Enhancing Deep Learning in Blended Learning Environments by Investigating the Interplay of Self-Regulated Learning, Social Presence, Cognitive Load, and Learning Outcomes Among Pre-Service Teachers

Meriyati Meriyati*
Romlah Romlah
Eti Hadiati
Agus Jatmiko
Erwanto Erwanto
Universitas Islam Negeri Raden Intan Lampung, Indonesia

*Dr. Meriyati, meriyati@radenintan.ac.id is the corresponding author

Abstract
Blended learning has become central to higher education, yet its capacity to promote deep learning depends on how cognitive, self-regulatory, and social factors are designed across online and face-to-face components. This study examined the relationships among cognitive load, self-regulated learning (SRL), social presence, deep learning, and learning outcomes among 450 Indonesian pre-service teachers in a structured blended learning environment. Data from survey responses and course-performance indicators were analyzed using partial least squares structural equation modeling (PLS-SEM) to test direct and mediated relationships. The results showed that cognitive load positively predicted deep learning but did not directly predict learning outcomes, indicating that cognitive demands can support achievement when they stimulate meaningful processing rather than overload learners. SRL also positively predicted deep learning but had no direct effect on outcomes, suggesting that regulation strategies improve performance mainly when translated into higher-order engagement. Deep learning strongly predicted learning outcomes and mediated the effects of cognitive load and SRL on achievement. Social presence did not significantly predict deep learning and negatively predicted learning outcomes, implying that interaction may be insufficient or distracting when not pedagogically structured. These findings identify deep learning as the central mechanism linking cognitive, self-regulatory, and social factors to academic performance. The study recommends blended learning designs that optimize cognitive challenge, scaffold SRL, and structure social interaction around purposeful inquiry, feedback, and knowledge construction.

Keywords: Blended learning, deep learning, cognitive load, self-regulated learning, social presence, learning outcomes

Meriyati, M., Romlah, R., Hadiati, E., Jatmiko, A. & Erwanto, W. (2026). Enhancing deep learning in blended learning environments by investigating the interplay of self-regulated learning, social presence, cognitive load, and learning outcomes among pre-service teachers. *Online Learning, 30*(3), 402-429. https://doi.org/10.24059/olj.v30i3.4991

Blended learning is a prominent instructional approach integrating face-to-face and online learning to optimize student engagement and learning outcomes (Singh et al., 2021). In practice, blended learning is not inherently student-centered; its effectiveness depends on how instructional activities, interactions, and cognitive demands are designed across online and in-person components. Within well-designed blended environments, deep learning processes, characterized by higher-order thinking, meaningful knowledge construction, and sustained cognitive engagement play a crucial role in determining the quality of students' learning experiences (Mystakidis et al., 2021). However, achieving deep learning in blended environments remains challenging due to varying levels of self-regulated learning (SRL), social presence, and cognitive load among students (Lobos et al., 2024; Wu, 2025; S. Zhao & Cao, 2023).

Self-regulated learning (SRL) has been widely recognized as a critical determinant of academic success, particularly in online and blended learning settings where students must independently manage their learning processes (ElSayad, 2024; Jiang et al., 2022; Li et al., 2024). Effective self-regulated learners engage in goal setting, self-monitoring, and self-reflection, which facilitates deep cognitive engagement and improves learning outcomes (Rui et al., 2024; Russell et al., 2022). Nevertheless, many university students, particularly in systems shaped by teacher-centered instructional traditions, struggle to sustain effective self-regulation in blended environments, resulting in inconsistent engagement and uneven learning outcomes.

Another key factor influencing deep learning in blended environments is social presence, a construct with a long and well-established history in educational technology research. Social presence was initially introduced in Social Presence Theory by Short et al. (1976) to explain how individuals perceive others as "real" in mediated communication. The construct was later incorporated into the Community of Inquiry (CoI) framework (Akyol & Garrison, 2008; Garrison et al., 1999), where social presence is conceptualized as a foundational element that supports both cognitive and teaching presence in online and blended learning environments. In the present study, social presence refers to the extent to which students perceive their peers and instructors as real, authentic, and accessible in online interactions (Ratan et al., 2022; Turk et al., 2022; Wut & Xu, 2021). High levels of social presence have been linked to a sense of belonging, increased motivation, and opportunities for collaborative discourse that can support deep learning (Mystakidis et al., 2021). However, social presence alone does not guarantee meaningful learning, as unstructured or poorly guided peer interactions may fail to promote higher-order thinking or shared regulation of learning (Heilporn et al., 2021). Prior research suggests that social presence contributes to learning outcomes most effectively when collaborative interactions are purposefully designed and cognitively oriented (Miao & Ma, 2022).

Cognitive load theory (Sweller, 2011) offers an additional perspective for understanding learning processes in blended environments. Cognitive load refers to the mental effort required to process information and is commonly distinguished into intrinsic load (task complexity), extraneous load (ineffective instructional design), and germane load (cognitive resources devoted to schema construction) (Kirschner, 2002). Rather than viewing cognitive load solely as a barrier to learning, contemporary perspectives emphasize that well-managed cognitive challenge, particularly germane load, can support deeper cognitive processing and conceptual understanding. In blended learning contexts, where students must navigate multiple formats, tools, and interactional demands, instructional designs that minimize extraneous load while supporting productive cognitive effort are essential for fostering deep learning (Müller & Wulf, 2024). Conversely, poorly designed tasks or limited self-regulatory capacity may result in cognitive overload that undermines meaningful engagement (Longo, 2022).

Although previous studies have examined self-regulated learning, social presence, and cognitive load as individual predictors of learning in online or blended environments, limited empirical research has investigated how these factors interact as an integrated system to shape deep learning and learning outcomes, particularly in non-Western higher education contexts. This gap is especially relevant for pre-service teachers, whose learning experiences not only affect their own academic development but also influence how they will design future learning environments for their students.

Therefore, this study investigates the structural relationships among self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in a blended learning environment among pre-service teachers in Indonesia. By examining both direct and indirect relationships, the study aims to clarify the mediating role of deep learning and to generate empirically grounded insights that can inform the design of cognitively engaging, socially structured, and pedagogically effective blended learning environments.

