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RESEARCH ARTICLE

Linking self-regulated learning to community of inquiry in online undergraduate courses: A person-centered approach

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Abstract

The Community of Inquiry (CoI) framework has gained widespread recognition as a theoretical model for understanding student learning in online environments. Despite its prevalence, CoI has been critiqued for its limited emphasis on learners' proactive roles in self-regulating their own learning. To address this, researchers have suggested integrating self-regulated learning (SRL) into the CoI framework. This integration calls for empirical research to explore the relationship between SRL and the three established CoI presences: teaching, social, and cognitive. Using a person-centered approach, this study examines how varying SRL skills among 750 undergraduate students in an online introductory mathematics course are related to the three CoI components. Latent profile analyses identified five distinct SRL profiles: *minimal regulators, low regulators with limited social skills, low regulators, moderate regulators, and competent regulators*. We found that students in higher SRL profiles demonstrated higher perception of CoI, whereas those in relatively lower SRL profiles showed lower levels of perceived CoI. Our findings underscore the importance of incorporating self-regulation in the CoI framework for a more comprehensive understanding of online learning.

Keywords Community of Inquiry · Learning presence · Self-regulated learning · Online learning · Person-centered approach

Introduction

While online learning has been a part of higher education for years, its role and prominence has grown rapidly in the last decade (Allen & Seaman, 2016). Many colleges and universities have invested in expanding their online programs and courses (Comer et al., 2015).

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Even courses that are taught face-to-face often utilize an online learning management system (LMS) to support student learning and engagement (Broadbent & Fuller-Tyszkiewicz, 2018). Understanding online learning environments and supporting college students' experiences in this environment is more important than ever.

The Community of Inquiry (CoI) framework (Garrison et al., 2001) has become a dominant theoretical model for research and practice in online learning, especially in higher education contexts (Garrison et al., 2001). CoI posits that successful online learning occurs through the interaction of three crucial components within a collaborative learning community: social presence, cognitive presence, and teaching presence. It has been assumed that, theoretically, these three presences are closely interrelated and influence each other. Empirical investigations have indeed confirmed this assumption; teaching presence affects both social and cognitive presence, and social presence mediates between teaching presence and cognitive presence (e.g., Garrison et al., 2010).

While CoI has been recognized as a useful framework for explaining student experience and success in online learning, researchers have criticized it for not considering on learners' active roles, such as self-regulation, during online learning (e.g., Cho et al., 2017; Kilis & Yıldırım, 2018; Shea & Bidjerano, 2010). Research has in fact shown that the use of self-regulatory strategies is positively related to academic achievements and satisfaction in online environments (Barnard-Brak et al., 2010; Broadbent & Poon, 2015; Li, 2019). Thus, some researchers argue that the concept of self-regulated learning (SRL) should be integrated into the CoI framework (Kilis & Yıldırım, 2018; Shea & Bidjerano, 2010; Shea et al., 2022). However, there is no consensus on *how* SRL fits within CoI (e.g., Garrison & Akyol, 2013). Furthermore, the idea of integrating SRL into CoI remains largely theoretical, necessitating more empirical testing.

While students' learning processes are usually invoked by their proper use of SRL strategies (Bernacki et al., 2021; Xu et al., 2023), these usage patterns are substantially complex and heterogeneous across individuals (e.g., Jeong & Feldon, 2023; Kizilcec et al., 2017). Thus, adopting a person-centered approach, such as latent profile analysis, has the potential to identify unique subgroups of students based on their SRL strategy usage patterns (i.e., SRL profiles) and to understand how student subgroup membership can be associated with the three presences of CoI. Therefore, the present study employs a person-centered approach to examine students' SRL strategies during online learning in relation to their perceptions of CoI. The following three research questions guide our study:

RQ1 What SRL latent profiles emerge in online learning settings?
RQ2 Do students' perceptions of the CoI presences differ by SRL profile membership?
RQ3 What are the predictors—gender, major, prior experiences, and time commitment—of SRL profile membership?

Literature review

The CoI framework

Building on social constructivism (Vygotsky, 1978), Community of Inquiry (CoI) was developed as a theoretical framework to explain how students create meaningful knowledge in online learning settings (Garrison et al., 2000). This framework posits that learning occurs in a community of learners and views the community as essential to

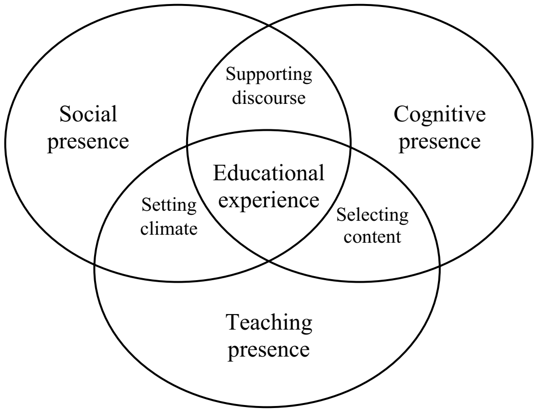

Fig. 1 A conceptual model of CoI (Adapted from Garrison et al., 2000, p. 88)

support collaborative meaning-making and sustained discourse to leverage this collaborative knowledge creation. Traditionally, CoI identifies three key dimensions of meaningful learning: cognitive presence, social presence, and teaching presence (see Fig. 1).

Cognitive presence

Drawing upon Dewey's idea of the construction of practical inquiry and critical thinking as meaningful learning outcomes (Dewey, 1933, as cited in Garrison et al., 2010), cognitive presence is operationalized as "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). Learners in online learning settings build cognitive presence by seeking information, developing meaningful ideas, and applying them to targeted tasks through sustained knowledge construction and reflection. According to a practical inquiry model (Garrison, 2007), cognitive presence can be progressively developed with four phases: (a) a triggering event, (b) exploration, (c) integration, and (d) resolution. Prior studies in higher education settings revealed that online learners with higher cognitive presences showed significantly higher perceived learning (Galikyan & Admiraal, 2019; Joo et al., 2011), actual course grades (Akyol & Garrison, 2011b; van der Merwe, 2014), and learning satisfaction (Joo et al., 2011; Kucuk & Richardson, 2019).

Social presence

Garrison et al. (2000) defines social presence as "the ability of participants in the community of inquiry to project themselves socially and emotionally, as 'real' people (i.e., their full personality), through the medium of communication being used" (Garrison et al., 2000, p. 94) under the framework of CoI. Through building personal but purposeful relationships and forming social bonds, learners can develop social presence. In the validation of factor structures of CoI instruments, Caskurlu (2018) found that social presence consists of three key components—open communication, group cohesion, and affective expression—which aligns with the operational definition proposed by Garrison et al. (2000). The importance of shaping social presence in online learning has been endorsed by empirical studies.

Indeed, Richardson et al. (2017) synthesized 26 correlation design studies and found that social presence was strongly associated with perceived learning ($r=0.56$, $p<0.001$) and learning satisfaction ($r=0.51$, $p<0.001$).

Teaching presence

Teaching presence is operationalized as "the design, facilitation, and direction of cognitive and social processes for the purpose of realizing personally meaningful and educationally worthwhile learning outcomes" (Anderson et al., 2001, p. 5). Teaching presence, therefore, is a set of instructional parameters to foster cognitive presence or social presence, or both. According to Anderson et al. (2001), teaching presence consists of three sub-components: (a) instructional design and organization, (b) facilitating discourse, and (c) direct instruction. In addition to social and cognitive presences, teaching presence plays a critical role in fostering students' learning in online settings. Two recent meta-analyses (Caskurlu et al., 2020; Martin et al., 2022) demonstrated that teaching presence was substantially correlated to perceived learning ($r=0.60$, $p<0.01$, Caskurlu et al., 2020), actual learning ($r=0.25$, $p<0.001$, Martin et al., 2022), and satisfaction ($r=0.59$, $p<0.01$, Caskurlu et al., 2020).

Situating SRL as a learning presence in CoI framework

Although prior research in online learning widely supported the CoI framework, certain aspects of CoI have been challenged. Researchers have argued that the original CoI framework has largely neglected the proactive roles of learners, such as setting goals, monitoring learning progress, and maintaining confidence (Kozan & Caskurlu, 2018; Shea & Bidjerano, 2010). For instance, Shea and Bidjerano (2010) stated that "the CoI framework may need an additional emphasis on the roles of strategic learners in online environments" (p. 1727). They thus proposed a revised CoI framework that incorporates '*learning presence'* as a fourth construct, emphasizing online learner self-regulation. Drawing upon self-regulated learning (SRL) theories (Winne & Hadwin, 2008; Zimmerman, 2000), learning presence can be operationalized as a set of learners' motivational and behavioral traits grounded in learners' self- and co-regulation (Cho et al., 2017; Shea & Bidjerano, 2010; Shea et al., 2012).

SRL includes a range of cognitive, metacognitive, and behavioral strategies for a series of learning phases, such as planning, monitoring, control, and reflection (Pintrich, 2004). For instance, the planning phase involves goal setting, strategic planning, and task analysis. The monitoring and control phases involve various regulatory strategies, such as time management, help-seeking, and environmental structuring. Finally, the reflection phase involves self-evaluation and causal attribution of performance and learning goals.

