The structure of Chinese beginning online instructors' competencies: evidence from Bayesian factor analysis

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Abstract With the popularity of online education, understanding and improving the beginning online instructors' teaching competencies is crucial to improve online education. The structure of beginning online instructors' perceived competencies was widely discussed, and it was also confirmed that the structure and level of online teaching competencies would be varied across countries and different cultural backgrounds. Followed U.S. theoretical framework, some studies discussed the differences between Chinese and U.S. online teaching and instructors. But how Chinese online instructors, especially beginning online instructors, perceiving the online teaching competencies, and how this framework would differ from the U.S. framework, was less discussed. To fill in this gap, this study explored the structure of Chinese beginning online instructors' competencies using the Bayesian factor analysis method. With a limited sample size, the traditional factor analysis trail reported undetermined results with three options. The results of Bayesian factor analysis indicated the three-factor solution is the most appropriate solution with the collected data. The three factors are named “preparing and supporting online teaching,” “creating an appropriate environment for students' learning,” and “conducting appraisals of student learning.” The contributions of this study are as follows: (1) discussing the structure of Chinese beginning online instructors' perceived competencies,

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(2) discussing why and how the structure of online teaching competencies varied across countries, (3) providing practical suggestions for online instructors' training programs, and (4) providing methodological guidelines in factor analysis with small sample sizes for applied researchers.

Keywords Online education · Teaching competencies · Data science applications · Bayesian analysis

Introduction

As online learning continues to mature and evolve in higher education, both faculty and supporting staff need instruction on how to design and deliver effective online courses (Martin, Budhrani, et al., 2019; Martin, Ritzhaupt, et al., 2019). It is reported that online enrollments of higher education in the U.S have continued to grow with about 31.6% of higher education enrollments in 2016, which has increased 4.5% compared with 2012 (Seaman et al. 2018). According to the 40th Chinese Internet Development Report (2020) of China Internet Network Information Center (CNNIC), the number of Chinese Internet users reached 940 million by June 2020, the number of online education users reached 381 million. The number of online education users grows more than 50-fold from 2001 to 2020, and this number is expected to continuously grow in the future (CNNIC, 2020). In 2020, as the COVID-19 pandemic swept the globe, millions of students participate online learning. Although online learning continues to grow, many teachers are still resistant to adopt online courses for the barriers, such as uncertainty about the effectiveness of online learning and the lack of confidence in online teaching competencies (Wingo et al. 2017). Notably, the structure of beginning online instructors' competencies can assist faculties with online course design and delivery. Thus, a great deal of attention has been paid to online instructors' competencies, especially for beginning online instructors who have less than three years of online teaching experience. They are key members in determining the quality of future online education (Lim & Newby, 2020). To measure the competencies of beginning online instructors, the Beginning Online Instructor Competencies Questionnaire (BOICQ) is designed with five dimensions: preparing him/herself to teach online, selecting appropriate tools, preparing learners to learn online, facilitating online learning, and conducting meaningful appraisals of student learning. The target population of BOICQ, as it was designed, is all the beginning online instructors (Wang et al. 2019). But the validation of BOICQ only includes a sample recruited from the beginning online instructors from the U.S. Similar to other measured abilities or skills, the construction of online instructors' perceived competencies may differ fundamentally due to different nationality, cultural background, policy, and other educational practices. Hence, as we try to understand and measure the perceived competencies of beginning

Fig. 1 Competencies' hierarchy in online education

online instructors from other countries, e.g., China, a further discussion of the structure of BOICQ is necessary.

The structure of online instructors' perceived competencies

The quality of online teaching is determined by the competencies of instructors (Thomas & Graham, 2019). It seems that the competencies demand for online instructors is fewer than traditional teachers since face-to-face communication and instant feedback are reduced in the online teaching process. However, such a limitation of instant feedback demands a more complex structure of competencies for instructors in an online learning environment.

It is necessary to illuminate the competencies' hierarchy before exploring the structure of online instructors' perceived competencies. Competence is a complex combination of knowledge, attitudes, skills, and values displayed in the context of task performance (Martin, Budhrani, et al., 2019; Martin, Ritzhaupt, et al., 2019). There are different insights on the competencies' hierarchy within a range of higher or lower order. On one hand, it is supported that competencies are between goals and objectives. Goals represent the broad outcomes of a program, while objectives are more specific learning outcomes. It is supported that the competencies' hierarchy in online education is shown in Fig. 1 (Martin, Budhrani, et al., 2019; Martin, Ritzhaupt, et al., 2019). On the other hand, it is recommended that competencies are linked to roles and skills. Martin, Budhrani, et al. (2019) and Martin, Ritzhaupt, et al. (2019) used the ordinates to identify competencies based on teacher roles as shown in Fig. 2. Thus, clarifying teacher roles, the specific competencies, and the tasks that instructors need to fulfill in online learning environments is helpful to construct the structure of online teaching competencies.

Concerning the online teaching competencies, Pulham and Graham (2018) analyzed 8 blended teaching documents and 10 online teaching documents to compare K12 online and blended teaching competencies and found seven global themes identified in both competency domains are (1) pedagogy, (2) management, (3) assessment, (4) technology, (5) instructional design, (6) dispositions, and (7) improvement. The top 20 blended teaching skills, include flexibility and personalization, mastery-based learning, data usage and interpretation, learning management system usage, online discussion facilitation, and software management. Martin, Budhrani, et al. (2019) and Martin, Ritzhaupt, et al. (2019) investigated eight award-winning online faculties in the U.S and found that online instructors used a systematic design process, backward design, considered learner needs, and designed learner interaction during the design process. Award-winning online faculty use a variety

Fig. 2 Competencies based on instructor roles

of assessments, including using traditional and authentic assessments and rubrics to assess students. Bigatel et al. (2012) identified the most important observable teaching behaviors in evaluation rubrics and how these items compare to established online teaching competencies. It indicates that online teaching competencies should be clarified by observable instructional behaviors. Bell et al. (2017) explored the Environmental Management competencies online through experimental study and found that the practice of authentic activities with group collaboration is essential to students' online learning. The Visible, Organized, Compassionate, Analytical, Leader-by-example (VOCAL) is a well-known online teaching competency framework. It consists of establishing a social presence; designing and organizing plans, presentations, and timing; handling students' problems; evaluating and improving the system; and modeling best online teaching practices (Savery, 2005).

