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Capturing students' cognitive engagement using the ICAP framework: A scoping review

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Student cognitive engagement (CE) is crucial as it reflects students' investment in academic achievement. To conceptualise different dimensions of CE, the Interactive, Constructive, Active, and Passive (ICAP) framework is widely adopted. While ICAP has been applied in higher education (HE), existing studies are often fragmented, context-specific, or limited to a specific learning environment. Although broader CE strategies have been reviewed, a comprehensive review of practices and methodologies used to capture CE through ICAP across diverse settings is lacking. Therefore, this study reviews 42 peer-reviewed articles using PRISMA methodology to explore current practices in capturing student CE via ICAP in HE. It highlights ICAP applications in face-to-face (36%), online (52%), and hybrid (12%) learning environments, and captures CE mainly across physical learning materials (29%), and online discussion forums (29%). Some studies employed interviews and questionnaire surveys to collect data, while others extracted data from learning management systems. Most studies manually mapped CE to ICAP (57%), which limits their scalability and generalisation. Therefore, there is a compelling need for automated approaches, such as the integration of machine learning models. This study offers valuable insights for educators and researchers on the relevance and versatility of ICAP in capturing CE across varied learning environments and contexts.

Keywords: cognitive engagement, higher education, ICAP, learning environments

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Introduction

Cognitive engagement (CE) is defined as "the integration and utilisation of students' motivations and strategies in the course of their learning" (Richardson & Newby, 2006, p. 25). It reflects students' investment in learning and is essential for academic success, emphasising the effort, strategies, and focus they apply (Wiggins et al., 2017). Higher education (HE), with its emphasis on independent and complex learning, highlights the importance of CE (Heikkilä & Lonka, 2006). However, capturing and assessing CE remains challenging due to its complex and often intangible nature (Gorgun et al., 2022). To navigate this complexity, Chi and Wylie (2014) developed the Interactive, Constructive, Active, and Passive (ICAP) framework, which categorises CE based on observable behaviours. The ICAP hypothesis suggests that CE increases when student engagement transitions from passive to interactive (Chi, 2009).

Although ICAP has gained recognition across educational contexts (Ahmad et al., 2022), its applications in HE research remain fragmented. Many studies have focused on specific disciplines, environments or cohorts, creating a scattered understanding of CE using ICAP (Prince et al., 2020). Recent reviews generalise CE without addressing whether ICAP applications are methodologically sound, contextually appropriate, or pedagogically meaningful (Sakeef et al., 2025). This fragmentation impedes practical implementation and systematic advancement of research, preventing standardised, evidence-based approaches to capture CE in HE. To address this gap, this paper reviews 42 peer-reviewed articles to explore current practices and methodologies for capturing student CE using the ICAP framework and summarises the characteristics of its applications in various HE contexts. The research question *How is the ICAP framework adopted and applied to capture student CE in HE?* includes three objectives:

1. To investigate how ICAP is used with other theories to capture CE;
2. To explore current practices and methodologies for capturing student CE using the ICAP framework;
3. To summarise the characteristics of the ICAP framework and its applications in various HE contexts.

HE contexts encompass online, face-to-face and hybrid learning environments in STEM (Science, Technology, Engineering. Mathematics) and non-STEM disciplinary domains in tertiary education.