Since Shea and Bidjerano (2010) initially proposed the revised CoI framework, attempts have been made to integrate SRL as a learning presence into CoI. For example, Shea et al. (2012) analyzed students' discussions and interactions and then examined the relationships among SRL as learning presence, course grades, and three presences in the original CoI framework. Their results showed that learning presence had a significant partial correlation with course grades (*partial* $r=0.49$), controlling for the other three presences in CoI. They also found that learning presence may uniquely contribute to the cognitive presence, social presence, and teaching presence. Similarly, Zhang and Lin (2021) operationalized learning presence as both self-efficacy and self-regulation and identified the mediating role of

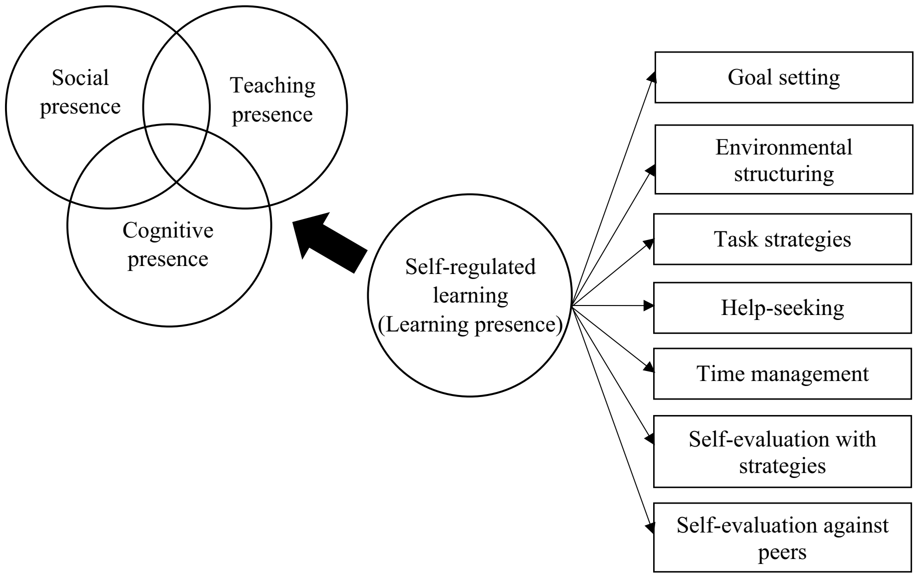

Fig. 2 An extended conceptual model of Community of Inquiry for the present study

self-regulation between teaching presence and cognitive presence. This result was aligned with the previous findings that in a lack of teaching and social presence, if students have a high level of learning presence (i.e., self-regulation), they can still attain cognitive presence (Shea & Bidjerano, 2012).

Recently, Wertz (2022) evaluated an alternative CoI framework which integrated self-regulated learning as learning presence. The results of confirmatory factor analyses revealed that the newly proposed learning presence consisted of motivational and behavioral indicators (adapted from Zimmerman's definition of SRL, 2008) and developmental indicators (adapted from the Online Self-Regulated Learning Questionnaire by Barnard et al., 2009) and this construct was correlated with teaching presence ($r=0.66$), social presence ($r=0.68$), and cognitive presence ($r=0.88$). Taken together, while theoretical controversy on integrating a new presence into CoI still exists (Akyol & Garrison, 2011a; Garrison & Akyol, 2013), our review supports that SRL as learning presence plays a critical role in CoI. Figure 2 represents an extension of the conceptual model of CoI for the present study.

Different levels of SRL profiles and their antecedents

Different levels of SRL profiles

SRL is defined as a multifaceted construct, and it has been stated that all learners can self-regulate their learning to some extent. Accordingly, most research that examines SRL has used a variable centered approach that explores the relationship between the sub-constructs of SRL and three presences. On the other hand, person-centered approaches extend the findings of variable-centered approaches by adding the distinct perspective that the individual is heterogeneous across the sample and, therefore, may have different levels of SRL strategies. For example, variable-centered approaches can provide information on whether a SRL served as a moderator between teaching presence and cognitive presence on average for all participants (Shea & Bidjerano, 2012). On the other hand, person-centered approaches inform us about individuals or a subgroup of students and whether or not they differ by the degree of SRL strategy uses. Indeed, Vanslambrouck et al. (2019) categorized such heterogeneous levels of self-regulated learning strategy uses (i.e., patterns of SRL profiles) into (a) quantitative differences in SRL profiles and (b) qualitative differences in SRL profiles. Generally, quantitative differences in self-regulated learning profiles are based on the assumption that "more is better" and focus more on the level of SRL scores or strategies being used by the learner. In this light, the levels of self-regulation were *categorized* or *grouped* into profiles representing high, average (or medium), and low (or no) SRL. These profiles were based on participants' self-reported SRL via questionnaires (e.g., Barnard-Brak et al., 2010). Put differently, these higher scores of SRL can be referred to how frequently or seldomly learners used SRL strategies in their learning.

In terms of the qualitative differences in SRL profiles, identifying which SRL strategies students are more or less engaged in is critical to understanding their learning processes (Vanslambrouck et al., 2019). As an example of the qualitative differences in SRL profiles, Broadbent and Fuller-Tyszkiewicz (2018) found that profiles with high motivation regulation and adaptation of SRL strategies, and low anxiety are associated with higher learning achievements in online and blended learning settings. Furthermore, previous studies on SRL profiles revealed that control of stress (Heikkilä et al., 2011), peer learning (Broadbent & Poon, 2015), help-seeking (Sun et al., 2018), goal orientation (Abar & Loken, 2010; Nelson et al., 2015), and self-efficacy (Chen & Usher, 2013) served as key indicators for identifying distinct subgroups of learners and at the same time, had a positive effect of students' learning processes.

The above-mentioned findings are promising with regard to unpacking the relationships between SRL profiles and the three CoI presences—cognitive presence, social presence, and teaching presence, especially for learners engaged in online Science, Technology, Engineering and Mathematics (STEM) courses. However, to our knowledge, there has been only one study (Cho et al., 2017) that examined how SRL profiles are associated with CoI. Cho et al. (2017) clustered 180 undergraduate students' SRL strategies using *K-means* analyses, and then investigated the relationships between these SRL profiles and three presences of CoI. While Cho et al. (2017) found that students in high levels of SRL cluster tend to perceive higher teaching, social, and cognitive presence, there are some limitations. Methodologically, since cluster analysis is a data-driven approach, there is no theoretical assumption of the number and characteristics of sub-profiles. Further, although Cho et al. (2017) found heterogeneous SRL profiles, they did not provide a clear explanation of why these SRL profiles emerged and how these profiles can be linked to individual difference variables (i.e., academic background variables). Therefore, there is a need to identify what SRL profiles emerge in online settings and to unpack the relationships between learners' individual differences, their SRL profiles, and perceived CoI sub-constructs using a person-centered approach.

Predictors of SRL profile membership

Previous studies focused on how individual differences among learners can contribute to the heterogenous SRL experiences. In other words, learners' demographic variables, their majors, prior experiences with online learning, and how much time they invested in a given course can shape different SRL experiences in online settings. We focused specifically on Kizilcec et al. (2017) due to the similarities between their work and the present study, including (a) employing large-scaled and fine-grained datasets and (b) entering comprehensive individual variables into the predictive models. Kizilcec et al. (2017) investigated how 27 individual difference features, including demographic factors, course intentions, and motivation, are linked to self-reported SRL strategies from 4831 online learners who attended Massive Open Online Courses (MOOCs). For example, learners who had prior experiences in these courses showed higher SRL, except for help-seeking, whereas female online learners use more help-seeking than males. While Kizilcec et al.'s (2017) research on individual SRL patterns is valuable, their research was broad in that it focused on students with diverse background characteristics across a number of different MOOCs. There is a need for research that explores whether individual differences in SRL patterns are replicated in a specific domain, such as a mathematics course, with a sample of undergraduate students who are all taking the same course. Table 1 summarizes the relationships between SRL patterns and individual difference variables used in this study.

Methodology

Research model

Figure 3 presents the hypothetical model in the present study.

Participants, contexts, and procedures

In the spring semester of 2020, we invited all of the undergraduate students enrolled in an online introductory mathematics course at a public university in South Korea. From the larger sample, 1024 undergraduate students consented to participate in the study. After excluding course withdrawals, non-responses in the SRL and CoI surveys, and incomplete demographic information, 750 undergraduate students were selected as a final sample. Of the 750 participants, 43.2% identified as male and 56.8% identified as female, with an average age of 21.3 and a range between 19 and 28. Approximately 57.1% of students are reported as majoring in STEM fields and a majority of the participants had experience taking at least more than one online course at the higher education level prior to the present study.