Although studies provide general descriptive instruction for online instructors' roles and competencies, these studies cannot guide beginning online instructors explicitly on how to design and conduct a successful online course from the process of online teaching.

Different from the studies mentioned above, the Activity Theory provides a simple but also useful framework for factors that contribute to a successful activity. It analyzes different forms of activities and development processes, providing a model of humans in their social and organizational context (Al-Huneini et al. 2020). The Activity Theory believes that a successful activity requires appropriate subjects, tools, and objects. That is, the learner, aim, and tool are three determinate factors to a successful online learning activity (Engeström, 1999). Although seems simple, the Activity Theory also provides explicit guidance for online instructors on organizing online teaching activities (Wang et al. 2019). Thus, the Activity Theory can work as a supplementary of beginning online instructors teaching competencies framework to brought detailed suggestions in improving online instructors' competencies. Despite the popularity of activity theory in the fields of education, few studies apply the most prominent elements of activity theory directly to the study of teaching competencies framework (Bligh & Flood, 2017).

Based on the VOCAL and Activity Theory, Stein and Wanstreet (2017) constructed the Beginning Online Instructor Competencies Questionnaire (BOICQ), a process-based measurement for beginning online instructors' teaching competence. As an integration of the VOCAL and Activity Theory, the beginning online teaching competencies were scaled from subjects, tools, and objects. As it is designed, BOICQ includes the following five dimensions as shown in Fig. 3: preparing instructors to teach online; selecting appropriate tools; preparing learners to learn online; conducting meaningful appraisals of student learning indicates the

Fig. 3 Beginning Online Instructor Competencies Questionnaire (BOICQ) based on Activity Theory

interaction between subjects and the objects; facilitating online learning emphasizes the overlapped issues among subjects, tools, and objects.

The target population of BOICQ is all the beginning online instructors. However, different backgrounds and practices in online education in different countries would lead to differences in the structure of online instructors' competencies fundamentally. In previous studies, Wang et al. (2019) explored the beginning online instructors' perceived difficulties in teaching online and the effects of their demographic information on their online teaching competencies using the Chinese version of BOICQ. But the measurement structure of this questionnaire is still to be verified. Considering the cultural and practical difference between the China and U.S. education system, it is necessary to analyze the measurement structure of the Chinese version of BOICQ, as well as the structure of perceived competencies for Chinese beginning online instructors. The following part of the literature review would provide more information about Chinese online education and instructors.

Online instructors in China

The online education system is growing rapidly in China in recent years, but the awareness and ability to integrate online technology with other teaching activities still need to be improved (Li, 2019; Ministry of Education of the People's Republic of China 2018). The *Chinese Ten-Year Development Plan of Education Informatization (2011–2020)* also pointed out that teachers' awareness and ability to integrate information technology with teaching should be improved in China (Jiang et al. 2018; Ministry of Education of the People's Republic of China, 2012). Online education has received favor from all education stages, including but not limited to primary and secondary education, vocational education, higher education, and continuing education. Although online education is applied widely, the differences between traditional teachers and online instructors, especially in competencies, are not highlighted in China. Traditional teachers occupy a great proportion of the population of online instructors in China. In the pre-service teacher training programs in China,

developing online teaching competencies is not included as a part of their content yet.

Under the background of soaring but lacking of professional training, studies focusing on online teaching in China often follow the framework in the U.S (Tsai et al. 2018). Some studies figured out the differences between Chinese and American online teaching, especially focusing on online instructors. From the perspective of communication and the interaction between teachers and audience, studies found Chinese teachers prefer to use teacher-centered and unidirectional strategies, no matter online or face-to-face. Xie and Teo (2020) examined how 160 top- and second-tier Chinese and American universities appraised themselves in the "About Us" texts on their official websites and found significant cross-country and cross-tier differences in the ways the universities project and position themselves to their stakeholders. Li et al. (2017) compared online instructors' perception of high-quality teaching between U.S. and China and found that instructors from both countries believe teaching design is determinate to students' engagement in learning, but Chinese instructors tend to use heuristic explanation, while U.S. instructors prefer to apply reflection, collaboration, and exploration in the teaching process. As for interaction with learners, the teacher-centered interaction is typical for Chinese instructors, while U.S. instructors prefer to facilitate student-centered interaction.

How to identify a "good teacher" is a critical issue in determining the structure of teaching competencies. Previous studies also indicated significant differences in the characteristics and preferences of competitive teachers, among different countries. Liu and Meng (2009) compared the perceptions of effective online instructors' personalities between China and the U.S. and found a high consistency within the two countries. Gao and Liu (2012) analyzed the narrative data from 80 U.S. and 75 Chinese teacher candidates and found that American pre-service teachers attached greater importance to teachers' adaptability, sense of humor, and responsibility, while the Chinese attached greater importance to patience, agreeableness, caring, and friendliness.

Although studies indicated various differences exist between the situation of online education between China and the U.S., less studies focus on what the structure of Chinese online instructors' competencies looks like, and how it differs from the framework of the U.S. Especially, studies indicated the instructors' personalities and ideal characteristics were significantly different between two countries. The difference in the perception of competitive instructors' characteristics implies the structure of perceptions in competencies may differ fundamentally between Chinese and the U.S. beginning online instructors. As a result, we have a strong reason to believe that the structure of the perceived online teaching competencies between the two groups of online teachers may be different fundamentally. For beginning online instructors, since they are lacking of experience, the perception of competitive characteristics may relate to their perception of competencies closely. Hence, it is extremely necessary to explore the structure of teaching competencies in Chinese online instructors and how it differed from the U.S. framework directly.

In summary, although Wang et al. (2019) already applied the structure of Stein and Wanstreet (2017) in Chinese beginning online instructors, it is still necessary to examine the structure of the online teaching competencies in Chinese beginning

online instructors through the Beginning Online Instructor Competencies Questionnaire (BOICQ). Since Wang et al. (2019) only have a limited sample size in their data, a set of traditional factor analyses was performed as a trail to explore the possible structure of Chinese beginning online instructors' perceived competencies.

Factor analysis trial on Chinese beginning online instructors with its undeterminal results

To investigate the structure of Chinese beginning online instructors' perceived competencies, before formal data analysis, we applied traditional factor analysis methods to Wang et al.'s (2019) data. In these data, Chinese online instructors' perceived competencies were measured by BOICQ. The methods include Principle Component Analysis (PCA), Explanatory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA). The results indicated there was no determined, or best, solution generated by traditional factor analysis. The results of the three methods could not converge with each other.

