

Cognitive-state Sensing and Computational Analysis of Serial Multiple Mediation from Cognitive Load and Emotional Experience to Learning Difficulty

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(Received July 9, 2026; accepted September 1, 2026)

Keywords: cognitive-state sensing, perception sensing, cognitive load, learning analytics, structural equation modeling, latent profile analysis

Instructional design competency is essential for elementary education majors; however, the “knowing–doing” gap remains a common learning challenge. To strengthen the integration of educational analytics and intelligent sensing applications, we developed a computational cognitive-state modeling framework based on cognitive load (CL) theory and concepts relevant to future cognitive-state sensing applications. Using this framework, we investigated how CL affects perceived overall difficulty (CDP) through cognitive-emotional experience (CEE) and self-assessed design competence (DCS). A total of 630 elementary education majors participated in this study, and questionnaire-derived cognitive-state indicators were analyzed using structural equation modeling (SEM) to validate the relationships among the proposed latent constructs. Exploratory factor analysis identified a four-factor structure with a cumulative variance explanation rate of 74.23%, while confirmatory factor analysis demonstrated good model fit (comparative fit index = 0.967, root mean square error of approximation = 0.061). Path analysis revealed that CL significantly positively affected CEE ($\beta = 0.890, p < 0.001$), CEE significantly positively affected DCS ($\beta = 0.512, p = 0.014$), and DCS significantly positively affected CDP ($\beta = 0.180, p = 0.010$). Mediation analysis confirmed a significant serial indirect effect of CL on CDP through CEE and DCS. Latent profile analysis further identified three heterogeneous learner groups with different cognitive-load characteristics. The findings demonstrate that learning difficulty can be quantitatively analyzed through cognitive-state sensing and computational modeling approaches, providing potential applications for intelligent educational sensing systems and adaptive learning environments.

1. Introduction

Instructional design competency, as the core mechanism for transforming theoretical knowledge into practical instructional plans, is a critical component of the professional

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<https://doi.org/10.18494/SAM6513>

competence of students majoring in elementary education. This competency not only affects learners' educational performance but also fundamentally influences their future professional development. However, in teacher education practice, a persistent and profound contradiction has become increasingly evident: learners can systematically study educational theories and achieve satisfactory academic results, yet they often encounter difficulties when independently completing high-quality instructional design tasks. This "knowing–doing" gap represents a common learning bottleneck that urgently requires further investigation from the perspectives of cognitive processing and cognitive-state sensing. From a computational cognitive perspective, completing instructional design tasks involves the continuous processing and integration of multiple interrelated subtasks. Learners must simultaneously manage several decision-making components, including student analysis, objective setting, content organization, activity design, and assessment design, under the constraints of limited working memory resources.

This multi-component integration characteristic makes instructional design learning a highly cognitive-load-intensive task. However, previous studies have mainly focused on static competency evaluation or outcome-oriented effectiveness assessment, making it difficult to reveal the dynamic cognitive-processing characteristics that occur during instructional design construction. As a result, many existing interventions remain limited to external instructional support and fail to effectively identify learners' internal cognitive-processing bottlenecks through computational cognitive-state analysis. Cognitive load theory (CLT), first proposed by Sweller in his seminal research on problem-solving and learning,⁽¹⁾ provides an important theoretical foundation for cognitive-state sensing and learning analytics. The core concept of CLT, "cognitive load (CL)," refers to the total amount of cognitive resources required by working memory during task execution.⁽²⁾ CLT further suggests that effective instructional design should minimize extraneous CL unrelated to schema construction, optimize germane CL associated with meaningful learning, and ensure that the total CL does not exceed the learner's working memory capacity.⁽³⁾ CLT is based on three assumptions regarding human cognitive architecture.⁽⁴⁾ First, working memory has severe capacity limitations. Miller estimated that working memory can process approximately 7 ± 2 chunks of information.⁽⁵⁾

CLT further extended this concept by indicating that such limitations can be reduced when information has already been organized into schemas within long-term memory.⁽⁶⁾ Second, long-term memory is hierarchically organized through schemas that represent generalized domain knowledge.^(7,8) Therefore, meaningful learning requires learners to construct high-quality and accessible schemas. van Gog *et al.* further connected schema theory with deliberate practice to improve instructional design for advanced learning tasks.⁽⁹⁾ Third, effective instruction requires compatibility between external information structures and learners' existing cognitive structures, a concept referred to as "cognitive structure and information structure compatibility."⁽⁶⁾ On the basis of these assumptions, CLT distinguishes three major types of CL. Intrinsic CL originates from the inherent complexity and element interactivity of learning tasks and can be regulated through task decomposition.⁽¹⁰⁾ Extraneous CL results from suboptimal instructional design and redundant information unrelated to schema construction.⁽¹¹⁾ Germane CL refers to the cognitive resources intentionally invested by learners in schema construction and meaningful learning processes. These three types of CL are additive, and learning

performance decreases when the total CL exceeds the limited capacity of working memory.⁽¹²⁾ Consequently, instructional design should minimize extraneous load while maximizing germane load under fixed intrinsic-load conditions.

Early CLT studies generally assumed a stable negative relationship between CL and learning performance, and this assumption has been supported by substantial empirical evidence.⁽¹³⁾ However, Schnotz and Kurschner suggested that the direction and strength of this relationship may vary according to learners' prior knowledge levels.⁽¹⁴⁾ Therefore, CL should not be regarded solely as a negative factor but rather as an inevitable component of complex learning activities. At the computational modeling level, CLT has provided an important theoretical basis for learning analytics and intelligent educational sensing research. Mayer and Moreno introduced CLT into multimedia learning studies,⁽¹⁵⁾ while Brünken *et al.* systematically discussed dual-task methodologies for cognitive-load measurement.⁽¹⁶⁾ Grounded in schema theory and resource-allocation principles, CLT explains learning processes from the perspective of cognitive resource distribution, providing a systematic framework for analyzing complex professional learning tasks.⁽¹⁷⁾ Consequently, CLT has become one of the most influential theories in learning science and educational technology research, and its role in intelligent learning-environment design and cognitive-state sensing applications has been widely recognized.⁽¹⁸⁾ Sweller *et al.* further reviewed the developmental trajectory and future directions of CLT on the 20th anniversary of the theory.⁽¹⁹⁾

To clarify the sensing-oriented contribution of this study, the proposed framework should be distinguished from a physical sensor system. In addition to cognitive-resource limitations, emotional experience is increasingly recognized as an important component of complex learning processes. CL and emotional states are not independent; rather, they may interact dynamically during demanding learning tasks. Previous studies have demonstrated significant associations between emotional states and CL in multimedia and technology-supported learning environments.^(20,21) When task demands approach or exceed available cognitive resources, learners may experience confusion, frustration, anxiety, or emotional strain, particularly when they cannot organize information or identify an effective problem-solving strategy. These emotional responses may, in turn, affect attention, working-memory efficiency, persistence, and engagement, thereby modifying how cognitive demands are processed. Recent evidence further suggests that CL can function as an intermediate mechanism linking emotional states with learning outcomes.⁽²²⁾ Therefore, cognitive-emotional experience (CEE) is conceptualized in this study as an intermediate cognitive-emotional mechanism through which perceived cognitive demands may affect subsequent self-assessed competence and overall learning difficulty. This interaction is also consistent with the stimulus-organism-response perspective adopted in the present framework, in which cognitive demands act as task-related stimuli, cognitive-emotional responses represent internal learner states, and subsequent competence and difficulty perceptions reflect downstream responses.