Introductory mathematics is a prerequisite course to majoring in both engineering and science fields. It covers basic level mathematics, such as functions and the basic theorems for calculus. As a completely online course, it operated in an LMS developed by the university for 15 weeks. All courses were delivered in the local language. Students could access learning resources prepared by lecturers, such as syllabus, recording lectures, a set of practice problems, and lecture notes. Moreover, when students have questions on lectures, they were allowed to email a professor, get help from teaching assistants (in week 5, 6, 13, and 14), or solve problems with their peers in online discussion boards. This course administrated two exams, including midterm exam in week 7 and final exam in week 15. All survey data were collected via web-based surveys linked in the course LMS. In the first week, participants were asked to answer the demographic survey on demographic background information (gender, and major) and academic background information (the number of online courses previously taken in the higher education, and estimated commitment

Table 1 Summary of the relationships between individual difference variables and SRL patterns

Variables	Study results	References
Gender	Studies on gender found mixed results. Some studies found that females reported higher levels of help seeking, goal setting, and task strategies than males. Whereas other studies did not find any gender differences in use of SRL strategies	Kizilcec et al. (2017), Bidjerano (2005), Yukselturk and Bulut (2009)
Major	Compared to those who majored in the non-STEM fields, students in STEM fields showed relatively less use of SRL strategies	Chen and Lin (2018)
Prior experiences	Students who have more prior experience with online learning were more likely to report using more SRL strategies to support their learning than students who have less experience with online learning	Li (2019)
Time commitment	Students who spent more time logged into the MOOC and completed more of the assessments were more likely to use SRL strategies, including goal setting, strategic planning, self-evaluation, and task strategies	Kizilcec et al. (2017)

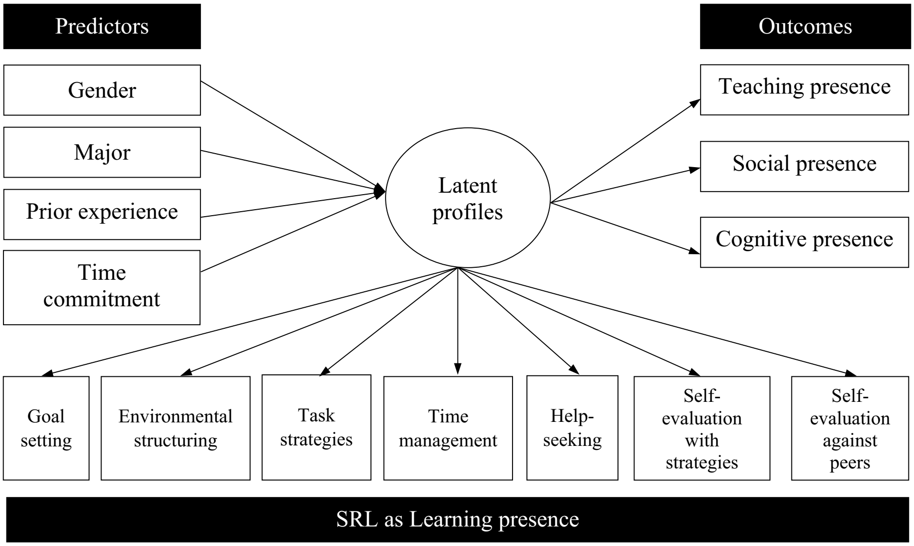

Fig. 3 Hypothetical research model

time (hours) for the course). They were asked to respond to surveys on SRL (Barnard et al., 2009) and CoI (Arbaugh et al., 2008) in week 14.

Measures

Individual difference variables

Individual differences were measured by four variables: (a) gender (male or female), (b) majors, which were recoded to STEM or non-STEM, (c) the number of online courses previously taken in the university as a proxy to assess prior online learning experience and (d) time commitment as time spent for online learning per week.

SRL as learning presence

SRL was measured by 24 items adapted from Online Self-regulation Learning Questionaries (OSLQ, Barnard et al., 2009) using a 5-point Likert scale (see Table 2). This measure primarily assesses students' perception on the usage of SRL strategies in online settings and consists of six sub-constructs: goal setting, environmental structuring, time strategies, time management, help-seeking and self-evaluation. However, after conducting CFAs, our dataset is better fitted to seven sub-construct models by splitting self-evaluation to self-evaluation with strategies and self-evaluation against peers (see more details in Measurement Models section in Results). The internal reliability coefficients (McDonald's ω) of all sub-constructs were acceptable, ranging from 0.76 (task strategies) to 0.93 (self-evaluation against peers).

Table 2 Information on used measures for self-regulation learning and perceived community of inquiry

Variable	Sub-scales	Number of items	Example of items	Reliability (McDonald's ω)
Self-regulated learning Bernard et al., (2009)	Goal settings	5	I set standards for my assignments in online courses	0.88
	Environment structuring	4	I choose a time with few distractions for studying for my online courses	0.87
	Task strategies	4	I work extra problems in my online courses in addition to the assigned ones to master the course content	0.76
	Time management	3	I allocate extra studying time for my online courses because I know it is time demanding	0.81
	Help seeking	4	I find someone who is knowledgeable in course content so that I can consult with him or her when I need help	0.77
	Self-evaluation with strategies	2	I summarize my learning in online courses to examine my understanding of what I have learned	0.84
	Self-evaluation against peers	2	I communicate with my classmates to find out how I am doing in my online classes	0.93
Perceived sense of community of inquiry Arbaugh et al., (2008)	Teaching presence	11	The instructor provided clear instructions on how to participate in course learning activities	0.96
	Social presence	8	Online or web-based communication is an excellent medium for social interaction	0.96
	Cognitive presence	12	Reflection on course content and discussions helped me understand fundamental concepts in this class	0.97

CoI

Students' perceptions of CoI are measured by 34 items adopted from a Community of Inquiry instrument (CoI Instrument, Arbaugh et al., 2008) using a 5-point Likert scale (see Table 2). This scale comprised three sub-constructs, teaching presence, social presence, and cognitive presence. Participants were asked to report how meaningfully they created knowledge through social and intellectual interactions with instructors' scaffoldings. The internal reliability coefficients (McDonald's ω) for three presences of CoI were substantially high, ranging from 0.96 (social presence) to 0.97 (cognitive presence).

The measures of two key constructs—SRL (measured by OSLQ, Barnard et al., 2009) and perceptions of CoI (measured by a CoI instrument, Arbaugh et al., 2008)—were developed in the western context. Through the forward–backward translation procedure (Brislin, 1970; Klotz et al., 2023), we attempted to minimize the potential semantic and linguistic biases between the Korean and English versions of the measures. First, a Korean-English bilingual professor in the US and two professors in a Korean university independently reviewed the translation from English to Korean. After reviewing the initial translation, three different versions of the Korean translated measures were collected and checked for discrepancies. After reconciliation of identified discrepancies in the previous step, the Korean version of the measures was translated back into English and reviewed by two bilingual Korean graduate students. After reviewing the back-translated version of measures, we adopted the final version of the Korean measures of OSLQ and CoI used in the present study.

Analytic strategies

First, we conducted a series of confirmatory factor analyses (CFAs) to build measurement models of two variables: SRL and perceptions of CoI. To establish appropriate measurement models, we tested model fit through model fit statistics: the Comparative Fit Index (CFI), the Tucker–Lewise Index (TLI), the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR). The CFI and TLI values higher than 0.95 were recommended but higher than 0.90 were regarded as acceptable. Regarding RMSEA and SRMR, acceptable values were lower than 0.80 (Hu & Bentler, 1999). However, these guidelines for fit indices depend on the complexity of models, such as the number of indicators per factors and their reliabilities (McNeish & Wolf, 2023); thus, we comprehensively evaluated measurement models through multiple indicators, such as global model fit statistics, factor loadings, and qualitative features of each item statement.

Second, we performed latent profile analyses (LPA, Collins & Lanza, 2010) to cluster individuals into emerging profiles with regard to their usage patterns of SRL strategies. Mean scores of sub-constructs of SRL were used as continuous indicators for LPA. We use model fit indices to select LPA model, including the Akaike information criterion (AIC), the Bayesian information criterion (BIC), Entropy, Low-Mendell-Rubin Adjusted Likelihood Test (LMR-LRT) and the portion of the smallest profile. Regarding the AIC and BIC, the lower values were preferred. As an indication to the degree of cluster separation, entropy values closing to 1 are better and above 0.80 was acceptable. The significant results ($p < 0.05$) on the LMR-LRT test indicated that the model with k profiles fit better than the model with $k\text{-}1$ profiles. Lastly, when the portion of the smallest profile is lower than 5%, the power of the interpretability of that profile is weak (Marsh et al., 2009).

After selecting the optimal profiles, a series of multivariate analysis of variance (MANOVA) were conducted by entering obtained students' SRL profile membership as an independent variable and students' perceptions of CoI toward online learning as dependent variables. This analysis was aimed to detect potential mean differences in distal outcomes according to the level of students' SRL profile membership. Lastly, we ran multinomial logistic regressions to investigate the predictive relationships between individual difference variables (e.g., gender, major, previous online learning experience, and time commitment) and SRL profile membership. CFAs and LPAs were performed with *Mplus* version 8.8 (Muthén & Muthén, 1998–2017), and all other analyses were conducted with *Jamovi* version 2.3 (The Jamovi project, 2023).

Results

Descriptive statistics

Table 3 represents descriptive statistics and correlations of the SRL and CoI sub-constructs. The sub constructs of SRL were significantly correlated to three sub-constructs of the perceptions of the CoI ($0.48 < r < 0.77$). We also see that, of the seven SRL sub-constructs, environment structure had the highest mean ($M = 4.09$, $SD = 0.72$) and task strategies had the lowest means ($M = 3.37$, $SD = 0.87$). In terms of perceptions of CoI, the means of teaching presence, social presence, and cognitive presence were ($M = 3.84$, 3.22, and 3.59, respectively). Lastly, the skewness and kurtosis of all variables were below 2 and 7, respectively, indicating the normality assumptions were not violated.

