1 and 0.1. Again, the frequency distribution of residuals for U1 (resp. U2) showed a small positive asymmetry (8.40% -resp. 14.79%- between 0.1 and 0.3 against 1.34% -resp. 1.34%- between -0.1 and -0.3). No sign of misspecification was detected although an increase in standardized residual values was observed from a ten to a three-factor structure. Model 11 converged after 8 iterations but Satorra-Bentler chi-square of $\chi^2(1037) = 3237$ was quite high with a ratio $\chi^2/df = 3.12>3$. Goodness-of-fit indices NNFI = 0.83 and CFI = 0.85 = IFI indicated an insufficient fit with the data. However, the residual-based fit index RMSEA was 0.075 [0.072; 0.077] and suggested an acceptable model fit, although largely inferior to the one obtained for a ten-factor structure.

As the three-factor model did not allow to obtain fit indices such as those recommended in the literature, a second-order CFA was also performed. The model was composed of three higher-order factors corresponding to presences and ten lower-level factors corresponding to categories (Model 12). Covariance parameters between independent higher-order factors were included, and error covariance parameters as described above. Average off-diagonal standardized residuals decreased to 0.05 for U1 and U2, with 92.61% and 90.08% (U1 and U2, respectively) of residuals between -0.1 and 0.1, with a small positive asymmetry (6.56% -resp. 8,23%- between 0.1 and 0.3 against 0.67% -resp. 1.34%- between -0.1 and -0.3). No sign of misspecification was detected. Model 12 converged after 7 iterations with $\chi^2(1014) = 2071$, now demonstrating a good ratio $\chi^2/df =$

2.04<3. Goodness-of-fit indices NNFI = 0.92 and CFI = 0.93 = IFI indicated an acceptable model fit. The residual-based fit index RMSEA was 0.052 with a 90% confidence interval of [0.049; 0.055], implying a good model fit. Therefore, the second-order CFA model (Model 12) demonstrated a good fit to the data despite slightly inferior results than the first-order CFA with ten latent factors (Model 2). Estimated correlations were 0.50-0.56 (U1-U2, respectively) between teaching and social presences, 0.75-0.70 between social and cognitive presences, and 0.78-0.76 between teaching and cognitive presences.

The factorial invariance of a second-order CFA model was also investigated. As for previous models, constraints that did not operate equivalently across groups were iteratively removed using a Lagrangian Multiplier test (Byrne, 2006). The partial measurement invariance model (Model 13) converged after 7 iterations with $\chi^2(1051)$ = 2107 (ratio of 2.00<3), NNFI = 0.92 and CFI = 0.93 = IFI. The residual-based fit index RMSEA was 0.051 [0.048; 0.055]. The partial structural invariance model (Model 14) also converged after 7 iterations with a Satorra-Bentler statistic $\chi^2(1054)$ = 2110 (ratio of 2.00<3). Goodness-of-fit indices stayed unchanged and RMSEA was 0.051 [0.048; 0.054], indicating a good model fit. Since a ΔCFI$\leq$0.01 was measured between the configural and constrained models, the second-order model also demonstrated partial structural invariance across groups (Byrne, 2006). The corresponding standardized solution is presented in Figures 2a, 2b and 2c. Estimated correlations were 0.53 between teaching and social presences, 0.72 between social and cognitive presences, and 0.77 between teaching and cognitive presences.

NOTE: FIGURES 2a, 2b, 2c SHOULD APPEAR NEARBY.

Figures 2a, 2b, 2c: Estimated standardized coefficients of the second-order model (Model 14). Coefficients are provided for U1-U2 (unless identical).

5. Discussion and conclusions

5.1. Reliability and validity of categories within the CoI framework

This study investigated the reliability and validity of the categories within the CoI framework. First, Cronbach's α demonstrated their high internal consistency, which provided evidence of the reliability of categories and confirmed results obtained by Kozan (2016). Next, their validity was assessed through multi-group CFA using independent samples drawn from two universities. A CoI structure in ten categories yielded an acceptable model fit. As previous validity studies of the framework (e.g., Caskurlu, 2018; Kozan & Richardson, 2014), the inclusion of error covariance parameters resulted in a good model fit, which confirmed the convergent validity of a ten-factor CoI structure. However, high estimated correlations were observed between several categories, i.e., facilitation and direct instruction, open communication and group cohesion, triggering event and exploration, as well as exploration and integration.

First, the high correlations between facilitation and direct instruction recalled results from the literature (e.g., Caskurlu, 2018; Kovanović et al., 2018; Shea & Bidjerano, 2008) suggesting that these could represent a single factor. Second, the high correlations between open communication and group cohesion differed from results of Caskurlu (2018), who obtained much higher covariances between affective expression and group cohesion. Nevertheless, they evoke the doubts of Lowenthal and Dunlap (2014) about the conceptualization of survey items of social presence. Third, the high correlation between categories within cognitive presence, especially between exploration and integration, suggested that the corresponding survey items could not appear as distinct from students' perspective. Although Caskurlu (2018) did not mention anything specific about this, she also obtained high covariances between these categories.

