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Evaluating Quality over Quantity: A Systematic Review of Discussion Forum Metrics in Online Learning

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ABSTRACT

Discussion forums have become an integral component of online learning environments, providing a platform for interaction and exchange of knowledge among learners. However, the number of posts is an inadequate indicator of engagement or educational outcomes, as it often fails to reflect the true depth and relevance of learners' contributions. Despite their widespread use, the typical evaluation of these forums relies heavily on such quantitative indicators, thereby failing to capture meaningful engagement. Therefore, this systematic literature review examines methods used to evaluate participation in discussion forums over the last 5 years. Utilizing Boolean search techniques, relevant studies from 2020 to 2025 were extracted from the Scopus and Web of Science databases. The review identifies four key analytical approaches: Social Dimension, Cognitive Dimension, Framework-Guided Analysis, and AI-Assisted Analysis. Studies focusing on the social dimension employed Social Network Analysis to map interaction patterns and influential participants. Cognitive dimension studies primarily used content and sequential analyses to assess the depth of critical thinking and knowledge construction. Framework-guided analyses employed established theoretical models such as the Community of Inquiry (CoI) to systematically evaluate learning processes. Finally, AI-assisted analyses leveraged machine learning and deep learning to automate content classification, sentiment analysis, and detection of engagement patterns. Overall, the review suggests that combining traditional analytical methods with AI-driven insights can enhance the depth and accuracy of analysing student learning in online forums. The findings emphasize the need for a shift towards quality-based metrics that prioritize meaningful interactions, thereby guiding educators toward more effective evaluation and fostering deeper cognitive and social engagement in online learning environments.

1. Introduction

Online discussion forums have become a fundamental component of modern digital education, fostering interaction, collaboration, and knowledge exchange among learners. These platforms support both simultaneous and asynchronous interactions, enabling learners to engage in a social

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and interactive learning process and to form a community of inquiry [1]. As online learning continues to expand, forums play a vital role in maintaining engagement and facilitating higher-order cognitive skills, especially when distance or time constraints are a factor. They serve as dynamic spaces that cultivate a sense of community, encourage diverse perspectives, and enable peer learning. Furthermore, forums provide opportunities for students to express their thoughts, critique ideas, and engage in meaningful discussions, thereby enhancing learning performance [2].

Despite their significant role, the evaluation of discussion forums often relies on simple quantitative metrics such as post counts and reply frequencies. While these indicators are easy to measure, they do not fully capture the structural and relational dimensions of student interactions [3]. Research indicates that merely tracking the number of posts may fail to reflect students' learning engagement or critical thinking skills [4]. In fact, the post quantity alone is irrelevant for assessing students' performance in discussion forums [5]. Although several studies acknowledge these limitations, there remains a clear research gap regarding effective methodologies that go beyond these basic quantitative measures, particularly, methods capable of capturing deeper cognitive processes, quality of interactions, and the meaningfulness of student engagement.

Given the limitations of relying solely on quantitative assessment methods, this systematic literature review aims to explore and synthesize recent research on the use and evaluation of online discussion forums. By examining these dimensions, the review seeks to identify innovative methods and best practices that go beyond simple post counts, thus prioritizing meaningful, high-quality interactions. The ultimate goal is to guide educators and researchers in leveraging discussion forums more effectively and enhancing the overall learning experience.

2. Methodology

The primary objective of this research was to evaluate the metrics used for assessing online discussion forums, with a focus on identifying metrics that prioritize quality and effectively measure meaningful engagement. To ensure a systematic and transparent approach, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was employed to guide the selection and reporting of relevant studies [6]. A comprehensive literature search was conducted using two of the largest academic research databases: Scopus and Web of Science. These databases were selected for their extensive coverage of scholarly articles across educational technology and online learning disciplines.

The PRISMA framework facilitated the identification, screening, eligibility assessment, and inclusion of studies through a structured four-phase process. The following sections break down each phase, highlighting the criteria applied at each stage to ensure the selection of relevant and high-quality studies.

2.1 Identification

Several key steps in the systematic review process were employed to retrieve relevant literature for this study. Firstly, keywords were specifically chosen based on their relevance to the evaluation of online discussion forums. Once the search strings were identified, all relevant terms were incorporated into the search queries for the Scopus and Web of Science (Table 1). During the first stage of the systematic review process, a large number of publications were successfully retrieved from both databases.

Table 1
Boolean search query

Database	Search Query	No. of Document
Scopus	(TITLE-ABS-KEY ("discussion forum" OR "online discussion" OR "discussion board") AND TITLE-ABS-KEY (examin* OR evaluat* OR asses* OR analy*) AND TITLE-ABS-KEY ("online learning" OR "distance learning" OR "distance education"))	1301
Web of Science	TS=("discussion forum" OR "online discussion") AND TS=(examin* OR evaluat* OR asses* OR analy*) AND TS=("online learning" OR "distance learning" OR "distance education")	417

The search strategy focuses on identifying studies related to discussion forums, online discussions, and discussion boards within the context of online learning and distance education. Also, the queries incorporate terms such as “examine”, “evaluate”, “assess”, and “analyse” to ensure the inclusion of studies that assess or analyse these discussion environments. The search resulted in 1,301 documents from Scopus and 417 documents from Web of Science, requiring further screening and analysis to determine their relevance to the study.

2.2 Screening

During the screening process, the projected results were thoroughly filtered to ensure alignment with the study’s focus. Specific inclusion criteria were applied to refine the selection: (i) publication year between 2020 and 2025, (ii) studies published in English, (iii) document type limited to peer-reviewed research articles, and (iv) publication stage as final (fully published articles only). This approach was chosen to prioritize recent studies and provide insights into current trends and methodologies. The following Table 2 summarizes the inclusion criteria used for the screening process.