In current intelligent learning environments, learners' cognitive and emotional states can be monitored using physical sensing devices, such as electroencephalography (EEG) sensors for neural activity, electrodermal activity (EDA) or galvanic skin response (GSR) sensors for autonomic arousal, photoplethysmography (PPG) or electrocardiography (ECG) sensors for

heart-rate and heart-rate-variability measurements, and eye-tracking sensors for gaze, fixation, and pupil responses. These physical signals can provide objective observations associated with CL, emotional arousal, attention, and learning difficulty. However, raw sensor signals alone do not directly explain the relationships among CL, emotional experience, perceived competence, and perceived difficulty. Therefore, we focus on developing and validating the computational inference layer required to transform cognitive-state observations into interpretable learner-state information. Although questionnaire-derived indicators are used in the present implementation rather than direct physiological measurements, the CL–CEE–self-assessed design competence (DCS)–perceived overall difficulty (CDP) framework defines the latent cognitive variables and analytical relationships that can subsequently be coupled with physical sensor measurements. Accordingly, the contribution of this study to sensing applications lies not in the development of new sensor hardware, but in establishing a computational cognitive-state model that can serve as the analytical layer of future multimodal educational sensing systems.

2. Methodology

On the basis of the core framework of CLT, we developed a computational serial multiple mediation model for cognitive-state analysis. The proposed model assumes that the cognitive challenges generated during instructional design learning, represented by CL, first influence learners' CEE. This cognitive-state perception further affects learners' DCS, which subsequently influences CDP. The model structure is grounded in the “stimulus-organism-response” (S-O-R) paradigm from environmental psychology⁽²³⁾ and is suitable for the computational cognitive-state analysis of learners' internal cognitive-processing mechanisms.

H1: CL has a significant positive effect on CEE.

H2: CEE has a significant positive effect on DCS.

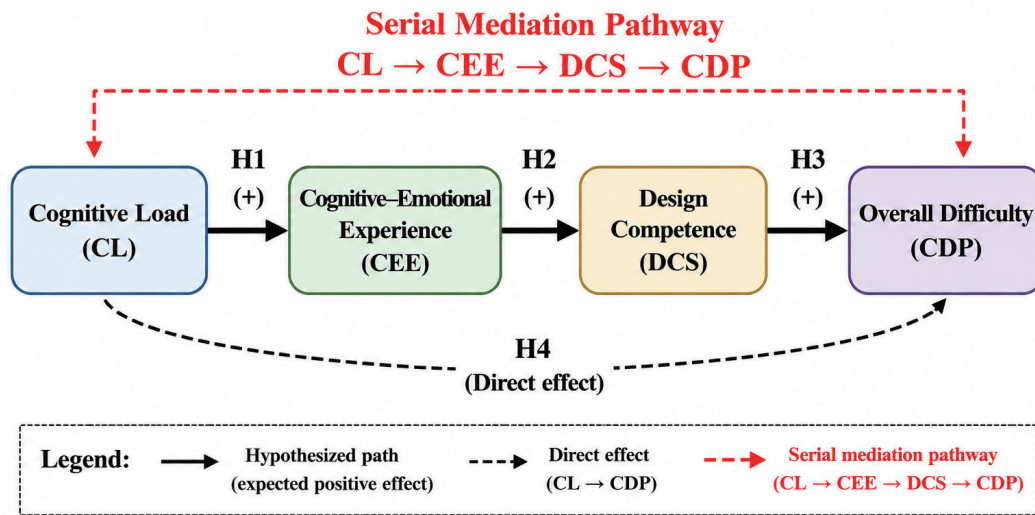
H3: DCS has a significant positive effect on CDP.

H4a: CEE mediates the relationship between CL and CDP.

H4b: DCS mediates the relationship between CL and CDP.

H4c: CEE and DCS serve as serial mediators in the relationship between CL and CDP.

In addition, practical experience was employed as a grouping variable for exploratory comparison. Independent-samples t-tests were conducted to compare learners with and without practical experience across the four core cognitive-state variables. On the basis of the above theoretical derivation, the overall conceptual framework of this study is presented in Fig. 1. The participants were full-time junior and senior undergraduate students majoring in elementary education at universities in Guangdong Province. To reduce institutional bias, “Double First-Class” normal universities were excluded and 12 general undergraduate institutions were selected as survey units. The survey was conducted from January 13 to 25, 2025, through the “Questionnaire Star” online platform, which served as an online interface for collecting questionnaire-derived cognitive-state indicators. In the present study, CL, CEE, DCS, and CDP were measured using questionnaire-derived indicators. These data were used to validate the proposed computational relationships among the four constructs. No physiological or behavioral sensors were used at this stage. The broader sensing framework represents a future



Note: H1, H2, and H3 denote positive hypothesized relationships.
H4 represents the direct effect of CL on CDP.

Fig. 1. (Color online) Conceptual model highlighting the hypothesized serial mediation pathway from CL through CEE and DCS to CDP.

implementation in which physiological or behavioral signals may be integrated with the validated computational model.

For clarity, the terminology used throughout this study distinguishes the current implementation from the broader sensing concept. “Questionnaire-derived cognitive-state indicators” refers specifically to the self-reported data collected and analyzed in the present model-validation stage, whereas “cognitive-state sensing framework” refers to the broader conceptual architecture intended for future integration with physiological and behavioral sensors. Accordingly, questionnaire responses are not treated as physical sensor measurements in the present study. A total of 806 questionnaires were initially collected. Within the proposed cognitive-state sensing framework, the questionnaire platform functioned as a data-acquisition layer for model validation. CL, CEE, self-assessed DCS, and CDP were treated as questionnaire-derived cognitive-state indicators representing learners’ self-reported cognitive responses during instructional design activities.

In this study, the online questionnaire platform functioned as a data-collection interface for obtaining learners’ self-reported cognitive-state indicators. From an intelligent sensing-system perspective, the proposed framework can be implemented as a three-layer architecture consisting of physical sensing, cognitive-state inference, and educational decision layers. The physical sensing layer may acquire physiological and behavioral signals using EEG, EDA/GSR, PPG/ECG, and eye-tracking devices. For example, EEG spectral features and pupil responses can provide information associated with mental workload and attention; EDA-related features can characterize variations in physiological arousal; and PPG/ECG-derived heart-rate variability can provide complementary information regarding cognitive and emotional responses. After preprocessing, artifact removal, normalization, and feature extraction, these multimodal sensor

features can be mapped to the cognitive-state constructs examined, particularly CL and CEE. Note that the four cognitive-state constructs considered in this study differ in their direct observability through physical sensors. Rapidly varying states associated with CL and CEE may be partially characterized using physiological and behavioral features, such as EEG spectral activity, pupil responses, electrodermal arousal, and heart-rate variability. In contrast, higher-level constructs such as DCS and CDP cannot presently be measured directly by a single physiological sensor. Therefore, the proposed framework adopts a hybrid sensing-and-inference concept in which directly observable physiological features can support the estimation of CL and CEE, while the validated computational relationships are used to infer their potential influence on higher-level competence and difficulty perceptions.