Measurement models

The CFA model using the original OSLQ scales (i.e., six factor model) yielded an acceptable model fit, $\chi^2(237) = 1327.30$, CFI = 0.90, TLI = 0.89, RMSEA = 0.08, SRMR = 0.06. However, upon review of the CFA results, we noted that item statements and factor loadings of the first two items (i.e., item 21 and 22) and the last two items (i.e., item 23 and 24) in the self-evaluation scale were markedly different. Hence, we determined that self-evaluation should be divided into two sub-facets, which we refer to as *self-evaluation with strategies* (i.e., item 21 and 22) and *self-evaluation against peers* (i.e., item 23 and 24), respectively, thus indicating a seven-factor model (see Table 3). Accordingly, we found that the seven-factor model showed a better fit than the original six-factor model, $\chi^2(231) = 904.82$, CFI = 0.94, TLI = 0.93, RMSEA = 0.06, SRMR = 0.04. Our findings are aligned with research conducted by Vanslambrouck et al. (2019) in which they used a seven-factor model of the OSLQ with 213 adults in a blended learning setting.

The results of CFA using original CoI measures (i.e., 34 items) showed a relatively unsatisfactory model fit, $\chi^2(524) = 4360.24$, CFI = 0.86, TLI = 0.85, RMSEA = 0.10, SRMR = 0.09. After checking the factor loadings, model modifications and item description, we noticed that item 10 and item 11 in cognitive presence and item 13 in social presence were not aligned with the course context. Indeed, the course instructor promoted students to collaboratively solve tasks, but relatively less focused on shaping shared affective values. After deleting three items, the adjusted model yielded an acceptable model

Table 3 Descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10
SRL										
1. Goal setting	–									
2. Environmental structuring	0.65**	–								
3. Task Strategies	0.67**	0.54**	–							
4. Time management	0.70**	0.57**	0.73**	–						
5. Help-seeking	0.51**	0.48**	0.63**	0.59**	–					
6. Self-evaluation with strategies	0.59**	0.49**	0.71**	0.65**	0.64**	–				
7. Self-evaluation against peers	0.51**	0.42**	0.60**	0.56**	0.77**	0.68**	–			
Perceptions of CoI										
8. Teaching presence	0.51**	0.52**	0.49**	0.47**	0.61**	0.54**	0.51**	–		
9. Social presence	0.55**	0.43**	0.59**	0.54**	0.61**	0.58**	0.62**	0.63**	–	
10. Cognitive presence	0.61**	0.54**	0.61**	0.59**	0.63**	0.65**	0.60**	0.74**	0.77**	–
Mean	3.75	4.09	3.37	3.60	3.55	3.59	3.39	3.84	3.22	3.59
SD	0.82	0.72	0.87	0.91	0.85	0.94	1.14	0.78	1.03	0.82
Skewness	− 0.32	− 0.54	− 0.04	− 0.35	− 0.07	− 0.34	− 0.32	− 0.27	0.03	0.00
Kurtosis	− 0.13	0.14	− 0.09	− 0.10	− 0.29	− 0.08	− 0.67	− 0.06	− 0.55	− 0.06

** $p < 0.01$

fit, $\chi^2(431) = 2331.85$, CFI = 0.93, TLI = 0.92, RMSEA = 0.08, SRMR = 0.04; thus, we employed 31 items with three factor models for this analysis.

Research question 1: Profiling SRL

To answer research question 1, a series of latent profile analyses were conducted starting with a one-profile model to an eight-profile model. As shown in Table 4, both information criteria, AIC and BIC, continued to decrease without the lowest point as the number of profiles increased. However, the LMR-LRT was not significant starting from the six-profile model, which means that the five-profile model fit the data better than the six-profile model. Furthermore, the entropy value of the five-profile model was 0.88, indicating the accuracy of clustering the five-profile is acceptable. Lastly, compared to the four or six-profile models, the smallest cluster of the five-profile model is more interpretable. Considering all model fit indices, we determined the five-profile model as a final solution.

The five SRL profiles are presented in Fig. 4. The profiles are based on the levels of the SRL sub-constructs. Descriptive statistics can be found in Table 6. Profile 1 is named "*minimal regulators*" because students in this profile have the lowest scores for each of the sub-scales of SRL. This is the smallest group and accounts for about 5.7% of the sample (n = 43). Profile 2, or the "*low regulators with limited social skills*" have relatively high scores for goal setting and environmental structuring but slightly lower than average scores for help-seeking and self-evaluation against peers. About 13.6% of students (n = 102) are in Profile 2. Profile 3, the "*low regulators*" have SRL sub-scale scores that are slightly lower than the mean. This profile includes 28.4% of students (n = 213). Profile 4 is called "*moderate regulators*" because their SRL sub-scale scores are slightly higher than the mean. Profile 4 is the largest group (n = 277) or about 36.9% of the sample. Profile 5 is called the "*competent regulators*" because students in this group have high scores for all the SRL sub-scales. This group accounts for 15.3% of the sample (n = 115).

To examine the significant differences in seven sub-constructs of SRL across the retained profiles, we conducted MANOVA with seven SRL sub-scales as a dependent variable and five profiles as an independent variable, *Pillai's Trace*: 1.43, F(28,

Table 4 Fit indices for different models with the number of profiles from 1 to 8

# of Profiles	# of Free parameters	Log Likelihood	AIC	BIC	Entropy	LMR-LRT ***p***-value	Smallest group portion (%)
1	14	– 6799.98	13,627.96	13,692.64	–	–	–
2	22	– 5828.09	11,700.18	11,801.82	0.87	0.00	40.7
3	30	– 5409.80	10,879.59	11,018.19	0.88	0.00	17.6
4	38	– 5191.61	10,459.21	10,634.78	0.90	0.00	4.9
5	**46**	**– 5083.87**	**10,259.75**	**10,472.27**	**0.88**	**0.01**	**5.7**
6	54	– 5008.16	10,124.32	10,373.80	0.87	0.14	4.7
7	62	– 4971.91	10,067.82	10,354.27	0.84	0.24	4.5
8	70	– 4938.36	10,016.72	10,340.12	0.85	0.13	0.9

The bolded numbers indicated a final solution

AIC refers to Akaike's Information Criterion, *BIC* refers to Bayesian Information Criterion, *LMR-LRT* refers to Lo-Mendell-Rubin Adjusted Likelihood Ratio Test

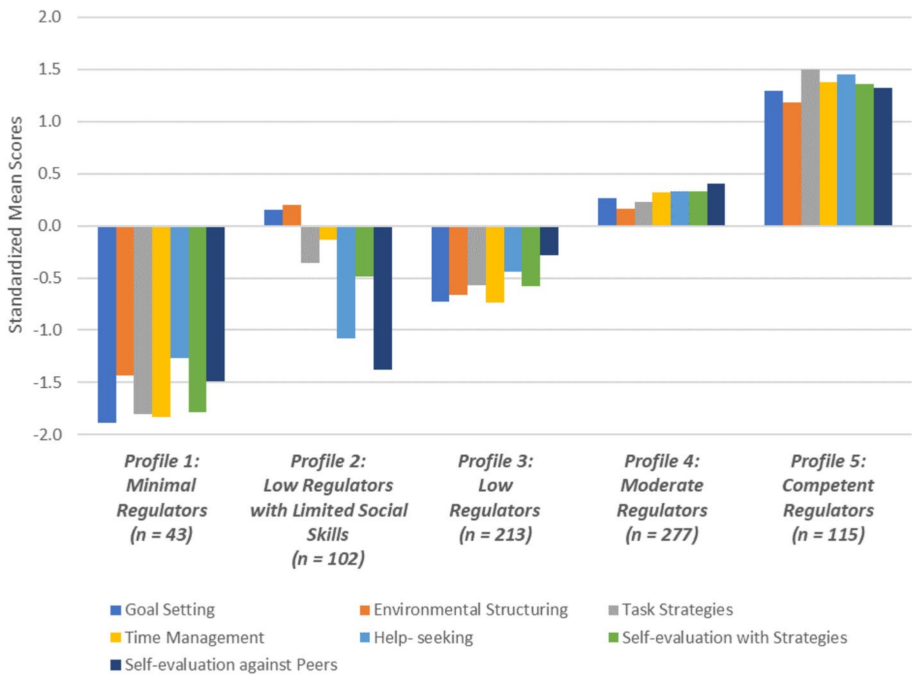

Fig. 4 Standardized means of the five SRL profiles solutions

2986) = 58.82, $p < 0.001$ (see details in Table 6). This implies that the emerging five SRL profiles are qualitatively and quantitatively differentiated.