The PCA result generated a single-factor solution. In the screen plots generated from PCA. In the screen plot,¹ the only “elbow” appears between the first and second components, which implies that a one-factor solution is reasonable for these data. Also, the first component explains 47.2% of the total variance among all items, and the second component only explains 5.8%. Finally, all the items report high loadings ($r > 0.448$) on the first component. Base on all the evidence, we can conclude the PCA generates a single-factor solution that fits the data well. The Eigenvalue of the first component was 16.519, and for the second it was 2.041.

However, in the EFA, the parallel analysis indicates a three-factor solution would be reasonable for the data. The EFA result indicates the 3-factor solution fits the data well, with $\chi^2(493) = 640.310$, $p < 0.001$, RMSEA = 0.058. The factorial structure of EFA was explainable. They can be named as “preparing and supporting online teaching,” “conducting appraisals of student learning,” and “creating an appropriate environment for student learning” respectively.

Finally, the CFA with originally designed 5-factor structure also indicated reasonable model fits with $\chi^2(550) = 610.284$, $p = 0.038$, RMSEA = 0.035, SRMR = 0.077. Although the Chi-square statistics are not trustworthy in this situation, both the RMSEA and SRMR reported the 5-factor solution fitted the data well. When checking the factor loading for each item, only the first item reports standardized factor loading lower than 0.4 ($r = 0.348$). Basing on this result, we can also conclude that the CFA confirmed the 5-factor solution fitted the data well.

As a summary of the traditional factor analysis trial results, all the three-factor analysis methods reported seemed reasonable model fits and seemed appropriate factor loadings. But the factorial solutions of different methods were different

¹ To reduce the number of pages of this article, we only provided the general descriptions of traditional factor analysis. For more details (screen plots, factor loadings, etc.), please visit <https://drive.google.com/drive/folders/1NsYMcdUCdd77MVfZqXRYPWBhw2S5aoKd?usp=sharing>.

fundamentally. This fact implied at least one of these results was misleading. We can hardly determine the most correct factorial structure with traditional methods. However, this factor analysis trial provided three possible solutions for the structure of Chinese online instructors' perceived competencies. As a result, a more advanced factor analysis method was necessary to explore which, among the three solutions, would be the most appropriate structure of perceived competencies among Chinese online instructors.

Traditional and Bayesian factor analysis

Traditional factor analysis methods include principal component analysis (PCA), explanatory factor analysis (EFA), and confirmatory factor analysis (CFA). The nature of factor analysis is linear regression using the latent variable to predict the observed variables, or the items. The factor loadings are regression coefficients by their nature.

However, since we do not know what the latent variable is in factor analysis, this equation is solved by matrix algebra. The three methods in traditional factor analysis use different strategies in matrix algebra to estimate the parameters and hold different statistical assumptions. Generally speaking, both EFA and CFA require larger sample sizes (Kline, 2016; Mundfrom et al. 2005). The PCA, on the other hand, seems does not have a rigorous limitation of sample size due to its mathematical nature. However, the PCA also cannot utilize the information contained in the data perfectly. Also, as a result of its mathematical nature, the PCA cannot provide definite answers for the exact factorial solution. Researchers have to work subjectively to determine the number of factors and which factor should be loaded on for each item. For traditional factor analysis with a smaller sample size ($n < 300$), researchers are suggested with a small number of factors to keep the results stable (Kline, 2016). As a result, as we try to conduct factor analysis with a small sample size ($n = 89$ in this study), none of the traditional methods would provide us a definite, clear, and stable factorial solution, though they may all provide reasonable and well-fitted results.

On the other hand, the Bayesian analysis would help solve the problem brought from a small sample size. The Bayesian statistical method combines the pre-setting prior with the information get from data, to estimate the posterior probability distributions (Gates et al. 2020). Different from traditional hypothesis testing that focuses on the possibility that given the data, to which possibility that the null hypothesis (H_0) is true in the population, the Bayesian method solves the problem that given the information from the population, to which possibility we can get a sample as the data collected. The given information from the population is set as the *prior*, and the information from the data is called *likelihood* in Bayesian analysis. Studies indicated since we utilize the information from priors, as well as use Markov Chain Monte Carlo (MCMC) simulation strategy, Bayesian statistics are more stable when we have a relatively small sample size, especially dealing with complex models (Lee, 1981; Song & Lee, 2012).

The Bayesian factor analysis shares the same model with traditional factor analysis. In Bayesian factor analysis, one posterior distribution would be estimated for factor loading with each item. Another posterior distribution would be the estimated each item for the errors or the variance within the specific item but cannot be explained by the latent variable (Lee, 1981; Song & Lee, 2012).

This study

The purpose of this study is to investigate the factorial structure of Chinese Beginning online instructors' perceived competencies through the Chinese version of the Beginning Online Instructor Competencies Questionnaire (BOICQ). The factor analysis trial did not provide a determined solution yet, but it provided three options: single-factor solution, three-factor solution, and five-factor solution. The research question of this study is to determine which solution among the three is the most appropriate factorial structure of Chinese Beginning Online Instructors' perceived competencies.

Investigating the framework of online instructors' competencies under Chinese circumstances contributed significantly to the area. The training of online instructors still needs to be improved in China. Lacking empirical investigation of how the competencies of online instructors contributed to this blank essentially. This study filled in the gap of lacking study focuses on online instructors' competencies in China. For online instructor training programs, this study can guide educational practitioners in the training programs following the framework for the competencies. For current online teaching practice in China, this study guided teachers and their supervisors and let them understand the basic competency framework and corresponding skills of online teaching. For pre-service and on service online instructors, this study helped them reflect on their teaching activities and make appropriate adjustments, which is key to improve the quality of online teaching.

In this study, since we only have a limited sample size, we would apply Bayesian factor analysis to determine which factor structure would be the best. This study would also guide applied researchers in this area with more optional methods as they encountered unstable or undetermined factorial structure and limited sample sizes.

Research question

Emerging from the understanding generated and the gaps identified in the literature, the study thus seeks to explore the following research question:

What is the factorial structure of Chinese Beginning online instructors' perceived competencies?