Research methodology

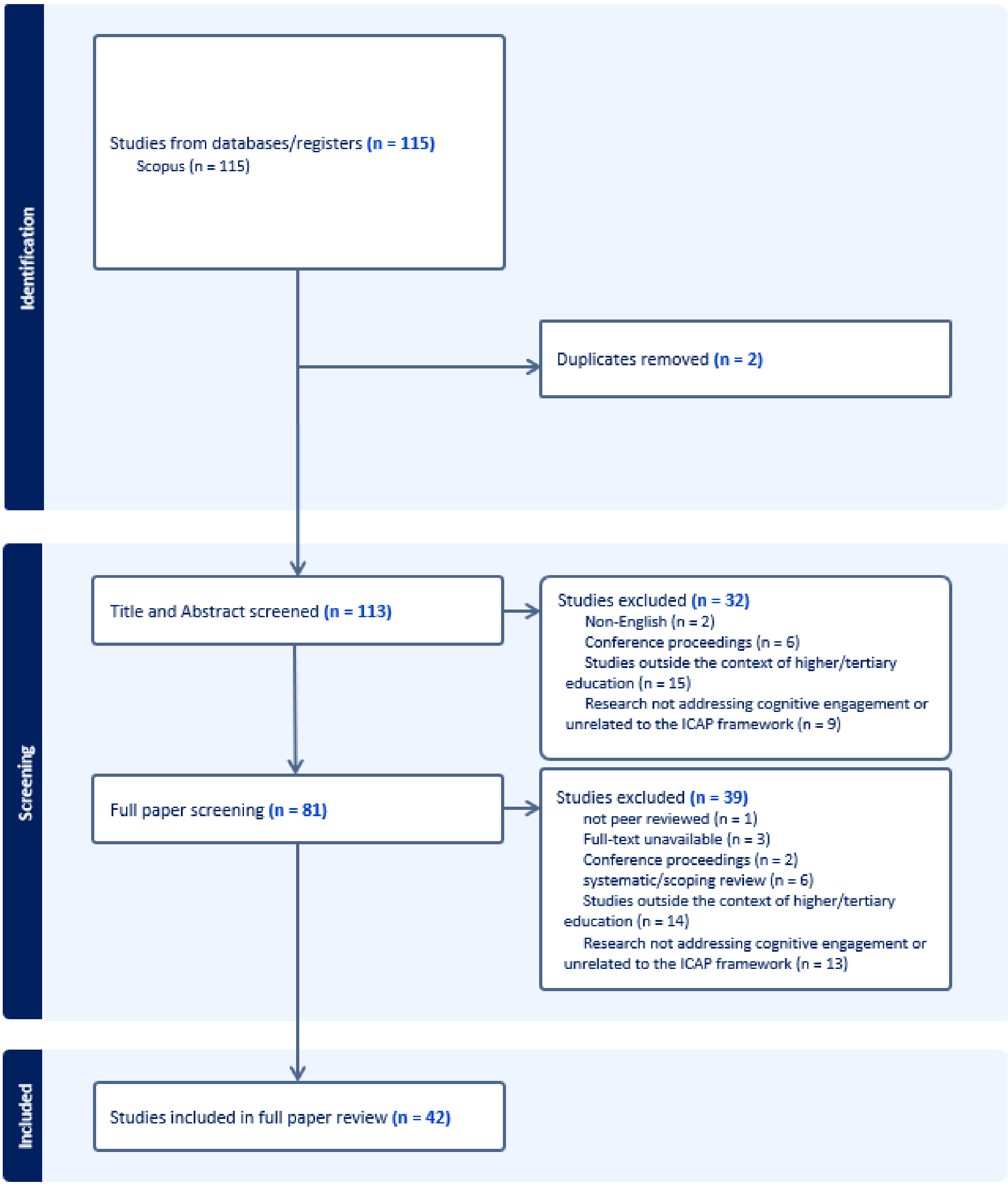
This scoping review was conducted using the PRISMA tool (Veroniki et al., 2025) to map literature on capturing student CE using ICAP framework in HE. A comprehensive keyword search was conducted in Scopus and Web of Science to obtain articles published from 2016 to 2025 using the following query:

> *TITLE-ABS-KEY ("ICAP" OR "Interactive, Constructive, Active, Passive") AND TITLE-ABS-KEY ("Cognitive") AND TITLE-ABS-KEY ("Engag*" OR "learn*" OR "presen*") AND TITLE-ABS-KEY ("theor*" OR "framework*" OR "tool*" OR "model*" OR "Instrumen*" OR "concept*" OR "method*" OR "technique*")*

The keywords *student* and *higher education* were deliberately excluded as they are implicit in the ICAP framework research (Chi & Wylie, 2014). Including them would unnecessarily narrow the scope and risk omitting relevant studies. Terms like *practices* and *methodologies* were not included as they are embedded within broader the methodological terms used. *Cognitive engagement* was addressed by combining *cognitive* (mandatory) with *engag**, *learn**, or *presen** to capture related constructs like *cognitive learning* and *cognitive presence* that are used interchangeably in literature.

Figure 1 illustrates the PRISMA steps. Initial search results were imported into Covidence software, and duplicates removed. Then title, keywords, abstract and full-paper screenings were conducted. Exclusion criteria included: non-peer-reviewed, non-English, literature reviews, lack of ICAP use for CE, unavailable texts, and non-HE contexts. Selected articles underwent data extraction for descriptive and thematic analysis. Descriptive analysis retrieved bibliographic information including source, publication year, location, and research methods. Thematic analysis examined article content, identifying themes related to the research question, aim and objectives.

Figure 1: PRISMA search process



Results and findings

Descriptive analysis

Of the 115 articles initially identified, 42 were included (Figure 1). As indicated in Table 1, 55% were journal articles and 45% were conference articles. Interest in ICAP has grown since 2019, with a notable rise in 2024 (24%). Most research was conducted in the United States of America (USA) (49%), followed by China (12%) and Canada (9%). Among the studies, the common method, study context, learning mode and tool were quantitative methods (55%), STEM (64%), online (52%) and online discussion forums (29%), respectively. Only 21% relied solely on ICAP, indicating a shift toward integrating multiple frameworks. See the Appendix for further details.

Table 1: Characteristics of articles

	Count	%
Publication type		
Journal articles	23	55
Conference articles	19	45
Publication year		
2016	2	5
2018	1	2
2019	5	12
2020	2	5
2021	5	12
2022	8	19
2023	5	12
2024	10	24
2025	4	10
Country of origin		
Canada	4	9
China	5	12
Germany	3	7
India	3	7
Japan	1	2
Singapore	1	2
South Korea	1	2
United Kingdom	4	9
USA	21	49
Methodology		
Quantitative	23	55
Qualitative	6	14
Mixed-method	13	31
Study context		
STEM	33	79
Non-STEM	9	21
Leaning environment		
Online	22	52
Face-to-face	15	36
Hybrid	5	12
Learning tool		
Online discussion platforms	12	29
Physical learning materials or activities	12	29
Learning platform or environment	6	14
Digital learning tools or software	6	14
Instructional videos or modules	6	14
Theoretical framework		
ICAP only	9	21
ICAP and other(s)	33	79