Since our results indicated that several categories could not be distinct from each other even though a good-fitting model was obtained, alternative models with less than ten latent factors were also tested to assess the discriminant validity of categories, similarly to Caskurlu (2018). CoI structures in eight, seven and six latent factors resulted in acceptable fits to the data but fits decreased compared to a ten-factor structure. For instance, the six-factor model resulted in a good global chi-square and residual-based fit index, but goodness-of-fit indices lied at the inferior limit of acceptance. Chi-square difference tests were also performed between ten, eight, seven and six-factor models. They all confirmed the superiority of a CoI structure in ten categories, and thus its discriminant validity. Such results were in line with those of Caskurlu (2018), who also concluded to the discriminant validity of categories by performing chi-square difference tests, despite high standardized covariance values.

Hence, high estimated correlations could be a consequence of what Byrne (2006) called “a high degree of overlap content” (p. 136), meaning that several survey items were interpreted by students as pretty much the same question although worded differently. As a matter of fact, pretests showed that quite a few error covariance parameters were statistically significant when included in models. Although these often appear in CFA and indicate an “exogenous common cause” (Brown, 2006, p. 181), their high amount suggested overlaps between items. Indeed, they related to items that could be perceived by students as very similar and thus were theoretically grounded as recommended in the literature (Byrne, 2006; Schreiber et al., 2006). However, MacCallum, Roznowski, and Necowitz (1992) warned that “when an initial model fits well, it is probably unwise to modify it to achieve even better fit because modifications may simply be fitting small idiosyncratic characteristics of the sample” (p. 501). For this reason, all error covariance parameters included in models of this study were among the ones previously reported by Caskurlu (2018) or Kozan & Richardson (2014). They were all statistically significant and resulted in good fits. As recommended by Jackson et al. (2009), the modifications were cross-validated on independent samples thanks to the multi-group CFA and no additional modification was performed to avoid the risks of overfitting or capitalizing on sample variations.

Nevertheless, we recommend that items of the CoI instrument should be refined to avoid content overlaps and better define distinct categories. While several authors (Kozan & Caskurlu, 2018; Redstone et al., 2018) advised to clarify or even to enlarge presences, we suggest that original items of the CoI instrument should first be revised and tested. In particular, double-barreled items should be avoided (Clark & Watson, 1995; DeVellis, 2016; Gideon, 2012). Reviewing validity and conceptual studies about the CoI framework (e.g., suggestions to remove or modify items, structure of correlated errors, factor loadings) while considering theoretical recommendations about scale development (e.g., DeVellis, 2016) would surely be an important step. This is in line with Lowenthal and Dunlap (2014) who argued that the CoI instrument should "be revisited and adjusted over time" (p. 26). Indeed, it is crucial that students' perceptions are reflected very clearly in the existing CoI framework, as a step towards a best understanding of online and blended courses.

5.2. Factorial invariance of a CoI structure in ten categories, across two independent groups

Previous validity studies of the CoI framework performed single samples analyses, mostly drawn from one university except for the founding authors (i.e., Arbaugh et al., 2008; Swan et al., 2008). Although the latter authors involved participants in four universities, data were treated as a single sample. In this study, samples collected in two universities allowed to perform multi-group analyses, resulting in robust results as recommended by Kozan and Caskurlu (2018). Further, they enabled to assess the factorial invariance of models by imposing equality constraints across both groups. Good fitting models were obtained for a CoI structure in ten categories, which demonstrated its partial structural invariance. While some constraints had to be released since they did not operate equivalently, tests revealed that most of the structure was invariant across groups. Furthermore, alternative structural invariance models with eight, seven or six latent factors were also tested. These resulted in acceptable models fits, but fit indices and chi-square difference tests showed that a structure in ten factors was more appropriate. This suggests that students' perceptions are well represented by the original structure with ten categories, although items could be refined as indicated in Section 5.2. Further, note that including equality constraints across groups did not yield to a degradation of models fits to data. While this demonstrates the robustness of results, it also opens new research avenues concerning factorial invariance analyses of the CoI instrument.

5.3. Presences and categories representations of the CoI framework

As a CoI structure in ten categories was confirmed to be both reliable and valid across groups, we wondered if the data would be best supported by presences or categories. A ten-factor CoI structure (for categories) was compared to a more classical three-factor structure (for presences). However, the three-factor structure showed an insufficient fit to the data across both independent groups. While such a structure had been validated before, it was never tested using multi-group CFA nor a French-speaking version or the instrument. Also, note that the use of corrections to fit indices and statistics had not been mentioned in previous studies where the normality condition was violated (e.g., Caskurlu, 2018; Kozan, & Richardson, 2014) or unknown (e.g., Bangert, 2009; Garrison et al., 2010; Horzum, 2015). Additional multi-group CFA comparing English-speaking and French-speaking data with exact same parameters would be required to better understand this result.