Table 2
Summary of Applied Inclusion Criteria

Inclusion Criteria	Criteria Applied
Publication Year	2020-2025
Language	English
Document Type	Articles
Publication Stage	Final

The literature search was conducted up to February 2025, as this was the most recent period for which published studies were available at the time of the review. Articles published after this date were excluded to maintain a consistent timeframe, ensuring that the findings reflect the most up-to-date research available. To maintain a clear research focus, only peer-reviewed research articles discussing online discussion forum metrics were included. Other document types, such as book chapters and non-peer-reviewed sources, were excluded. Additionally, the review was restricted to English-language and fully published articles to ensure accessibility and consistency in analysis.

2.3 Eligibility

During the screening process, the projected results were thoroughly filtered to ensure alignment with the study’s focus. Figure 1 visualizes the selection process using a PRISMA chart.

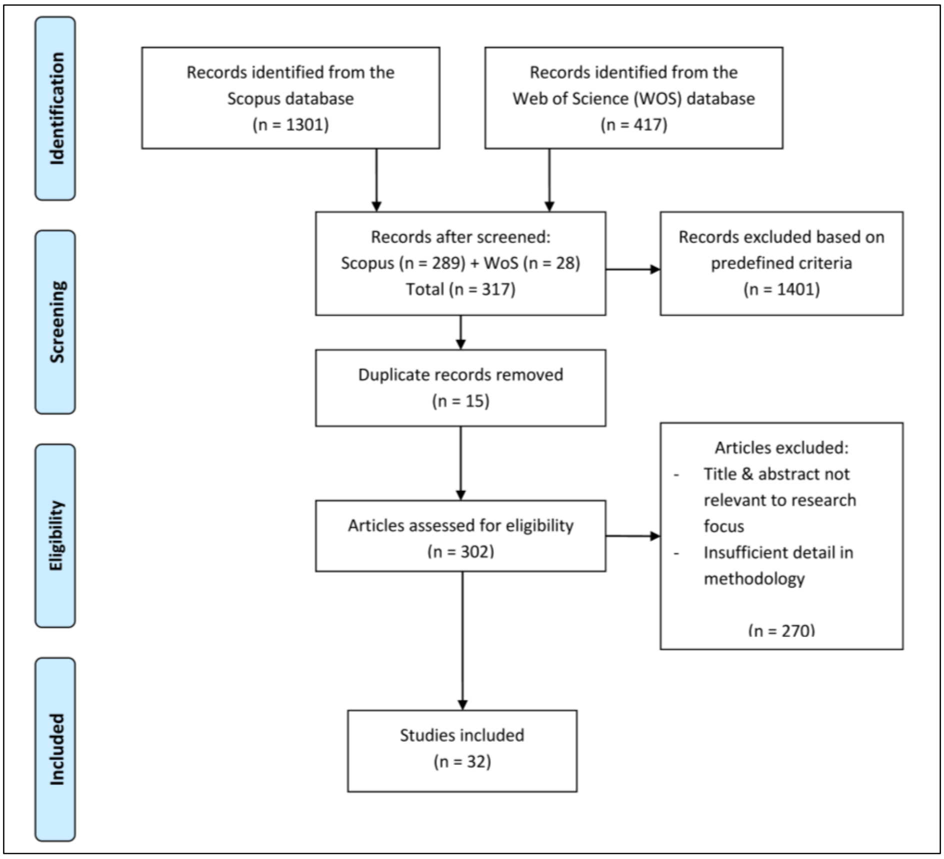

Fig. 1. PRISMA Flowchart of the Article Selection Process

A collection of 302 articles was assessed during this stage, known as the eligibility evaluation. This phase involved a detailed review of the titles and abstracts of each article to ensure they met the inclusion criteria and were relevant to the research goals of the study. A total of 270 articles were excluded during this evaluation for reasons including irrelevance to the research focus and insufficient detail in the methodology. Consequently, 32 articles have been selected for detailed analysis as they meet the focus of the study.

2.4 Data Abstraction and Analysis

In this study, data extraction was conducted by a single reviewer, ensuring consistency in identifying and summarizing key information from the selected studies. The extracted data included author, year, objective, methodology, and relevant findings related to the research objectives. For data synthesis, a qualitative analysis approach was applied, focusing on quantitative methods to identify key themes and subtopics. A thematic analysis was employed to analyse patterns emerging from the included studies. The final themes were refined to ensure consistency and alignment with research objectives. Given the nature of the study, no statistical meta-analysis was performed.

3. Results and Discussion

Online discussion forums in educational settings have been examined from various perspectives to understand how they support student learning. A thematic analysis was conducted to identify patterns and trends emerging from the included studies. The findings were categorized into four key themes, each representing a significant dimension of student learning in online discussion forums. The following sections break down each of the identified themes.

3.1 Social Dimension of Students' Learning

Recent literature examining the social dimension of online discussion forums demonstrates a variety of analytical methods that extend beyond simple post-count metrics. The used methods evaluate how students interact, form communities, and develop meaningful dialogue within online learning spaces. Through this systematic review, four main analytical approaches have been identified: Social Network Analysis (SNA), content analysis, temporal-relational analysis, and qualitative thematic analysis. Table 3 below highlights the specific studies, the approaches taken, and key findings.

First of all, a common approach to understanding social interactions in online discussion forums is SNA, which examines how students connect within discussions. Careful selection of SNA techniques ensures a more accurate representation of student interaction [7]. Studies consistently highlight that students with a higher social presence tend to occupy central or influential positions in discussion networks [8,9]. For example, in a distance learning context, Tsoni *et al.,* [9] used SNA combined with factor analysis to cluster students based on academic performance, social behaviour, and participation levels, allowing instructors to identify those requiring additional support. Moreover, findings suggest a strong correlation between students' network centrality (such as in-degree and betweenness measures) and their influence within discussions [8]. These insights highlight the importance of fostering social presence to enhance meaningful engagement in forums.

Another widely used approach is content analysis of discussion transcripts, which evaluates the quality of interactions rather than just their frequency. Several studies demonstrate that structured interventions, such as training students in e-moderation skills, can significantly enhance the depth of social discourse [10,11]. For instance, Vasodavan *et al.,* [10] found that following training, students progressed from basic information sharing to more complex forms of interaction, such as elaboration, application of ideas, and reflective discussions. Furthermore, research suggests that well-designed forum prompts play a crucial role in shaping engagement, with structured activities leading to increased collaborative learning and help-seeking behaviour [11]. These findings emphasise that effective instructional design can elevate the quality of peer interaction in online discussions.