Literature Review

Blended learning has become a prominent instructional approach in higher education by integrating face-to-face instruction with online learning activities, thereby offering flexibility, accessibility, and opportunities for richer learning experiences. This modality has been widely adopted due to its potential to support deep learning, which involves higher-order thinking, the construction of meaningful knowledge, critical reflection, and long-term retention (Shi & Lan, 2024; Wu, 2025). However, evidence suggests that simply combining online and face-to-face components does not automatically result in deep learning. Instead, the quality of learning in blended environments is shaped by complex interactions among cognitive, behavioral, and social factors, particularly self-regulated learning (SRL), social presence, and cognitive load. Understanding how these factors operate as an interconnected system is especially important in teacher education programs, where pre-service teachers must not only master content knowledge but also develop pedagogical competencies that they will later transfer into their own instructional practices.

Self-regulated learning has consistently been identified as a key determinant of academic success in online and blended learning contexts, where learners are required to manage their learning processes with greater autonomy (Jansen, 2021; Onah et al., 2022; Vargas-Mendoza & Gallardo, 2023). SRL encompasses goal setting, strategic planning, self-monitoring, effort regulation, and reflective evaluation, all of which support sustained engagement and adaptive learning behaviors. In blended learning environments, students with stronger SRL skills are more capable of navigating digital platforms, allocating cognitive resources effectively, and engaging deeply with instructional content (Xu et al., 2023). Conversely, students with limited

SRL skills often experience difficulties in managing time, monitoring understanding, and sustaining motivation, leading to surface-level engagement and weaker learning outcomes. Prior studies emphasize that scaffolding SRL through guided reflection, metacognitive prompts, and structured learning tasks can enhance students' capacity for deep engagement and meaningful learning (Shao et al., 2023).

Within online and blended learning research, the role of self-regulated learning has increasingly been conceptualized through the Community of Inquiry (CoI) framework (Akyol & Garrison, 2008; Garrison et al., 1999). Originally comprising teaching presence, social presence, and cognitive presence, the CoI framework has been extended to incorporate learners' regulatory processes explicitly. Recent work argues that SRL constitutes a central component of learning presence, enabling learners to sustain inquiry, manage cognitive demands, and coordinate participation in collaborative learning environments (Shea et al., 2022). From this perspective, SRL is not merely an individual skill but a key mechanism that supports cognitive presence and deep learning within blended environments.

Social presence represents another critical dimension influencing learning processes in blended contexts. The concept has a long theoretical history, originating from Social Presence Theory (Short et al., 1976), which described the extent to which individuals perceive others as "real" in mediated communication. In online learning research, social presence was later incorporated into the CoI framework as a core element that supports discourse, interaction, and the development of shared understanding (Garrison et al., 1999; Akyol, 2009). Contemporary definitions emphasize learners' perceptions of peers and instructors as authentic, accessible, and emotionally engaged in online interactions (Ratan et al., 2022; Turk et al., 2022; Wut & Xu, 2021). High levels of social presence have been linked to increased motivation, satisfaction, and participation, thereby fostering opportunities for collaborative knowledge construction and deep learning (Parrish et al., 2021; Zhao & Qin, 2021).

However, recent research cautions against assuming that social presence alone guarantees meaningful learning. Shea et al. (2022) argue that social interaction must be accompanied by co-regulation and socially shared regulation of learning to support cognitive presence effectively. In complex collaborative learning environments, learners must jointly monitor progress, negotiate goals, and adapt strategies to sustain productive inquiry. Without such regulatory processes, peer interaction may remain affectively engaging but cognitively shallow. Empirical studies further suggest that poorly structured discussions, limited instructor facilitation, and unstructured peer interaction can weaken the educational value of social presence, reducing its contribution to deep learning (Demir et al., 2023; Dunmoye et al., 2024). These findings underscore the importance of designing socially rich yet pedagogically guided learning environments, where social presence aligns with cognitive and regulatory demands.

Cognitive load theory provides an additional lens for understanding learning in blended environments. Cognitive load refers to the mental effort required to process information and is commonly categorized into intrinsic load, extraneous load, and germane load (Kirschner, 2002; Sweller, 2011). In blended learning contexts, learners must often navigate multiple instructional formats, digital tools, and self-paced activities, making cognitive load management particularly critical. When extraneous load is excessive, due to unclear instructions, fragmented materials, or poorly designed interfaces, students' capacity for deep learning is compromised (Seufert et al., 2024; Wang & Lajoie, 2023). Conversely, well-designed instructional materials that optimize intrinsic load and promote germane processing can support schema construction and deeper cognitive engagement.

Importantly, recent research suggests that cognitive load does not operate independently but interacts with learners' regulatory capacities and social learning conditions. Students with strong SRL skills are better equipped to manage cognitive demands, filter relevant information, and remain focused on learning goals (Hartelt & Martens, 2024; T. Wang et al., 2023). Likewise, socially supportive environments can help learners seek clarification, distribute cognitive effort, and maintain engagement during challenging tasks (Costley, 2019; Doo & Bonk, 2020). Within the CoI framework, these interactions underscore the interdependence of cognitive presence, social presence, and learning presence in fostering deep learning.

Despite a growing body of research examining SRL, social presence, and cognitive load, much of the existing literature has explored these constructs in isolation. There remains limited empirical evidence on how they function collectively as an integrated system influencing deep learning and learning outcomes, particularly in non-Western contexts. This gap is especially salient in teacher education, where pre-service teachers must learn to regulate their own learning while simultaneously developing competencies for designing effective learning environments for others. Accordingly, this study aims to investigate the interrelated roles of self-regulated learning, social presence, and cognitive load in shaping deep learning and learning outcomes among pre-service teachers in a blended learning environment, thereby contributing both empirically and theoretically to ongoing discussions in online and blended learning research.

Hypothesis Development

Direct Effect Hypotheses

Blended learning can be designed to integrate cognitive and social factors influencing deep learning and academic outcomes. This study examines the relationships between self-regulated learning (SRL), social presence, cognitive load, deep learning, and learning outcomes among pre-service teachers.