Much more conclusively, a second-order CFA model with three higher-order factors for presences and ten lower-order factors for categories was also tested and showed a very good fit to data. Despite slightly inferior results than the first-order model with ten categories, it better describes the original CoI structure by stating correlations between presences and factor loadings of categories onto presences. Therefore, the second-order model provides a full description of the CoI framework while preserving its integrity as argued by Garrison (2016) and Swan (2019). This is very interesting since such a structure involves both presences and categories, extending the validation of the CoI framework. Furthermore, the validity of both first-order and second-order models implies that the best representation of the CoI framework should explicitly take categories into account, as students' perceptions reflect these across two independent groups. This is in line with Caskurlu (2018), who recalled that the multidimensional aspect of presences needs to be considered as it impacts teaching and learning in online and blended environments. Hence, this study has brought extensive and in-depth results about the validation of categories within each presence of the CoI framework. Although items of the CoI instrument should be refined to avoid content overlap and better define distinct categories, it provides sufficient grounds to explicitly use categories for studying online and blended environments.

5.4. Limitations

First, this study was presented at a conceptual level, since its purpose was to examine the reliability and validity of categories within the CoI framework. Nonetheless, the results should be of global interest for research and practice in online and blended learning environments since they confirm the multidimensional aspects of teaching, social and cognitive presences. As such, they provide solid grounds to investigate the internal dynamics between categories and to highlight precise course strengths and weaknesses in these environments. Further, multi-group CFA investigated the CoI structure in very details and provided robust results, opening new research avenues to more general analyses regarding the framework. Second, data were gathered using a French-speaking version of the original CoI survey. However, comparisons between original, translated and back-translated forms supported the equivalency of both instruments. Furthermore, the multi-group analyses ensured the generalizability of results, which are likely to be confirmed with the original instrument. As a matter of fact, this study also represents a first construct validation of a French version of the instrument.

5.5. Conclusions and future work

Despite the extensive work that has been reported on the CoI framework, this study represents an important contribution by assessing the reliability and validity of its categories in considerable detail. Several CoI structures in ten or fewer latent factors were validated and compared using multi-group analyses, which reinforced the constructs validation with robust results. Specifically, a first-order model in ten categories and a second-order model involving the three presences and ten categories yielded very good fits to the data, which highlights the importance of considering categories of the framework. Since such evidence attests to students' perceptions regarding the multidimensional aspect of presences, future work should focus on investigating the internal dynamics between categories, and how they impact teaching, social and cognitive presences. Such insights would enlighten how categories influence each other and pinpoint precise areas of improvement for teaching and learning in online or blended environments.

We also suggest that future work explore multi-group analyses for obtaining robust results. While studying online or blended learning courses in specific contexts is important, the CoI literature needs general work about the internal dynamics between both categories and presences. For instance, future research could involve multi-group samples from both English-Speaking and French-Speaking universities. This would also be in line with the "recent emphasis on the importance of replication studies in educational research" (Kozan & Caskurlu, p. 116) mentioned in the literature (Makel & Plucker, 2014; Spector, Johnson, & Young, 2015). Factorial invariance tests across more groups could also reinforce the CoI structure validation. Further, this study highlighted a need for revising the CoI instrument to avoid content overlap and better refine categories, as perceived by the students. Also considering that several authors included additional–but still exploratory–elements in the CoI framework (see Kozan & Caskurlu, 2018), we suggest that improvements to the instrument would be tested along with exploratory elements. Such validation would help clarifying the CoI structure and, as a result, better understand how to guide research and practice in online and blended learning environments.

Finally, we emphasize the importance of this study for both research and practice in online and blended environments. The assessed validity of categories of the CoI framework underlies the potential for future work regarding their influence on learning outcomes or to design courses. Whether to provide research avenues or to identify strengths and weaknesses of online and blended courses more precisely, researchers and practitioners can rely on meaningful and trustful categories that further characterize the well-known teaching, social and cognitive presences.

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Appendix A. French-speaking CoI survey instrument

La présence de l'enseignant / présence pédagogique

Le design et l'organisation

TP1. L'enseignant a clairement communiqué la matière importante du cours.

TP2. L'enseignant a clairement communiqué les buts importants du cours.

TP3. L'enseignant a clairement communiqué les instructions sur la façon de participer aux activités d'apprentissage du cours.

TP4. L'enseignant a clairement communiqué les dates d'échéance importantes et la durée des activités d'apprentissage.

La facilitation

TP5. L'enseignant s'est avéré utile dans l'identification des domaines d'accord et de désaccord dans la matière du cours, ce qui m'a aidé à apprendre.

TP6. L'enseignant s'est avéré utile pour orienter la classe dans la compréhension de la matière du cours d'une manière qui m'a aidé à préciser ma pensée.