Beyond structural analyses, recent research has explored temporal and relational dynamics in online interactions. Using a Relational Event Model (REM), Chen and Poquet [12] found that students' posting behaviours are shaped by prior engagement, familiarity, and prompt reciprocity. Notably, they observed that students who received a reply were more likely to respond quickly, suggesting that immediate feedback reinforces continued participation. This aligns with prior research highlighting that consistent and timely interactions foster stronger student engagement over time.

While quantitative methods map interaction patterns, qualitative thematic analyses provide deeper insights into the affective and social aspects of discussion. Studies indicate that when forum tasks encourage students to share personal experiences, discussions become more authentic, emotionally engaging, and community-driven [13]. For example, in a South African university, Essa *et al.,* [13] found that students who engaged in personal sharing and reflective dialogue reported feeling a greater sense of connection and reduced isolation in online learning. However, the same study cautioned that while forums can foster community and empathy, careful facilitation is necessary to prevent superficial agreement and manage negative interactions.

Table 3
Summary of related studies and methods used to analyse social dimension in online discussion

Author	Research Objective	Method	Findings
Vasodavan *et al.,* [10]	To investigate the difference in the patterns of interactions in a discussion forum before and after e-moderation training among undergraduates.	Content analysis	The results revealed that training had contributed to a significant increase in domains of social interaction, sharing information, egocentric elaboration, allocentric elaboration, application and transfer, coordination, and reflection.
Tsoni *et al.,* [9]	To propose a multilayered approach to analysing distance learning students' data to understand their learning progress, both individually and within a learning community.	SNA, Factor analysis, and clustering	Academic performance, social behaviour, and online participation are key factors in clustering students, aiding tutors in monitoring learning processes and intervening when necessary.
Yen *et al.,* [8]	To examine how online social presence predict students' social connections in an online course discussion board, using network analysis.	SNA	Students' online social presence significantly predicts various aspects of their social interconnectivity within online course discussion boards.
Rothstein *et al.,* [11]	To investigate the ways that students used the forum to engage with their peers and course material.	Content analysis	Collaborative engagement and help-seeking behaviors in asynchronous online discussions are influenced by the design of discussion prompts and the structure of the online environment.
Chen and Poquet [12]	To analyse the socio-temporal dynamics of online discussions by applying relational event modelling to examine how multiple factors collectively influence student interactions in online discussion activities.	Relational Event Model	Various collaborative engagement patterns, such as asking technical questions, providing answers, and validating responses, promoted group knowledge acquisition, and that social presence influenced knowledge construction in blended learning environments.
Essa *et al.,* [13]	To explore students' interactions in online forums and examine how these forums enable or restrict the humanization of the online learning environment.	Thematic content analysis	Interactive, asynchronous online discussion forums can facilitate humanizing pedagogy by enabling students to use their authentic voices, form social connections, and reflect on their personal experiences.
Tsoni *et al.,* [14]	To identify students' behaviour patterns based on their login activity in the discussion forum of a distance learning module.	SNA	By applying Social Network Analysis to clickstream data from discussion forums in distance learning courses, significant differences in student communication patterns can be identified, which extend beyond mere participation metrics, using tools like HITS and PageRank algorithms.
Xing *et al.,* [15]	To examine student groups in an asynchronous online discussion community, focusing on their interaction patterns and the quality of their mathematical engagement.	SNA and Topic modelling	The X-periphery group, despite its lower activity levels, exhibits the highest math literacy and discussion success rates, demonstrating that reduced activity does not compromise communication efficiency within online math learning communities, compared to the more active core and periphery groups.

While these analytical methods provide valuable insights into social engagement, they also reveal several challenges. Studies highlight potential limitations such as superficial participation [13] and unequal student contributions [12]. Additionally, forum design plays a critical role in shaping interaction quality, with structured prompts and guided facilitation proving essential for maintaining productive discussions [11]. That being said, technological tools like SNA and content analysis help educators better understand student interactions in online discussions. These data-driven insights allow instructors to apply pedagogical strategies and well-structured discussion prompts to foster stronger social connections and more meaningful engagement.

3.2 Cognitive Dimension of Students' Learning

Understanding the cognitive dimension of students' learning in online discussions is crucial for evaluating cognitive engagement, critical thinking, knowledge construction, and cognitive presence. Research in this area predominantly uses content analysis, learning analytics, sequential analysis, and machine learning to assess and categorise levels of cognitive involvement. These methods help uncover patterns of engagement and highlight factors that influence deeper learning. Table 4 summarizes these methods, highlighting specific studies and their approaches, providing a comprehensive overview of how each method enhances our understanding of the cognitive aspects in educational settings. Table 4 highlights the specific studies, the approaches taken, and key findings.

Content analysis is one of the most common approaches to analysing cognitive engagement in online discussions, as it categorises students' contributions based on cognitive depth. Content analysis methods have been shown to be reliable and effective for assessing critical thinking in large-scale online discussions [22] However, studies consistently show that online discussions are often dominated by lower-order cognitive processes, such as simple information sharing, with fewer instances of higher-order thinking [16,19,20].

For example, Galikyan *et al.,* [16] analysed over 6,000 posts in MOOC forums and found that more than 70% of contributions were classified as "New Information", with significantly fewer instances of evaluative or reflective thinking. Similarly, Husni *et al.,* [19] examined forum discussions in an inquiry-based learning environment and found that while students frequently engaged in surface-level interactions, they surprisingly reported high knowledge retention, suggesting that cognitive retention is not solely dependent on deep discussion.

Additionally, Lijun and Yoshida [20] applied sequential analysis to track cognitive engagement in university forums, categorising posts according to critical thinking sub-skills such as interpretation, analysis, evaluation, inference, explanation, and self-regulation. Their findings indicate that most discussions were dominated by lower-order thinking, yet when students engaged in altruistic behaviours, such as helping peers, they exhibited higher-order cognitive skills like self-regulation. These findings highlight that social motivation can enhance cognitive depth in discussions.