The computational inference layer can subsequently use the validated CL–CEE–DCS–CDP relationships to estimate how sensor-observed changes in cognitive and emotional states are associated with competence perception and overall learning difficulty. Finally, the educational decision layer can use the inferred learner state to trigger adaptive instructional support, such as reducing task complexity, providing additional guidance, or adjusting learning content. The present experiment validates the computational inference relationships using questionnaire-derived cognitive-state indicators and therefore should be regarded as a model-validation stage rather than a complete physiological sensing experiment. Accordingly, no physiological or behavioral sensor signals were acquired in the present study, and the questionnaire-derived indicators should not be interpreted as substitutes for direct sensor measurements. The role of the current analysis is limited to validating the computational relationships among CL, CEE, DCS, and CDP. Integration with physiological sensing remains a subsequent experimental stage that will require the synchronized sensor acquisition and independent validation of the mappings between sensor-derived features and the proposed cognitive-state constructs.

Importantly, this separation allows the analytical framework to remain independent of a specific sensor modality. Future implementations can replace or supplement questionnaire-derived CL and CEE indicators with synchronized physiological measurements while retaining the same cognitive-state inference structure. This architecture therefore provides a technically defined interface between physical sensor acquisition and computational educational decision-making. After data screening, 630 valid questionnaires were retained, corresponding to an effective response rate of 78.2%. The demographic characteristics of the participants are summarized in Table 1. Detailed data-cleaning criteria and factor-analysis procedures are

Table 1
Demographic characteristics of the sample ($N = 630$).

Characteristic	Category	Frequency	Percentage (%)
Grade	Junior	343	54.44
	Senior	287	45.56
Average academic performance	Top 30%	205	32.54
	Middle 40%	394	62.54
	Bottom 30%	31	4.92
Prior experience in elementary school teaching practicum or internship	Yes	556	88.25
	No	74	11.75
Total		630	100.0

provided in Supplemental Information. Construct validation and structural modeling were performed to evaluate the proposed CL–CEE–DCS–CDP framework. The analyses included factor analysis, structural equation modeling, mediation analysis, group comparison, and latent profile analysis using SPSS 26.0 and Mplus 8.0. Detailed statistical procedures, model-selection criteria, goodness-of-fit indices, reliability and validity assessments, and complete statistical results are provided in Supplemental Information. Detailed statistical procedures for mediation analysis, group comparison, and latent profile analysis are provided in Supplemental Information.

3. Computational Modeling and Cognitive-state Sensing Results

For visual clarity, Fig. 2 presents only the structural relationships among the four principal cognitive-state constructs, with the serial mediation pathway emphasized and measurement-level indicators omitted because they are reported separately in Supplemental Information. Table 2 shows the standardized path coefficients and significance levels used to evaluate the primary hypotheses. Its purposes are to show which direct relationships among CL, CEE, DCS, and CDP.

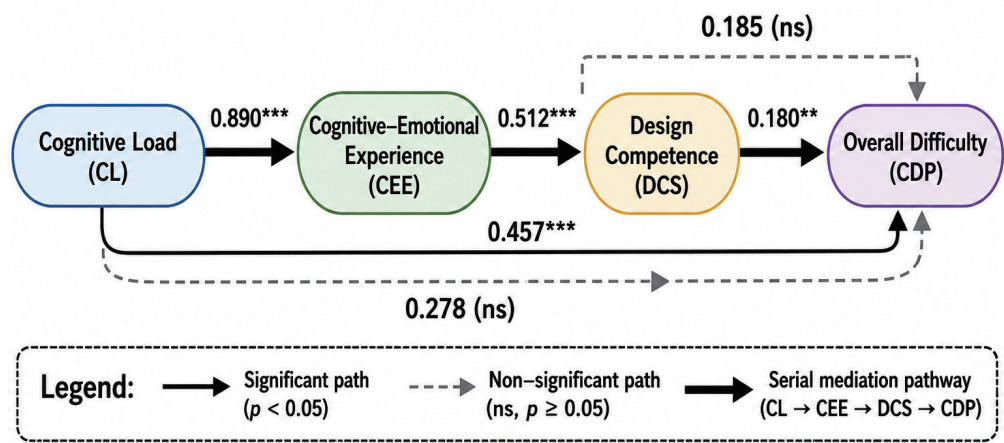


Fig. 2. (Color online) Simplified structural model showing standardized path coefficients and the supported serial mediation pathway. Solid bold arrows indicate the principal CL → CEE → DCS → CDP mediation chain, whereas dashed arrows indicate nonsignificant paths.

Table 2
Path coefficients and hypothesis testing.

Path		Estimate	<i>S.E.</i>	<i>C.R.</i>	<i>p</i>	Conclusion
CL	→ CEE	.890	.079	13.507	***	H1 supported
CEE	→ DCS	.512	.206	2.452	.014	H2 supported
CL	→ DCS	.278	.234	1.403	.161	Not supported
DCS	→ CDP	.180	.082	2.590	.010	H3 supported
CL	→ CDP	.457	.219	2.921	.003	Direct effect
CEE	→ CDP	.185	.199	1.084	.278	Not supported

Note: *S.E.* = standard error; *C.R.* = critical ratio.

and CDP are statistically supported and to provide the numerical basis for the structural paths illustrated in Fig. 2. Beyond statistical significance, the standardized coefficients also indicate meaningful differences in the relative strength of the proposed relationships. The CL $\rightarrow$ CEE path ($\beta = 0.890$) was the strongest association in the structural model, suggesting that changes in perceived CL are closely accompanied by changes in learners' CEE. The CEE $\rightarrow$ DCS ($\beta = 0.512$) and CL $\rightarrow$ CDP ($\beta = 0.457$) paths showed substantial associations, indicating that emotional experience and CL have practically relevant relationships with competence and difficulty perceptions. In comparison, the DCS $\rightarrow$ CDP path ($\beta = 0.180$), although statistically significant, was relatively smaller and should therefore be interpreted as a more limited contribution. These differences suggest that reducing excessive CL and supporting learners' emotional regulation may be more practically influential than focusing on competence perception alone. Preliminary descriptive and correlation analyses were conducted before structural modeling. The structural model showed an acceptable overall fit, supporting the subsequent evaluation of the proposed CL–CEE–DCS–CDP relationships. Detailed descriptive statistics, correlation coefficients, and model-fit indices are provided in Tables S5 and S6 of Supplemental Information. The fit indices of the structural model are presented in Table S6, while the path-analysis results are summarized in Table 2 and illustrated in Fig. 2.

H1 (CL $\rightarrow$ CEE) was supported. CL had a significant positive effect on CEE ($\beta = 0.890$, $p < 0.001$), indicating that the higher CL perceived during instructional design tasks was associated with stronger mental confusion and emotional distress in learners' cognitive-state sensing responses.

H2 (CEE $\rightarrow$ DCS) was supported. CEE had a significant positive effect on DCS ($\beta = 0.512$, $p = 0.014$), indicating that learners' emotional-perception states significantly influenced their self-evaluation of instructional DCP.