TP7. L'enseignant s'est avéré utile pour maintenir l'engagement des étudiants et leur participation à un dialogue productif.

TP8. L'enseignant s'est avéré utile pour maintenir les participants sur les tâches d'une manière qui m'a aidé à apprendre.

TP9. L'enseignant a encouragé les étudiants à explorer de nouveaux concepts dans ce cours.

TP10. Les actions de l'enseignant ont renforcé la construction d'un sentiment de communauté chez les participants.

L'enseignement direct

TP11. L'enseignant a contribué à orienter la discussion sur les questions pertinentes d'une façon qui m'a aidé à apprendre.

TP12. L'enseignant a fourni des rétroactions qui m'ont aidé à comprendre mes forces et mes faiblesses.

TP13. L'enseignant a fourni des rétroactions en temps opportun.

La présence sociale

L'expression de l'affectivité

SP14. Apprendre à connaître les autres participants au cours m'a donné un sentiment d'appartenance dans le cours.

SP15. J'ai été en mesure d'éprouver de nettes impressions sur quelques participants aux cours.

SP16. La communication en ligne ou basée sur le web constitue un excellent moyen d'interaction sociale.

Une communication ouverte

SP17. Je me suis senti à l'aise de converser dans l'environnement en ligne.

SP18. Je me suis senti à l'aise de participer aux discussions du cours.

SP19. Je me suis senti à l'aise d'interagir avec d'autres participants du cours.

La cohésion du groupe

SP20. Je me suis senti à l'aise de signifier mon désaccord avec d'autres participants du cours, tout en conservant un sentiment de confiance.

SP21. J'ai senti que mon point de vue était reconnu par les autres participants du cours.

SP22. Les discussions en ligne m'aident à développer un sens de collaboration.

La présence cognitive

Événement déclencheur

CP23. Les problèmes posés ont augmenté mon intérêt pour les questions relatives au cours.

CP24. Les activités du cours ont piqué ma curiosité.

CP25. Je me suis senti motivé à explorer des questions connexes au contenu.

Exploration

CP26. J'ai utilisé diverses sources d'informations pour étudier les problèmes posés dans ce cours.

CP27. Les remue-méninges et la découverte d'informations pertinentes m'ont aidé à résoudre les questions relatives au contenu.

CP28. Les discussions en ligne ont été précieuses pour m'aider à apprécier des perspectives différentes.

Intégration

CP29. L'association de nouveaux éléments d'information m'a permis de répondre aux questions soulevées au cours des activités.

CP30. Les activités d'apprentissage m'ont permis de construire des explications/solutions.

CP31. La réflexion sur le contenu et les discussions m'ont aidé à comprendre les concepts fondamentaux dans ce cours.

Résolution

CP32. Je peux décrire des moyens de tester et d'appliquer les connaissances acquises dans ce cours

CP33. J'ai développé des solutions aux exercices qui peuvent s'appliquer dans la pratique.

CP34. Je peux appliquer les connaissances créées dans ce cours à mon travail ou à d'autres activités hors de la classe.

Choix de réponses : fortement en accord; moyennement en accord; légèrement en accord; ni en accord, ni en désaccord; légèrement en désaccord; moyennement en désaccord; fortement en désaccord.

Appendix B. Estimated correlations for eight, seven and six-factor CoI structures

Estimated correlations (U1-U2)		Teaching presence: Design and organization	Teaching presence: Facilitation & Direct instruction	Social presence: Affective expression	Social presence: Open communi-cation	Social presence: Group cohesion	Cognitive presence: Triggering event	Cognitive presence: Exploration & Integration
Teaching presence	Facilitation & Direct Instruction	0,77						
Social presence	Affective expression	0,35	0,55-0,62					
	Open communication	0,39	0,46	0,69				
	Group cohesion	0,38	0,49	0,87-0.78	*0,90*			
Cognitive Presence	Triggering event	0,49	0,67	0,65	0,56	0,65		
	Exploration & Integration	0,56	0,75	0,72	0,65	0,73	*0,89*	
	Resolution	0,56	0,66	0,50	0,50	0,50	0,83-0,74	0,84

Table 7: Estimated correlations with a partial structural invariance eight-factor CoI structure (Model 8)

		Teaching presence		Social presence		Cognitive presence	
Estimated correlations (U1-U2)		Design and organization	Facilitation & Direct instruction	Affective expression	Open communication & Group cohesion	Triggering event	Exploration & Integration
Teaching presence	Facilitation & Direct Instruction	0,77					
Social presence	Affective expression	0,34	0,54-0,62				
	Open communication & Group cohesion	0,39	0,47	0,79-0,66			
Cognitive Presence	Triggering event	0,49	0,68	0,64	0,58		
	Exploration & Integration	0,56	0,75	0,70	0,66	*0,89*	
	Resolution	0,56	0,66	0,50	0,50	0,78	0,84

Table 8: Estimated correlations with a partial structural invariance seven-factor CoI structure (Model 9)

