2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #53397

Perspectives on Learning Analytics from Online Learning Facilitators

William David Masarik, Rowan University

William Masarik is a junior in the mechanical engineering technology department. He earned his associate's degree in engineering science from Rowan College of South Jersey. His interests include Mechanics and machining precision parts, as well as understanding the trajectory of online engineering education.

Jayanto Das, Rowan University

Jayanto Das is a PhD student in the Department of Mechanical Engineering at Rowan University. His work focuses on advancing engineering education through statistical analysis and data-driven methods. His research interests include uncertainty quantification in additive manufacturing processes, where he investigates how variability affects the quality and performance of printed components.

Dr. Paromita Nath, Rowan University

Dr. Paromita Nath is an Assistant Professor in Mechanical Engineering at Rowan University. She earned her Ph.D. in Civil Engineering from Vanderbilt University. She is passionate about advancing engineering education through machine learning and data analysis, building on her expertise in uncertainty quantification, Bayesian inference, process design and control under uncertainty, and probabilistic digital twin. Her research spans diverse applications, including additive manufacturing and public health.

Dr. Smitesh Bakrania, Rowan University

Dr. Smitesh Bakrania is a Professor of Mechanical Engineering at Rowan University. He earned his Ph.D. at University of Michigan-Ann Arbor working on combustion synthesis research. With background in thermal-fluid science and nanomaterials, he has taught a variety of relevant courses. His passion for teaching has allowed him to explore engineering education research and develop study abroad program tied to an innovative engineering history course.

Perspectives on Learning Analytics from Online Learning Facilitators

Abstract

Learning analytics (LA) enables the identification of learning patterns, monitoring of student behaviors, and support for targeted interventions, which are particularly important in online learning environments. However, traditional LA approaches based on data from learning management system (LMS) often rely on metrics such as content access frequency and assignment completion rates, which provide an incomplete view of student behavior and limit their usefulness for informing instructional decisions. Given their responsibility for designing assignments, structuring learning activities, and providing formative feedback, faculty and instructional designers are instrumental in shaping the online learning environment. This study explores the gap between LMS-derived quantitative data and the qualitative understanding required to interpret student behavior and preferences effectively through the perspectives of online learning facilitators, that is, faculty and instructional designers. Using a mixed-methods approach that integrates thematic analysis (TA) with the community of inquiry (CoI) model, the qualitative interviews of online learning facilitators were analyzed to gain a comprehensive understanding of the effectiveness and challenges of online STEM instruction. The preliminary analysis shows that faculty rely on contextual, experience-based interpretations of student behavior such as motivation, self-pacing, course design quality, and interpersonal dynamics that are not captured by LMS data. Faculty view flexibility and pacing as essential to cognitive engagement, perceive tools such as discussion boards as insufficient for building authentic social presence, and see teaching presence as strongly shaped by institutional infrastructure and support. Comparing large language model (LLM)-generated themes with human-coded themes revealed that while LLMs are effective at detecting explicit instructional elements such as structured activities, resources, and communication channels, they are less sensitive to the implicit, contextual, and relational nuances that human coders identify.

Introduction

The growth of online learning has dramatically increased the relevance of learning analytics (LA). Using LA in online learning can provide answers to important questions that are often difficult to assess, especially in the absence of in-person interactions, such as: "How effective is the course? Is it meeting the needs of the students? How can the needs of learners be better supported? What interactions are effective? How can they be further improved?"[1]. While LA excels at tracking quantitative data such as the number of times students have logged in or viewed assignments, it often lacks the nuance needed to fully understand a student's progress.

Previous research highlights the limitations of relying solely on quantitative LA. Sherin, Kersting, and Berland argue that LA frequently misses interpretive and contextual information typically available in face-to-face learning[2]. A study on students' perspectives on online learning[3] found that qualitative data can provide more insightful information for improving online learning. Amaya, Restrepo-Calle, and Ramírez-Echeverry[4] demonstrate that using a mixed-methods framework to analyze both quantitative and qualitative data strengthens the interpretability of both datasets. A study at Cornell University[5] compared regression models with varying levels of contextual input for predicting students' online behavior and performance. Models enriched with contextual data performed better, emphasizing the importance of complementing quantitative behavioral data with contextualized information.