Other than that, Alwafi [17] conducted a quasi-experimental study where content analysis was used to evaluate cognitive presence by coding discussion messages, while SNA was applied to examine interaction patterns. The intervention group received learning analytics feedback in the form of visualisations of their cognitive presence and interaction patterns, while the control group did not. The analysis showed that students who received feedback demonstrated higher cognitive presence and more complex interaction networks, underscoring the effectiveness of content analysis in capturing the depth and quality of student contributions in online discussions.

Beyond traditional content analysis, researchers have examined patterns of cognitive participation by classifying students into cognitive engagement profiles. Prestridge and Cox [21] used thematic analysis on over 3,000 chat-based forum posts (Microsoft Teams) and identified six levels of cognitive complexity: lurk, superficial, task, respond, expand, and create. These contributions were further categorised into four distinct cognitive social learning profiles: bench sitter, hustler, striker, and champion, demonstrating that students engage at different levels of cognitive intensity. Their findings suggest that even in self-directed discussions, varying cognitive engagement profiles emerge, with some students remaining passive while others actively expand discussions.

Table 4
Summary of studies and methods used to analyse cognitive dimension in online discussions

Author	Objective	Method	Findings
Galikyan *et al.,* [16]	To identify levels of cognitive engagement and how it relates to learning performance in MOOC.	Content analysis	Learner contributions in MOOC discussions, reflecting cognitive engagement, are intricately linked to performance, emphasizing the importance of integrating cognitive and social factors in MOOC design and instructional strategies to enhance learning.
Alwafi [17]	To investigate the impact of using a discussion strategy with learning analytics on the level of student cognitive presence and interaction.	Content analysis and SNA	Using a discussion strategy with learning analytics significantly enhanced students' cognitive presence, interaction, and motivation in an online learning community compared to those without learning analytics.
Lee *et al.,* [18]	To examine how students develop higher-order thinking in online discussion forums, compare cognitive presence trends between a MOOC and a graduate-level online course, and apply a machine learning model to classify cognitive presence in student forum posts.	Content analysis and machine learning	Deeper cognitive engagement with course concepts, as expressed by higher cognitive presence in discussion forums, is associated with better learning outcomes for students, with an ML model achieving 92.5% accuracy in classifying cognitive presence.
Husni *et al.,* [19]	To examine how IBL functions by enhancing students' cognitive engagement, cognitive retention and motivation via LMS.	Content analysis and data mining	The study found that while students exhibited a higher rate of low-level cognitive engagement, they also demonstrated strong cognitive retention and motivation, with a significant relationship observed between cognitive engagement, motivation, and cognitive retention.
Lijun and Yoshida [20]	To examine university students' online scholarly discussions and determine how they demonstrate critical thinking (CT).	Sequential analysis	Students primarily demonstrated lower-level critical thinking skills in discussions, but when altruism was present, they engaged in higher-order cognitive processes, actively seeking information and reassessing topics.
Prestridge and Cox [21]	To identify how students engage cognitively across a socially constructed chat-based environment.	Thematic analysis	The study identified six types of student engagement: lurk, superficial, task, respond, expand, and create, which were grouped into four cognitive-social learning profiles: bench sitter, hustler, striker, and champion, based on complexity and intensity of engagement.

While manual content analysis provides valuable insights, it is labour-intensive and difficult to scale for large datasets. Recent studies have leveraged machine learning techniques to automate the classification of cognitive presence in online discussions. Lee *et al.,* [18] developed a fine-tuned BERT transformer model to classify cognitive presence in discussion posts, achieving 92.5% accuracy, which nearly match human-level performance. Their findings suggest that automated classifiers can reliably identify cognitive engagement levels and predict learning outcomes based on discussion quality. Additionally, the study highlights that students who engage more deeply in discussions tend to perform better in their courses. This underscores the potential of machine learning in tracking and improving cognitive engagement in online education.

Although these analytical methods provide valuable insights into cognitive engagement, they also reveal several challenges. Studies consistently show that lower-order thinking frequently occurs in online discussions, with many students engaging only at a surface level [16,19]. However, research suggests that specific interventions, such as socially motivated participation [20], cognitive engagement profiling [21], and learning analytics feedback [17], can enhance higher-order cognitive engagement. Furthermore, advancements in machine learning [18] offer scalable solutions for tracking and improving cognitive presence in online forums.

That being said, both traditional methods and technological advancements, such as machine learning and learning analytics, help educators assess and track students' cognitive presence in discussions. These data-driven insights enable instructors to implement effective teaching strategies, such as structured forum design and personalised feedback, to enhance cognitive engagement and support deeper learning in online environments.

3.3 Framework-Guided Analysis of Students' Learning

The use of theoretical frameworks and models to analyse online discussion forums has been a widely adopted approach in education research. Researchers use established coding schemes and analytical models to measure how deeply students engage, how they construct knowledge, and how their learning behaviours align with theoretical expectations. Studies in this domain predominantly employ frameworks such as the ICAP framework [23], the Interaction Analysis Model (IAM) [24], the Community of Inquiry (CoI) framework [25], Practical Inquiry Model [26], and hybrid analytical methods. Table 5 highlights the specific studies, the approaches taken, and key findings.

A widely used model for analysing students' cognitive engagement in discussions is the ICAP Framework [23], which categorises student interactions into passive, active, constructive, and interactive engagement modes. Research shows that higher levels of interaction lead to improved learning outcomes [27]. For instance, Raković *et al.,* [27] applied ICAP to forum content analysis, coding rhetorical moves such as asking questions, requesting justification, building on others' contributions, giving reasons, and making claims. Their findings indicate that specific interactive moves trigger more responses from classmates, promoting deeper discussion. Additionally, certain moves were found to be linked to individual learning outcomes, underscoring the role of interaction in knowledge construction.