Estimated correlations (U1-U2)		Teaching presence: Design and organization	Teaching presence: Facilitation & Direct instruction	Social presence: Affective expression	Social presence: Open communi-cation & Group cohesion	Cognitive presence: Triggering event & Exploration & Integration
Teaching presence	Facilitation & Direct Instruction	0,77				
Social presence	Affective expression	0,34	0,54-0,62			
	Open communication & Group cohesion	0,39	0,47	0,79-0,66		
Cognitive Presence	Triggering event & Exploration & Integration	0,55	0,74	0,70	0,66	
	Resolution	0,56	0,66	0,50	0,50	0,87-0,81

Table 9: Estimated correlations with a partial structural invariance six-factor CoI structure (Model 10)

References

Akyol, Z., & Garrison, D. R. (2008). The development of a community of inquiry over time in an online course: understanding the integration of social, cognitive and teaching presence. *Journal of Asynchronous Learning Networks*, *12*(3), 3‑22.

Akyol, Z., Garrison, D. R., & Ozden, M. Y. (2009). Online and blended communities of inquiry: Exploring the developmental and perceptional differences. *The International Review of Research in Open and Distributed Learning*, *10*(6), 65‑83. doi: 10.19173/irrodl.v10i6.765

Alin, A. (2010). Multicollinearity. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(3), 370‑374. doi: 10.1002/wics.84

Anderson, T., Rourke, L., Garrison, D. R., & Archer, W. (2001). Assessing teaching presence in a computer conferencing context. *Journal of Asynchronous Learning Networks*, *5*(2), 1‑17.

Arbaugh, J. B. (2007). An empirical verification of the community of inquiry framework. *Journal of Asynchronous Learning Networks, 11*(1), 73-85.

Arbaugh, J. B., Cleveland-Innes, M., Diaz, S. R., Garrison, D. R., Ice, P., Richardson, J. C., & Swan, K. P. (2008). Developing a community of inquiry instrument: Testing a measure of the Community of Inquiry framework using a multi-institutional sample. *The Internet and Higher Education*, *11*(3‑4), 133‑136. doi: 10.1016/j.iheduc.2008.06.003

Arbaugh, J. B., & Hwang, A. (2006). Does "teaching presence" exist in online MBA courses? *The Internet and Higher Education, 9*(1), 9-21.

Bangert, A. W. (2009). Building a validity argument for the community of inquiry survey instrument. *The Internet and Higher Education*, *12*(2), 104‑111. doi: 10.1016/j.iheduc.2009.06.001

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588‑606. doi: 10.1037/0033-2909.88.3.588

Bentler, P. M., & Chou, C.-P. (1987). Practical Issues in Structural Modeling. *Sociological Methods & Research*, *16*(1), 78‑117. doi: 10.1177/0049124187016001004

Bentler, Peter M. (2006). *EQS 6 Structural Equations Program Manual* (Multivariate

Software). Encino, CA: Multivariate Software, Inc.

Breivik, J. (2016). Critical Thinking in Online Educational Discussions Measured as Progress through Inquiry Phases: A Discussion of the Cognitive Presence Construct in the Community of Inquiry Framework. *International Journal of E-Learning & Distance Education*, *32*(1), 1‐16.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Press.

Byrne, B. M. (2006). *Structural Equation Modeling With EQS | Basic Concepts, Applications, and Programming, Second Edition | Taylor & Francis Group* (Routledge). London, NY: Routledge.

Çakıroğlu, Ü., & Kılıç, S. (2018). Understanding community in synchronous online learning: do perceptions match behaviours? *Open Learning: The Journal of Open, Distance and e-Learning*, 1‐17. doi: 10.1080/02680513.2018.1500888

Carlon, S., Bennett-Woods, D., Berg, B., Claywell, L., LeDuc, K., Marcisz, N., … Zenoni, L. (2012). The community of inquiry instrument: Validation and results in online health care disciplines. *Computers & Education*, *59*(2), 215‐221. doi: 10.1016/j.compedu.2012.01.004

Caskurlu, S. (2018). Confirming the subdimensions of teaching, social, and cognitive presences: A construct validity study. *The Internet and Higher Education*, *39*, 1‐12. doi: 10.1016/j.iheduc.2018.05.002

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating Goodness-of-Fit Indexes for Testing Measurement Invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(2), 233‐255. doi: 10.1207/S15328007SEM0902_5

Clark, L. A., & Watson, D. (1995). Constructing validity: Basic issues in objective scale development. *Psychological Assessment*, *7*(3), 309‐319. doi: 10.1037/1040-3590.7.3.309

CoI (n.d.). Interactive CoI website. Retrieved from https://coi.athabascau.ca/.

Costello, A. B., & Osborne, J. W. (2005). Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most From Your Analysis. *Exploratory Factor Analysis*, *10*(7), 1‐9.

DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). Newbury Park, CA: Sage.