H3 (DCS $\rightarrow$ CDP) was supported. DCS had a significant positive effect on CDP ($\beta = 0.180$, $p = 0.010$). Notably, this positive relationship suggested that learners with higher self-assessed competence tended to perceive instructional design tasks as more difficult, reflecting a "competence-standard matching" effect.

Direct and mediation effects. The direct effect of CL on CDP was significant ($\beta = 0.457$, $p = 0.003$), whereas the CEE $\rightarrow$ CDP and CL $\rightarrow$ DCS paths were not significant. Mediation analysis showed significant indirect effects of CL on CDP through CEE (0.147), DCS (0.139), and the serial CEE $\rightarrow$ DCS pathway (0.082), with all 95% bootstrap confidence intervals excluding zero. The overall mediation effect accounted for 44.3% of the total effect, indicating that CEE and DCS contributed both independently and sequentially to the relationship between CL and CDP. The model including CL, CEE, and DCS explained a substantial proportion of the variation in CDP (adjusted $R^2 = 0.535$). Detailed bootstrap, effect-decomposition, and regression results are provided in Supplemental Information.

After selecting the three-class solution, Table 3 shows the characterized cognitive-state pattern of each latent profile using standardized scores. Profile 1 consistently showed above-average levels across the four dimensions, Profile 2 remained close to the sample average, and Profile 3 showed consistently below-average levels. The largest separation among the profiles occurred for CDP, indicating that perceived difficulty was particularly important in

Table 3

Standardized means (standard deviations) of the four dimensions across the three latent profiles.

Dimension	Profile 1 (34.7%)	Profile 2 (46.8%)	Profile 3 (18.4%)
CL	0.76 (0.68)	0.05 (0.71)	−1.02 (0.59)
CEE	0.58 (0.72)	−0.12 (0.69)	−0.85 (0.63)
DCS	0.49 (0.69)	−0.08 (0.73)	−0.76 (0.66)
CDP	0.85 (0.65)	0.10 (0.74)	−1.13 (0.62)

Note: Values in parentheses are standard deviations.

distinguishing the three learner groups. Overall, CDP exhibited the largest variation among the three latent profiles, with the difference between Profiles 1 and 3 approaching two standard deviations. These findings suggested that instructional interventions and intelligent educational sensing strategies should be differentiated according to learner characteristics. For Profile 1 (High-Load, High-Perception), interventions should emphasize cognitive-load reduction and emotional regulation. For Profile 2 (Moderate-Load, Moderate-Perception), structured cognitive-support and adaptive learning tools should be provided to optimize cognitive-load distribution. For Profile 3 (Low-Load, Low-Perception), instructional strategies should focus on enhancing intrinsic motivation and progressively increasing task complexity.

4. Discussion and Analysis

4.1 Major findings and theoretical contributions

First, the core cognitive-state constructs of instructional design learning exhibited a stable four-factor structure (DCS, CL, CEE, and CDP), accounting for 74.23% of the total variance. This finding validates the applicability of CLT to professional-practice learning in teacher education and further supports the feasibility of applying cognitive-state sensing and computational learning analytics to instructional design research. Notably, the eight instructional design subtasks converged into a single DCS factor, indicating that learners without mature instructional-design schemas tended to perceive these subtasks holistically as a unified competence construct rather than as independent instructional components. Furthermore, the emergence of CEE and CDP as independent one-dimensional factors supports the necessity of separately measuring emotional-perception states and difficulty-perception responses within intelligent educational sensing frameworks.

Second, CL influenced CDP through three mediation pathways: CEE parallel mediation (0.147), DCS parallel mediation (0.139), and the CEE→DCS serial mediation pathway (0.082). The total mediation effect accounted for 44.3% of the total effect (indirect effect = 0.368 / total effect = 0.830). The direct effect of CEE on CDP was not significant ($\beta = 0.185$, $p = 0.278$), indicating that emotional-perception states influenced difficulty perception entirely through DCS. The positive DCS→CDP pathway ($\beta = 0.180$, $p = 0.010$) suggested that learners with higher self-assessed competence tended to perceive instructional design tasks as more difficult, reflecting a “competence-standard matching” effect. Although the effect size of this pathway

was relatively small, the serial mediation pathway remained statistically significant ($p < 0.001$), supporting the applicability of the S-O-R paradigm within cognitive-state sensing research. In addition, the nonsignificant direct path from CL to DCS ($p = 0.161$) and the significant CEE→DCS pathway ($\beta = 0.512$, $p = 0.014$) indicated that CL influenced self-assessed competence indirectly through emotional-perception responses. Although the significant CL → CEE → DCS → CDP pathway supports the proposed serial mediation mechanism, it should not be interpreted as a universal or exclusive cognitive process. The strength and direction of these relationships may vary according to learner-level and instructional-level conditions. For example, prior knowledge may reduce the cognitive resources required for complex tasks, resilience may influence how learners respond emotionally to increased cognitive demands, and instructional quality may alter both perceived load and learning difficulty. These potential moderating factors were not explicitly modeled in the present analysis. Future studies should therefore compare alternative structural pathways and employ moderated-mediation models to examine whether prior knowledge, resilience, instructional quality, or other contextual factors modify the proposed mediation relationships. Such analyses would help establish the boundary conditions and broader applicability of the current computational cognitive-state model.

Third, no statistically significant differences were identified between students with and without elementary school practicum or internship experience across the four core cognitive-state variables ($p > 0.05$). Although descriptive statistics showed slightly higher mean values in the experienced group, the effect sizes were relatively small. Possible explanations include sample imbalance, differences in practicum quality, and the limited ability of cross-sectional perception-sensing data to capture delayed learning effects. These findings suggest that practical experience may primarily enhance classroom teaching execution rather than front-end instructional-design decision-making processes. Fourth, latent profile analysis (LPA) identified three heterogeneous learner groups: “high-load, high-perception” (34.7%), “moderate-load, moderate-perception” (46.8%), and “low-load, low-perception” (18.4%). The high-load group demonstrated a “high investment–high self-assessment–high difficulty perception” pattern, whereas the moderate-load group represented typical effort-oriented learners. In contrast, the low-load group exhibited a “low investment–low self-assessment–low difficulty perception” pattern, which may reflect insufficient intrinsic learning motivation or learned helplessness. These findings further demonstrate the effectiveness of computational cognitive-state sensing approaches for identifying heterogeneous learner characteristics in instructional design learning environments.

From a sensing perspective, the innovation of this study lies in transforming conventional questionnaire responses into a structured cognitive-state sensing framework. The proposed framework can be regarded as a computational cognitive-state inference framework that analyzes learners’ internal cognitive responses using questionnaire-derived indicators rather than direct physiological sensor measurements. Specifically, CL, CEE, DCS, and CDP are treated as questionnaire-derived cognitive-state indicators for computational model validation. By integrating cognitive-state sensing with computational modeling, the framework enables the quantitative identification of latent cognitive mechanisms, mediation pathways, and learner heterogeneity. This computational approach extends educational analytics beyond traditional

outcome evaluation and provides a conceptual and analytical basis for future intelligent learner-state monitoring and adaptive educational support. From a computational perspective, the principal contribution of this study lies in establishing a structured cognitive-state inference model from questionnaire-derived indicators. The present framework should not be interpreted as a physical sensing system, because no physiological or behavioral sensor signals were collected. Instead, the validated relationships among CL, CEE, DCS, and CDP provide an analytical basis that may subsequently be integrated with physiological sensing systems. Therefore, the current findings support the feasibility of the computational inference stage, whereas real-time sensor-based cognitive-state estimation remains to be experimentally demonstrated.