Thematic analysis

Adoption and interpretation of ICAP dimensions

The adoption of ICAP dimensions is shaped by methodological and contextual constraints. In online education, passive engagement is often excluded, as platforms cannot reliably track whether students read the content (Parmar et al., 2024; Farrow et al., 2020, 2021a, b, 2022; Sharma & Li, 2022; Sharma et al., 2024). Consequently, minimal responses are classified as active (Burke et al., 2024; Lee et al., 2019). Similarly, interactive engagement is sometimes omitted when learning tools do not support peer exchange, as seen in adaptive or video-based learning designs (Bai et al., 2022; Fahid et al., 2021; Wang et al., 2023). These exclusions illustrate the limitations of online environments for the full application of ICAP.

Interpretation of ICAP dimensions is linked to learning activities. In concept mapping and group quizzes, passive engagement aligns with lecturer-centred approaches (such as group quizzes and concept mapping), while active and constructive engagement reflect student-centred approaches (Li et al., 2024; Lim et al., 2019). In online discussions, only responses with reasoning and continuity are considered, though many posts are superficial (Burke et al., 2024; Lee et al., 2019; Farrow et al., 2020-2022; Gorgun et al., 2022). Constructive engagement generated new insights, while active engagement remained surface-level (Roeben et al., 2025). Consequently, while ICAP provides a structured lens for analysing engagement, its application requires clearer operational definitions linking observable behaviours to cognitive depth (Wekerle et al., 2024).

Theoretical integration and extensions of ICAP

Conceptual flexibility of ICAP has led to several theoretical integrations and extensions, strengthening its explanatory nature. The addition of "social" and "behavioural" dimensions acknowledges that CE also involves interactional and tacit processes, particularly in virtual reality (VR) environments (Dunmoye et al., 2023, 2024; Gorgun et al., 2022). Dunmoye et al. (2024) showed a significant association between participants' interactions that enhance CE. Zhao et al. (2024) found that behavioural patterns supported interpreting CE through robot-supported collaborative learning.

ICAP is also frequently paired with cognitive load theory (CLT) to improve learning outcomes. Beege and Ploetzner (2024) highlighted the alignment of the two frameworks, noting that both promote effective learning through "germane processes" such as schema acquisition. Bai et al. (2022) applied ICAP as a foundation and CLT as a moderator, demonstrating that excessive cognitive load from self-explanation prompts hinders knowledge transfer. Similarly, Burgher et al. (2016) found interactive engagement effective for complex concepts, where collaborative tasks and physical models help manage cognitive load.

In addition, Bloom's Taxonomy is often combined with ICAP to guide instructional design based on cognitive complexity, with ICAP serving as the analytical model (Gorgun et al., 2022; Zhao et al., 2024). The Community of Inquiry (CoI) framework is another common pairing, used to analyse online discussions. Farrow et al. (2021a, b, 2022) noted that while CoI suits online contexts, ICAP offers broader insights, though combining both showed limited improvement in predictive performance.

ICAP conceptualisation in different learning environments and learning tools

Studies are grouped and compared across learning environments and tools. In online environments, discussion forums are often used for collecting engagement data. Many studies used built-in forums, others adopted external platforms such as Slack (Sharma et al., 2024), Yellowdig (Faulconer & Griffith, 2025) and Perusall (Lee et al., 2019) to enhance collaboration and peer interaction. Other tools, complemented by surveys to triangulate engagement evidence, include instructional videos and modules that fostered engagement through interactive instructions (Adesope et al., 2019; Beege & Ploetzner, 2024), assessments (Fahid et al., 2021) or explanation prompts (Bai et al. 2022). Simulation-based environments with extended ICAP such as VR for civil engineering (Dunmoye et al., 2023, 2024) and PyGuru for computer science (Singh & Rajendran, 2022, 2024), supported CE through immersive digital experiences.

In face-to-face or hybrid learning environments, physical materials like articles, worksheets, and quizzes supported CE through kinaesthetic experiences and are often paired with qualitative interviews/surveys like the Student Course Cognitive Engagement Instrument (Ajeigbe et al., 2024; Barlow et al., 2020; Barlow & Brown, 2019). Digital tools, including educational chatbots (Hobert et al., 2023), collaborative robotic systems (Zhao et al., 2024), and mind mapping software (Wekerle et al., 2024; Xanat et al., 2023), are integrated. Overall, ICAP conceptualisation varies across learning environments and tools in interpreting engagement.

Contextual factors influencing ICAP application in STEM and non-STEM environments

ICAP framework applications are varied between STEM and non-STEM disciplines due to differences in pedagogical focus and learning context. When applying ICAP to understand student CE, STEM often focuses more on how learning of technologies such as VR and visualisation tools (Dunmoye et al., 2024; Faulconer & Griffith, 2025) can be improved. In contrast, non-STEM studies prioritise enhancing online learning through discussions and evaluating the broader pedagogical relevance, such as chatbot-based learning (Hobert et al., 2023) and frameworks for classifying engagement in general online discussions (Parmar et al., 2024).