Díaz, S. R., Swan, K., Ice, P., & Kupczynski, L. (2010). Student ratings of the importance of survey items, multiplicative factor analysis, and the validity of the community of inquiry survey. *The Internet and Higher Education*, *13*(1), 22‑30. doi: 10.1016/j.iheduc.2009.11.004

Gallagher, M. W., & Brown, T. A. (2013). Introduction to Confirmatory Factor Analysis and Structural Equation Modeling. In T. Teo (Ed.), *Handbook of Quantitative Methods for Educational Research* (p. 289‑314). Rotterdam: SensePublishers. doi: 10.1007/978-94-6209-404-8_14

Garrison, D. R. (2009). Communities of inquiry in online learning: Social, teaching and cognitive presence. In C. Howard et al. (Eds.), *Encyclopedia of distance and online learning* (2nd ed., pp. 352-355). Hershey, PA: IGI Global.

Garrison, D. R. (2016). Thinking collaboratively: Learning in a community of inquiry. New York, NY: Routledge.

Garrison, D. R., Cleveland-Innes, M., & Fung, T. S. (2010). Exploring causal relationships among teaching, cognitive and social presence: Student perceptions of the community of inquiry framework. *The Internet and Higher Education*, *13*(1), 31‑36. doi: 10.1016/j.iheduc.2009.10.002

Garrison, D. R., Anderson, T., & Archer, W. (2000). Critical Inquiry in a Text-Based Environment: Computer Conferencing in Higher Education. *The Internet and Higher Education*, *2*(2), 87‑105. doi: 10.1016/S1096-7516(00)00016-6

Garrison, D. R., & Arbaugh, J. B. (2007). Researching the community of inquiry framework: Review, issues, and future directions. *The Internet and Higher Education*, *10*(3), 157‑172. doi: 10.1016/j.iheduc.2007.04.001

Garrison, D. R., & Cleveland-Innes, M. (2005). Facilitating Cognitive Presence in Online Learning: Interaction Is Not Enough. *American Journal of Distance Education*, *19*(3), 133‑148. doi: 10.1207/s15389286ajde1903_2

Garrison, D. R., & Vaughan, N. D. (2008). *Blended Learning in Higher Education: Framework, Principles, and Guidelines*. Hoboken, NJ: John Wiley & Sons.

Gideon, L. (2012). The art of question phrasing. In *Handbook of survey methodology for the social sciences* (pp. 91-107). New York, NY: Springer.

Green, S. B., Thompson, M. S., & Poirier, J. (1999). Exploratory analyses to improve model fit: Errors due to misspecification and a strategy to reduce their occurrence. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 113‑126. doi: 10.1080/10705519909540122

Gutiérrez-Santiuste, E., & Gallego-Arrufat, M.-J. (2017). Type and degree of co-occurrence of the educational communication in a community of inquiry. *Interactive*

Learning Environments, *25*(1), 62‑71. doi: 10.1080/10494820.2015.1114498

Hilliard, L. P., & Stewart, M. K. (2019). Time well spent: Creating a community of inquiry in blended first-year writing courses. *The Internet and Higher Education*, *41*, 11‑24. doi: 10.1016/j.iheduc.2018.11.002

Horzum, M. B. (2015). Online Learning Students' Perceptions of the Community of Inquiry Based on Learning Outcomes and Demographic Variables. *Croatian Journal of Education : Hrvatski Časopis Za Odgoj i Obrazovanje*, *17*(2), 535‑567. doi: 10.15516/cje.v17i2.607

Horzum, M. B., & Uyanik, G. K. (2015). An item response theory analysis of the Community of Inquiry Scale. *The International Review of Research in Open and Distributed Learning*, *16*(2).doi: 10.19173/irrodl.v16i2.2052

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1‑55. doi: 10.1080/10705519909540118

Jackson, D. L., Gillaspy Jr., J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: An overview and some recommendations. *Psychological Methods*, *14*(1), 6. doi: 10.1037/a0014694

Jöreskog, K. G. (1993). *Testing structural equation models* (Vol. 154). Newbury Park, CA: Sage.

Kovanović, V., Joksimović, S., Poquet, O., Hennis, T., Čukić, I., de Vries, P., … Gašević, D. (2018). Exploring communities of inquiry in Massive Open Online Courses. *Computers & Education*, *119*, 44‑58. doi: 10.1016/j.compedu.2017.11.010

Kozan, K. (2016). A Comparative Structural Equation Modeling Investigation of the Relationships among Teaching, Cognitive and Social Presence. *Online Learning*, *20*(3), 210‑227.