Research question 2: Associations between SRL profiles and three presences of CoI framework

In order to answer research question 2, we conducted MANOVA by entering obtained SRL profile membership as an independent variable and the three presences of CoI as dependent variables. Significant differences were found across the five SRL profiles in the three-subscales for CoI (*Pillai's Trace*: 0.59, $F(12, 2235) = 46.03$, $p < 0.001$). Specifically, follow-up analysis (see Fig. 5 and Table 7) suggests that participants in profiles with relatively high levels of SRL (i.e., *moderate regulators* and *competent regulators*) perceived significantly higher teaching presence, social presence, and cognitive presence compared to participants in other three SRL profiles. There was no significant difference in teaching presence and cognitive presence between the *low regulators with limited social skills* profile and the *low regulators* profile. However, the *low regulators* profile had significantly higher social presence than the *low regulators with limited social skills* profile. For students in the *moderate regulator*s profile and the *competent regulators* profile, the more they used SRL strategies, the more likely they were to highly perceive teaching presence, social presence, and cognitive presence.

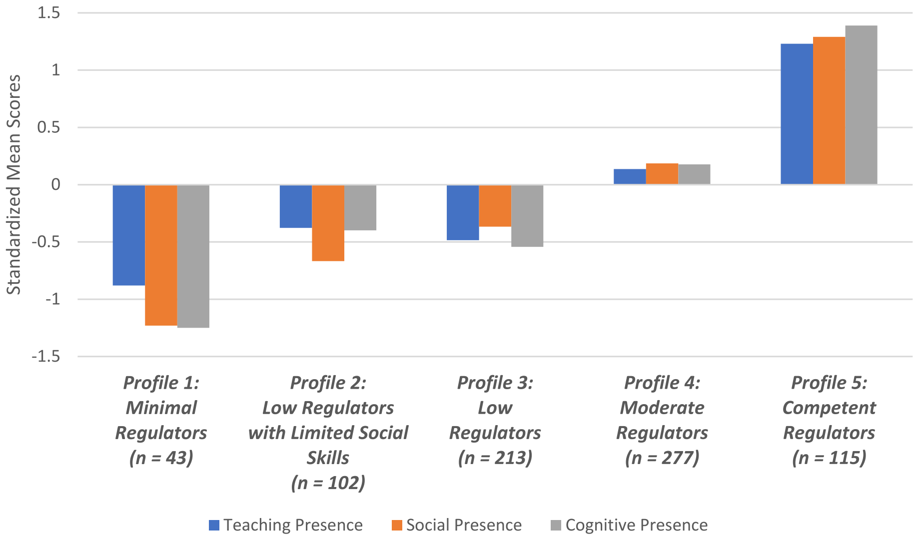

Fig. 5 Standardized means in community of inquiry across five SRL profiles

Research question 3: Predicting SRL profiles by individual difference variables

To address research question 3, we investigated how individual difference variables predicted profile membership; thus, multinomial logistic regression analyses were performed with gender, major, previous online learning experience and time commitment as predictors to SRL profile membership (see Table 5). In this analysis, *competent*

Table 5 Multinominal logistic regressions predicting SRL profiles by individual difference variables

	Profile 1 vs. Profile 5		Profile 2 vs. Profile 5		Profile 3 vs. Profile 5		Profile 4 vs. Profile 5	
	B (SE)	*OR* [95% CI]	*B* (SE)	*OR* [95% CI]	*B* (SE)	*OR* [95% CI]	*B* (SE)	*OR* [95% CI]
Intercept	− 0.93 (0.52)	0.40 [0.14, 1.10]	− 0.68 (0.37)	0.51 [0.25, 1.05]	0.90** (0.34)	2.47 [1.27, 4.82]	0.97** (0.31)	2.64 [1.45, 4.81]
Major	0.72 (0.37)	2.05 [0.99, 4.24]	0.45 (0.29)	1.57 [0.90, 2.75]	0.44 (0.25)	1.55 [0.96, 2.51]	0.42 (0.24)	1.52 [0.96, 2.41]
Gender	0.86* (0.37)	2.36 [1.14, 4.86]	0.61* (0.28)	1.84 [1.06, 3.20]	0.50* (0.24)	1.64 [1.02, 2.64]	0.23 (0.23)	1.26 [0.80, 2.00]
Prior experience	− 0.02 (0.05)	0.98 [0.90, 1.08]	0.00 (0.03)	1.00 [0.94, 1.07]	− 0.07 (0.04)	0.93 [0.87, 1.01]	− 0.02 (0.03)	0.98 [0.93, 1.04]
Time commitment	− 0.03 (0.02)	0.97 [0.94, 1.00]	0.00 (0.01)	1.00 [0.99, 1.02]	− 0.01 (0.01)	0.99 [0.98, 1.01]	− 0.01 (0.01)	0.99 [0.98, 1.01]

Profile 1: *Minimal regulators*, Profile 2: *Low regulators with limited social skills*; Profile 3: *Low regulators*; Profile 4: *Moderate regulators*; Profile 5: *Competent regulators*; For major, STEM was set to the reference group; For gender, female was set to the reference group

B refers to Regression coefficient, *SE* refers to Standard error of coefficient, *OR* refers to Odd ratio

$*p<0.05$, $**p<0.01$

regulators profile (Profile 5) was set to the reference group. As shown in Table 5, male students were more likely to be in the *minimal regulators* profile ($OR = 2.36$, 95% CI [1.14, 4.86], $p = 0.020$ in Profile 1 vs. Profile 5), *low regulators with limited social skills* profile ($OR = 1.84$, 95% CI [1.06, 3.20], $p = 0.030$ in Profile 2 vs. Profile 5) and *low regulators* profile ($OR = 1.64$, 95% CI [1.02, 2.64], $p = 0.041$ in Profile 3 vs. Profile 5) than *competent regulators* profile, while no significant difference was found between *moderate regulators* profile and *competent regulators* profile ($OR = 1.26$, 95% CI [0.80, 2.00], $p = 0.320$ in Profile 4 vs. Profile 5). We did not find any significant effects of the other three individual difference variables (i.e., major, prior experience, and time commitment) on determining SRL profile membership.

Discussion

General discussion

The present study aims to explore the role of SRL as a learning presence under the framework of the community of inquiry from a large dataset collected in online introductory mathematics courses. We first identified SRL profiles and their features when students engaged in large-scale online courses (RQ 1). Second, we explored whether the three presences of the community of inquiry and attitudes toward online learning differed across SRL profiles (RQ 2), and which individual difference variables predicted SRL profiles. Further discussion of key findings is presented in the following sections (RQ 3).

Identifying SRL profiles (RQ 1)

Using a person-centered approach, we identified five distinct profiles of SRL, including *minimal regulators* profile (5.7%), *low regulators with limited social skills* profile (13.6%), *low regulators* profile (28.4%), *moderate regulators* profile (36.9%), and *competent regulators* profile (15.3%). The identified profiles varied both quantitatively and qualitatively. Most profiles were categorized by their "amount of SRL or frequencies of SRL strategies used". Such patterns are aligned with quantitative differences in SRL profiles (i.e., quantitative point of SRL in Vanslambrouck et al., 2019, p. 127) which represents an extremely low regulated level to a highly regulated level of SRL profiles. Indeed, the quantitative differences in SRL profiles are, for the most part, in line with the result of previous studies that identified SRL profiles in higher education online settings (Barnard-Brak et al., 2010; Vanslambrouck et al., 2019). On the other hand, in terms of the qualitative differences in SRL profiles (i.e., qualitative point of SRL in Vanslambrouck et al., 2019, p. 127), an interesting profile was *low-regulated profiles with limited social skills*. Contrary to other profiles in which the overall sub-scales within the four profiles were substantially homogeneous, this profile has relatively low scores in help-seeking and self-evaluation against peers, both of which are related to socialization. These diverse profiles in SRL can allow us to design and develop adaptive scaffolding based on students' profiles. Students' SRL skills are trainable, so this adaptive scaffolding can help students enhance their SRL skills (Munshi et al., 2023; Newman, 1998).

Linking SRL profiles to three presences of CoI framework (RQ 2)

Regarding research question 2, our results supported that SRL skills as a learning presence are critical components under the framework of the community of inquiry (Cho et al., 2017; Shea & Bidjerano, 2012). Specifically, consistent with Cho et al. (2017), highly self-regulated learners, such as those in *moderate regulators* profile and *competent regulators* profile, are likely to perceive a high level of cognitive, social, and teaching presences, compared to students with lower levels of SRL. This means that one way to improve the quality of students' online learning is to increase students' SRL skills. Further, the CoI framework could be enhanced by adding SRL processes as a learning presence (Shea & Bidjerano, 2012). It should be noted that the features of *low regulators with limited social skills* profile are related to the levels of social presence. Related to the CoI framework, this profile tends to show a relatively lower level of social presence than cognitive and teaching presence. One possible explanation is that relatively low SRL skills related to socialization, including help-seeking and self-evaluation against peers, can be related to low social presence. This conjecture is supported by our analysis that *low regulators with limited social skills* profile showed significantly lower levels of social presence than *low regulators* profile, whereas there were no significant differences in teaching and cognitive presence (see Fig. 5 and Table 7). In this regard, we should consider how to support students with lower socialization skills (DiBenedetto & Bembenutty, 2013) because these students tend to be maladaptive to online learning settings, even though they have a high level of goal setting and environmental structuring (see Fig. 4 and Table 6).