All ICAP dimensions are addressed across domains, though STEM studies placed greater emphasis on fostering active, constructive, and interactive engagement to enhance complex problem-solving and critical thinking (El-Mansy et al., 2021; Lim et al., 2019; Singh & Rajendran, 2024). Passive engagement has received less attention, typically serving as a contrast to higher engagement modes (Fahid et al., 2021) or in contexts like video lectures (Bai et al., 2022). Overall, findings of STEM research often agree with the ICAP hypothesis, proving that higher engagement modes in technology-enhanced activities lead to improved learning outcomes and deeper understanding (He et al., 2022; Singh & Rajendran, 2024). Non-STEM studies focus on enriching online discussions and digital resource usage (Techawitthayachinda & Iriya, 2025). These patterns show that contextual priorities shape the interpretation of ICAP and the pedagogical strategies used to foster engagement.

Methodologies for operationalising and measuring ICAP

Mapping data onto the ICAP dimensions involves manual, automated and hybrid approaches, each with distinct strengths and limitations. Automated and hybrid methods (combined manual and automated approaches) are predominant in large-scale online discussions due to scalability, while methodological choices depend on data type, analysis techniques, approaches and practical considerations (Farrow et al., 2022).

Manual mapping approaches, such as labelling learning artefacts like posts or transcripts using behavioural and linguistic indicators (Gorgun et al., 2022), remain the most common. These approaches, often supported by coding schemes and software like NVivo (Nelms & Segura-Totten, 2019), are appropriate for qualitative data but time-consuming, subjective, labour-intensive, and cannot be scaled to large datasets (Wekerle et al., 2024). Automated mapping approaches, such as natural language processing (Parmar et al., 2024), machine learning (Sharma et al., 2024) and large language models (Techawitthayachinda & Iriya, 2025), have increased adoption for large-scale textual data and have been observed with more efficiency. For instance, Sharma et al. (2024) classified over 4650 posts using automation within a fraction of the manual time. Automated video and log analyses further support CE with in-depth behavioural tracking (e.g., clicks, views) (Fahid et al., 2021). Conclusively, these methodological shifts reflect a broader move from manual to data-driven approaches, enhancing objectivity, scalability, and efficiency in measuring CE.

Discussion

This review demonstrates the conceptual and methodological flexibility of using ICAP to capture CE across diverse educational settings; however, this produces variation in interpretation and implementation of ICAP. The majority of the studies are conducted in the USA, indicating that research on ICAP remains geographically and culturally narrow. The recent rise of publications between 2022 and 2024 aligns with the post-pandemic shift towards online and hybrid learning. It reveals the growing role of digital tools in facilitating ICAP-based analyses of CE (Capone & Lepore, 2022).

Theoretical implications of ICAP applications show both reliance on Chi’s (2009) original ICAP framework and its integration with other frameworks. In online environments, distinguishing between general and meaningful engagement is challenging due to the absence of physical interaction and verbal communication, often leading to the exclusion of the passive and interactive engagement dimensions. These challenges highlight the context-sensitive nature of CE and the potential of artificial intelligence tools to broaden ICAP application (Zaim et al., 2025). Extending ICAP using social and behavioural dimensions offers a more comprehensive perspective, capturing relational and tacit aspects of CE (Dunmoye et al., 2024; Sakeef et al., 2025). The predominance of STEM studies reflects the emphasis on problem-solving and complex concept proficiency, where technology-rich environments such as VR facilitate higher-order engagement modes predicted by ICAP (Ahmad et al., 2022). This suggests that STEM disciplines leverage ICAP not only to measure CE but to design tasks that inherently promote constructive and interactive learning. Methodological choices shape how ICAP captures engagement. Manual coding provides rich qualitative insight but is limited in scale, while automated methods offer efficiency yet risk misrepresenting engagement across contexts or cultures (Ahmad et al., 2022). Hybrid approaches balance depth and scalability but add complexity. These findings indicate that the ICAP framework cannot be uniformly applied; its effective use depends on measurement approaches aligned with the learning environment and the nature of the data (Sakeef et al., 2025).

Implications for theory and practice

This review contributes to theory by highlighting how ICAP is reconceptualised beyond its original focus to holistically include social and contextual dimensions of engagement to support deep learning (Sakeef et al., 2025). It contributes theoretically by advancing ICAP’s applicability beyond behavioural analysis and addressing cultural and disciplinary diversity in CE research. Methodologically, it identifies hybrid analytic approaches that combine computational and qualitative techniques, enhancing scalability and contextual accuracy. Practically, the findings guide educators and institutions in designing data-informed, engagement-focused learning environments, positioning ICAP as a dynamic framework for assessing and optimising student engagement in HE.

Conclusions

This review analysed the adaptability of ICAP across HE contexts, particularly in online and hybrid environments. While many studies adhered to the original ICAP framework, others modified or integrated it with other frameworks to enhance interpretive depth. STEM disciplines favoured automated, quantitative tools, whereas non-STEM fields leaned on survey-based methods. These approaches must align with evolving educational needs.