Cognitive load can hinder excessive deep learning but supports schema construction when well-managed. Poor instructional design increases extraneous load, reducing students' ability to engage in higher-order thinking. Thus, it is hypothesized that: **H1**: *Cognitive load negatively influences deep learning.*

Cognitive load also affects learning outcomes, as excessive cognitive demands impair knowledge retention and performance. Thus, it is hypothesized that:

H2: *Cognitive load negatively influences learning outcomes.*

Deep learning fosters critical thinking, promotes meaningful knowledge construction, and enhances long-term retention, thereby directly improving academic performance. Thus, it is hypothesized that:

H3: *Deep learning positively influences learning outcomes.*

Self-regulated learning (SRL) enables students to plan, monitor, and adjust their strategies, allowing them to manage cognitive load effectively and engage in deep learning. Thus, it is hypothesized that:

H4: *Self-regulated learning positively influences deep learning.*

Beyond deep learning, SRL improves academic performance by helping students stay motivated and optimize their cognitive efforts. Thus, it is hypothesized that:

H5: *Self-regulated learning positively influences learning outcomes.*

Social presence enhances engagement, collaboration, and knowledge-building, which fosters deeper learning in blended environments. Thus, it is hypothesized that:

H6: *Social presence positively influences deep learning.*

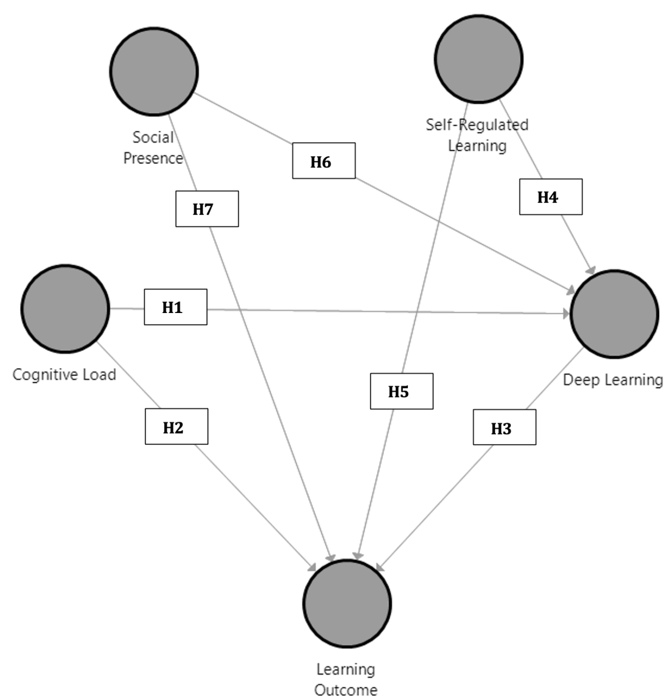
Additionally, social presence contributes directly to learning outcomes by increasing motivation and student participation. Thus, it is hypothesized that:

H7: *Social presence positively influences learning outcomes.*

These hypotheses align with the structural model (Figure 1), illustrating deep learning as a key mediating factor in blended learning environments.

Figure 1

Structural Model



Indirect Effect Hypotheses

Deep learning may mediate the effects of cognitive and behavioral factors on learning outcomes. Accordingly, the following indirect hypotheses are proposed:

Cognitive load can impair learning, but deep learning facilitates the construction of meaningful knowledge, potentially mitigating its adverse effects. Thus, it is hypothesized that:

H8: *Deep learning mediates the relationship between cognitive load and learning outcomes.*

SRL fosters deeper engagement with content, which improves academic performance through deep learning strategies. Thus, it is hypothesized that:

H9: *Deep learning mediates the relationship between self-regulated learning and learning outcomes*.

Social presence enhances interaction and engagement, but its impact on learning outcomes may depend on the type of learning involved. Thus, it is hypothesized that:

H10: *Deep learning mediates the relationship between social presence and learning outcomes.*

Method

This study investigates the interplay of self-regulated learning (SRL), social presence, and cognitive load in shaping deep learning outcomes among pre-service teachers in a blended learning environment. The blended learning environment examined in this study was intentionally designed to integrate structured face-to-face instruction with systematically organized online learning activities over a 12-week academic semester. Learning activities were distributed across synchronous (face-to-face) and asynchronous (online) modes. Face-to-face sessions were conducted weekly, focusing on interactive lectures, guided discussions, collaborative problem-solving, microteaching simulations, and project-based presentations. These sessions emphasized conceptual clarification, instructor scaffolding, dialogic interaction, and immediate formative feedback.

The asynchronous component was delivered through the university's Moodle-based learning management system (LMS), *elearning.radenintan.ac.id*, which served as the central digital learning hub. Through the LMS, students accessed weekly learning modules consisting of pre-recorded video lectures, academic readings, presentation slides, and supplementary learning resources. Each module included structured discussion forums, reflective prompts, and graded assignments designed to extend classroom learning and promote deeper cognitive engagement beyond face-to-face sessions.

Online discussion activities required students to respond to instructor-generated prompts, provide critical comments on peers' postings, and synthesize multiple perspectives. These discussions were moderated by the course instructor, who provided guiding questions, conceptual clarification, and integrative summary feedback to maintain alignment with learning objectives. Students also completed individual and group-based tasks, including lesson design assignments, short analytical essays, reflective journals, and collaborative projects, all of which were submitted via the LMS. Peer feedback and self-assessment features within Moodle were selectively utilized to promote reflection, self-monitoring, and the regulation of learning strategies.

Interaction between students and instructors occurred through multiple channels, including in-class dialogue, LMS discussion forums, written feedback on assignments, and periodic synchronous online consultations. This blended design aimed to balance learner autonomy with instructional guidance, allowing students to regulate their learning pace while remaining cognitively and socially engaged across modalities.

A quantitative approach with a correlational research design was employed, using Structural Equation Modeling with Partial Least Squares (SEM-PLS) to analyze the relationships among SRL, social presence, cognitive load, deep learning, and learning outcomes.