Qualitative research has emphasized the importance of contextualized insights for making LA meaningful in practice. Researchers examining learner interactions with dashboards show that meaningful analytics use depends on data relevance, accuracy, and contextual framing[6]. Distance learners also emphasized the importance of process-focused feedback (e.g., "How can I improve?") and expressed the need to co-design analytics tools rather than simply receiving data passively[7].

Student success in online learning depends heavily on communication, engagement, evaluation, and course design. Students' transition to online learning is often accompanied by reduced communication and a diminished sense of fulfillment[8]. Relying solely on replicating in-person pedagogy (e.g., lecture videos or discussion boards) has been shown to be insufficient for addressing these gaps[9]. Research also demonstrates that increased communication between students and instructors positively impacts learning experiences and that well-structured courses and timely instructor feedback are integral features of high-quality online learning[10]. Instructors and instructional designers play a crucial role in determining how communication, feedback, and engagement unfold online. Their ability to interpret and act on LA data determines whether data-driven strategies support learning or merely monitor it. However, many instructors struggle to meaningfully incorporate analytics into their practice, largely because quantitative data often fail to capture the nuanced pedagogical and social contexts that shape student learning. Understanding instructors' and designers' perspectives is therefore critical to interpreting LA more effectively and creating learning environments where both educators and students can engage meaningfully with analytic insights.

Although qualitative data offer essential context, traditional qualitative methods are resource-intensive and difficult to scale for large datasets. Recent methodological advancements have explored the use of large language model (LLM) to expand qualitative analysis while maintaining interpretive depth. When guided by established coding frameworks[11], LLMs can systematically analyze interview transcripts, identify thematic patterns, and assist in categorizing responses. However, the use of LLM to analyze stakeholder perspectives for the contextualization of behavioral analytics remains limited. While some studies indicate that LLM-assisted coding may achieve satisfactory agreement with human experts when appropriately tested[12], researchers emphasize the necessity of human oversight to ensure interpretive validity and address context-dependent subtleties[13].

To address these challenges, this study captures the perceptions of online learning facilitators, that is, faculty and instructional designers, through semi-structured interviews. These insights help interpret LA and improve online courses. This study employs a hybrid human–LLM approach to enable scalable qualitative analysis. Interview responses were analyzed using the community of inquiry (CoI) framework to align with cognitive, social, and instructional presences. A human coder ensured coding accuracy, while an LLM supported categorization and theme identification. This work focuses on: (1) contextualizing online teaching LA data using stakeholder perspectives analyzed through the CoI framework to better interpret engagement and learning challenges and (2) introducing and evaluating a hybrid human–LLM method that expands the scalability of qualitative analysis while preserving interpretive rigor.

Methodology

The methodology in this study integrates qualitative inquiry with a hybrid human–LLM analytical approach to examine instructors' and instructional designers' perspectives on online learning. The methodology includes developing survey questionnaires for faculty and instructional designers, collecting data through semi-structured interviews, conducting human thematic coding guided by the CoI framework, performing LLM-assisted coding using the same framework, and carrying out a comparative analysis of the coding results.

Survey questionnaire

Surveys were selected as the primary data collection method because prior research demonstrates that understanding online STEM teaching requires capturing instructors' and instructional designers' lived experiences and perspectives. Wu et al. show that the effectiveness of online learning analytics and instructional technologies hinges on how instructors interpret and act on them. Their study uses surveys and interviews to uncover these pedagogical responses and challenges[14]. Similarly, Wang and Hu's systematic review identifies surveys as one of the most common and essential methodological tools in research on teachers' online professional learning, emphasizing that practitioner perceptions are central to evaluating online learning environments and identifying influential factors shaping teaching practices[15].

Faculty survey

The faculty survey was designed to examine how instructors conceptualize and implement key components of online teaching, including course design, student engagement, and broader institutional factors influencing instructional effectiveness. The questionnaire consisted of nine open-ended items organized into four categories.

(a) *Background and Experience* section captured instructors' histories with online teaching and the types of courses they have taught.

(b) *Course Design and Delivery* section explored how instructors structure online course components such as videos, readings, and activities and their perspectives on student engagement.