From a theoretical perspective, we extend the application of CLT to preservice teacher education and support previous findings that cognitive-load-oriented instructional strategies can improve professional-skill development.⁽²⁴⁾ More importantly, we constructed and empirically validated a multiple mediation framework ($CL \rightarrow CEE \rightarrow DCS \rightarrow CDP$), revealing a multi-channel psychological transmission mechanism from cognitive challenge to difficulty perception. The significant serial mediation pathway further supports the applicability of the S-O-R paradigm in educational sensing contexts, suggesting that learners' difficulty judgments are gradually formed through the sequential process of "stimulus $\rightarrow$ emotion $\rightarrow$ cognition $\rightarrow$ response." In addition, the nonsignificant effect of practical experience challenges the assumption that practicum participation necessarily improves instructional-DCP, indicating that the effectiveness of practical experience depends heavily on its quality and the extent to which learners participate in higher-order instructional decision-making processes. From a computational perspective, the proposed framework demonstrates that questionnaire-derived cognitive-state indicators can be systematically analyzed to characterize relationships among latent learner states. The results suggest that cognitive-state sensing can serve as a practical sensing paradigm for intelligent educational analytics and learner-state monitoring.

4.2 Practical implications

First, instructional strategies should shift from simple "content input" toward "cognitive support" and cognitive-state sensing assistance. Learners' primary difficulty lies not in lacking knowledge but in being unable to effectively organize and apply knowledge under limited cognitive resources. Therefore, structured instructional-design templates, the understanding by design (UbD) framework, and step-by-step guidance tools should be incorporated to reduce unnecessary organizational CL. Second, educational interventions should emphasize the mediating role of emotional-perception states. Since CEE functions as a key mediating variable between CL and DCS, helping learners manage mental confusion and emotional distress through peer discussion, collaborative learning, and instructor feedback may more effectively enhance design confidence than simply reducing task complexity. Third, differentiated instructional and intelligent educational sensing strategies should be implemented for the three learner groups identified by LPA. For the "high-load, high-perception" group, interventions should emphasize cognitive-load reduction and emotional regulation through structured templates, sequential

guidance, and collaborative support. For the “moderate-load, moderate-perception” group, optimized cognitive-support tools, case analyses, and UbD-based frameworks should be provided. For the “low-load, low-perception” group, instructional strategies should focus on enhancing intrinsic motivation, rebuilding self-efficacy, and providing personalized feedback and positive reinforcement.

Fourth, the significant serial mediation effect suggests that instructional interventions should not focus solely on a single component, such as reducing CL or improving emotional experience. Instead, interventions should be systematically designed along the complete chain of “CL → CEE → DCS → CDP.” For example, while structured templates are used to reduce CL, instructors should simultaneously provide emotional support and opportunities for successful instructional-design practice to strengthen learners’ self-assessed competence. Finally, the design of practical experience should be reconsidered. The educational value of practicum lies not merely in participation itself but in whether learners are allowed to engage in higher-order instructional decision-making processes. Therefore, practicum supervision should focus more on instructional-design reasoning and decision processes rather than on classroom teaching performance. Opportunities should also be created for learners to participate in curriculum planning, objective setting, and assessment design activities.

The present findings also provide practical implications for the design of physical sensor-assisted educational systems. In a future multimodal implementation, physiological sensors do not need to reproduce all four constructs directly. Instead, continuously measurable physiological variables can be used primarily to estimate rapidly changing states such as CL and CEE, whereas DCS and CDP can function as higher-level cognitive variables inferred through the computational model. The sensing contribution of the present study should therefore be interpreted at the computational inference level rather than at the sensor-hardware level. Physiological sensing devices can provide high-temporal-resolution observations of neural, autonomic, cardiovascular, and visual responses, but these measurements do not directly yield educationally interpretable constructs such as perceived competence and overall learning difficulty. The proposed CL–CEE–DCS–CDP model provides a structured inference mechanism for connecting sensor-observable cognitive and emotional changes with these higher-level learner states. Accordingly, the present questionnaire-based analysis serves as an initial validation of this inference structure, while physiological sensing represents the next stage required for real-time implementation and experimental validation.

For example, increases in the number of EEG- or pupil-derived workload indicators accompanied by increased EDA arousal or altered heart-rate variability can be interpreted as possible increases in CL and CEE. According to the significant pathways identified in this study, these changes can then be propagated through the computational model to estimate their potential influence on perceived competence and learning difficulty. The three learner profiles identified by LPA can further provide individualized baseline states or decision thresholds for sensor-assisted monitoring. This application scheme highlights the sensor-related value of the proposed framework: physical sensors provide objective and continuous physiological observations, whereas the computational model provides an interpretable mechanism for translating these measurements into educationally meaningful cognitive-state information. Such

integration may enable a closed-loop sensing architecture in which physiological signals are acquired in real time, cognitive states are estimated computationally, learner profiles are updated, and appropriate instructional interventions are selected dynamically.

Although the proposed three-layer architecture provides a structured pathway from physical sensing to computational inference and educational decision-making, the complete closed-loop system has not yet been implemented or evaluated in a real-world intelligent learning environment. In particular, we do not experimentally demonstrate whether inferred cognitive states can be used to trigger effective real-time interventions, such as adjusting task complexity, providing additional guidance, and modifying learning content. Therefore, the architecture should currently be regarded as an implementation framework rather than a validated adaptive learning system. Future studies should integrate real-time physiological and behavioral sensing with the computational inference model and experimentally evaluate whether state-triggered adaptive interventions improve learning performance, reduce excessive CL, or enhance learning experience compared with nonadaptive instruction.

Nevertheless, because physiological sensor data were not collected, the correspondence between specific sensor features and the four latent constructs remains to be experimentally validated. An important limitation of this study concerns the homogeneity of the participant sample. Although the relatively large sample ($N = 630$) was drawn from multiple universities, all participants were elementary education majors in Guangdong Province. Therefore, the identified relationships among CL, CEE, DCS, and CDP, as well as the three latent learner profiles, should not be assumed to generalize directly to students in other academic disciplines, cultural contexts, or professional learning environments. Future studies should replicate the proposed cognitive-state framework using more diverse populations from different disciplines, geographic regions, educational systems, and professional settings. Cross-cultural and cross-disciplinary validation will further determine the robustness and generalizability of the proposed computational cognitive-state inference model.