Research Design

The study adopts a correlational cross-sectional survey design to examine the relationships among self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in the blended learning context described above. Data were collected at the end of the semester, after students had completed all face-to-face and online learning activities, ensuring that participants had sufficient exposure to the blended learning design. SEM-PLS was employed to analyze both direct and indirect relationships among latent variables (Hair et al., 2022). SEM-PLS was selected due to its suitability for complex models involving multiple constructs, mediation effects, and non-normal data distributions, as well as its robustness with large sample sizes and exploratory theory-building objectives.

Research Population and Participants

The research population consists of pre-service teachers enrolled in teacher education programs at Universitas Islam Negeri (UIN) Raden Intan Lampung who actively engage in blended learning courses. A stratified random sampling technique was employed to ensure proportional representation across teacher education programs. The final sample comprises 450 participants from various study programs, academic levels, and backgrounds. Participation was voluntary, without incentives or academic requirements, and all respondents signed informed consent forms in accordance with institutional ethical guidelines. The high participation rate was facilitated by coordinated communication through program coordinators and class representatives. This broad and representative sample provides a robust foundation for examining the dynamics of self-regulated learning, social presence, and cognitive load in blended learning environments for pre-service teachers. Ethical approval for this study was obtained from the university’s research ethics committee, and all procedures adhered to the principles of voluntary participation, confidentiality, and informed consent. The demographic characteristics of the participants, including study programs, gender distribution, academic year, and blended learning experience, are summarized in Table 1. This diverse and representative sample provides a strong basis for examining self-regulated learning, social presence, and cognitive load in blended learning environments for pre-service teachers.

Table 1

Demographic Profile of Participants (n = 450)

Demographic Variable	Category	Frequency (N)	Percentage (%)
Teacher Education Program	Mathematics Education	50	11.11%
	Physics Education	45	10.00%
	Biology Education	55	12.22%
	Elementary Teacher Education	60	13.33%
	Early Childhood Teacher Education	40	8.89%
	English Education	50	11.11%
	Islamic Education	70	15.56%
	Arabic Education	30	6.67%
	Guidance and Counseling Education	50	11.11%
Total		450	100.00%
Gender	Male	180	40.00%
	Female	270	60.00%
Total		450	100.00%
Year of Study	First Year	120	26.67%
	Second Year	110	24.44%
	Third Year	115	25.56%
	Fourth Year	105	23.33%
Total		450	100.00%
Blended Learning Experience	Less than 1 year	150	33.33%
	1–2 years	200	44.44%
	More than 2 years	100	22.22%
Total		450	100.00%

Instrument

The instrument used in this study was designed to comprehensively measure self-regulated learning (SRL), social presence, cognitive load, deep learning, and learning outcomes in a blended learning environment, aligning with previous research. Details of the whole survey instrument, including all items and response formats, are provided in Appendix A. SRL was assessed through goal setting (SRL1), self-monitoring (SRL2), self-reflection (SRL3), effort regulation (SRL4), and metacognitive strategy use (SRL5), which are essential for independent learning in digital and face-to-face settings (Rovers et al., 2019). Social presence was measured based on peer interaction (SP1), instructor presence (SP2), emotional engagement (SP3), communication openness (SP4), and collaborative learning (SP5), as social connectedness has been shown to enhance engagement and motivation in online learning (Kreijns et al., 2022).

To examine students' cognitive load, the study utilized intrinsic load (CL1), extraneous load (CL2), germane load (CL3), perceived task difficulty (CL4), and cognitive effort (CL5), reflecting the balance between mental effort and instructional design in blended learning

(Sweller et al., 2011). Deep learning was evaluated through meaningful knowledge construction (DL1), critical thinking (DL2), application of concepts (DL3), reflective thinking (DL4), and integration of prior knowledge (DL5), as these elements are fundamental for higher-order learning (Slack et al., 2003). Lastly, learning outcomes were measured using final course grades (LO1), assignment and project scores (LO2), and assessment performance (LO3), ensuring an objective indicator of academic success.

Data Collection Procedures

Data were collected at the end of the academic semester after students had sufficient exposure to the blended learning environment. The online questionnaire was distributed through the institutional LMS, ensuring accessibility and consistency in administration. Prior to completing the survey, participants received an explanation of the study's purpose, ethical assurances, and instructions for completion. Only fully completed responses were included in the analysis.

Data Analysis and SEM-PLS Procedures

The data were analyzed using Structural Equation Modeling with Partial Least Squares (SEM-PLS), which is appropriate for examining complex relationships among latent constructs and testing both direct and indirect effects. The analysis followed a two-stage procedure: (1) measurement model evaluation, in which construct reliability and validity were assessed using indicator loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the Fornell–Larcker criterion; and (2) structural model evaluation, in which path coefficients, t-statistics, and p-values were examined using bootstrapping procedures. Model fit was assessed using multiple indices, including the Standardized Root Mean Square Residual (SRMR), Squared Euclidean Distance (d_ULS), Geodesic Distance (d_G), Normed Fit Index (NFI), and Root Mean Square Theta (RMS theta).

This analytical approach enabled the examination of both direct effects (e.g., SRL, cognitive load, and social presence on deep learning and learning outcomes) and indirect effects mediated by deep learning, providing a comprehensive understanding of the learning processes in the blended environment.

Validity and Reliability

Content Validity

The content validity of the questionnaire was ensured through a rigorous validation process, which confirmed that the items accurately represented the theoretical constructs of self-regulated learning, social presence, cognitive load, deep learning, and learning outcomes in the context of blended learning among pre-service teachers. The validation process involved an expert panel review of three specialists in educational psychology, instructional design, and blended learning. These experts evaluated each item based on clarity, relevance, and theoretical alignment, leading to minor refinements to enhance interpretability. A content validity index (CVI) was then calculated, where items with an item-level CVI (I-CVI) of 0.78 or higher were retained, ensuring their appropriateness. The scale-level CVI (S-CVI/Ave) of 0.90 or higher confirmed overall strong content validity.