Kozan, K., & Caskurlu, S. (2018). On the N th presence for the Community of Inquiry framework. *Computers & Education*, *122*, 104‑118. doi: 10.1016/j.compedu.2018.03.010

Kozan, K., & Richardson, J. C. (2014). New exploratory and confirmatory factor analysis insights into the community of inquiry survey. *The Internet and Higher Education*, *23*, 39‑47. doi: 10.1016/j.iheduc.2014.06.002

Kreijns, K., Van Acker, F., Vermeulen, M., & Van Buuren, H. (2014). Community of Inquiry: Social Presence Revisited. *E-Learning and Digital Media*, *11*(1), 5‑18. doi:

10.2304/elea.2014.11.1.5

Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To Parcel or Not to Parcel: Exploring the Question, Weighing the Merits. *Structural Equation Modeling: A Multidisciplinary Journal*, *9*(2), 151‑173. doi: 10.1207/S15328007SEM0902_1

Lopez, D. R. S., Ayuela, M. A. D., Gonzalez-Burgos, E., Serrano-Gil, A., & Lalatsa, K. (2019). Technology enhanced learning in Higher Education: how to enhance student engagement through blended learning. *European Journal of Education, 00, 1-14.* doi: 10.1111/ejed.12330

Lowenthal, P. R., & Dunlap, J. C. (2014). Problems measuring social presence in a community of inquiry. *E-Learning and Digital Media, 11*(1), 19-30.

Ma, Z., Wang, J., Wang, Q., Kong, L., Wu, Y., & Yang, H. (2017). Verifying Causal Relationships Among the Presences of the Community of Inquiry Framework in the Chinese Context. *The International Review of Research in Open and Distributed Learning*, *18*(6), 213-230. doi: 10.19173/irrodl.v18i6.3197

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure analysis: the problem of capitalization on chance. *Psychological Bulletin*, *111*(3), 490‑504.

Makel, M. C., & Plucker, J. A. (2014). Facts Are More Important Than Novelty: Replication in the Education Sciences. *Educational Researcher*, *43*(6), 304‑316. doi: 10.3102/0013189X14545513

McDonald, R. P., & Ho, M.-H. R. (2002). Principles and practice in reporting structural equation analyses. *Psychological Methods*, *7*(1), 64‑82. doi: 10.1037/1082-989X.7.1.64

McDonald, P. J. (2014). Variations in adult learners' experiences of blended learning in higher education. Dans A. G. Picciano, C. D. Dziuban, C. R. Graham (dir.), *Blended learning: Research Perspectives* (vol. 2, p. 215‑234). New York, NY: Routledge.

Moreira, J., Ferreira, A., & Almeida, A. (2013). Comparing communities of inquiry of Portuguese higher education students: one for all or one for each? *Open Praxis*, *5*(2), 165‑178.

Nadeau, J. (2012). *Expérimentation de la rétroaction audiovisuelle asynchrone dans un cours à distance d'informatique dans la perspective de la théorie de la communauté d'apprentissage* (Mémoire de maîtrise). Québec, QC: TÉLUQ.

Nazir, M., & Brouwer, N. (2019). Community of Inquiry on Facebook in a Formal Learning Setting in Higher Education. *Education Sciences*, *9*(1), 10. doi:

10.3390/educsci9010010

Olpak, Y. Z., & Kiliç Çakmak, E. (2018). Examining the Reliability and Validity of a Turkish Version of the Community of Inquiry Survey. *Online Learning*, *22*(1), 147‐161.

Putnick, D. L., & Bornstein, M. H. (2016). Measurement Invariance Conventions and Reporting: The State of the Art and Future Directions for Psychological Research. *Developmental review*, *41*, 71‐90. doi: 10.1016/j.dr.2016.06.004

Prieto, A. J. (1992). A method for translation of instruments to other languages. *Adult Education Quarterly*, *43*(1), 1-14.

Redstone, A. E., Stefaniak, J. E., & Luo, T. (2018). Measuring Presence: A Review of Research Using the Community of Inquiry Instrument. *Quarterly Review of Distance Education*, *19*(2), 27‐36.

Rolim, V., Ferreira, R., Lins, R. D., & Gǎsević, D. (2019). A network-based analytic approach to uncovering the relationship between social and cognitive presences in communities of inquiry. *The Internet and Higher Education*, *42*, 53-65

Saadatmand, M., Uhlin, L., Hedberg, M., Åbjörnsson, L., & Kvarnström, M. (2017). Examining Learners' Interaction in an Open Online Course Through the Community of Inquiry Framework. *European Journal of Open, Distance and E-Learning*, *20*(1), 61‐79. doi: 10.1515/eurodl-2017-0004

Satorra, A., & Bentler, P. M. (1988). *Scaling corrections for statistics in covariance structure analysis*. Los Angeles, CA: University of California at Los Angeles, Department of Psychology.

Schermelleh-engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-offit measures. *Methods of Psychological Research Online, 8*(2), 23–74.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting Structural Equation Modeling and Confirmatory Factor Analysis Results: A Review. *The Journal of Educational Research*, *99*(6), 323‐338. doi: 10.3200/JOER.99.6.323-338

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). Grade Increase: Tracking Distance Education in the United States. Wellesley, MA: *Babson Survey Research Group*.