A further limitation is the cross-sectional nature of the present study. CL, CEE, DCS, and CDP were assessed at a single stage, and the current results therefore represent relationships among cognitive-state indicators rather than their temporal evolution during instructional design tasks. CL and emotional experience may fluctuate as learner's progress through task analysis, objective setting, content organization, activity design, and assessment design. Future studies should employ repeated-measures or time-series designs to collect cognitive-state indicators at multiple task stages. Such longitudinal observations will enable the proposed computational model to examine within-learner changes and temporal relationships among CL, CEE, DCS, and CDP. Future work should therefore combine synchronized EEG, EDA/GSR, PPG/ECG, or eye-tracking measurements with the present framework to evaluate multimodal fusion accuracy, temporal sensitivity, and real-time adaptive-learning performance.

5. Conclusions

In this study, we developed a sensor-assisted computational learning analytics framework based on CLT and cognitive-state sensing concepts to investigate the relationships among CL,

CEE, DCS, and CDP in instructional design learning. The results demonstrated that the proposed framework successfully identified stable cognitive-state structures and significant mediation pathways among the four core variables. In particular, the serial mediation pathway of “CL → CEE → DCS → CDP” confirmed the applicability of the S-O-R paradigm in educational sensing research and highlighted the importance of emotional-perception states in learners’ difficulty judgment processes. The findings further revealed that instructional design learning is characterized by significant learner heterogeneity, with three latent learner profiles identified through LPA. These results suggest that intelligent educational sensing and computational modeling approaches can effectively support the identification of learners’ cognitive-state characteristics and provide a foundation for personalized instructional interventions. Moreover, the nonsignificant effect of practical experience indicates that the quality and depth of participation in instructional decision-making may be more important than practicum participation alone. Note that we do not treat questionnaire responses as physical sensor measurements. Instead, the questionnaire-derived indicators were used to establish and validate the computational relationships among CL, CEE, DCS, and CDP. From the perspective of sensor applications, the principal contribution of the present study is the validation of a computational cognitive-state inference structure that may subsequently be integrated with physiological and behavioral sensing systems. In such an implementation, EEG, EDA/GSR, PPG/ECG, and eye-tracking sensors can provide objective and continuous measurements associated with cognitive workload, emotional arousal, cardiovascular response, attention, and visual behavior, while the computational framework can transform these sensor-derived features into interpretable cognitive-state information for learner assessment. The significant mediation pathways and three learner profiles identified provide an analytical basis for developing such sensor-assisted learner-state monitoring systems. Nevertheless, because physical physiological signals were not collected in the present experiment, direct mapping between sensor-derived features and the proposed cognitive-state constructs remains to be experimentally established. Future work will therefore integrate synchronized EEG, EDA/GSR, PPG/ECG, and eye-tracking measurements with the present computational framework to experimentally establish sensor-to-construct mappings and evaluate real-time cognitive-state estimation, multimodal fusion accuracy, and closed-loop adaptive-learning performance.

Acknowledgments

This work was supported by the 2024 Guangdong Province Undergraduate Teaching Quality and Teaching Reform Engineering Construction Project, Dongguan City College - Dongguan Nanshe Ancient Village College Student Social Practice Teaching Base, Project Number: 177. This work was also supported by Summit-Tech Resource Corp. and by projects under Nos. NSTC 113-2221-E-390-011 and NSTC 114-2622-E-390-001.

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Supplemental Information

A multi-stage data-cleaning procedure was implemented to improve the reliability of the questionnaire-derived data and analytical accuracy. Questionnaires with a standard deviation of zero (identical responses across all items), near-regular response patterns (standard deviation < 0.2), or extremely short response times (<30 s) were excluded. After the cleaning process, 176 invalid questionnaires were removed, resulting in 630 valid samples and an effective response rate of 78.2%. The demographic characteristics of the participants are summarized in Table 1. Exploratory factor analysis (EFA) was conducted on the 14 core items (Q4–Q17) using sample A. Principal component analysis was employed for factor extraction, and Kaiser-normalized varimax rotation was applied.^(S1) The factor-retention criteria included the following: (1) eigenvalue > 1.0, (2) factor loading ≥ 0.5, (3) no significant cross-loadings (loading difference > 0.2), and (4) consistency with the theoretical cognitive-state constructs. The results demonstrated a Kaiser-Meyer-Olkin (KMO) value of 0.907 and a significant Bartlett's test of sphericity ($\chi^2 = 1988.957$, $df = 91$, $p < 0.001$), indicating that the questionnaire-derived data were highly suitable for factor analysis.

Table S1 is used to determine the appropriate number of latent factors underlying the questionnaire items. Four components had eigenvalues greater than 1 and jointly explained 74.23% of the total variance, supporting the retention of a four-factor structure for subsequent analysis. Table S2 shows how the 14 questionnaire items were grouped into the four latent constructs after factor rotation. The strong factor loadings and the absence of substantial cross-loadings indicate that the items were clearly associated with their intended dimensions,

Table S1
Total variance explained (sample A, $n = 250$).

Component	Initial eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total %			Total %			Total %		
	of variance	cumulative %		of variance	cumulative %		of variance	cumulative %	
1	6.592	47.084	47.084	6.592	47.084	47.084	5.207	37.190	37.190
2	1.769	12.637	59.721	1.769	12.637	59.721	2.334	16.675	53.865
3	1.215	8.677	68.398	1.215	8.677	68.398	1.810	12.927	66.792
4	1.016	5.830	74.228	1.016	5.830	74.228	1.041	7.435	74.228
5	.542	3.871	78.099						
6	.475	3.390	81.489						
7	.454	3.244	84.733						
8	.397	2.836	87.569						
9	.380	2.714	90.283						
10	.321	2.296	92.579						
11	.308	2.201	94.779						
12	.284	2.027	96.806						
13	.245	1.751	98.557						
14	.202	1.443	100.000						

Table S2
Rotated component matrix (sample A, $n = 250$).

Item	Component			
	1	2	3	4
Q4. Mental effort		.826		
Q5. Time pressure		.821		
Q6. Degree of effort		.833		
Q7. Clarity of thinking			.887	
Q8. Emotional experience			.867	
Q9. Overall difficulty				.932
Q10. Student analysis	.778			
Q11. Objective setting	.777			
Q12. Content organization	.791			
Q13. Activity design	.778			
Q14. Question design	.803			
Q15. Technology integration	.793			
Q16. Assessment design	.836			
Q17. Lesson plan integration	.734			

providing support for the construct structure used in the subsequent CFA and SEM analyses. Table S3 is shown to evaluate whether the four-factor measurement model adequately represents the observed data. All major goodness-of-fit indices satisfied the recommended criteria, indicating that the proposed measurement structure was acceptable for further structural analysis. Table S4 shows the results of evaluating the reliability and convergent validity of the latent constructs. The reported factor loadings, *AVE*, and *CR* values indicate that the indicators provide an acceptable representation of their corresponding constructs, supporting the use of CL, CEE, and DCS in the subsequent structural model.

Table S3
CFA model fit indices (sample B, $n = 380$).

<i>CMIN</i>	<i>df</i>	<i>CMIN/df</i>	<i>NFI</i>	<i>IFI</i>	<i>TLI</i>	<i>CFI</i>	<i>GFI</i>	<i>RMSEA</i>
148.301	62	2.392	0.945	0.968	0.959	0.967	0.943	0.061
standard		<3	>0.8	>0.9	>0.9	>0.9	>0.8	<0.1

Note: *CMIN* = chi-square minimum; *df* = degrees of freedom; *NFI* = normed fit index; *IFI* = incremental fit index; *TLI* = Tucker–Lewis index; *CFI* = comparative fit index; *GFI* = goodness-of-fit index; *RMSEA* = root mean square error of approximation.