To further validate the instrument, a pilot study was conducted with 50 pre-service teachers, assessing the clarity and comprehensibility of the items. Participants provided qualitative feedback, leading to minor modifications to enhance readability and reduce ambiguity. The final questionnaire reflects a high level of content validity, ensuring that it effectively captures the key dimensions of blended learning experiences among pre-service teachers while aligning with established theoretical frameworks in self-regulated learning, social presence, cognitive load, and deep learning.

Reliability and Convergent Validity

The reliability and convergent validity of the measurement model were assessed using Composite Reliability (CR), Cronbach's Alpha, and Average Variance Extracted (AVE), as presented in Table 2.

Table 2

Results of Model Constructs

Construct	Loadings	Composite Reliability (CR)	Cronbach's Alpha	AVE
Cognitive Load	0.745-0.918	0.928	0.902	0.721
Deep Learning	0.915-0.956	0.970	0.962	0.868
Learning Outcome	0.978-0.989	0.988	0.982	0.965
Self-Regulated Learning	0.817-0.924	0.944	0.925	0.771
Social Presence	0.871-0.924	0.958	0.946	0.822

Note. Indicator loadings ≥ .70 indicate acceptable item reliability. Composite Reliability (CR) and Cronbach's Alpha values ≥ .70 demonstrate satisfactory internal consistency. Average Variance Extracted (AVE) values of 0.50 or higher indicate adequate convergent validity.

The results demonstrate strong internal consistency across all constructs, with CR and Cronbach's Alpha values exceeding the recommended threshold of 0.7, indicating a high level of reliability. Additionally, the AVE values for all constructs exceed 0.5, confirming adequate convergent validity, which means that each construct explains a significant portion of the variance in its respective indicators. These findings suggest that the measurement model effectively captures the intended latent variables.

Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion, as shown in Table 3.

Table 3

Discriminant Validity of Constructs

Construct	Cognitive Load	Deep Learning	Learning Outcome	Self-Regulated Learning	Social Presence
Cognitive Load	0.849				
Deep Learning	0.892	0.931			
Learning Outcome	0.691	0.791	0.983		
Self-Regulated Learning	0.913	0.882	0.658	0.878	
Social Presence	0.903	0.873	0.633	0.905	0.906

The square root of the AVE for each construct exceeds the intercorrelations with other constructs, confirming that each variable is distinct and not overly correlated with others. These results indicate that the constructs in the model measure separate theoretical concepts, ensuring their validity for structural analysis.

Model Fit Indices

The overall model fit was evaluated using multiple goodness-of-fit indicators commonly applied in Partial Least Squares Structural Equation Modeling (SEM-PLS), including the Standardized Root Mean Square Residual (SRMR), squared Euclidean distance (d_ULS), geodesic distance (d_G), Chi-square statistic, Normed Fit Index (NFI), and Root Mean Square Theta (RMS Theta), as reported in Table 4.

Table 4

Model Fit Indices

Index	Saturated Model	Estimated Model
SRMR	0.09	0.09
d_ULS	0.737	0.737
d_G	0.657	0.657
Chi-Square	1027.768	1027.768
NFI	0.052	0.052
RMS Theta	0.170	

Note. SRMR < 0.10 indicates acceptable model fit; lower values of d_ULS and d_G reflect minor discrepancies between observed and model-implied correlations; RMS Theta values below 0.20 suggest adequate outer model quality.

The SRMR, which measures the standardized difference between observed and predicted correlations, indicates an acceptable model fit when values are below 0.10. The reported SRMR value meets this criterion. The d_ULS and d_G indices assess the discrepancy between empirical and model-implied correlation matrices, with lower values indicating better fit; the obtained values suggest that the estimated model adequately represents the data structure. The Chi-square statistic reflects overall model–data correspondence and, as expected in large-sample SEM-PLS applications, should be interpreted cautiously due to its sensitivity to sample size.

The Normed Fit Index (NFI) compares the proposed model with a null model and is often conservative in PLS-based estimation. Although the NFI value appears low, this outcome is not uncommon in complex PLS models and does not necessarily indicate poor model quality. Finally, the RMS Theta, which evaluates the degree of residual variance in the outer model, remains within acceptable limits, further supporting the adequacy of the measurement and structural models. Taken together, these indices indicate that the proposed model demonstrates an acceptable overall fit and is suitable for hypothesis testing and further structural analysis.