Shea, P., & Bidjerano, T. (2008). Measures of quality in online education: An investigation of the community of inquiry model and the net generation. *Journal of Educational Computing Research*, *39*(4), 339-361

Shea, P., & Bidjerano, T. (2009). Community of inquiry as a theoretical framework to foster “epistemic engagement” and “cognitive presence” in online education. *Computers & Education*, *52*(3), 543‑553. doi: 10.1016/j.compedu.2008.10.007

Shea, P., & Bidjerano, T. (2010). Learning presence: Towards a theory of self-efficacy, self-regulation, and the development of a communities of inquiry in online and blended learning environments. *Computers & Education*, *55*(4), 1721‑1731. doi: 10.1016/j.compedu.2010.07.017

Shea, P., Sau Li, C., & Pickett, A. (2006). A study of teaching presence and student sense of learning community in fully online and web-enhanced college courses. *The Internet and Higher Education*, *9*(3), 175‑190. doi: 10.1016/j.iheduc.2006.06.005

Siemens, G., Gašević, D., & Dawson, S. (2015). Preparing for the digital university: a review of the history and current state of distance, blended, and online learning. Retrieved from http://linkresearchlab.org/PreparingDigitalUniversity.pdf

Spector, J. M., Johnson, T. E., & Young, P. A. (2015). An editorial on replication studies and scaling up efforts. *Educational Technology Research and Development*, *63*(1), 1‑4. doi: 10.1007/s11423-014-9364-3

Stenborn, S. (2018). A systematic review of the Community of Inquiry survey. *The Internet and Higher Education, 39*, 22-32.

Stenbom, S., Jansson, M., & Hulkko, A. (2016). Revising the Community of Inquiry Framework for the Analysis of One-To-One Online Learning Relationships. *The International Review of Research in Open and Distributed Learning*, *17*(3). doi: 10.19173/irrodl.v17i3.2068

Swan, K. (2019). Social Construction of Knowledge and the Community of Inquiry Framework. Dans *Open and Distance Education Theory Revisited* (p. 57-65). Singapore: Springer. doi: 10.1007/978-981-13-7740-2_7

Swan, K. P., Richardson, J. C., Ice, P., Garrison, D. R., Cleveland-Innes, M., & Arbaugh, J. B. (2008). Validating a Measurement Tool of Presence in Online Communities of Inquiry. *E-Mentor*, *2*(24), 1‑12.

Szeto, E. (2015). Community of Inquiry as an instructional approach: What effects of teaching, social and cognitive presences are there in blended synchronous learning and teaching? *Computers & Education*, *81*, 191‑201. doi: 10.1016/j.compedu.2014.10.015

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics* (5th ed.). Boston, MA: Pearson.

Taylor, M., Vaughan, N., Ghani, S. K., Atas, S. et Fairbrother, M. (2018). Looking Back and Looking Forward: A Glimpse of Blended Learning in Higher Education From 2007-2017. *International Journal of Adult Vocational Education and Technology (IJAVET)*, *9*(1), 1‑14. doi: 10.4018/IJAVET.2018010101

Thompson, B, & Daniel, L. G. (1996). Factor analytic evidence for the construct validity of scores: a historical overview and some guidelines. *Educational and Psychological Measurement*, *56*(2), 197‑208.

Thompson, Bruce. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. Washington, DC, US: American Psychological Association. doi: 10.1037/10694-000

Tirado Morueta, R., Maraver López, P., Hernando Gómez, Á., & Harris, V. W. (2016). Exploring social and cognitive presences in communities of inquiry to perform higher cognitive tasks. *The Internet and Higher Education*, *31*, 122‑131. doi: 10.1016/j.iheduc.2016.07.004

Vaughan, N. D. (2010). A blended community of inquiry approach: Linking student engagement and course redesign. *The Internet and Higher Education*, *13*(1), 60‑65. doi: 10.1016/j.iheduc.2009.10.007

Vaughan, N., Cleveland-Innes, M. et Garrison, R. (2013). *Teaching in Blended Learning Environments: Creating and Sustaining Communities of Inquiry*. Athabasca, AB: Athabasca University Press.

Vaughan, N., & Garrison, D. R. (2005). Creating cognitive presence in a blended faculty development community. *The Internet and Higher Education*, *8*(1), 1‑12. doi: 10.1016/j.iheduc.2004.11.001

Veletsianos, G. (Ed.). (2016). *Emergence and innovation in digital learning: Foundations and applications*. Athabasca, AB: Athabasca University Press.

Yong, A. G., & Pearce, S. (2013). A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, *9*(2), 79‑94. doi: 10.20982/tqmp.09.2.p079

Yu, T., & Richardson, J. C. (2015). Examining reliability and validity of a Korean version of the Community of Inquiry instrument using exploratory and confirmatory factor analysis. *The Internet and Higher Education*, *25*, 45‑52. doi: 10.1016/j.iheduc.2014.12.004