Limitations

Although a broader search scope was applied to increase article volumes, studies of varying methodological quality were included without formal critical appraisal due to the nature of a scoping review. Moreover, given evolving educational technology and learning environments, the methodological gaps identified may no longer be valid.

Future directions

Future studies should prioritise scalable, culturally diverse, and hybrid analytic methods, exploring how emerging educational technologies more effectively operationalise and measure CE while supporting varying engagement levels.

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Disclosure of the use of AI-assisted technologies during writing

No AI-assisted technologies were used during the writing process.

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Appendix

Author(s) & Year	Title	Journal / conference	Country	Study Context	Learning Environment	Methodology	Theories used with ICAP	Learning tools used	Type of mapping	Output
Adesope et al. 2019	Work-in-progress: Fostering cognitive engagement with hands-on learning pedagogy	Conference	USA	STEM	Face-to-face	Quantitative	No	Instructional videos / recordings /modules	Manual	Insights into the effectiveness of low-cost desktop learning modules (LC-DLM) in fostering cognitive engagement in engineering education.
Ajeigbe et al. 2024	Work-in-progress: Enhancing engineering education: A comparative analysis of low-cost desktop learning module impact on student engagement and outcomes	Conference	USA	STEM	Face-to-face	Quantitative	No	Instructional videos / recordings / modules	Manual	Insights on the effectiveness of LC-DLMs and hands-on instructional methods in engineering education
Bai et al. 2022	Embedding self-explanation prompts to support learning via instructional video	Journal	China	STEM	Online	Quantitative	Cognitive load measured according to the framework of cognitive load theory	Instructional videos / recordings / modules	Manual	Learner-produced materials found that a majority of learners engaged in the constructive mode when focused self-explanation prompts were implemented. However, the scaffolded condition outperformed the focused condition on the retention test, while no significant differences were observed among the three conditions on the transfer test. Regression analyses suggested that the forms of prompts may interact with different sets of explanatory factors during learning.
Ballard et al. 2023	Cognitive discourse during a group quiz activity in a blended learning organic chemistry course	Journal	USA	STEM	Hybrid	Qualitative	Marzano's taxonomy	Physical materials or activities	Manual	Outcomes for research question 1:groups demonstrate varying degrees ofengagement – low, medium, and highly interactive dialogue. When comparing groups on the same prompt, groups engaging in high-quality dialogue may not necessarily lead to accurate answers and vice versa. However,groups that were characterised as high interaction had discussions that included constructive and interactive talkthat were likely to benefit the learning of all students in the group.Outcomes for research question 2:The highest and most consistent levels of constructive and interactive dialogue occurred when quiz prompts were at Marzano Level 3 or higher. Marzano level 3 prompts required students to compare and contrast concepts or extend their understanding of concepts by developing an analogy which promotes higher interaction quality, suggesting that studentscollaborate and build on each other's statements and responses. Higher interactional quality also indicates that students ask more "why" and "how" questions which typically leads to deeper learning.
Barlow & Brown 2019	WIP: Measuring student cognitive engagement using the ICAP framework in and outside of the classroom	Conference	USA	STEM	Face-to-face	Quantitative	Expanded ICAP into interactive, constructive, active thinking, active doing, passive, and disengaged.	Physical materials or activities	Manual	Student course cognitive engagement instrument (SCCEI)
Barlow et al. 2020	Development of the student course cognitive engagement instrument (SCCEI) for college engineering courses	Journal	USA	STEM	Face-to-face	Quantitative	Basic steps of scale development as recommended by DeVellis	Physical materials or activities	Manual in the sense that teachers or researchers use the self-report instrument to gather data from students, who then manually respond to the items. The analysis of data collected is automated using statistical methods like exploratory factor analysis and	Validated SCCEI, a quantitative, self-report instrument designed to measure in-class cognitive engagement of college engineering students across five factors: 1. Interactivity with peers,2. Constructive notetaking, 3. Active processing, 4. Active notetaking and 5. Passive processing.