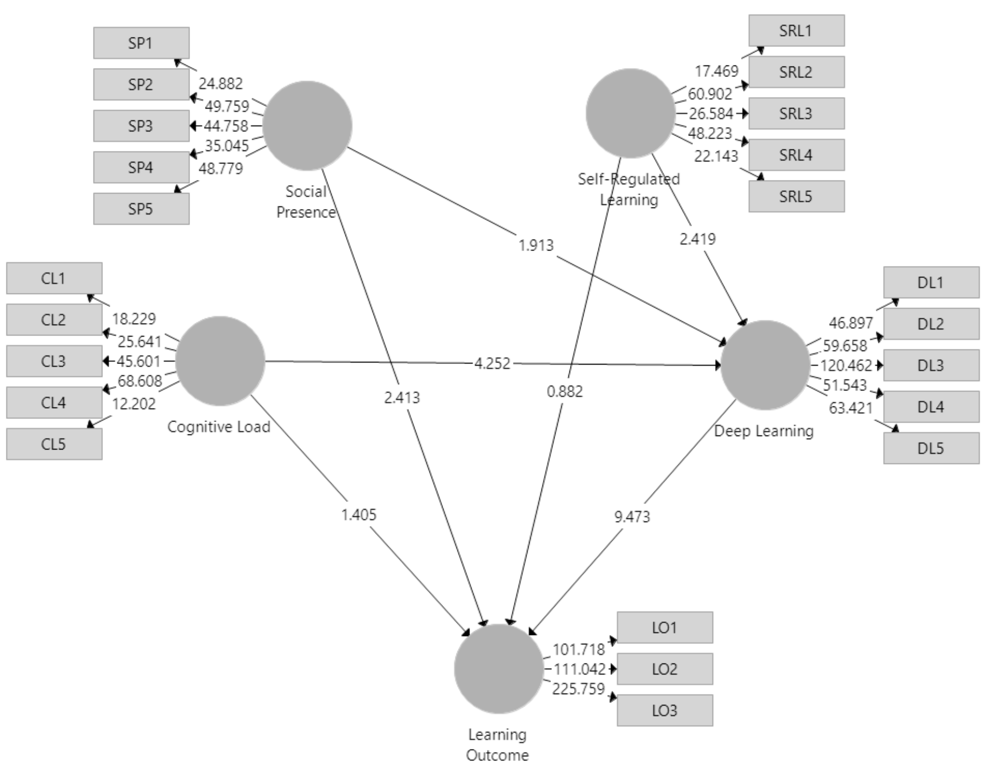
Results

Path Coefficients Analysis

The structural model was evaluated using path coefficient analysis, as presented in Figure 2 and Table 6. The results provide empirical insights into the relationships between cognitive load, self-regulated learning, social presence, deep learning, and learning outcomes within a blended learning environment.

Figure 2

Path Coefficient



The findings indicate that cognitive load has a significant influence on deep learning (β = 0.409, t = 4.252, p < 0.001), contradicting H1, which hypothesized an adverse effect. This suggests that cognitive load, when well-managed, can facilitate deep learning rather than hinder it. However, the direct effect of cognitive load on learning outcomes was not statistically significant (β = 0.153, t = 1.405, p = 0.161), failing to support H2, which implies that cognitive load alone does not directly determine academic success but rather operates through deep learning.

Deep learning emerged as a strong predictor of learning outcomes (β = 0.974, t = 9.473, p < 0.001), providing strong support for H3, which proposed that deep learning directly enhances academic performance. While the analysis confirms the directional influence of deep learning on outcomes, it is also plausible, based on reciprocal learning theories, that positive academic outcomes may, in turn, reinforce students' engagement in deeper learning strategies. However, this reciprocal effect was not examined in the present model and warrants further investigation.

Table 5

Path Coefficient

Hypotheses	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
Cognitive Load -> Deep Learning	0.409	0.406	0.096	4.252	< 0.001*
Cognitive Load -> Learning Outcome	0.153	0.141	0.109	1.405	0.161
Deep Learning -> Learning Outcome	0.974	0.979	0.103	9.473	< 0.001*
Self-Regulated Learning -> Deep Learning	0.29	0.284	0.12	2.419	0.016*
Self-Regulated Learning -> Learning Outcome	-0.104	-0.09	0.118	0.882	0.378
Social Presence -> Deep Learning	0.241	0.248	0.126	1.913	0.056
Social Presence -> Learning Outcome	-0.262	-0.265	0.108	2.413	0.016*

Note. Standardized path coefficients are shown. Paths marked with an asterisk () are statistically significant (p < .05); T statistics greater than 1.96 indicate significant effects based on bootstrapping.*

Self-regulated learning was found to significantly predict deep learning (β = 0.290, t = 2.419, p = 0.016), supporting H4, which posited that students with strong SRL skills are more likely to engage in deep learning. As indicated in Table 5, however, self-regulated learning did not have a direct impact on learning outcomes (β = -0.104, t = 0.882, p = 0.378), failing to support H5. This suggests that while SRL enhances learning engagement, its effects on academic performance are primarily indirect, operating through the process of deep learning.

Social presence exhibited a moderate but statistically insignificant effect on deep learning (β = 0.241, t = 1.913, p = 0.056), failing to support H6, which hypothesized a positive relationship. This indicates that while interaction and perceived connectedness may contribute to engagement, their direct influence on deep learning is not substantial. Interestingly, social presence had a negative influence on learning outcomes (β = -0.262, t = 2.413, p = 0.016), contradicting H7, which predicted a positive effect. This unexpected finding suggests that while social presence can foster engagement, excessive reliance on social interactions without structured learning strategies may detract from academic performance.

Indirect Effects Analysis

The indirect effects analysis examined whether deep learning mediates the relationships between cognitive load, self-regulated learning, social presence, and learning outcomes. The results in Table 6 provide empirical evidence supporting some of the proposed mediation effects.

Table 6

Path Coefficient for Indirect Effects.

Hypotheses	**Original Sample (O)**	**Sample Mean (M)**	**Standard Deviation (STDEV)**	**T Statistics (|O/STDEV|)**	**P Values**
Cognitive Load -> Deep Learning -> Learning Outcome	0.399	0.397	0.101	3.948	< 0.001*
Self-Regulated Learning -> Deep Learning -> Learning Outcome	0.282	0.276	0.118	2.385	0.017*
Social Presence -> Deep Learning -> Learning Outcome	0.235	0.246	0.135	1.743	0.082

Note. Indirect effects were tested using bootstrapping. Asterisks () indicate statistically significant mediation effects (p < .05). Indirect paths with T statistics > 1.96 are considered significant.*

The mediation analysis indicates that cognitive load indirectly influences learning outcomes through deep learning (β = 0.399, t = 3.948, p < 0.001), confirming H8. This finding suggests that while cognitive load does not directly affect learning outcomes, it influences students' engagement in deep learning, thereby enhancing their academic performance. This emphasizes the importance of managing cognitive load effectively in blended learning environments to foster more profound learning experiences.

Similarly, self-regulated learning has a significant influence on learning outcomes through deep learning (β = 0.282, t = 2.385, p = 0.017), supporting H9. This suggests that students with strong self-regulation skills are more likely to engage in deep learning strategies, resulting in improved academic performance. The result reinforces the critical role of self-regulation as an enabler of deep learning, rather than a direct predictor of academic success.

However, the indirect effect of social presence on learning outcomes through deep learning was not statistically significant (β = 0.235, t = 1.743, p = 0.082), failing to support H10. This suggests that while social presence may enhance student engagement, it does not necessarily lead to improved academic performance unless accompanied by other effective learning strategies. This finding suggests that social presence alone is insufficient for improving learning outcomes and must be supplemented by instructional designs that foster meaningful cognitive engagement.