Table S4
Reliability and convergent validity (sample B, $n = 380$).

Latent Variable	Indicator std.	Factor loading	<i>SE</i>	<i>z</i>	<i>AVE</i>	<i>CR</i>
CL	Mental effort	0.788	—	—	0.558	0.791
	Time pressure	0.746	0.073	14.189		
	Degree of effort	0.704	0.072	13.373		
CEE	Clarity of thinking	0.808	—	—	0.524	0.684
	Emotional experience	0.628	0.067	11.510		
DCS	Student analysis	0.668	—	—	0.569	0.913
	Objective setting	0.706	0.084	12.430		
	Content organization	0.770	0.085	13.397		
	Activity design	0.767	0.091	13.361		
	Question design	0.794	0.085	13.755		
	Technology integration	0.722	0.089	12.676		
	Assessment design	0.750	0.088	13.101		
	Lesson plan integration	0.842	0.088	14.436		

On the basis of the eigenvalue-greater-than-one criterion, four factors were extracted, accounting for 74.23% of the total variance (Table S1). After rotation, all factor loadings exceeded 0.7 without significant cross-loadings (Table S2). The extracted factors were identified as follows: Factor 1, DCS, containing eight items; Factor 2, CL, containing three items; Factor 3, CEE, containing two items; and Factor 4, CDP, containing one item. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were subsequently performed using sample B ($n = 380$). The measurement model demonstrated satisfactory goodness-of-fit indices (Table S3), including $\chi^2/df = 2.392$, comparative fit index (*CFI*) = 0.967, Tucker–Lewis index (*TLI*) = 0.959, and root mean square error of approximation (*RMSEA*) = 0.061.^(S2) The reliability and convergent validity results are summarized in Table S4. All average variance extracted (*AVE*) values exceeded 0.5, and all composite reliability (*CR*) values exceeded 0.68, indicating acceptable measurement reliability and validity for cognitive-state analysis. Statistical analyses were performed using SPSS 26.0 and Mplus 8.0. SEM was conducted using Mplus 8.0 to evaluate the hypothesized relationships (H1–H3). Mplus is widely used for computational modeling and structural analysis involving continuous and categorical variables.^(S3) Model fit was evaluated using χ^2/df , *CFI*, *TLI*, *RMSEA*, and the standardized root mean square residual (*SRMR*).

The bias-corrected percentile bootstrap method with 5,000 resamples was applied to examine serial mediation effects.^(S4) Mediation effects were considered statistically significant when the 95% confidence interval did not include zero. The purpose of the mediation analysis was to determine whether the influence of CL on CDP occurred only through a direct relationship or was transmitted indirectly through intermediate cognitive-state variables. Specifically, the analysis examined two parallel indirect pathways, $CL \rightarrow CEE \rightarrow CDP$ and $CL \rightarrow DCS \rightarrow CDP$, as well as the serial pathway $CL \rightarrow CEE \rightarrow DCS \rightarrow CDP$. The serial mediation test therefore evaluates whether increased CL is associated first with changes in CEE, which are subsequently related to perceived design competence and, finally, overall learning difficulty. The bootstrap procedure was used to estimate the uncertainty of these indirect effects without relying on a normal-distribution assumption; an indirect pathway was considered statistically supported when its 95% bootstrap confidence interval excluded zero. Independent-samples t-tests were conducted to compare learners with practical experience ($n = 556$) and those without practical experience ($n = 74$) across the four cognitive-state dimensions as an exploratory analysis. LPA was conducted using the standardized scores of the four core cognitive-state dimensions as observed variables for the full sample ($N = 630$). The optimal number of latent classes was determined using the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size-adjusted BIC (aBIC), entropy, Lo-Mendell-Rubin (LMR) test, and bootstrap likelihood ratio test (BLRT).^(S5) Entropy values greater than 0.8 indicated high classification accuracy, while significant p-values for the LMR and BLRT tests indicated that the k-class model demonstrated higher fitting performance than the ($k-1$)-class model.^(S6)

Table S5 provides two forms of preliminary information: the central tendency and dispersion of the four cognitive-state variables, and the pairwise relationships among them. The significant positive correlations among CL, CEE, DCS, and CDP provide initial empirical support for examining their direct and mediated relationships in the structural model. Unlike Table S3, which shows the results of evaluation using the measurement model, Table S6 shows the overall fit of the hypothesized structural model after the directional relationships among CL, CEE, DCS, and CDP are introduced. The satisfactory fit indices indicate that the proposed structural

Table S5
Descriptive statistics and correlation matrix for all variables ($N = 630$).

Variable	<i>M</i>	<i>SD</i>	CDP	CEE	DCS	CL
1. CDP	3.482	0.934	1			
2. CEE	3.071	0.848	0.599**	1		
3. DCS	3.240	0.742	0.627**	0.600**	1	
4. CL	3.389	0.753	0.669**	0.657**	0.614**	1

Note: *M* = mean; *SD* = standard deviation. ** $p < .01$.

Table S6
Fit indices of the structural model (sample B, $n = 380$).

<i>CMIN</i>	<i>df</i>	<i>CMIN/df</i>	<i>NFI</i>	<i>IFI</i>	<i>TLI</i>	<i>CFI</i>	<i>GFI</i>	<i>RMSEA</i>
174.133	72	2.419	0.943	0.966	0.956	0.965	0.939	0.061
Criteria		< 3	> 0.8	> 0.9	> 0.9	> 0.9	> 0.8	< 0.1

Note: All fit indices met the recommended criteria, indicating that the model exhibited a good fit to the data.

relationships provide an acceptable representation of the observed data. Prior to conducting SEM, descriptive statistics and Pearson product-moment correlation analyses were performed on the core cognitive-state variables using the full sample ($N = 630$). Descriptive statistics indicated that the variable means ranged from 3.10 to 3.52, while standard deviations ranged from 0.72 to 0.91. The questionnaire-derived cognitive-state data exhibited normal distributions without significant skewness or kurtosis, indicating acceptable suitability for subsequent computational analysis. The correlation analysis results are presented in Table S5. CL was significantly positively correlated with CEE ($r = 0.657$, $p < 0.001$), DCS ($r = 0.614$, $p < 0.001$), and CDP ($r = 0.669$, $p < 0.001$). All correlations among the cognitive-state variables were statistically significant, providing preliminary support for the subsequent mediation and cognitive-state sensing analyses. SEM was conducted on the conceptual framework using sample B ($n = 380$).

As summarized in Table S7, the total effect was 0.830, whereas the direct effect was 0.462. The overall mediation effect accounted for 44.3% of the total effect (indirect effect = 0.368/total effect = 0.830). The effect sizes of the three mediation pathways were as follows: CEE parallel mediation, 0.147 (17.7%); DCS parallel mediation, 0.139 (16.7%); and serial mediation, 0.082 (9.9%). In addition, the regression analysis results from the mediation model test (Table S8) further supported the above conclusions. Table S7 shows the decomposition of the indirect effect of CL on CDP into the two parallel mediation pathways and the serial mediation pathway. The bootstrap confidence intervals for all three indirect effects exclude zero, demonstrating that CEE and DCS contribute both independently and sequentially to the relationship between CL and CDP. Table S8 provides complementary regression evidence for the mediation model by showing how explanatory power changes as additional mediating variables are introduced. The model including CL, CEE, and DCS showed the highest explanatory power for CDP

Table S7
Decomposition of mediation effects and bootstrap test (sample B, $n = 380$).