Table 1 Demographic information for the sample

Demographics	<i>N</i> = 89	Proportion
<i>Gender</i>		
Male	25	28.1%
Female	64	71.9%
<i>Age</i>		
< 30 years old	63	70.8%
≥ 30 years old	26	29.2%
<i>Educational level</i>		
Bachelor's degree	41	46.1%
Master/higher	48	53.9%
<i>Online teaching experience</i>		
< 1 year	53	59.6%
≥ 1 year	36	40.4%
<i>Online learning experience</i>		
< 3 years	53	59.5%
≥ 3 years	36	40.5%

Methods

Participants

This study used Wang et al. (2019) data. It contained 89 participants from online instructor preparation programs from central China. The participants responded to the Chinese version of the Beginning Online Instructor Competencies Questionnaire (BOICQ) and other demographic questions. The demographic information about the participants is listed in Table 1. All the participants had online teaching experience of fewer than three years at the time they responded to the survey. This fact indicated they belonged to the target population of BOICQ.

Measure

Designed by Stein and Wanstreet (2017), the Beginning Online Instructor Competencies Questionnaire (BOICQ) was a 5-factor survey: preparing him/herself to teach online (7 items), selecting appropriate tools (7 items), preparing learners to learn online (5 items), facilitating online learning (13 items), and conducting meaningful appraisals of student learning (5 items). The items and the correspondence between items and subscales are presented in Appendix A. The Chinese version of BOICQ was translated by Wang et al. (2019). As the survey was administered, a 4-point Likert scale (1 = “I do not know anything about this topic,” 4 = “I have conceptual and experiential knowledge of this competency”) was presented to participants to make their selections. After data cleaning, there were no missing data in this study.

Data analysis

Three sets of Bayesian factor analysis were performed with the data, corresponding to the one-factor, three-factor, and five-factor solutions generated from traditional factor analysis trials. All the Bayesian factor analysis were performed in the *RStan* package in R (Stan Development Team, 2017). Within each set, two models were estimated. The first model was estimated with small iterations as the default setting of *RStan*. Each model included four chains, and within each chain, the withdrawal warm-up iteration was 1000 and the total iteration was 2000. That means for each model, the valid iterative sample size would be 4000 for all four chains. In this study, these models were called “small iteration models.” For the second model, a larger number of warm-ups and iterations would be applied. For each of the four chains, the iteration in the warm-up process was 4000 and the total iteration number was 14,000. That means for each model, the valid sample size was 40,000. In this study, we called these models “large iteration models.” We use both small and large iteration models because the *RStan* manual indicates the small iteration models are suggested to small sample size data (Stan Development Team, 2017). However, large iteration models would be more helpful in generating stable results and observing how the parameter estimation was stabilized. As a result, six BCFA models would be estimated in total. The results of these two sets of models for each solution would be compared and discussed.

Parameter estimation, prior and likelihood

Since the factor analysis predicting individual item answer with latent variables which cannot be observed, we estimated the linear mixed model (LMM), then transformed the regression coefficient α_i of each item to standardized factor loading λ_i (Kamata & Bauer, 2008).

Because the regression coefficients have to be non-negative in LMM, we use non-informative Log-Normal prior for α_i . Since we had a small sample size, we used hyperparameters before stabilizing the parameter estimation (Stan Development Team, 2017). Also, according to the *RStan* manual (Stan Development Team, 2017), *Half – Cauchy*(0, 5) would be a good choice for hyperparameters for the variance of the regression coefficients. Thus, the prior of α_i was

$$\alpha_i \sim \text{Log} - \text{Normal}(0, \sigma_\alpha),$$

where

$$\sigma_\alpha \sim \text{Half} - \text{Cauchy}(0, 5).$$

The priors of β_i and ε_i^2 were also non-informative:

$$\beta_i \sim \text{Normal}(0, 1000),$$

$$\varepsilon_i^2 \sim \text{Inverse} - \text{Gamma}(0.001, 0.001).$$

Since the individual factor scores are latent, they were estimated by Cholesky decomposition with LKJ priors as the *RStan* manual suggested (Stan Development Team, 2017). Thus, this is another hierarchical prior structure:

$$\theta_j \sim \text{MVN}(0, \mathbf{R}_j),$$

where

$$\mathbf{R}_j \sim \text{lkj_corr_cholesky}(\text{Numberoffactors}).$$

After the models were estimated, the convergence of each model was checked. Only models that reported all four chains were converged within themselves and with each other were treated as a valid model and discussed. The convergence situation was checked by the tracing plot, the $\hat{R}$ from the Gelman and Rubin Statistic, and the number of effective cases. The tracing plots provide general information about both the convergence between and within difference chains (Stan Development Team, 2017).

As the model was determined as valid, the posterior distributions of factor loadings and residuals were checked. To determine the most reasonable factorial solution, the shape, mean, and standard deviations were checked and compared. The results from the small and large iteration models were compared, to discuss the effect of large iterations, as well as the stability of teaching factorial solution. Both the stability and effect of large iterations help determine the most reasonable factorial solution.

Results

Convergence for the models

Figures 4 and 5 present the tracing plots for one-factor and three-factor solutions for small iteration numbers after the warming-up processes, respectively.² According to the tracing plots, for the standardized factor loadings of one-factor and three-factor solutions, the iterations were converged both within and between chains, for both small and large iteration numbers. But the 5-factor solution did not report the same convergence situation. Figures 6 and 7 present the tracing plots after the warming up process for the 5-factor solution. We can observe from these figures, the four chains did not converge with each other and even did not reach a stable estimation within each chain. In general, the one-factor and three-factor models reported well convergence but the five-factor solution did not. This means the one-factor and three-factor solutions were valid, but the five-factor solution was not, no matter the number of iterations. But for the item residuals, all the models reported well convergence both within and between the chains.

² For the tracing plots of large iteration models and other information about this study, please visit <https://drive.google.com/drive/folders/1NsYMcdd77MVFZqXRYPBhw2S5aoKd?usp=sharing>.