Discussion

The findings of this study provide significant insights into how cognitive load, self-regulated learning, and social presence influence deep learning and learning outcomes within a blended learning environment intentionally designed to promote student-centered learning. In this context, the blended approach combined asynchronous online modules (delivered via Moodle at elearning.radenintan.ac.id) with in-person class sessions, incorporating reflective activities, group discussions, and problem-based assignments to encourage cognitive engagement, metacognition, and collaborative interaction. These findings are particularly relevant for Indonesia's higher education system, where blended learning has been increasingly adopted, but challenges persist in fostering deep engagement and self-regulated learning among students (Supriyadi et al., 2023; Widjaja & Aslan, 2022). Since many Indonesian students come from educational backgrounds emphasizing rote memorization and teacher-centered instruction (Haryanto, 2024), transitioning to student-centered blended learning requires instructional strategies that effectively support cognitive engagement, metacognition, and meaningful interaction.

A notable finding of this study is that cognitive load has a positive influence on deep learning. This challenges the conventional assumption that cognitive load primarily hampers learning (Brockbank & Feldon, 2024). Instead, the results suggest that when cognitive load is well-managed, it can facilitate schema construction and deeper cognitive processing (Clark, 2024; Frey et al., 2022). While this reflects a cognitive perspective, the study adopts a socio-cognitive theoretical framework, which integrates both individual information processing and social interaction in learning. Within this framework, cognitive development occurs not only through individual internalization but also through collaborative meaning-making and co-regulated learning. The use of structured collaboration in the blended environment aligns with this view, as collaborative tasks were designed to activate germane cognitive load while enabling shared regulation and social negotiation of understanding. This is consistent with Cognitive Load Theory, which distinguishes between extraneous, intrinsic, and germane cognitive load. While excessive extraneous load may hinder learning, an optimal level of intrinsic and germane load—especially within collaborative settings—can enhance comprehension and problem-solving abilities (Leppink et al., 2013). However, cognitive load was not found to directly influence learning outcomes, indicating that its impact on academic performance is realized primarily through deep learning. This finding has significant implications for instructional design in Indonesia, where students often struggle with self-directed learning due to their reliance on structured, instructor-led teaching (Asyhari & Islamia, 2023). The challenge for educators is to design learning experiences that promote meaningful engagement and peer collaboration while carefully managing cognitive demands.

The results also confirm that self-regulated learning plays a crucial role in deep learning, supporting previous research that emphasizes the importance of metacognitive strategies in student learning (Panadero et al., 2021). Self-regulated learners tend to engage more deeply with course content, effectively managing their time and cognitive resources to enhance understanding. However, this study found no significant direct effect of self-regulated learning on learning outcomes, indicating that self-regulation alone does not guarantee academic success unless it is channeled into deep learning processes. This aligns with research suggesting that self-regulated learning must be combined with structured scaffolding and instructional supports to be fully effective (Munshi et al., 2023). In the Indonesian education system, where students often rely on external motivation rather than intrinsic learning strategies (Asyhari & Islamia, 2023; Misbah et al., 2022), providing explicit guidance on self-regulated learning techniques, such as self-monitoring, goal setting, and reflective practices, can help students develop autonomy in their learning.

One of the more unexpected findings is that social presence did not significantly influence deep learning and had a negative impact on learning outcomes. Prior research has highlighted the role of social presence in fostering engagement and motivation in online and blended learning environments (Shi et al., 2021; Zhong et al., 2022), yet the results of this study suggest that social presence alone is insufficient for promoting deeper cognitive engagement. This finding aligns with studies indicating that while social presence enhances student satisfaction, it does not necessarily contribute to conceptual understanding unless interaction is structured to facilitate higher-order thinking (Lee, 2014). In Indonesia, where students often participate in online discussions passively or superficially, more structured collaborative learning activities, such as inquiry-based discussions, debate tasks, and problem-solving exercises, may be needed to ensure that social presence translates into meaningful academic engagement. Furthermore, the adverse effect of social presence on learning outcomes in this study likely stems from the design of the learning environment, in which asynchronous peer interactions were not always clearly aligned with instructional goals. As a result, some students may have engaged in off-task or non-substantive discussions, reducing the overall effectiveness of their learning experience. This suggests that excessive reliance on peer interaction without clear instructional goals, as observed in several discussion forums during the course, may serve as a distraction rather than a facilitator of learning (Wang et al., 2023). This highlights the importance of designing social interactions directly tied to learning objectives, ensuring they enhance rather than hinder student comprehension.

The mediation analysis further underscores the importance of deep learning as a mechanism linking cognitive, self-regulatory, and social factors to academic success. The significant mediation effect of deep learning in the relationship between cognitive load and learning outcomes supports the view that optimal cognitive challenges can enhance academic performance when they lead to deeper engagement (Jeong et al., 2024; Martin, 2018; Skulmowski & Xu, 2022). Similarly, the mediation effect of deep learning in the relationship between self-regulated learning and learning outcomes confirms that self-regulation alone is not a direct predictor of academic achievement but plays a crucial role in fostering deep learning behaviors (Panadero et al., 2021). However, the non-significant mediation effect of deep learning in the relationship between social presence and learning outcomes suggests that social presence does not inherently improve academic success unless coupled with structured, cognitively engaging learning activities.