Another widely adopted model is the IAM [24], which tracks knowledge co-construction through five progressive phases, from information sharing to the application of newly gained knowledge. Floriasti [33] applied IAM to analyse teacher-training forum discussions and found that most interactions remained in lower phases (e.g., sharing and comparing information), while only 6% of discussions reached the highest phase (applying knowledge). This suggests that while students engage in collaborative discourse, they often fail to synthesise and apply new knowledge. These findings highlight the need for instructional strategies that encourage students to progress beyond basic knowledge exchange.

The CoI framework [25] is extensively used to assess cognitive, social, and teaching presence in online learning environments. Studies have applied CoI to examine discussion dynamics, depth of reflection, and instructional design effectiveness [28,29,35]. For example, Sezgin [28] used Practical Inquiry Model [26] to categorise forum discussions into four phases: Triggering, Exploration, Integration, and Resolution. The analysis revealed that most student contributions were in Exploration and Triggering phases, suggesting that higher-order phase like Integration and Resolution were rare. Interestingly, learning style (field-dependent vs. field-independent) did not significantly impact the depth of cognitive engagement.

Table 5
Summary of studies and frameworks used in the analysis of student learning in online discussions

Author	Objective	Method	Findings
Raković *et al.,* [27]	To label and analyse content in students' posts.	ICAP Framework	Certain rhetorical moves in discussion posts, such as asking questions, requesting justification, building on ideas, giving reasons, and making claims, were more likely to generate peer responses. Posts with disagreement, comparisons, and claims were also linked to better performance on tests and writing tasks.
Sezgin [28]	To investigate the change of cognitive presence in online discussion.	Practical Inquiry Model	The most common phases of cognitive presence in online discussions were exploration and triggering events. Cognitive presence did not vary significantly based on participants' cognitive styles or affect their word count or participation levels. However, the study found moderate to strong links between different cognitive presence phases, suggesting they develop together.
Gillingham *et al.,* [29]	To explore whether online discussion forums demonstrate community presence and reflective learning among medical students.	Community of Inquiry Framework	Medical students used online discussion forums to collaborate and share ideas despite being geographically apart. However, their reflections were mostly shallow, with deeper insights being rare. Limited faculty involvement and a lack of structured prompts may have contributed to this, highlighting the need for improvements to encourage deeper reflection.
Kim *et al.,* [30]	To define learning leadership in online asynchronous discussions, introduce the Leader Identification Method, and test it using real data to examine how learning leaders differ from peers in behavioural, cognitive, and emotional engagement.	Leader Identification Method	Learning leaders in online discussion forums demonstrate higher levels of engagement in behaviour, cognition, and emotions compared to their peers. Specifically, they exhibit more transformational leadership, greater cognitive engagement, and more frequent emotional expression.
Kim *et al.,* [31]	To explore how different leadership styles in online discussions relate to learner engagement and contribute to the emergence of learning leaders.	Leader Identification Method	Students are more likely to become leaders by exhibiting transformational leadership behaviour and productively interacting with one another in an online discussion community.
Eryilmaz *et al.,* [32]	To propose a structured approach to analysing unstructured text data using mixed- and multi-methods to better understand collaboration in asynchronous online discussions.	Community of Inquiry Framework	Participants in an online discussion formed three distinct clusters, with those in the middle cluster playing a key role by expressing uncertainty, which helped the group collectively resolve misunderstandings. Also, the topics participants chose and how they discussed them influenced how these clusters formed.

Floriasti [33]	To analyse knowledge construction and collaborative behaviour in online discussion forums used by preservice teachers.	Interactive Analysis Model	The study found that most interactions in the online discussion forums were focused on sharing and comparing information. In contrast, the least engagement occurred in applying newly constructed knowledge.
Ba *et al.,* [34]	To enhance Epistemic Network Analysis (ENA) by incorporating discussion flow directionality and stanza-based trajectory tracking to gain deeper insights into online discussion strategies and dynamics in a CoI-based learning environment.	Community of Inquiry Framework	This study extends Epistemic Network Analysis (ENA) to track directional connections and thinking trajectories in online discussions. It found that different groups and individuals use varied discussion strategies, with the sequence of discourse influencing meaning.
deNoyelles *et al.,* [35]	To examine how a photo-based discussion protocol influences community interactions within an online discussion.	Community of Inquiry Framework	Photo-based discussion protocol effectively supported social, cognitive, and teaching presence within the learning community. Cognitive presence was the most prominent, as students engaged in exploring concepts through shared photos.

Similarly, Gillingham *et al.,* [29] examined reflective learning in medical students' discussion forums. Their analysis found that social presence (sharing cases and experiences) was evident, but deep reflection and critical inquiry were limited. Notably, teaching presence was weak, as faculty members tended to provide direct answers rather than prompting deeper discussion. These findings suggest that for forums to foster reflective learning, instructors must actively guide discussions and encourage deeper inquiry.

Expanding on CoI-based interventions, deNoyelles *et al.,* [35] tested a photo-based protocol to stimulate student engagement. Their study found that structured visual prompts enhanced all three CoI presences, with cognitive presence being the most prominent. Social interactions emerged as students discussed shared images, and peer feedback facilitated teaching presence. This study demonstrates how CoI can be used not only for evaluating discussions but also for designing interventions to improve engagement and interaction quality.

Beyond established frameworks, researchers have developed new models and multi-method approaches to analyse online discussions. These studies integrate multiple analytical techniques such as SNA, content analysis, and machine learning to derive deeper insights into student interactions [30,32,34].

One such approach is the Leader Identification Method (LIM), proposed by Kim *et al.,* [30], which combines content- and network-based metrics to identify students who take on leadership roles in online discussions. Their research defined learning leadership based on behavioural, cognitive, and emotional engagement. Using forum data from graduate courses, they found that students identified as leaders exhibited greater cognitive engagement, more frequent positive emotional expressions, and a tendency towards transformational leadership behaviours. These findings suggest that structured interventions can foster leadership in peer learning settings.

Furthering this work, Kim *et al.,* [31] examined how students develop into leaders over time, finding that emerging leaders consistently engaged with peers, responded supportively, and synthesised group ideas. This longitudinal analysis highlights that transformational leadership in discussion forums is built through sustained, thoughtful participation.