Fig. 4 Tracing plot of factor loadings for small iteration model in one-factor solution

Fig. 5 Tracing plot of factor loadings for small iteration model in three-factor solution

Fig. 6 Tracing plot of factor loadings for small iteration model in five-factor solution

Fig. 7 Tracing plot of factor loadings for large iteration model in five-factor solution

Table 2 Number of effective cases in estimating standardized factor loadings and item residuals for all the items

	Small Iteration Models						Large Iteration Models					
	1-factor solution		3-factor solution		5-factor solution		1-factor solution		3-factor solution		5-factor solution	
	Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual
Item 1	868	4000	919	4000	9	3560	10,529	40,000	8331	40,000	5	40,000
Item 2	650	4000	1004	4000	9	2010	10,224	40,000	8604	40,000	5	40,000
Item 3	634	4000	915	4000	10	2286	8974	40,000	7365	40,000	5	40,000
Item 4	891	4000	1052	4000	11	3468	10,909	40,000	9944	40,000	5	40,000
Item 5	781	4000	1013	4000	10	2865	9790	40,000	8287	40,000	5	40,000
Item 6	1694	4000	1568	4000	9	2810	16,443	40,000	12,278	40,000	5	40,000
Item 7	1109	4000	1807	4000	12	2333	15,916	40,000	18,943	40,000	6	40,000
Item 8	1961	4000	4000	4000	10	2834	18,507	40,000	22,351	40,000	5	40,000
Item 9	1044	3158	2623	4000	12	2345	16,425	40,000	21,394	34,740	6	40,000
Item 10	4000	4000	4000	4000	10	2900	26,996	40,000	26,831	40,000	5	40,000
Item 11	2300	4000	4000	4000	10	4000	18,477	40,000	19,044	40,000	5	40,000
Item 12	4000	4000	4000	4000	11	3034	40,000	40,000	17,100	40,000	6	40,000
Item 13	679	3337	1073	4000	9	2730	9451	40,000	7763	40,000	5	40,000
Item 14	1490	2907	4000	4000	9	3084	15,781	40,000	7674	40,000	5	40,000
Item 15	2970	2853	2457	4000	11	2187	40,000	40,000	22,203	40,000	5	30,184
Item 16	1457	3199	1069	4000	10	3025	15,672	40,000	8375	40,000	5	40,000
Item 17	4000	4000	2972	4000	11	2972	32,418	40,000	26,122	40,000	5	40,000
Item 18	2836	3055	2720	4000	12	2552	31,486	40,000	18,166	40,000	6	40,000
Item 19	3127	4000	4000	4000	10	2941	40,000	40,000	27,702	40,000	5	40,000
Item 20	3324	4000	4000	4000	10	3389	31,264	40,000	30,436	40,000	5	40,000
Item 21	4000	4000	2010	4000	10	3421	40,000	40,000	17,553	40,000	5	40,000
Item 22	4000	4000	2601	4000	10	2994	33,370	40,000	25,728	32,499	5	40,000
Item 23	2868	4000	4000	4000	10	3089	27,222	40,000	27,689	40,000	5	40,000

Table 2 (continued)

		Small Iteration Models						Large Iteration Models					
		1-factor solution		3-factor solution		5-factor solution		1-factor solution		3-factor solution		5-factor solution	
		Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual	Loadings	Residual
Item 24	235	1770	4000	824	4000	13	2369	5533	40,000	5567	22,185	6	40,000
Item 25	525	2848	4000	4000	4000	12	2761	12,425	40,000	23,693	31,486	6	40,000
Item 26	1237	4000	3450	2131	3450	12	2728	20,570	40,000	18,723	33,203	6	40,000
Item 27	4000	3299	4000	2902	4000	10	3466	24,423	40,000	24,914	40,000	5	40,000
Item 28	3101	4000	4000	4000	4000	11	3192	34,422	40,000	23,749	40,000	5	40,000
Item 29	3443	4000	4000	2507	4000	11	3285	34,522	40,000	19,115	29,651	6	40,000
Item 30	2734	2938	4000	4000	4000	11	3315	27,603	40,000	23,728	40,000	5	40,000
Item 31	4000	4000	4000	2573	4000	10	3538	35,388	40,000	23,920	33,421	5	40,000
Item 32	3109	3499	4000	4000	4000	10	2895	40,000	40,000	16,259	40,000	5	40,000
Item 33	4000	4000	4000	4000	4000	10	2234	40,000	40,000	22,083	40,000	5	40,000
Item 34	2337	2799	4000	1738	4000	22	440	31,515	40,000	13,743	24,158	12	250
Item 35	2307	3430	4000	2596	4000	11	2205	19,525	40,000	22,762	40,000	6	27,784

The $\hat{R}s$ from the Gelman and Rubin Statistic indicated the same conclusion as tracing plots for model convergence.³ Generally, the $\hat{R}s$ higher than 1 indicates not well-converged models. All the factor loadings for one-factor and three-factor models were all-around 1, no matter the number of iterations. For both the one-factor and three-factor models, the chains were converged with each other in both small and large iteration models. Especially, the convergence situations of the three-factor solution were slightly better than the one-factor solution in small iteration cases. But for the five-factor solutions, most $\hat{R}s$ for standardized factor loadings were much higher than 1.00, no matter for small or large iteration models. For the small iteration model, the minimum $\hat{R}$ was 1.23 and most of the $\hat{R}s$ were larger than 1.5 for factor loadings. For the large iteration model, 27 out of 35 items reported $\hat{R}s$ larger than 1.2. This also indicated the convergence of the 5-factor solution was problematic. The $\hat{R}$ also indicated chains converged with each other in estimating the item residual for all models.

The number of effective cases indicates how many cases were effective in estimating the parameters. It can be treated as a measure of stability in parameter estimation for each model roughly. Table 2 presents the number of effective sample sizes in estimating both standardized factor loadings and item residuals for all the models. Both small and large iteration models for the 5-factor solution indicated an extremely low number of effective sample sizes for all items when estimating the factor loadings. A more serious problem was, for this solution, the large iteration model reported a smaller number of effective cases than the small iteration model. Hence, for the 5-factor solution, increasing the number of iterations could not increase the number of effective sample sizes. This implies the 5-factor structure could not fit the data well.

For the factor loadings of a one-factor structure with a small number of iterations, the number of effective cases ranged from 235 to 4000. The average number of effective cases for the small iteration model in estimating the standardized factor loadings was 2334.60. For the factor loading of a one-factor structure with a large number of iterations, the numbers of effective cases ranged from 5533 to 40,000. The average number of effective cases for the large iteration model in estimating the standardized factor loadings was 24,165.10.

For the factor loadings of the three-factor structure with a small number of iterations, the numbers of effective items ranged from 824 to 4000. For the factor loadings of the three-factor structure with a large number of iterations, the numbers of effective cases ranged from 5567 to 30,436. The average number of effective cases in estimating the factor loadings was 2659.26 for the small iteration model, and 18,232.5 for the large iteration model.