(c) *Effective Practices and Barriers* section solicited reflections on strengths, challenges, and limitations associated with teaching online at Rowan University.

(d) *Opportunities and Challenges Ahead* section asked instructors to identify ways online teaching might be improved and to discuss potential obstacles to future progress.

All the questions for the faculty survey are provided in Appendix A.

Instructional designer survey

The survey for instructional designers was developed to investigate how instructional designers conceptualize and support the design and delivery of online courses at Rowan University. The questionnaire consisted of eleven open-ended items organized into four categories, aimed at capturing designers' professional experiences, design practices, collaborative processes, and perspectives on improving online instruction.

(a) *Background and Experience* section captured instructional designers' professional histories, the number and types of online courses they have supported, and the disciplines they most frequently work with.

(b) *Course Design and Engagement* section explored how designers structure course components such as videos, readings, activities, and assessments to support learning, ensure accessibility and inclusivity, and address challenges related to fostering student engagement.

(c) *Collaboration with Instructors* section examined how designers work with faculty during course development, the emphasis placed on the quality and content of lecture videos, and the effectiveness of these collaborations in shaping course structure, content, and assessment strategies.

(d) *Evaluation and Recommendations* section asked designers how they assess whether an online course supports student learning outcomes and invited suggestions for improvements and best practices in online course design at Rowan University.

All the questions for the instructional designer survey are provided in Appendix B.

The survey questions were derived from faculty instructors' experiences supporting online STEM course development at Rowan University and were further guided by existing literature on online learning, course design, and student engagement. The surveys were approved by the Institutional Review Board of Rowan University (IRB PRO-2025-211).

Participants

The recruitment process focused on faculty and instructional designers with experience teaching or designing online STEM courses. These individuals were invited to participate in one-on-one interviews to share their perspectives on online instruction and course design. Recruitment was carried out through targeted email invitations and face-to-face outreach. Interested participants were provided with study information and asked to provide informed consent before scheduling an interview. Interviews were conducted via the video conferencing tool Zoom and ranged from 20 to 45 minutes in duration. A total of 9 participants have currently taken part in this ongoing study.

Data analysis

The analysis was conducted following established qualitative research procedures to ensure that the resulting findings were systematically derived from the interview data.

Data collection

All interviews were conducted via Zoom, and both the interview recordings and auto-generated transcripts were collected for analysis. The recordings were used to verify the accuracy of the transcripts and ensure that participants' responses were captured correctly. All transcripts were subsequently anonymized to protect participant confidentiality.

Thematic analysis

Thematic analysis (TA) is widely used to analyze qualitative data as it provides a framework for identifying, analyzing, and recording patterns and themes in qualitative datasets[16]. As demonstrated by Dai et al., thematic analysis of open-ended responses can effectively reveal patterns and themes in complex human contexts, supporting its use in studies of online learning and teaching[17]. In this study, thematic analysis was used to systematically examine interview transcripts and identify recurring ideas expressed by faculty and instructional designers.

The analysis followed Braun and Clarke's six-step process of familiarizing oneself with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report[18]. Familiarization involved multiple close readings of each transcript to gain an in-depth understanding of participants' experiences. Initial codes were generated using a hybrid deductive–inductive approach. Coding began with deductive assumptions informed by the research questions and existing literature, after which inductive analysis was used to refine and expand the codes based on concepts emerging directly from the data. This combined strategy reflects the approach described by Fereday and Muir-Cochrane, who emphasize the value of integrating deductive thematic structures with inductive insights to strengthen qualitative rigor[19].

The resulting themes served as the foundation for subsequent analysis using the CoI framework.

Community of inquiry framework

For a theoretically grounded interpretation of the themes, all codes were subsequently organized using the CoI framework[20,21]. The CoI model identifies three essential *presences* that define effective online learning environments.

(i) **Cognitive presence** refers to the process through which learners construct meaning through sustained reflection and discourse. It is described as a multi-phased process beginning with a triggering event and followed by exploration, integration, and resolution. Codes related to factors that prompted or hindered these learning processes were categorized under cognitive presence.

(ii) **Social presence** captures the ability of participants to project themselves socially and emotionally in an online environment. Indicators include emotional expression, open communication, and group cohesion. Codes involving engagement or disengagement with the online social environment were placed in this category.