Predictive roles of individual differences (RQ 3)

The results of a series of multinominal logistic regressions revealed that gender was the only significant predictor to determine SRL profiles. Specifically, women were more likely to be included in higher SRL profiles, whereas men were more likely to be included in lower SRL profiles. This result is consistent with other studies that found females are more likely to engage in SRL strategies than their male peers (Bidjerano, 2005; Lin, 2019; Meece & Painter, 2008). In a literature review on gender differences in SRL strategies, Meece and Painter (2008) pointed out that these differences showed different patterns depending on the academic domain, and in the case of mathematics courses, these gender differences in the use of SRL strategies are more salient (e.g., Patrick et al., 1999). Our findings also align with those of Schwam et al. (2021), who, in their study of 477 undergraduates enrolled in an online class, found that females reported a higher use of SRL strategies compared to males. However, in contrast to our expectations, the other three individual difference variables—major, prior experiences, and time commitment—did not predict the students' SRL profile membership. One possible explanation is that given that this mathematics online course (i.e., introductory mathematics) was targeted at mostly freshmen or those who were prospective students majoring in STEM fields, our sample was somewhat homogeneous in terms of their major and prior experiences. Additionally, we relied on students' self-reported questionnaires rather than using more accurate and traceable methods, such as their activity logs in LMS (e.g., Castellanos-Reyes et al., 2023; Muljana et al., 2023), which may have limited the power of predicting SRL profile membership.

Practical implications

The findings of the current study support the need to develop online learning environments that embed adaptive scaffolding for undergraduate students to foster SRL (Azevedo et al., 2004). We identified five distinct SRL profiles that represent students in different ways while influencing how they perceive the social, teaching, and cognitive presence of CoI. This suggests that in order to promote the three presences of CoI framework, we need to vary the kinds of SRL scaffolding we design into online courses. While students in higher self-regulated profiles, such as *competent regulators* profile did not necessarily require additional supports on SRL, promoting them to exert interactive and reciprocal influence on peers (e.g., Gikandi & Morrow, 2016) has the potential to help students who fall into relatively moderate and low SRL profiles co-regulate their learning processes (Räisänen et al., 2016). On the other hand, for students in relatively moderate or lower SRL profiles, instructors should consider SRL interventions to promote their SRL skills, given that SRL can be trainable in online settings (Azevedo & Cromley, 2004). One feasible intervention is to integrate short learning skills training into the online learning courses (Bernacki et al., 2021). For example, Bernacki et al. (2021) showed that embedding a short training course called "The Science of Learning to Learn" into online STEM courses encouraged undergraduate students to use planning, monitoring and cognitive strategies, thereby promoting their STEM academic achievements. It should be noted that the effectiveness of training interventions showed similar levels of effects for first-generation college students who are less likely to persist in STEM courses. We therefore expect that providing SRL resources as a format of training program can be a scalable and viable approach to promote SRL skills especially for students with relatively low SRL. Lastly, among lower SRL profiles, we found an interesting profile, *low regulators with limited social skills* profile, which was newly discovered in this study. For these students who cannot socially engage in online learning, instructors should encourage students to share their information or express their own beliefs by providing discussion prompts. Also, instructors should express agreement or provide timely feedback, which makes students in this profile feel more comfortable with the online learning environments (Martin & Bolliger, 2018; O'Shea et al., 2015).

Limitations

Our findings offer empirical evidence on identification of heterogeneous SRL profiles in STEM online courses and how students' SRL serves as a crucial role in fostering perceptions of teaching, social, and cognitive presences. Despite these contributions, there are still some limitations in this study. First, we could not collect students' learning outcomes, such as GPA. Recent systematic reviews consistently demonstrated that both students' SRL (e.g., Jansen et al., 2019) and perceptions of the CoI (e.g., Martin et al., 2022) are significant factors in promoting successful online learning in higher education, respectively. Given these findings, there remains a need for empirical investigation into the relationship among these three constructs. Therefore, future studies should explore how SRL profiles affect perceptions of CoI and students' learning outcomes.

Second, this study was conducted in a large-scale online mathematics course, but it is still questionable whether our results can be replicated in non-STEM and other small-size online courses. Future research is needed to explore whether these distinct SRL profiles and gender differences are detected in various online learning settings.

Lastly, this study heavily relied on the self-reported questionnaire to investigate students' SRL. Considering the growing attention to seeing SRL as contextual, dynamic, and situated perspectives (Greene, 2020; Greene et al., 2024; Jeong & Feldon, 2023), our methodological approach can be limited to deeply understanding the dynamic features of students' SRL. In this light, the future study will employ various sources of data, including log-data (Fan et al., 2022), verbal transcripts (Greene et al., 2011), and standardized diary measures (Schmitz & Wiese, 2006), with multiple time points. This innovative approach allows for more sophisticated insights into how students' SRL skills are used, and how that usage affects three sub-constructs of the CoI framework.

Conclusion

This work is significant as it is one of the few studies to examine SRL strategies in relation to students' perceptions of the community of inquiry in online STEM courses. Our findings indicate that there were five distinct SRL profiles, ranging from the lowest SRL to high SRL, in the context of introductory online STEM courses. In the association between SRL profiles and CoI, undergraduates in higher SRL profiles (i.e., *moderate regulators* and *competent regulators* profiles) were more likely to positively perceive CoI compared to those in other lower SRL profiles (e.g., *minimal regulators* profile). This implies that students in *competent regulators* profile are more suited for online learning settings by exerting their SRL strategies than others. Moreover, it is noteworthy that as a unique profile, *low regulators with limited social skills* profile, were newly detected in the current study. Considering the lack of socialization opportunities in large-scale online learning courses, students in this profile were more likely to be maladaptive to the online learning context than others. This study provides empirical insights into designing online STEM learning. Promoting SRL strategies can be critical to enhancing students' learning by helping them adapt to the online learning settings. Given that varying patterns of SRL were detected and differently affected students' perceptions of CoI, it is pivotal to design scaffolding to support SRL from a personalized perspective for future research.

Appendix

See Tables 6 and 7.

Table 6 Descriptive statistics and post-hoc ANOVA results for SRL profile membership

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Post-hoc ANOVAs
Goal setting	2.20^{2345} (0.59)	3.87^{35} (0.59)	3.15^{45} (0.49)	3.96^{5} (0.50)	4.81 (0.34)	$F(4, 745) = 329.91$, $p < 0.001$, $\eta_p^2 = 0.64$
Environmental structuring	3.06^{2345} (0.86)	4.23^{35} (0.55)	3.61^{45} (0.57)	4.21^{5} (0.51)	4.94 (0.18)	$F(4, 745) = 165.72$, $p < 0.001$, $\eta_p^2 = 0.47$
Task strategies	1.81^{2345} (0.56)	3.07^{345} (0.57)	2.88^{45} (0.50)	3.57^{5} (0.50)	4.67 (0.46)	$F(4, 745) = 360.13$, $p < 0.001$, $\eta_p^2 = 0.66$
Time management	1.94^{2345} (0.75)	3.48^{345} (0.66)	2.94^{45} (0.50)	3.90^{5} (0.51)	4.86 (0.29)	$F(4, 745) = 393.53$, $p < 0.001$, $\eta_p^2 = 0.68$
Help-seeking	2.48^{345} (0.68)	2.63^{345} (0.56)	3.18^{45} (0.47)	3.82^{5} (0.48)	4.77 (0.41)	$F(4, 745) = 368.45$, $p < 0.001$, $\eta_p^2 = 0.66$
Self-evaluation with strategies	1.92^{2345} (0.80)	3.13^{45} (0.76)	3.05^{45} (0.54)	3.90^{5} (0.54)	4.87 (0.35)	$F(4, 745) = 321.11$, $p < 0.001$, $\eta_p^2 = 0.63$
Self-evaluation against peers	1.70^{345} (0.68)	1.82^{345} (0.58)	3.07^{45} (0.62)	3.84^{5} (0.62)	4.89 (0.34)	$F(4, 745) = 523.24$, $p < 0.001$, $\eta_p^2 = 0.74$

Superscripts denoted the profiles that statistically differ from the designated profiles at the alpha levels adjusted according to Tukey's method

Profile 1: *Minimal regulators*; Profile 2: *Low regulators with limited social skills*; Profile 3: *Low regulators*; Profile 4: *Moderate regulators*; Profile 5: *Competent regulators*

Table 7 Descriptive statistics and post-hoc ANOVA results for community of inquiry across five SRL profiles

	Profile 1	Profile 2	Profile 3	Profile 4	Profile 5	Post-hoc ANOVAs
Teaching presence	3.15^{2345} (0.84)	3.54^{45} (0.76)	3.46^{45} (0.61)	3.94^{5} (0.58)	4.79 (0.45)	$F(4, 745) = 109.29$, $p < 0.001$, $\eta_p^2 = 0.37$
Social presence	1.96^{2345} (0.62)	2.54^{345} (0.72)	2.85^{45} (0.74)	3.41^{5} (0.81)	4.54 (0.75)	$F(4, 745) = 154.04$, $p < 0.001$, $\eta_p^2 = 0.45$
Cognitive presence	2.57^{2345} (0.75)	3.26^{45} (0.62)	3.15^{45} (0.55)	3.74^{5} (0.59)	4.74 (0.49)	$F(4, 745) = 189.02$, $p < 0.001$, $\eta_p^2 = 0.50$

Superscripts denoted the profiles that statistically differ from the designated profiles at the alpha levels adjusted according to Tukey's method

Profile 1: *Minimal* regulators, Profile 2: *Low regulators with limited social skills*; Profile 3: *Low regulators*; Profile 4: *Moderate regulators*; Profile 5: *Competent regulators*

Author contributions Conceptualization: Chungsoo Na, Soojeong Jeong, Jody Clarke-Midura, Youngin Shin; Methodology: Chungsoo Na, Soojeong Jeong; Formal analysis and investigation: Chungsoo Na; Writing—original draft preparation: Chungsoo Na, Soojeong Jeong, Jody Clarke-Midura; Writing—review and editing: Soojeong Jeong, Jody Clarke-Midura, Youngin Shin; Funding Acquisition – Non-related; Resources: Chungsoo Na, Youngin Shin; Supervision: Soojeong Jeong, Jody Clarke-Midura.