Generally, for all models, the numbers of effective cases were approximate to the maximum number (4000 or 40,000), which also indicated reasonable convergence when estimating the residuals, for all models.

³ To reduce the number of pages of this article, we only provided the general descriptions about $\hat{R}s$. For the exact value of $\hat{R}s$, please visit the following link and check Table 1 in the Tables & Figures file: <https://drive.google.com/drive/folders/1NsYMcdd77MVFZqXRyPWBhw2S5aoKd?usp=sharing>.

Table 3 Point estimation and standardized deviations of posterior distribution of standardized factor loadings in all models

	1-factor solution		3-factor solution		5-factor solution	
	Mean	SD	Mean	SD	Mean	SD
Item 1	0.79	0.04	0.80	0.03	0.72	0.13
Item 2	0.84	0.03	0.85	0.03	0.82	0.09
Item 3	0.82	0.03	0.83	0.03	0.84	0.08
Item 4	0.75	0.04	0.76	0.04	0.78	0.08
Item 5	0.83	0.03	0.85	0.03	0.86	0.07
Item 6	0.85	0.03	0.85	0.03	0.80	0.09
Item 7	0.83	0.03	0.85	0.03	0.86	0.06
Item 8	0.84	0.03	0.86	0.03	0.82	0.08
Item 9	0.89	0.02	0.89	0.02	0.85	0.06
Item 10	0.84	0.03	0.85	0.03	0.81	0.08
Item 11	0.85	0.03	0.86	0.02	0.83	0.08
Item 12	0.83	0.03	0.81	0.03	0.83	0.07
Item 13	0.85	0.03	0.87	0.02	0.85	0.08
Item 14	0.80	0.03	0.79	0.03	0.74	0.11
Item 15	0.89	0.02	0.88	0.02	0.89	0.05
Item 16	0.85	0.03	0.85	0.03	0.83	0.08
Item 17	0.87	0.02	0.87	0.02	0.85	0.06
Item 18	0.90	0.02	0.89	0.02	0.89	0.05
Item 19	0.88	0.02	0.88	0.02	0.84	0.07
Item 20	0.88	0.02	0.90	0.02	0.84	0.07
Item 21	0.86	0.03	0.86	0.02	0.80	0.09
Item 22	0.90	0.02	0.91	0.02	0.84	0.07
Item 23	0.91	0.02	0.92	0.02	0.87	0.06
Item 24	0.93	0.02	0.92	0.02	0.91	0.03
Item 25	0.92	0.02	0.92	0.02	0.91	0.04
Item 26	0.91	0.02	0.92	0.02	0.90	0.04
Item 27	0.90	0.02	0.91	0.02	0.87	0.06
Item 28	0.91	0.02	0.92	0.02	0.89	0.05
Item 29	0.88	0.02	0.92	0.02	0.86	0.05
Item 30	0.89	0.02	0.91	0.02	0.87	0.05
Item 31	0.87	0.02	0.90	0.02	0.84	0.06
Item 32	0.85	0.03	0.85	0.03	0.81	0.08
Item 33	0.85	0.03	0.85	0.03	0.81	0.07
Item 34	0.89	0.02	0.92	0.02	0.93	0.03
Item 35	0.87	0.02	0.90	0.02	0.88	0.05

Little difference existed between one-factor and three-factor solutions in convergence when checking the screen plots, $\hat{R}$ s, and the number of effective cases. The tracing plots indicated three items (items 1, 7, and 24) in the one-factor solution reported a slightly worse convergence situation in the small iteration

Fig. 8 Posterior distributions of standardized factor loadings in small iteration models in one-factor solution

model when comparing with the three-factor solutions, though they reached the convergence. When considering the $\hat{R}$ s, the estimated factor loadings of one-factor small iteration model reported 10 items with $\hat{R}$ s higher than 1.00, with the maximum value of 1.02. But for the three-factor small iteration models, only one item reported $\hat{R}$ equals to 1.01 and all other $\hat{R}$ s were equal to 1.00. Finally, when considering the number of effective cases, the one-factor solution reported a smaller number of effective cases in small iteration models. According to the Stan manual, the small iteration models should be valued more comparing with the large iteration models (Stan Development Team, 2017). In summary, we can conclude that the three-factor solution reported a slightly better convergence situation than the one-factor solution. This better convergence situation also implies the 3-factor solution fitted the data slightly better than the single-factor solution.

Posterior distributions of standardized factor loadings

The point estimations (means) and standardized deviations of the estimated posterior distribution of standardized factor loadings of small factor loading models are presented in Table 3. The standardized factor loadings indicate commonalities

Fig. 9 Posterior distributions of standardized factor loadings in small iteration models in three-factor solution

between the items and the latent variables. For both one- and three-factor models, minor differences were reported between small and large iteration models.⁴

For the one-factor solution, both the factor loadings ranged from 0.75 to 0.93, and their standardized deviations ranged from 0.02 to 0.04. For a three-factor solution, the standardized factor loadings ranged from 0.76 to 0.92. Five items reported point estimation of standardized factor loadings slightly lower than the point estimation of standardized factor loadings in the one-factor solution. Twenty-one items reported the point estimation of standardized factor loadings larger than the standardized factor loadings in the one-factor solution.

In the five-factor solution, the estimations of small and large iteration models were not consistent. In total, 31 out of 35 items reported differences in point estimation of standardized factor loadings between the small and large iteration models, and twenty-two items reported differences in estimated standardized deviations of factor loadings between the small and large iteration models.

The posterior distributions of standardized factor loadings in all small iteration models are presented in Figs 8, 9, and 10. It could be observed from these figures

⁴ To reduce the number of pages of this article, we only reported the mean and standardized deviation of factor loadings in small iteration models. For the large iteration models, please visit the following link and check Table 2 in the Tables & Figures file: <https://drive.google.com/drive/folders/1NsYMcduCd477MVfZqXRyPWBhw2S5aoKd?usp=sharing>.

Fig. 10 Posterior distributions of standardized factor loadings in small iteration models in five-factor solution

that for one-factor and three-factor solutions, all the distributions of four chains are generally overlapped with each other. Besides, the three-factor model also reported a better convergence situation than the one-factor model. But for the five-factor solution, the chains reported different posterior distributions. This also indicated the five-factor solution was not stable with these data.