Despite the methodological rigor of this study, several potential threats to validity merit consideration. First, the reliance on self-reported data introduces the possibility of self-report bias, particularly for constructs such as self-regulated learning and social presence that are closely tied to learners' self-perceptions. In the Indonesian higher education context, where students may be inclined toward compliance-oriented responses, social desirability effects cannot be entirely excluded. To mitigate this risk, participation was voluntary and anonymous, with no academic incentives or consequences, thereby reducing evaluation apprehension and encouraging candid responses. Second, common method bias may arise because most constructs were measured using a single survey administered at one time point. To address this concern, the study employed procedural remedies, including careful item wording and separation of construct indicators across the questionnaire, as well as statistical checks. Evidence of discriminant validity using the Fornell–Larcker criterion indicates that the constructs were empirically distinct, reducing the likelihood that observed relationships were driven primarily by shared measurement artifacts rather than substantive theoretical links. Third, the correlational SEM-PLS design limits causal inference. Although the structural model specifies theoretically grounded directional paths, the findings should be interpreted as associative rather than causal. This limitation is particularly relevant given the potentially reciprocal relationships between deep learning and learning outcomes. Path directions were therefore justified through established theoretical frameworks, including Cognitive Load Theory and socio-cognitive perspectives on learning, while recognizing that longitudinal or experimental designs are needed to establish causal mechanisms more conclusively. Finally, contextual and cultural specificity represents both a strength and a limitation. Conducted within a single Indonesian public university, the study reflects pedagogical traditions shaped by teacher-centered instruction and varying levels of learner autonomy and digital readiness. While this enhances ecological validity and contextual relevance, it constrains generalizability beyond similar settings. To support transferability, the blended learning design, instructional practices, and LMS-mediated activities were described in detail.

Limitation

This study has several limitations that should be taken into account when interpreting the findings. First, the sample was drawn from a single public university in Indonesia, which may limit the generalizability of the results to other institutional, cultural, or disciplinary contexts. Second, although the sample size was relatively large, participation was voluntary, raising the possibility of self-selection bias. Third, the reliance on self-reported data may not fully capture students' actual learning behaviors or cognitive engagement. Finally, the non-experimental and cross-sectional design prevents conclusions about causal mechanisms or developmental changes over time.

Conclusion

This study highlights the critical role of deep learning in mediating the effects of cognitive load, self-regulated learning, and social presence on learning outcomes in a blended learning environment, with implications for Indonesia's higher education system. The findings reveal that cognitive load, when well-managed, fosters deep learning, emphasizing the need for instructional designs that optimize rather than minimize cognitive demands. Self-regulated learning significantly enhances deep learning but does not directly influence learning outcomes, reinforcing the importance of structured interventions to develop students' metacognitive skills. Social presence, while often associated with engagement, was found to have no significant effect on deep learning and negatively impacted learning outcomes, suggesting that unstructured peer interactions may serve as distractions rather than facilitators of academic success. These results underscore the necessity of carefully designing blended learning environments that promote meaningful cognitive engagement, provide explicit support for self-regulation, and structure social interactions to enhance rather than hinder learning. Given the growing adoption of blended learning in Indonesia, future research should further explore the role of instructional strategies and technological innovations in strengthening deep learning processes to optimize student success in digital and hybrid classrooms.

Implications for Instructional Design, Policy, and Educational Technology

The findings carry important implications for instructional design and higher education policy. At the pedagogical level, the results suggest that blended learning should not merely reduce cognitive demands but instead optimize cognitive challenge through carefully structured tasks that promote deep learning. Explicit scaffolding for self-regulated learning, such as guided reflection, goal-setting activities, and formative feedback, should be embedded within both online and face-to-face components. From a policy perspective, institutions should move beyond modality-based adoption of blended learning and invest in faculty development focused on learner-centered design, co-regulated collaboration, and assessment for deep learning. At the technological level, adaptive learning systems and learning analytics tools could be leveraged to monitor students' cognitive load and self-regulatory behaviors, enabling timely instructional interventions.

Future Research Directions

Future studies should extend this work by employing multi-institutional samples to enhance external validity and cross-cultural comparison. Longitudinal designs would enable researchers to investigate how self-regulation, cognitive load, and deep learning develop over time. Experimental or quasi-experimental studies could further clarify causal pathways by manipulating instructional design features, levels of cognitive challenge, or forms of structured collaboration within blended environments.

Declarations

Ethics Statement

This study was reviewed and approved by the Research Ethics Committee of Universitas Islam Negeri Raden Intan Lampung. All participants provided informed consent prior to data collection. Participation was voluntary, and respondents were assured of anonymity and confidentiality throughout the research process.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest associated with this study.

Funding Statement

This research received no external funding. Universitas Islam Negeri Raden Intan Lampung provided institutional support.

AI Use Statement
No generative artificial intelligence tools were used in data collection, analysis, or interpretation.

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Appendix A. Survey Instrument

All constructs in this study were measured using a structured questionnaire with multiple items per construct. Items were developed based on a review of relevant literature and adapted to the blended learning context for pre-service teachers. Each item used a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

1. Self-Regulated Learning (SRL)

No	Item Statement
1.1	I set specific learning goals before starting my online or offline study.
1.2	I monitor my learning progress regularly during blended courses.
1.3	I reflect on my performance and try to improve my learning strategies.
1.4	I continue studying even when the content is difficult or uninteresting.
1.5	I use techniques such as summarizing and creating concept maps to better understand the material.

2. Social Presence

No	Item Statement
2.1	I feel comfortable communicating with my classmates online.
2.2	I perceive my instructor as present and responsive in the learning process.
2.3	I feel emotionally connected with peers during collaborative activities.
2.4	I can openly share ideas and opinions in online or in-person discussions.
2.5	Working in teams helps me better understand the course material.

3. Cognitive Load

No	Item Statement
3.1	The content of this course is inherently complex.
3.2	I find it challenging to follow the instructions and navigate the LMS.
3.3	I make extra effort to organize information for better understanding.
3.4	I feel overwhelmed by the number of tasks required in this course.
3.5	I concentrate hard to make sense of the learning materials.

4. Deep Learning

No	Item Statement
4.1	I try to relate new concepts to what I already know.
4.2	I critically evaluate information before accepting it as accurate.
4.3	I apply what I have learned to solve real-world problems.
4.4	I often think about how I can improve my understanding of the material.
4.5	I integrate knowledge from different topics or courses.

5. Learning Outcomes

No	Item Statement
5.1	I have achieved high grades in this course.
5.2	I perform well in assignments and collaborative projects.
5.3	I can demonstrate my understanding through assessments and exams.

This survey instrument was pilot-tested for content validity and reliability with a sample of 50 students before full deployment. The Cronbach's alpha for each construct exceeded 0.80, confirming internal consistency. Future studies are encouraged to validate this instrument across diverse educational contexts.