Other innovative methods extend framework-based analyses using SNA, topic modelling, and Epistemic Network Analysis (ENA). Eryilmaz *et al.,* [32] combined qualitative and computational techniques to explore discussion dynamics, identifying that students who express uncertainty often play a central role in fostering deeper inquiry. Ba *et al.,* [34] advanced ENA by integrating directional and temporal modelling, revealing how cognitive, social, and teaching presences evolve in discussions over time. Their findings suggest that discussions flow differently in various learning groups, with some groups naturally transitioning from social to cognitive interactions, while others follow the reverse pattern.

While framework-guided approaches provide structured insights into online learning behaviours, they also revealed several challenges. Studies consistently indicate that students often remain at lower levels of cognitive engagement, with many discussions failing to progress to higher-order reflection and application [28,33]. However, findings suggest that specific instructional strategies, such as prompting interactive moves [27], facilitating deeper reflection [29], and designing structured interventions [35], can address this gap.

Additionally, hybrid analytical models [30,32,34] show great potential in tracking engagement patterns over time. These methods combine computational tools with established educational theories to provide deeper, data-driven insights. Future research should explore how these frameworks can be further adapted to guide both evaluation and pedagogical interventions, ensuring that online discussions not only foster interaction but also enhance meaningful learning.

3.4 AI-Assisted Analysis of Content

With the growing volume of online discussions in Massive Open Online Courses (MOOCs) and other distance learning environments, the large amount of data generated by popular MOOCs makes manual content analysis impractical and time-consuming. Researchers have turned to Artificial Intelligence (AI) and Natural Language Processing (NLP) to analyse discussion content on a large scale. Learning analytics, which uses AI to track engagement and predict performance, has become a valuable tool in higher education [36]. Table 6 below highlights the specific studies, the approaches taken, and key findings.

Based on the identified literature, AI-assisted methods enable automated classification, clustering, sentiment analysis, and deep learning insights, making it easier to monitor student engagement, cognitive processes, and social interactions. These approaches prioritise algorithm performance (e.g., accuracy, precision) while also providing valuable educational insights that can inform instructional strategies and improve learning outcomes.

First of all, a key area of AI-related research involves automatically classifying discussion forum posts by their content, structural role, and sentiment. Yee *et al.,* [41] developed an AI system to classify MOOC discussion posts along multiple dimensions, including content category, structure, and sentiment. Using manually labelled training data, they fine-tuned advanced NLP models (including BERT-based classifiers) to tag thousands of discussion posts. Their findings indicate that AI models achieved 82% accuracy in categorising posts by type (e.g. question, knowledge sharing), 76% accuracy in recognising the structural role of posts (e.g. thread initiation vs. reply), and 87% accuracy in sentiment detection. By automating these classifications, the study identified patterns in content interaction, such as how topics, structural roles, and sentiment trends appear together in long discussions. These are tasks that would be difficult to analyse manually.

Table 6
Summary of studies and methods used in AI-assisted analysis of content in online discussions

Author	Objective	Method	Findings
Onan and Toçoğlu [37]	To identify question topics on discussion posts.	Unsupervised learning and text mining	Combining weighted word-embedding schemes with clustering algorithms improves the accuracy of document clustering and topic modelling in MOOC discussion forums, outperforming conventional methods.
Zou *et al.,* [38]	Exploring the relationship between social presence and learners' prestige.	Machine learning and SNA	Positive social presence indicators, such as asking questions, expressing gratitude, self-disclosure, sharing resources, and using vocatives, enhance learners' prestige in MOOCs, while negative expressions like disagreement, criticism, and negative emotions reduce it.
Hu *et al.,* [39]	To propose the adoption of a deep learning method to automate the categorisation of online discussion messages.	Deep learning and Explainable AI	A Convolutional Neural Network (CNN) classifier performed similarly to a random forest classifier in identifying cognitive presence phases in online discussions. Explainable AI visualisations revealed key word-level patterns, suggesting that combining deep learning with traditional machine learning could improve accuracy.
Chanaa and El Faddouli [40]	To explore learner sentiment expressed in their comments using machine learning and multi-factor analysis methods.	Machine learning	Sentiment analysis on MOOC discussion forums can be highly accurate (94.1%) and effectively track changes in learner sentiment over time.
Yee *et al.,* [41]	To develop AI-assisted techniques for analysing the content, structure, and sentiment of discussion forum posts in MOOCs.	Machine learning and Deep learning	AI-assisted labelling can effectively classify forum posts in online learning platforms, reducing manual effort while maintaining high accuracy. Analysis of labelled posts revealed significant differences in forum participation based on learners' age, gender, and course outcomes, particularly in how they seek help, provide help, and express emotions.
Alsuhaimi and Almatrafi [42]	To develop an automated system to detect and address learner confusion in Massive Open Online Course (MOOC) discussion forums.	Deep transfer learning and Explainable AI	Deep transfer learning model can effectively classify confused posts in MOOC discussion forums with 91% accuracy, improving generalizability by 11% using data augmentation.
Žitnik and Gordon Smith [43]	To develop an automated system to assist teachers in monitoring and guiding fourth-grade students during online discussions.	Machine Learning	Computer algorithm could accurately predict whether students' online discussion posts were relevant to their eBook content 90% of the time, demonstrating that automated tools can assist teachers in moderating discussions and keeping students on-topic. Also, small group online discussions in web-based eBooks can be effective and meaningful for fourth-grade learning.

Wei *et al.,* [44]	To develop an AI-based text analysis approach for detecting learning experiences in MOOC discussions, define students' interactive roles and examine their influence on learning experiences, and explore the impact on learning achievement.	Text mining and Social Network Analysis	An AI-based text analysis approach accurately identified learning experience patterns in MOOC discussions. Highly active but less influential students often felt boredom or flow, while less active but more influential students experienced anxiety or apathy. Learning achievement was less affected by experience for highly active students, but flow improved achievement for less active learners.
Castellanos-Reyes *et al.,* [45]	To automate the content analysis of students' discussion board text.	Large Language Models	A fine-tuned model with a one-shot prompt achieved moderate reliability compared to human analysis, especially in the Integration phase of Practical Inquiry Model. While AI-driven approaches proved cost-effective and efficient, successful implementation still requires strong data literacy skills.