Almost all the items reported a slightly right-skewed distribution in posterior distributions, no matter for one-factor or three-factor solution. Generally, more than half of the items reported slightly higher standardized factor loadings in the three-factor solution comparing to the one-factor solution.

Posterior distributions of item residuals

Table 4 presents the point estimations (means) and standardized deviations of the posterior distribution of item residuals in small iteration models.⁵ For all three solutions, less difference was reported between the small and large iteration models.

⁵ To reduce the number of pages of this article, we only reported the mean and standardized deviation of item residuals in small iteration models. For the large iteration models, please visit the following link and check Table 3 in the Tables & Figures file: <https://drive.google.com/drive/folders/1NsYMcUcdd77MVfZqXRyPBhw2S5aoKd?usp=sharing>.

Table 4 Point estimations and standardized deviations of posterior distributions of Item residual variance in all models

	1-factor solution		3-factor solution		5-factor solution	
	Mean	SD	Mean	SD	Mean	SD
Item 1	0.50	0.08	0.48	0.08	0.49	0.08
Item 2	0.35	0.05	0.33	0.05	0.30	0.05
Item 3	0.40	0.07	0.38	0.06	0.27	0.05
Item 4	0.64	0.10	0.63	0.10	0.47	0.08
Item 5	0.36	0.06	0.33	0.05	0.24	0.04
Item 6	0.35	0.06	0.33	0.05	0.35	0.06
Item 7	0.39	0.06	0.36	0.06	0.27	0.05
Item 8	0.39	0.06	0.35	0.06	0.33	0.06
Item 9	0.30	0.05	0.28	0.05	0.32	0.06
Item 10	0.39	0.06	0.37	0.06	0.36	0.06
Item 11	0.35	0.05	0.33	0.05	0.31	0.05
Item 12	0.45	0.07	0.47	0.07	0.36	0.06
Item 13	0.30	0.05	0.28	0.05	0.22	0.04
Item 14	0.50	0.08	0.51	0.08	0.51	0.08
Item 15	0.25	0.04	0.27	0.04	0.18	0.03
Item 16	0.32	0.05	0.32	0.05	0.28	0.05
Item 17	0.32	0.05	0.31	0.05	0.29	0.05
Item 18	0.24	0.04	0.26	0.04	0.19	0.04
Item 19	0.28	0.04	0.28	0.04	0.28	0.05
Item 20	0.28	0.05	0.25	0.04	0.29	0.05
Item 21	0.34	0.05	0.32	0.05	0.36	0.06
Item 22	0.25	0.04	0.21	0.04	0.28	0.05
Item 23	0.21	0.03	0.19	0.03	0.20	0.03
Item 24	0.20	0.03	0.22	0.04	0.18	0.03
Item 25	0.21	0.04	0.20	0.04	0.18	0.03
Item 26	0.24	0.04	0.20	0.04	0.20	0.03
Item 27	0.22	0.04	0.21	0.04	0.21	0.04
Item 28	0.21	0.03	0.19	0.03	0.18	0.03
Item 29	0.30	0.05	0.20	0.04	0.26	0.04
Item 30	0.28	0.05	0.22	0.04	0.26	0.04
Item 31	0.34	0.05	0.24	0.04	0.31	0.05
Item 32	0.36	0.06	0.34	0.06	0.34	0.06
Item 33	0.37	0.06	0.37	0.06	0.34	0.06
Item 34	0.28	0.05	0.21	0.04	0.14	0.04
Item 35	0.29	0.05	0.22	0.04	0.19	0.04

Table 5 Point estimations for standardized factor loadings and residual variances for each Item in the final 3-factor solution

	Factor 1		Factor 2		Factor 3	
	Factor Loading	Residual	Factor Loading	Residual	Factor Loading	Residual
Item 1	0.8	0.48				
Item 2	0.85	0.33				
Item 3	0.83	0.38				
Item 4	0.76	0.63				
Item 5	0.85	0.33				
Item 6					0.85	0.33
Item 7	0.85	0.36				
Item 8	0.86	0.35				
Item 9					0.89	0.28
Item 10	0.85	0.37				
Item 11	0.86	0.33				
Item 12			0.81	0.47		
Item 13	0.87	0.28				
Item 14			0.79	0.51		
Item 15	0.88	0.27				
Item 16			0.85	0.32		
Item 17					0.87	0.31
Item 18					0.89	0.26
Item 19	0.88	0.28				
Item 20	0.9	0.25				
Item 21					0.86	0.32
Item 22					0.91	0.21
Item 23	0.92	0.19				
Item 24	0.92	0.22				
Item 25			0.92	0.2		
Item 26			0.92	0.2		
Item 27	0.91	0.21				
Item 28			0.92	0.19		
Item 29			0.92	0.2		
Item 30			0.91	0.22		
Item 31			0.9	0.24		
Item 32			0.85	0.34		
Item 33					0.85	0.37
Item 34					0.92	0.21
Item 35					0.9	0.22

In the one-factor solution, the point estimations of item residual variances ranged from 0.20 to 0.64, and their standardized deviations ranged from 0.03 to 0.10. In the three-factor solution, the point estimations of item residual variances ranged from 0.19 to 0.63, and their standardized deviations ranged from 0.03 to 0.10. There were 27 out of a total of 35 items reported residual variances in the three-factor model were less than the residual variances in one-factor solution, and the decrease ranged from 0.01 to 0.07. For the five-factor solution, though the estimations of factor loadings were not valid, the posterior distribution of item residual variance seemed reasonable still. The point estimations of item residual variance ranged from 0.15 to 0.50, and their standardized deviations ranged from 0.03 to 0.08.

In summary, the three-factor solution reported the best convergence situation, the highest standardized factor loadings, and the least item residuals. Thus, the three-factor solution was the best factorial solution. Although the Beginning Online Instructor Competencies Questionnaire (BOICQ) is designed with five factors, the five-factor solution was not an appropriate result for Chinese data.

Discussion and conclusion

Implications for educational practitioners

In this study, we tried to explore the structure of perceived competencies in Chinese beginning online instructors, through BOICQ. The results indicated the three-factor structure, instead of the five-factor structure as designed, was more applicable to Chinese beginning online instructors. We summarized all the point estimations of standardized factor loadings and residual variances of each item in Table 5, to indicate the correspondence between items and factors. The items of the first factor were mainly about preparing for the online course and support students' learning, so it can be named as "preparing and supporting online teaching." Items in the second factor are about how the instructors give feedback to students' learning. So the second factor can be named as "conducting appraisals of student learning." Items in factor 3 are mainly about generating an appropriate environment for online learning. Thus, the third factor can be named as "creating an appropriate environment for students' learning."