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Data availability Data and Code of this study will only be made available to other researchers if specific requests for amendments are made to the current approvals and will be considered on a case-by-case basis.

Declarations

Competing interests The authors declare they have no financial interests.

Ethical approval The questionnaire and methodology for this study was approved by the Human Research Ethics committee (IRB) of Utah State University.

Informed consent Informed consent was obtained from all individual participants included in the study.

References

Abar, B., & Loken, E. (2010). Self-regulated learning and self-directed study in a pre-college sample. *Learning and Individual Differences, 20*(1), 25–29. https://doi.org/10.1016/j.lindif.2009.09.002

Akyol, Z., & Garrison, D. R. (2011a). Assessing metacognition in an online community of inquiry. *The Internet and Higher Education, 14*(3), 183–190. https://doi.org/10.1016/j.iheduc.2011.01.005

Akyol, Z., & Garrison, D. R. (2011b). Understanding cognitive presence in an online and blended community of inquiry: Assessing outcomes and processes for deep approaches to learning. *British Journal of Educational Technology, 42*(2), 233–250. https://doi.org/10.1111/j.1467-8535.2009.01029.x

Allen, I. E., & Seaman, J. (2016). *Online report card: Tracking online education in the United States.* In Babson Survey Research Group (pp. 1–4). Babson Survey Research Group. Retrieved from https://eric.ed.gov/?id=ED572777

Anderson, T., Rourke, L., Garrison, R., & Archer, W. (2001). Assessing teaching presence in a computer conferencing context. *Online Learning, 5*(2), 1–17. https://doi.org/10.24059/olj.v5i2.1875

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), 133–136. https://doi.org/10.1016/j.iheduc.2008.06.003

Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students' learning with hypermedia? *Journal of Educational Psychology, 96*(3), 523–535. https://doi.org/10.1037/0022-0663.96.3.523

Azevedo, R., Cromley, J. G., & Seibert, D. (2004). Does adaptive scaffolding facilitate students' ability to regulate their learning with hypermedia? *Contemporary Educational Psychology, 29*(3), 344–370. https://doi.org/10.1016/j.cedpsych.2003.09.002

Barnard, L., Lan, W. Y., To, Y. M., Paton, V. O., & Lai, S.-L. (2009). Measuring self-regulation in online and blended learning environments. *The Internet and Higher Education, 12*(1), 1–6. https://doi.org/10.1016/j.iheduc.2008.10.005

Barnard-Brak, L., Paton, V. O., & Lan, W. Y. (2010). Profiles in self-regulated learning in the online learning environment. *The International Review of Research in Open and Distributed Learning, 11*(1), 61–80. https://doi.org/10.19173/irrodl.v11i1.769

Bernacki, M. L., Vosicka, L., Utz, J. C., & Warren, C. B. (2021). Effects of digital learning skill training on the academic performance of undergraduates in science and mathematics. *Journal of Educational Psychology, 113*(6), 1107–1125. https://doi.org/10.1037/edu0000485

Bidjerano, T. (2005). *Gender differences in self-regulated learning* [Online Submission]. Annual Meeting of the Northeastern Educational Research Association, Kerhonkson, NY. Retrieved from https://eric.ed.gov/?id=ED490777

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Broadbent, J., & Fuller-Tyszkiewicz, M. (2018). Profiles in self-regulated learning and their correlates for online and blended learning students. *Educational Technology Research and Development, 66*(6), 1435–1455. https://doi.org/10.1007/s11423-018-9595-9

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education, 27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

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

Caskurlu, S., Maeda, Y., Richardson, J. C., & Lv, J. (2020). A meta-analysis addressing the relationship between teaching presence and students' satisfaction and learning. *Computers & Education, 157*, 103966. https://doi.org/10.1016/j.compedu.2020.103966

Castellanos-Reyes, D., Koehler, A., & Richardson, J. C. (2023). The i-SUN process to use social learning analytics: A conceptual framework to research online learning interaction supported by social presence. *Frontiers in Communication, 8*, 1212324. https://doi.org/10.3389/fcomm.2023.1212324

Chen, J. A., & Usher, E. L. (2013). Profiles of the sources of science self-efficacy. *Learning and Individual Differences, 24*, 11–21. https://doi.org/10.1016/j.lindif.2012.11.002

Chen, Y.-H., & Lin, Y.-J. (2018). Validation of the short self-regulation questionnaire for Taiwanese college students (TSSRQ). *Frontiers in Psychology, 9*, 259. https://doi.org/10.3389/fpsyg.2018.00259

Cho, M.-H., Kim, Y., & Choi, D. (2017). The effect of self-regulated learning on college students' perceptions of community of inquiry and affective outcomes in online learning. *The Internet and Higher Education, 34*, 10–17. https://doi.org/10.1016/j.iheduc.2017.04.001

Collins, L. M., & Lanza, S. T. (2010). *Latent class and latent transition analysis: With applications in the social behavioral, and health sciences*. Wiley.

Comer, D. R., Lenaghan, J. A., & Sengupta, K. (2015). Factors that affect students' capacity to fulfill the role of online learner. *Journal of Education for Business, 90*(3), 145–155. https://doi.org/10.1080/08832323.2015.1007906

Dewey, J. (1933). *How we think: A Restatement of the relation of reflective thinking to the educative process*. Heath & Co Publishers.

DiBenedetto, M. K., & Bembenutty, H. (2013). Within the pipeline: Self-regulated learning, self-efficacy, and socialization among college students in science courses. *Learning and Individual Differences, 23*, 218–224. https://doi.org/10.1016/j.lindif.2012.09.015

Fan, Y., Lim, L., van der Graaf, J., Kilgour, J., Raković, M., Moore, J., Molenaar, I., Bannert, M., & Gašević, D. (2022). Improving the measurement of self-regulated learning using multi-channel data. *Metacognition and Learning, 17*(3), 1025–1055. https://doi.org/10.1007/s11409-022-09304-z

Galikyan, I., & Admiraal, W. (2019). Students' engagement in asynchronous online discussion: The relationship between cognitive presence, learner prominence, and academic performance. *The Internet and Higher Education, 43*, 100692. https://doi.org/10.1016/j.iheduc.2019.100692

Garrison, D. R. (2007). Online community of inquiry review: Social, cognitive, and teaching presence issues. *Journal of Asynchronous Learning Networks, 11*(1), 61–72. https://doi.org/10.24059/olj.v11i1.1737

Garrison, D. R., & Akyol, Z. (2013). Toward the development of a metacognition construct for communities of inquiry. *The Internet and Higher Education, 17*, 84–89. https://doi.org/10.1016/j.iheduc.2012.11.005

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. https://doi.org/10.1016/S1096-7516(00)00016-6

Garrison, D. R., Anderson, T., & Archer, W. (2001). Critical thinking, cognitive presence, and computer conferencing in distance education. *American Journal of Distance Education, 15*(1), 7–23. https://doi.org/10.1080/08923640109527071

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. https://doi.org/10.1016/j.iheduc.2009.10.002

Gikandi, J. W., & Morrow, D. (2016). Designing and implementing peer formative feedback within online learning environments. *Technology, Pedagogy and Education, 25*(2), 153–170. https://doi.org/10.1080/1475939X.2015.1058853

Greene, J. A. (2020). Building upon synergies among self-regulated learning and formative assessment research and practice. *Assessment in Education: Principles, Policy & Practice, 27*(4), 463–476. https://doi.org/10.1080/0969594X.2020.1802225

Greene, J. A., Bernacki, M. L., & Hadwin, A. F. (2024). Self-regulation. In P. A. Schutz & K. R. Muis (Eds.), *Handbook of Educational Psychology* (4th ed., pp. 314–334). Routledge. https://doi.org/10.4324/9780429433726-17

Greene, J. A., Robertson, J., & Costa, L.-J.C. (2011). Assessing self-regulated learning using think-aloud methods. In B. J. Zimmerman & D. Schunk (Eds.), *Handbook of self-regulation of learning and performance* (pp. 313–328). Routledge/Taylor & Francis Group.