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									confirmatory factor analysis	
Beege & Ploetzner 2024	Learning from interactive video: the influence of self-explanations, navigation, and cognitive load	Journal	Germany	STEM	Online	Quantitative	Cognitive load theory	Instructional videos / recordings/modules	Not applicable - (experimental study design focused on measuring learning outcomes and cognitive load based on manipulated variables).	Research findings on the effects of self-explanation prompts and navigation features on learning and cognitive load from instructional videos.
Burgher et al. 2016	Implementing and assessing interactive physical models in the fluid mechanics classroom	Journal	USA	STEM	Face-to-face	Quantitative	Bloom's taxonomy, Anderson's information processing theory, and cognitive load theory.	Physical materials or activities	Not applicable (the study compared learning outcomes based on the mode of interaction with physical models).	Evidence supporting the effectiveness of interactive physical models in enhancing learning gains.
Burke et al. 2024	Understanding cognitive engagement in virtual discussion boards	Journal	USA	Non-STEM	Online	Mixed	No	Online discussion platforms	Manual	Provides insights into the observed types and levels of cognitive engagement in asynchronous online discussions. It also generated a coding rubric for cognitive engagement (Table 1) and discussion prompt codes (Table 2).
Cunha & Jaiswal 2022	Resolving troublesome knowledge in engineering physiology using ICAP framework based problem-solving studio	Conference	United Kingdom	STEM	Hybrid	Quantitative	Troublesome knowledge, as explained by David Perkins.	Digital tools / software	Manual	Primary output is the Problem-Solving Studio (PSS) micro-insertion module, along with related educational materials such as worksheets and an online discussion board. It also provides findings and insights into the effectiveness of this approach.
Deepika et al. 2021	Implementation of ICAP principles through technology tools: Exploring the alignment between pedagogy and technology	Journal	India	STEM	Hybrid	Qualitative	TPACK (technological pedagogical content knowledge)	Digital tools / software	Manual	Detailed description of the successful online implementation of ICAP-aligned pedagogies using technology tools for engineering courses.
Dunmoye et al. 2023	Investigating cognitive engagement in collaborative desktop virtual reality (VR) statics activities based on ICAP framework	Journal	USA	STEM	Online	Qualitative	No	Learning platform / environment	Manual coding of transcripts	Analysis of cognitive engagement patterns in collaborative VR activities.
Dunmoye et al. 2024	An exploratory study of social presence and cognitive engagement association in a collaborative virtual reality learning environment	Journal	USA	STEM	Online	Quantitative	Social presence theory	Learning platform / environment	Transcripts were coded deductively using quantitative content analysis. Qualitative data was transformed into quantitative data by counting the number of occurrences of the codes.	Provides empirical insights into the association between social presence and cognitive engagement within VR learning environments.
El-Mansy et al. 2021	Investigating small-group cognitive engagement in general chemistry learning activities using qualitative content analysis and the ICAP framework	Journal	USA	STEM	Face-to-face	Qualitative	No	Physical materials or activities	Manual	Insights into mismatches between expected and observed engagement and identification of contributing themes to these mismatches.
El-Mansy et al. 2024	Factors affecting individuals' cognitive engagement during group work in general chemistry: timing, group size, and question type	Journal	USA	STEM	Face-to-face	Mixed	No	Physical materials or activities	Manual	Analysis of individual cognitive engagement patterns influenced by timing, group size, and question type.
Fahid et al. 2021	Adaptively scaffolding cognitive engagement with	Conference	USA	Non-STEM	Online	Qualitative	Deep reinforcement learning (RL), specifically batch-	Instructional videos / recordings / modules	The paper includes policies using a data-driven pedagogical	Proposes a deep RL framework for creating policies to scaffold cognitive engagement in adaptive learning environments. The output includes a data-driven pedagogical modelling framework

Author(s) & Year	Title	Journal / conference	Country	Study Context	Learning Environment	Methodology	Theories used with ICAP	Learning tools used	Type of mapping	Output
	batch constrained Deep Q-networks						constrained deep Q-networks (DQNs). Markov decision processes are also used to formalise the task		model based on batch-constrained deep Q-networks, which is an automated approach	based on batch-constrained deep Q-networks to induce policies for delivering ICAP-inspired scaffolding
Farrow et al. 2020	Dialogue attributes that inform depth and quality of participation in course discussion forums	Conference	Canada	STEM	Online	Quantitative	CoI framework	Online discussion platforms	Both	Identified key dialogue attributes that are highly predictive of both cognitive presence (CoI) phases and cognitive engagement (ICAP) modes in online discussion forums. The trained predictive classifiers serve as a tool for automatically identifying these attributes.
Farrow et al. 2021a	A network analytic approach to integrating multiple quality measures for asynchronous online discussions	Conference	United Kingdom	STEM	Online	Quantitative	CoI framework, specifically its cognitive presence element.	Online discussion platforms	Manual coding for both ICAP and Cognitive Presence categories.	A network analytic approach for integrating multiple quality measures (ICAP and Cognitive Presence) for asynchronous online discussions.
Farrow et al. 2021b	Ordering effects in a role-based scaffolding intervention for asynchronous online discussions	Conference	United Kingdom	STEM	Online	Quantitative	CoI framework, specifically cognitive presence (triggering event, exploration, integration, resolution, other)	Online discussion platforms	Manual	Provides insights into the effectiveness of role-based scaffolding and the minimal impact of role ordering on the quality of student contributions in asynchronous online discussions. It also demonstrates the utility of combining CoI and ICAP frameworks with Epistemic Network Analysis for analysing discussion data.
Farrow et al. 2022	Markers of cognitive quality in student contributions to online course discussion forums	Journal	Canada	STEM	Online	Quantitative	CoI	Online discussion platforms	Both manual annotation and automated content analysis (using predictive classifiers)	Provides findings that can inform the design of better discussion forums, guide educators in developing participation requirements, and inform automated feedback systems. Predictive models were developed to identify elements automatically
Faulconer & Griffith 2025	Unveiling engagement patterns of Yellowdig users: Analysis of learning behaviors in an online undergraduate course	Journal	USA	STEM	Online	Mixed	Social constructivism theory	Online discussion platforms	Automated	Profiles of learner engagement (Table 1) based on the ICAP framework that can be used as predictors of student performance.
Gorgun et al. 2022	Predicting cognitive engagement in online course discussion forums	Conference	Canada	Non-STEM	Online	Quantitative	Bloom's taxonomy was merged and aligned with ICAP to inform labelling decisions.	Online discussion platforms	Manual labelling of data for training, followed by automated classification using machine learning models.	Predictive models for automating the identification of cognitive engagement in online discussion posts. The best-performing model was the Support Vector Machine.
He et al. 2022	Analysis of group online collaborative learning based on log data and ICAP	Conference	China	STEM	Online	Quantitative	Automatic labelling of data, and analysis of group collaborative learning behaviour.	Learning platform / environment	Automated	Behavioural transition diagrams for collaborative learning groups (C1, C2, C3), and a statistical table of learning gain for each group type.
Hobert et al. 2023	Chatbots for active learning: A case of phishing email identification	Journal	United Kingdom, USA	Non-STEM	Online	Mixed		Digital learning tools / software	Not explicitly mentioned. The chatbot interactions were designed to reflect different learning strategies.	Provides insights into the design of chatbots for active learning, particularly regarding the ICAP framework.
Ironside et al. 2018	Student perspectives on cognitive engagement: Preliminary analysis from the course social and cognitive engagement surveys	Conference	USA	STEM	Face-to-face	Mixed	No	Physical materials or activities	Manual	Ongoing development of the In-Class Cognitive Engagement survey, including added questions to address unengaged students, modified questions to compare responses to in-class and out-of-class engagement alongside each other
Lee et al. 2019	Using social annotations to support collaborative learning in a life sciences module	Conference	Singapore	STEM	Hybrid	Mixed	SOLO taxonomy	Online discussion platforms	Manual	Provides insights into how the ICAP and SOLO taxonomies can be applied to analyse social annotations.