Similarly, Chanaa *et al.,* [40] applied machine learning-based sentiment analysis to examine emotional trends in MOOC discussions. Using models such as Naïve Bayes, Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines (GBM), they categorised student posts as positive, neutral, or negative. Their approach involved text preprocessing techniques, including tokenisation, lemmatisation, stopword removal, and TF-IDF, to improve classification accuracy. Beyond sentiment detection, the study explored multi-factor analysis, linking sentiment trends to variables such as instructor presence, course difficulty, and peer interactions. Their results suggest that student sentiment in discussions can provide meaningful insights into engagement and learning experiences, with AI enabling large-scale analysis of these patterns.

Beyond traditional supervised learning, Onan and Toçoğlu [37] employed unsupervised text mining techniques to automatically detect question topics in MOOC discussion forums. They implemented word embedding models (word2vec, fastText, GloVe, and Doc2Vec) combined with clustering algorithms (e.g. K-means variants, self-organising maps) to identify dominant discussion themes. Unlike manual topic labelling, this deep learning-based method required no pre-defined labels, instead discovering patterns of discussion based on linguistic similarity. Their results highlight the potential of unsupervised learning in identifying emerging discussion themes, which can help instructors detect common student concerns or areas of interest without requiring manual intervention.

AI-driven analysis has also been applied to examine social presence and interaction quality in online discussions. Zou *et al.,* [38] used an automated content analysis tool to detect social presence indicators in MOOC discussions and examined how these behaviours correlated with students' social standing (or "learner prestige"). Their findings indicate that prosocial behaviours, such as asking questions, expressing gratitude, self-disclosure, sharing resources, and addressing peers by name, were positively correlated with higher network centrality and peer recognition. In contrast, antisocial or disengaging behaviours correlated negatively with learner prestige. These results suggest that AI-assisted social presence analysis can help instructors identify socially engaged learners and assess community-building dynamics in online discussions.

Additionally, Wei *et al.,* [44] introduced a semi-supervised learning approach (BERT-SSL-AL) to analyse students' learning experiences and participation profiles in MOOC forums. Their method automatically clustered student posts based on engagement levels, identifying categories such as "leaders," "influencers," and "peripheral participants". The study further examined how different engagement profiles aligned with learning experiences, identifying patterns of flow, boredom, anxiety, and apathy. By mapping these behavioural profiles to course performance (pass vs. fail), the study demonstrated that active engagement in discussions correlates with richer learning experiences and higher course completion rates.

AI models have also been applied to detect student confusion or off-topic discussions, enabling instructors to intervene promptly. Alsuhaimi *et al.,* [42] developed an Explainable Deep Transfer Learning model to identify confusion in MOOC discussions. Their approach trained a deep learning classifier across multiple courses to detect confusion-related posts, achieving 91% accuracy—outperforming baseline models. By integrating explainability techniques such as LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), they identified key words and phrases (e.g. “I’m stuck” or “I don’t understand”) that triggered the AI’s classification. This interpretability enables instructors to understand why the AI flagged a post as confused, thereby enhancing trust in AI-driven feedback systems.

In a K-12 context, Žitnik and Smith [43] developed an AI-assisted monitoring tool to track elementary students’ online book discussions. Their natural language processing algorithm analysed students’ messages and successfully predicted whether a given post was on-topic or off-topic with 90% accuracy. By providing real-time alerts, the system enabled teachers to intervene when discussions drifted off course, offering scalable support for managing student discourse in large or concurrent discussions.

Recent research has explored the potential of Large Language Models (LLMs) in automating content coding and cognitive presence detection. Castellanos-Reyes *et al.,* [45] examined the feasibility of using GPT-3.5 to categorise discussion posts based on the Community of Inquiry (CoI) framework. The model was prompted to classify posts into cognitive presence phases, with results showing moderate agreement with human coders, particularly in identifying the Integration Phase. However, lower reliability in other phases suggests that LLMs require further refinement, such as fine-tuning or using few-shot learning with exemplars. Despite these limitations, the study highlights the potential of LLMs to support large-scale discussion analysis, reducing the time burden of manual coding while still requiring human oversight for nuanced classification tasks.

AI-assisted methods offer scalable, efficient solutions for analysing large volumes of online discussions, enhancing instructors’ ability to monitor engagement, social presence, and cognitive development. However, studies consistently highlight challenges, including the interpretability of AI models [42], the reliability of automated classification [45], and sentiment ambiguity [40]. Future research should explore hybrid approaches that combine machine learning with human oversight to keep AI insights transparent, reliable, and ethical.

While the reviewed studies show how AI can automate forum analysis, it is equally important to consider its broader educational impact. AI techniques such as machine learning and sentiment analysis enable rapid, large-scale monitoring of student engagement, helping instructors detect satisfaction, confusion, or disengagement in real time. This supports quicker feedback, adaptive learning, and personalised interventions. Topic detection also helps surface emerging discussion themes for responsive course adjustments. Emerging trends like Explainable AI (XAI) and Large Language Models (LLMs) improve the transparency and predictive power of forum analytics, offering new ways to identify at-risk students and tailor support. Overall, AI methods not only streamline forum evaluation but also reshape how educators interpret and act upon student interactions.

3.5 Summary of Methods Used for Social, Cognitive, Framework-Guided, and AI-Assisted Analysis of Students' Learning

Table 7 summarises the key methods used to analyse online discussions across four dimensions: social, cognitive, framework-guided, and AI-assisted analysis. This structured overview highlights the diverse methodological approaches used to assess the quality and depth of online discussions beyond simple post counts.