Heikkilä, A., Niemivirta, M., Nieminen, J., & Lonka, K. (2011). Interrelations among university students' approaches to learning, regulation of learning, and cognitive and attributional strategies: A person-oriented approach. *Higher Education, 61*(5), 513–529. https://doi.org/10.1007/s10734-010-9346-2

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. https://doi.org/10.1080/10705519909540118

Jansen, R. S., van Leeuwen, A., Janssen, J., Jak, S., & Kester, L. (2019). Self-regulated learning partially mediates the effect of self-regulated learning interventions on achievement in higher education: A meta-analysis. *Educational Research Review, 28*, 100292. https://doi.org/10.1016/j.edurev.2019.100292

Jeong, S., & Feldon, D. F. (2023). Changes in self-regulated learning profiles during an undergraduate peer-based intervention: A latent profile transition analysis. *Learning and Instruction, 83*, 101710. https://doi.org/10.1016/j.learninstruc.2022.101710

Joo, Y. J., Lim, K. Y., & Kim, E. K. (2011). Online university students' satisfaction and persistence: Examining perceived level of presence, usefulness and ease of use as predictors in a structural model. *Computers & Education, 57*(2), 1654–1664. https://doi.org/10.1016/j.compedu.2011.02.008

Kilis, S., & Yıldırım, Z. (2018). Investigation of community of inquiry framework in regard to self-regulation, metacognition and motivation. *Computers & Education, 126*, 53–64. https://doi.org/10.1016/j.compedu.2018.06.032

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education, 104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Klotz, A. C., Swider, B. W., & Kwon, S. H. (2023). Back-translation practices in organizational research: Avoiding loss in translation. *Journal of Applied Psychology, 108*(5), 699–727. https://doi.org/10.1037/apl0001050

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

Kucuk, S., & Richardson, J. C. (2019). A structural equation model of predictors of online learners' engagement and satisfaction. *Online Learning, 23*(2), 196–216. https://doi.org/10.24059/olj.v23i2.1455

Li, K. (2019). MOOC learners' demographics, self-regulated learning strategy, perceived learning and satisfaction: A structural equation modeling approach. *Computers & Education, 132*, 16–30. https://doi.org/10.1016/j.compedu.2019.01.003

Lin, X. (2019). Self-regulated learning strategies of adult learners regarding non-native status, gender, and study majors. *Journal of Global Education and Research, 3*(1), 58–70. https://doi.org/10.5038/2577-509X.3.1.1018

Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal, 16*(2), 191–225. https://doi.org/10.1080/10705510902751010

Martin, F., & Bolliger, D. U. (2018). Engagement matters: Student perceptions on the importance of engagement strategies in the online learning environment. *Online Learning, 22*(1), 1. https://doi.org/10.24059/olj.v22i1.1092

Martin, F., Wu, T., Wan, L., & Xie, K. (2022). A meta-analysis on the community of inquiry presences and learning outcomes in online and blended learning environments. *Online Learning, 26*(1), 325–359. https://doi.org/10.24059/olj.v26i1.2604

McNeish, D., & Wolf, M. G. (2023). Dynamic fit index cutoffs for confirmatory factor analysis models. *Psychological Methods, 28*(1), 61–88. https://doi.org/10.1037/met0000425

Meece, J. L., & Painter, J. (2008). Gender, self-regulation, and motivation. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 339–367). Lawrence Erlbaum Associates Publishers.

Muljana, P. S., Dabas, C. S., & Luo, T. (2023). Examining the relationships among self-regulated learning, homework timeliness, and course achievement: A context of female students learning quantitative topics. *Journal of Research on Technology in Education, 55*(2), 143–162. https://doi.org/10.1080/15391523.2021.1936703

Munshi, A., Biswas, G., Baker, R., Ocumpaugh, J., Hutt, S., & Paquette, L. (2023). Analysing adaptive scaffolds that help students develop self-regulated learning behaviours. *Journal of Computer Assisted Learning, 39*(2), 351–368. https://doi.org/10.1111/jcal.12761

Muthén, L. K., & Muthén, B. O. (1998). *Mplus user's guide* (8th ed.). Muthén & Muthén.

Nelson, K. G., Shell, D. F., Husman, J., Fishman, E. J., & Soh, L.-K. (2015). Motivational and self-regulated learning profiles of students taking a foundational engineering course. *Journal of Engineering Education, 104*(1), 74–100. https://doi.org/10.1002/jee.20066

Newman, R. S. (1998). Adaptive help seeking: A role of social interaction in self-regulated learning. In S. A. Karabenick (Ed.), *Strategic help seeking: Implications for learning and teaching* (pp. 13–37). Lawrence Erlbaum Associates Publishers.

O' Shea, S., Stone, C., & Delahunty, J. (2015). "I 'feel' like I am at university even though I am online." Exploring how students narrate their engagement with higher education institutions in an online learning environment. *Distance Education, 36*(1), 41–58. https://doi.org/10.1080/01587919.2015.1019970

Patrick, H., Ryan, A. M., & Pintrich, P. R. (1999). The differential impact of extrinsic and mastery goal orientations on males' and females' self-regulated learning. *Learning and Individual Differences, 11*(2), 153–171. https://doi.org/10.1016/S1041-6080(00)80003-5

Pintrich, P. R. (2004). A Conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16*(4), 385–407. https://doi.org/10.1007/s10648-004-0006-x

Räisänen, M., Postareff, L., & Lindblom-Ylänne, S. (2016). University students' self- and co-regulation of learning and processes of understanding: A person-oriented approach. *Learning and Individual Differences, 47*, 281–288. https://doi.org/10.1016/j.lindif.2016.01.006

Richardson, J. C., Maeda, Y., Lv, J., & Caskurlu, S. (2017). Social presence in relation to students' satisfaction and learning in the online environment: A meta-analysis. *Computers in Human Behavior, 71*, 402–417. https://doi.org/10.1016/j.chb.2017.02.001

Schmitz, B., & Wiese, B. S. (2006). New perspectives for the evaluation of training sessions in self-regulated learning: Time-series analyses of diary data. *Contemporary Educational Psychology, 31*(1), 64–96. https://doi.org/10.1016/j.cedpsych.2005.02.002

Schwam, D., Greenberg, D., & Li, H. (2021). Individual differences in self-regulated learning of college students enrolled in online college courses. *American Journal of Distance Education, 35*(2), 133–151. https://doi.org/10.1080/08923647.2020.1829255

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. https://doi.org/10.1016/j.compedu.2010.07.017

Shea, P., & Bidjerano, T. (2012). Learning presence as a moderator in the community of inquiry model. *Computers & Education, 59*(2), 316–326. https://doi.org/10.1016/j.compedu.2012.01.011

Shea, P., Hayes, S., Smith, S. U., Vickers, J., Bidjerano, T., Pickett, A., Gozza-Cohen, M., Wilde, J., & Jian, S. (2012). Learning presence: Additional research on a new conceptual element within the Community of Inquiry (CoI) framework. *The Internet and Higher Education, 15*(2), 89–95. https://doi.org/10.1016/j.iheduc.2011.08.002

Shea, P., Richardson, J., & Swan, K. (2022). Building bridges to advance the Community of Inquiry framework for online learning. *Educational Psychologist, 57*(3), 148–161. https://doi.org/10.1080/00461520.2022.2089989

The jamovi project (2023). jamovi (Version 2.3) [Computer Software]. Retrieved from https://www.jamovi.org

Sun, Z., Xie, K., & Anderman, L. H. (2018). The role of self-regulated learning in students' success in flipped undergraduate math courses. *The Internet and Higher Education, 36*, 41–53. https://doi.org/10.1016/j.iheduc.2017.09.003

van der Merwe, M. D. (2014). Community of inquiry framework: Employing instructor-driven measures in search of a relationship among presences and student learning outcomes. *International Journal of Learning Technology, 9*(3), 304–320. https://doi.org/10.1504/IJLT.2014.065754

Vanslambrouck, S., Zhu, C., Pynoo, B., Lombaerts, K., Tondeur, J., & Scherer, R. (2019). A latent profile analysis of adult students' online self-regulation in blended learning environments. *Computers in Human Behavior, 99*, 126–136. https://doi.org/10.1016/j.chb.2019.05.021

Vygotsky, L. S. (1978). *Mind in society: Development of higher psychological processes*. Harvard University Press. https://doi.org/10.2307/j.ctvjf9vz4

Wertz, R. E. H. (2022). Learning presence within the Community of Inquiry framework: An alternative measurement survey for a four-factor model. *The Internet and Higher Education, 52*, 100832. https://doi.org/10.1016/j.iheduc.2021.100832

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 297–314). Lawrence Erlbaum Associates Publishers.

Xu, Z., Zhao, Y., Liew, J., Zhou, X., & Kogut, A. (2023). Synthesizing research evidence on self-regulated learning and academic achievement in online and blended learning environments: A scoping review. *Educational Research Review, 39*, 100510. https://doi.org/10.1016/j.edurev.2023.100510

Yukselturk, E., & Bulut, S. (2009). Gender differences in self-regulated online learning environment. *Journal of Educational Technology & Society, 12*(3), 12–22. Retrieved from https://www.jstor.org/stable/jeductechsoci.12.3.12

Zhang, Y., & Lin, C.-H. (2021). Effects of community of inquiry, learning presence and mentor presence on K-12 online learning outcomes. *Journal of Computer Assisted Learning, 37*(3), 782–796. https://doi.org/10.1111/jcal.12523

Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183. https://doi.org/10.3102/0002831207312909

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