Author(s) & Year	Title	Journal / conference	Country	Study Context	Learning Environment	Methodology	Theories used with ICAP	Learning tools used	Type of mapping	Output
Li et al. 2024	Automatic detection and interpretable analysis of learners' cognitive states based on electroencephalogram signals	Journal	China	STEM	Face-to-face	Quantitative	Revised Bloom's taxonomy was used alongside the ICAP framework to develop learning activities.	Physical materials or activities	Automated mapping was performed using DL models and interpretable AI techniques. The study proposed Local Interpretable Model-agnostic Explanation-Brain Area (LIME-BA) for interpretable analysis based on EEG channels.	Developed a DL model, Convolutional Neural Network-LSTM model for cognitive state detection and proposed Local Interpretable Model-agnostic Explanation Brain Area for interpretable analysis. The research provides insights for educators to design cognitive-guided instructional activities. A dataset was constructed from the electroencephalogram data.
Lim et al. 2019	Active learning through discussion: ICAP framework for education in health professions	Journal	South Korea	STEM	Face-to-face	Quantitative	From AI: Elaborative retrieval theory is mentioned in the discussion as being consistent with findings related to mental effort during studying.	Physical materials or activities	Statistical analysis, kind of manual?	Empirical support for an effective learning model based on the ICAP framework and offers practical implications for medical education.
Liyanage et al. 2021	Student discourse networks and instructor facilitation in process oriented guided inquiry physical chemistry classes	Journal	USA	STEM	Face-to-face	Mixed	Graph theory was combined with the ICAP framework. Piaget's and Vygotsky's theories were also considered in the theoretical framework.	Physical materials or activities	Manual	A novel methodology for capturing student interactions and engagement modes by mapping discourse in Process Oriented Guided Inquiry Learning courses using graph theory and a modified ICAP framework. Discourse network graphs.
Nelms & Segura-Totten 2019	Expert–novice comparison reveals pedagogical implications for students' analysis of primary literature	Journal	USA	STEM	Face-to-face	Qualitative	Cognitive load theory	Physical materials or activities	Manual	Clearly delineates the qualitative and quantitative differences in how experts and novices approach scientific literature, providing a foundation for pedagogical interventions aimed at developing students' analytical and comprehension skills
Parmar et al. 2024	Cognitive engagement detection of online learners using GloVe embedding and hybrid long short-term memory (LSTM)	Conference	Canada	STEM	Online	Quantitative	no	Online discussion platforms	The study aims for automated detection of cognitive engagement. The process involves training machine learning models to classify student posts. Manual mapping used in first instance.	Method/system (a hybrid deep learning (DL) model) for classifying online discussion posts to detect cognitive engagement. This system could potentially be integrated into Learning Management System platforms. It also involves the use of GloVe embeddings.
Pitterson et al. 2016	Measuring cognitive engagement through interactive, constructive, active and passive learning activities	Conference	USA	STEM	Face-to-face	Mixed	Cognitive load theory. flow theory	Physical materials or activities	Not applicable, as the study focuses on instrument development and defining cognitive engagement, not mapping tools	
Roeben et al. 2025	Simulations in teacher education: Learning to diagnose cognitive engagement	Journal	Germany	Non-STEM	Online	Quantitative	Theories of diagnostic competence, professional vision, and aspects of self-regulated learning (self-efficacy and interest)	Learning platform / environment	Manual	A validated simulation-based learning environment designed to train diagnostic competence in cognitive engagement, along with video vignettes demonstrating different ICAP modes.
Sharma & Li 2022	Design of machine learning powered visualizations to support	Conference	USA	STEM	Online	Quantitative	Social network analysis to assess behavioural engagement and	Online discussion platforms	The initial labelling for ML training was manual (human-rater coded posts). Automated	Prototype of a of machine learning-powered learning analytics dashboard