Path	Effect	Boot <i>SE</i>	BootLLCI	BootULCI	<i>z</i>	<i>p</i>
CL→CEE→CDP	0.147	0.049	0.048	0.239	2.996	0.003
CL→DCS→CDP	0.139	0.036	0.079	0.216	3.850	0.000
CL→CEE→DCS→CDP	0.082	0.020	0.046	0.126	4.019	0.000

Note: Boot *SE* = bootstrap standard error; BootLLCI = bootstrap lower-limit confidence interval; BootULCI = bootstrap upper-limit confidence interval.

Table S8
Regression analysis for the mediation model.

Dependent Variable	Predictor(s)	<i>F</i>	R^2	Adjusted R^2	Significance
CEE	CL	F(1,378)=287.668	0.432	0.431	$p = 0.000$
DCS	CL, CEE	F(2,377)=151.124	0.445	0.442	$p = 0.000$
CDP	CL	F(1,378)=305.928	0.447	0.446	$p = 0.000$
CDP	CL, CEE, DCS	F(3,376)=146.417	0.539	0.535	$p = 0.000$

Note: All regression equations were statistically significant ($p < .001$). The final model, which included all variables, had the strongest explanatory power (adjusted $R^2 = 0.535$).

(adjusted $R^2 = 0.535$), indicating that the combined model accounted for a substantial proportion of the observed variation in CDP and therefore had practical explanatory relevance beyond the statistical significance of individual paths.

To further explore the influence of practical experience on instructional design learning and cognitive-state patterns, independent-samples t-tests were conducted to compare learners with practical experience ($n = 556$) and those without practical experience ($n = 74$) across the four core cognitive-state variables. As shown in Table S9, descriptive statistics indicated that the mean values of all variables were slightly higher in the group with practical experience than in the group without practical experience, including CEE (3.1016 vs 2.9932), DCS (3.2639 vs 3.1250), CDP (3.5198 vs 3.3378), and CL (3.4203 vs 3.3559). These results suggested that learners with practical experience tended to exhibit relatively stronger cognitive-state perception responses during instructional design tasks. The independent-samples t-test results demonstrated that the differences between the two groups were not statistically significant for CEE ($t = 1.034$, $p = 0.301$), DCS ($t = 1.555$, $p = 0.120$), CDP ($t = 1.614$, $p = 0.107$), or CL ($t = 0.719$, $p = 0.473$), with all p -values exceeding 0.05, and the results are shown in Table S10. Table S9 provides the descriptive basis for comparing students with and without prior practical experience. Although the experienced group showed slightly higher mean scores for all four cognitive-state variables, these descriptive differences alone do not establish statistical significance and were therefore further examined using independent-samples t-tests. Table S10 shows the results of testing whether the descriptive differences shown in Table S9 are statistically significant. None of the four cognitive-state variables showed a significant between-group difference (all $p > 0.05$), indicating that prior practical experience alone was not associated with a statistically detectable difference in CL, CEE, DCS, or CDP in the present sample.

Table S11 shows the results of comparing alternative two-, three-, and four-class LPA solutions to determine the most appropriate representation of learner heterogeneity. Considering classification accuracy, likelihood-ratio tests, class size, and theoretical interpretability together, the three-class solution provided the most balanced and interpretable model. To identify heterogeneous learner characteristics during instructional design learning, latent profile analysis (LPA) was conducted on the full sample ($N = 630$) using the standardized scores of the four core cognitive-state dimensions as observed indicators. The fitting indices of the two-class to four-class models were compared, and the results are summarized in Table S11. Considering both statistical performance and theoretical interpretability, the three-class model was selected as the optimal classification solution. First, the three-class model achieved an entropy value of 0.84, which was higher than those of the two-class (0.78) and four-class (0.79) models, indicating superior classification accuracy for cognitive-state analysis. Second, both the Lo-Mendell-Rubin (LMR) test ($p < 0.001$) and bootstrap likelihood ratio test (BLRT) ($p < 0.001$) were significant, demonstrating that the three-class model provided significantly higher fitting performance than the two-class model. Third, the four-class model contained a minimum class proportion of only 9.2%, whereas the LMR test became nonsignificant ($p = 0.073$), indicating that adding an additional latent class did not substantially improve classification performance.

Table S9
Descriptive statistics by group.

Variable	Practical Experience	<i>n</i>	<i>Mean</i>	<i>SD</i>	<i>SE</i>
CEE	Yes	556	3.1016	.84737	.03594
	No	74	2.9932	.84194	.09787
DCS	Yes	556	3.2639	.71831	.03046
	No	74	3.1250	.74971	.08715
CDP	Yes	556	3.5198	.90721	.03847
	No	74	3.3378	.94037	.10932
CL	Yes	556	3.4203	.72440	.03072
	No	74	3.3559	.72219	.08395

Note: *SD* = standard deviation; *SE* = standard error.

Table S10
Independent samples *t*-test results.

Variable		Levene's test for equality of variances		<i>t</i> -test for equality of means						
		<i>F</i>	<i>Sig.</i>	<i>t</i>	<i>df</i>	<i>Sig.</i> (2-tailed)	<i>Mean</i> difference	<i>SE</i> difference	95% <i>CI</i> (lower)	95% <i>CI</i> (upper)
CEE	Equal variances assumed	.877	.350	1.034	628	.301	.10838	.10478	−.09738	.31413
	Equal variances not assumed			1.039	93.786	.301	.10838	.10426	−.09865	.31540
DCS	Equal variances assumed	.005	.944	1.555	628	.120	.13894	.08935	−.03651	.31439
	Equal variances not assumed			1.505	91.747	.136	.13894	.09232	−.04443	.32231
CDP	Equal variances assumed	.008	.929	1.614	628	.107	.18195	.11274	−.03946	.40335
	Equal variances not assumed			1.570	92.020	.120	.18195	.11589	−.04822	.41211
CL	Equal variances assumed	.321	.571	.719	628	.473	.06441	.08961	−.11156	.24037
	Equal variances not assumed			.720	93.639	.473	.06441	.08940	−.11310	.24192

Note: CEE = cognitive-emotional experience; DCS = self-assessed design competence; CDP = perceived overall difficulty; CL = cognitive load; *CI* = confidence interval.

Table S11
Model fit comparison results for latent profile analysis (*N* = 630).

Model	AIC	BIC	aBIC	Entropy	LMR <i>p</i>	BLRT <i>p</i>	Minimum class proportion
2-class	2845.32	2890.11	2853.09	0.78	<0.001	<0.001	32.6%
3-class	2712.05	2774.43	2725.17	0.84	<0.001	<0.001	18.4%
4-class	2689.71	2769.68	2708.18	0.79	0.073	<0.001	9.2%

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