Table 7
Summary of methods used for social, cognitive, framework-guided, and AI-assisted analysis

Theme	Purpose	Method Used	Key Studies
Social Dimension of Students' Learning	Mapping social interaction patterns	Social Network Analysis	[8,9]
	Evaluating social engagement quality	Manual content analysis	[10]
	Temporal and relational analysis	Relational Event Model	[12]
	Explore the presence and nature of humanising pedagogy	Qualitative thematic analysis	[13]
	Identify response patterns	Manual content analysis	[11]
Cognitive Dimension of Students' Learning	Assessing cognitive engagement in forums	Manual content analysis	[16,17,19]
	Tracking critical thinking progression	Sequential analysis	[20]
	Identifying cognitive engagement profiles	Thematic analysis	[21]
	Automated cognitive presence detection	Manual content analysis and machine learning	[18]
Framework-Guided Analysis of Students' Learning	Classifying cognitive engagement based on theoretical frameworks	ICAP Framework	[27]
	Tracking knowledge construction progression	Interaction Analysis Model	[33]
	Evaluating cognitive, social, and teaching presence	Community of Inquiry	[28,29,35]
	Identifying leadership roles in discussions	Leader Identification Method	[30,31]
	Tracking discussion dynamics and group patterns	Community of Inquiry and Epistemic Network Analysis	[34]
	Detecting social influence and group dynamics	Community of Inquiry and mixed-methods approach	[32]
AI-Assisted Analysis of Content	Automated content classification	Deep learning and machine learning	[40,41]
	Sentiment analysis	Machine learning	[40]
	Topic detection	Unsupervised learning and text mining	[37]
	Social presence and engagement patterns	Semi-supervised learning and network analysis	[38,44]
	Detecting confusion and off-topic drift	Deep learning and Explainable AI (XAI)	[42,43]
	Automated cognitive presence analysis	Large Language Models (LLMs)	[45]

To provide a more critical evaluation of the methodological approaches employed in the reviewed studies, Table 8 summarises the key strengths and limitations associated with each method under the four identified themes. This overview is grounded in how the methods were applied in the respective studies, offering a clearer understanding of their practical advantages and constraints. It is hoped that by highlighting these considerations, future research and practice can make more informed choices in selecting and applying methods for analysing online discussion forums. Such critical assessment not only informs methodological improvements but also contributes to enhancing the overall quality of research in online learning environments.

Table 8
Overview of the strengths and limitations of methods used in the analysis of online discussion forums

Theme	Method	Strength	Limitation
Social Dimension of Students’ Learning	Social Network Analysis	Identifies influential participants	Ignores qualitative nuances
	Manual content analysis	Detailed qualitative insights	Subjective and labour-intensive
	Relational Event Model	Analyses interaction timing	Complex to implement
	Qualitative thematic analysis	Captures emotional/social aspects	Highly subjective interpretation
Cognitive Dimension of Students’ Learning	Manual content analysis	Categorizes cognitive levels clearly	Resource-intensive coding
	Learning analytics	Enhances engagement via analytics	Limited insight on cognitive quality
	Sequential analysis	Shows cognitive progression	Over-simplifies interactions
	Qualitative thematic analysis	Reveals diverse learner types	Subjective, limited generalizability
	Manual content analysis and machine learning	Reliable manual training, scalable ML classification (~92.5% accuracy).	Resource-heavy initial coding; model may not generalize well.
Framework-Guided Analysis of Students’ Learning	ICAP Framework	Identifies effective interaction moves	Rigid coding categories
	Practical Inquiry Model	Clearly reveals inquiry stages	Rarely identifies higher stages
	Community of Inquiry Framework	Integrated presence types of analysis	Doesn't explain underlying reasons
	Leader Identification Method	Highlights influential students	Activity-focused, misses quieter leaders
	Interaction Analysis Model	Shows knowledge construction depth	Rarely captures higher interaction levels
	Epistemic Network Analysis	Clearly visualizes idea links	Complex, needs specialized skills
	Mixed-Methods	Blends qualitative and quantitative insights	Complex, hard to replicate
AI-Assisted Analysis of Content	Automated Content Classification	Fast, scalable classification	Requires labelled examples
	Sentiment Analysis	Accurate sentiment monitoring	Poor with ambiguous expressions
	Topic Detection	Discovers hidden discussion themes	Manual interpretation required
	Content and Network Analysis	Integrates content/network insights	Complex analysis setup
	Deep Learning and Explainable AI	Identifies problematic posts quickly	High data demands
	Large Language Models	Quickly classifies cognitive levels	Moderate accuracy, human check needed

As shown in Table 8, while each method offers unique strengths in capturing different dimensions of student interaction and learning, they also present specific limitations that researchers and educators must consider. The choice of methodology significantly influences the depth, focus, and scalability of findings. Therefore, selecting an appropriate method, or combining complementary methods, can enhance the quality of analysis and lead to a more comprehensive understanding of students' engagement in online learning environments.

4. Conclusion

This review explored four key themes related to the analysis of student learning in online discussions: Social Dimension, Cognitive Dimension, Framework-Guided Analysis, and AI-Assisted Analysis. The findings highlight a diverse range of methods used to evaluate student engagement, knowledge construction, and interaction quality. The review also shows that combining traditional analytical methods with AI-driven insights can enhance the depth and accuracy of student learning analysis in online discussions.

Considering the growing popularity of AI in education, future research could focus on implementing AI-assisted or AI-driven approaches to analysing student learning in online discussions, with an emphasis on improving accuracy and precision. Recent studies highlight a rise in AI applications in education, with increasing interest from the academic community in using AI for tasks such as automated assessment [46]. Combining AI-driven insights with human interpretation can improve the depth and reliability of learning analysis while preserving the critical role of educators in guiding and interpreting learning outcomes.

Building on these findings, it is also important to consider practical strategies to help educators enhance forum interactions. Instructors can use Social Network Analysis (SNA) to identify isolated students and support peer connections. Well-structured, open-ended prompts can encourage deeper discussion and cognitive engagement. Providing feedback on students' cognitive presence using learning analytics can also promote more reflective participation. Training students in critical dialogue skills, such as justifying arguments or building on others' ideas, can enrich discussions. Additionally, basic sentiment analysis tools can monitor emotional engagement and allow timely intervention. These approaches move beyond post counts and help create more meaningful, high-quality learning experiences in online forums.

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