In the three-factor solution, items on the online learning environment were condensed into one dimension, "creating an appropriate environment for students' learning." The preference for teacher-centered interaction may be one of the reasons that cause this difference. *Since Chinese online instructors focus more on teacher-centered activities* (Huang et al. 2020; Li et al. 2017), *the detailed efforts to support students' online learning are often ignored. Thus, teacher training on how to create an appropriate environment for students' learning, such as selecting appropriate tools, preparing students' learning, and facilitating online learning, is helpful.* These training activities are helpful to construct a student-centered teaching philosophy for teachers. Besides, this difference also aligns with Chinese current online teaching policy which is more concerned with the construction of the teaching environment and resources (Zhu & Li, 2020). However, the construction of the teaching environment and resources is far from enough to facilitate students' online learning.

It is the teachers' support, instead of the learning environment, that determines students' online learning (Wang & Liu, 2019).⁶

Implications for applied researchers

As the results indicated, with limited sample size, though the CFA reported a model that seemed a “good fit” with the five-factor solution, the Bayesian analysis results indicated this five-factor solution cannot be trusted. Furthermore, as the number of factors increased, the stability of estimation decreased, though more variance was explained. Thus, factor analysis with more factors but small sample size is risky (Wolf et al. 2013). Hence, we recommend applied researchers use PCA and EFA rather than CFA, and reduce the number of factors with limited sample sizes.

Traditional factor analysis would hardly bring definite results with limited sample size. On the other hand, the Bayesian analysis can reach stable results when the sample size is limited. The convergence situation is visible in Bayesian analysis. Thus, we can figure out the stability and trustworthiness of the estimated model (Wolf et al. 2013). Hence, the Bayesian factor analysis could be a more reasonable choice when factor analysis encountered a small sample size.

Conclusion and future work

This study investigated the structure of Chinese beginning online instructors' perceived competencies. Through the different methodological approaches, we found that the three-factor solution fitted Chinese data best. The three factors are “preparing and supporting online teaching,” “conducting appraisals of student learning,” and “creating an appropriate environment for students' learning.” This structure was quite different from the five-factor structure that was appropriate in the U.S.

The difference between the structures of beginning online constructors' perceived competencies indicated detailed efforts to prepare and support students' online learning were ignored since Chinese online instructors' preferred teacher-centered activities. Based on the specific structure of Chinese beginning online instructors' perceived competencies, we provided some suggestions to Chinese online training programs. We highlighted the student-centered strategy and recommend both online instructors and training programs to pay more attention to supporting students from different aspects.

The contributions of this study are as follows: (1) constructing a reliable structure of Chinese beginning online instructors' perceived competencies, (2) explaining why and how the structure of online teaching competencies varied across countries, (3) providing practical suggestions for online instructors' training programs, and (4) providing methodological guides in factor analysis with small sample sizes.

⁶ To reduce the number of pages of this article, we only reported the mean and standardized deviation of factor loadings in small iteration models. For the large iteration models, please visit the following link and check Table 3 in the Tables & Figures file: <https://drive.google.com/drive/folders/1NsYMcduCd77MVFZqXRyPWbhw2S5aoKd?usp=sharing>.

The main limitation of this study would be the sampling method. Since Wang et al. (2019) used a convenient sample with a limited sample size, the sampling bias would be generated through this process. Also, since the Bayesian factor analysis's complexity makes it takes a longer time to investigate the relationship among factors, this study did not report any information about the relationship among three factors. Further studies would be addressed on the structure of Chinese beginning online instructors' perceived competencies with larger sample size, the relationship between different factors, and key variables that would affect individual levels on these factors.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval This study has been approved by the institutional review board of Central China Normal University.

Consent to participate This study was approved by all participants.

Consent for publication All authors consent for this publication.

Appendix A

The Beginning Online Instructor Competencies Questionnaire (BOICQ, Stein & Wanstreet, 2017).

The following is a list of competencies for instructors new to online environments. Competencies are expected knowledge, skills, and behaviors of instructors who teach online. Please indicate your level of competence by rating the following statements. Use the following code:

0=I do not know anything about this topic.

1=I have conceptual knowledge of this idea (I know what to do but have not done it).

2=I have experiential knowledge of this competency (I have done this but don't know the concepts or theory).

3=I have conceptual and experiential knowledge of this competency.

Preparing yourself to teach online

1. Understand time and space differences in online classrooms compared to face-to-face classes.
2. Build interaction and feedback into each online meeting.
3. Apply knowledge about copyright and legal issues when selecting and distributing online content. Assess learning materials for translation to an online environment.
4. Set online office hours.
5. Develop a communication plan for interactions with learners.
6. Develop or adapt instructional materials for an online environment.
7. Develop a syllabus with information specific to an online environment.

Selecting appropriate tools

8. Navigate through the spaces in the online instructional platform.
9. Build discussion spaces, for example, ask the instructor, or collaborative or group spaces.
10. Use the learner assessment features of the online instructional platform.
11. Understand different delivery modes, for example, blended, synchronous, and asynchronous and the types of interaction each mode promotes.
12. Use tools that support collaboration and individual work.
13. Select tools within (or outside) the online instructional platform.
14. Locate resources for technology support.

Preparing learners to learn online

15. Establish expectations for learners and the instructor.
16. Establish appropriate communication norms.
17. Help learners become acclimated to the online instructional platform, e.g., navigation scavenger hunt.
18. Create space and activities to develop a class identity.
19. Help students gain confidence in learning online (low-risk assignments).

Facilitating online learning

20. Send a welcome message.
21. Create a post-and-response routine.
22. Address learner issues and other barriers that detract from learning.
23. Respond to discussion postings and assignments in a timely fashion.
24. Ask questions and invite responses.
25. Sustain engagement.

26. Promote equality of voices.
27. Provide coaching.
28. Provide feedback.
29. Motivate students via positive attitudes.
30. Assess performance.
31. Make revisions to your course based on student feedback and instructor reflection.

Conducting meaningful appraisals of student learning

32. Create an online rubric that assesses higher-order thinking skills.
33. Create an online quiz or exam.
34. Provide corrective, supportive, confirming, and informational feedback on assignments and postings.
35. Write guidance describing rationale for assignments, including the grading criteria.

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