Author(s) & Year	Title	Journal / conference	Country	Study Context	Learning Environment	Methodology	Theories used with ICAP	Learning tools used	Type of mapping	Output
	rapid assessment of online student discussions						develop sociograms		classification of discourse data using the LSTM model.	
Sharma et al. 2024	Understanding student interaction and cognitive engagement in online discussions using social network and discourse analyses	Journal	USA	STEM	Online	Mixed	Group cognition as a basis for individual cognition; learning as an inherently social process Collaborative inquiry	Online discussion platforms	Semi-automated	An adapted ICAP framework A machine learning model (LSTM classifier) for automated discourse categorisation Behavioural engagement visualisers (sociograms) Cognitive engagement visualisers A Power BI Data dashboard
Singh & Rajendran 2022	Investigating learners' cognitive engagement in Python programming using ICAP framework	Conference	India	STEM	Online	Mixed	No	Learning platform / environment	Proposed to classify students' actions into different modes of cognitive engagement; the paper doesn't detail the specific mapping process or tools used for automation yet, but previous studies using ICAP for automated classification are mentioned.	PyGuru (a computer-based learning environment) for teaching-learning Python programming. The aim is to develop models to measure learners' cognitive engagement.
Singh & Rajendran 2024	Cognitive engagement as a predictor of learning gain in Python programming	Journal	India	STEM	Online	Mixed	no	Learning platform / environment	Manual	*Using log data:* Analysis of frequency of actions, the time-duration of the actions, comparative investigation of the relation between the frequency and time duration of different actions. *Using pre and post-test results:* Normalised learning gain is defined based on pre-post test results (formula provided). Then multiple linear regression analysis for normalised learning gain (y) is performed with predictors x1 representing the number of actions performed corresponding to passive engagement, x2 representing active engagement, and x3 corresponding to constructive engagement.
Techawitthayachinda & Iriya 2025	Automatic assessment of active learning in online discussions with large language models	Conference	USA	Non-STEM	Online	Quantitative		Online discussion platforms	Automated	Tools for automatic assessment of active learning in online discussions.
Wang et al. 2023	Benefits of prompting students to generate summaries during pauses in segmented multimedia lessons	Journal	China	STEM	Online	Quantitative	Cognitive Theory of Multimedia Learning (CTML) and Generative Learning Theory (GLT).	Instructional videos / recordings / modules	There is actually no mapping procedure in the paper. The pre-questionnaire, instructional materials, and cognitive load survey, retention test, and transfer test. Cognitive load was measured using two subjective rating scales: mental effort and perceived task difficulty. The measurement of learning outcomes consisted of a retention test and a transfer test.	Provides findings and implications for designing effective video lessons.
Wekerle et al. 2024	Putting ICAP to the test: How technology-enhanced learning activities are related to cognitive and affective-motivational learning outcomes in higher education	Journal	Germany	Non-STEM	Hybrid	Quantitative	Select-Organise-Integrate theory. Theories on student motivation (situational interest) and emotions (joy) in learning	Digital tools / software	Manual	Provides empirical evidence on the relationships between ICAP learning modes and student learning outcomes in authentic higher education settings.

Author(s) & Year	Title	Journal / conference	Country	Study Context	Learning Environment	Methodology	Theories used with ICAP	Learning tools used	Type of mapping	Output
							arrangements emphasising autonomy, control, usefulness, and belonging were also considered.			
Xanat et al. 2023	Semantic network analysis of a learning task among Japanese students of psychology	Conference	Japan	Non-STEM	Face-to-face	Mixed	Collaborative learning and computer-supported collaborative learning (CSCL)	Digital tools / software	Mixed. ICAP indicators were manually coded, while concept maps and conversations were analysed as networks using computer programs	Empirical evidence on the relationship between cognitive features in concept maps and conversations and learning outcomes within the ICAP framework. The study also provides recommendations for computer-supported collaborative learning (CSCL) systems and presents network graphs and quantitative data tables.
Zhao et al. 2024	Impact of pre-knowledge and engagement in robot-supported collaborative learning through using the ICAPB model	Journal	China	Non-STEM	Face-to-face	Mixed	Bloom's Taxonomy (for task design), social constructivist perspective, fine retrieval theory, and self-conscious student engagement theory.	Digital tools / software	Manual, using behavioural coding based on the ICAPB model	Yielded specific experimental data showing how students' prior knowledge and their level of engagement influenced their learning outcomes. It also generated detailed descriptions of how students behaved when they were highly engaged versus less engaged, categorised using the interactive, constructive, active, passive, and behavioural (ICAPB) model. Additionally, the study produced insights into students' opinions and experiences within the robot-supported collaborative learning environment, derived from interviews.