(iii) **Teaching presence** encompasses instructional design, facilitation, and direct instruction. Codes related to course structure, instructor guidance, feedback, and coordination with instructional designers were grouped within teaching presence.

In some cases, codes aligned with multiple presences depending on context. Following CoI guidance, the dominant meaning within the participant's statement was used to determine final placement. After classification, a codebook was developed to ensure consistent application across the dataset.

Large language model-assisted coding

A large language model (GPT-4) was used to conduct coding using the same CoI framework alongside human coding. The purpose of this approach was to compare the LLM and human-generated themes, identify additional patterns that might not emerge through manual analysis alone, and explore how computational methods can support qualitative inquiry in online learning research.

The first step involved preparing the CoI framework definitions for the LLM. The definitions, elements, and categories of the CoI framework were extracted directly from the article by Garrison et al.[20]. This information was provided to the LLM using the initial prompt *CoI definition* shown in Table 1. A human coder reviewed all definitions output by the LLM to verify their accuracy against the original article before proceeding to the next stage.

Table 1: Prompts used for LLM analysis.

Category	Prompt
CoI definition	”You are an expert researcher. I am providing you with an academic paper on the ”Community of Inquiry” (CoI) framework. Your goal is to extract the coding scheme definitions from this paper to be used for future classification tasks. Please output a structured guideline that : 1. Cognitive Presence, 2. Social Presence, 3. Teaching Presence. Format the output clearly so it can be used as a System Prompt for another LLM instance. Do not include preamble, categories or extra text, just the definitions found in this specific paper.”
Identifying and categorizing themes	”Extract specific, granular learning elements mentioned in the instructor interview from the textall file. Focus on items related to [cognitive/social/teaching] presence. Output each element as a concise phrase. List every specific mention without analysis or categorization.”

In the second step, the LLM was supplied with the interview transcripts as input and instructed (using the second prompt *Identifying and categorizing themes* from Table 1) to identify and extract themes aligned with the three CoI presences: cognitive, social, and teaching. The LLM processed each transcript independently and generated a detailed list of codes based on the framework. In addition to identifying themes, a frequency analysis was conducted on the LLM output to quantify how often specific codes and CoI-aligned concepts appeared across the interview transcripts. This enabled the identification of the pedagogical elements most commonly emphasized by participants and facilitated an assessment of the relative salience of cognitive, social, and teaching presence within the dataset. The LLM-generated themes and frequency counts were then compared with the manually coded themes to identify areas of convergence and divergence, and refine the interpretation of the data.

Results

This section presents an analysis and discussion of the preliminary results derived from applying the methodology outlined earlier to the 9 faculty survey responses. In their responses, faculty highlighted a range of factors that influence how students make meaning, persist through challenges, and stay engaged in online STEM coursework. As this study is still ongoing, interviews with instructional designers have not yet been conducted.

Cognitive Presence

Figure 1 summarizes the frequency of codes related to cognitive presence across human and LLM-generated analyses. Faculty often emphasized that the flexibility of online learning allows students to progress at their own pace, thereby better accommodating the individual requirements of each student. Human coding identified flexibility eight times, while the LLM detected four instances. This suggests that flexibility through adjustable pacing, modular course design, and opportunities to revisit content play an important role in how instructors conceptualize meaningful cognitive engagement in online learning. The higher count by human coder indicates that instructors may describe flexibility indirectly or within broader reflections on learning processes, which the LLM is less sensitive to. A similar pattern appears for *self-paced learning* (5 human vs. 2 LLM) and *student motivation* (4 human vs. 2 LLM). In contrast, *virtual help sessions* showed perfect alignment between methods (5 human vs. 5 LLM), indicating that discrete, clearly named supports are equally detectable computationally.

Additional themes identified as contributing to cognitive presence by the two approaches varied. The human coder tended to highlight broader pedagogical or contextual issues such as planning struggles, low-quality course design, academic integrity concerns, ineffective online course structures, and the suitability of certain courses for online delivery. In contrast, the LLM primarily extracted concrete instructional elements, including assignments, lecture videos, quizzes, synchronous sessions, projects, and discussion questions, treating these explicit course components as indicators of cognitive presence.

Flexibility, pacing, and motivation emerge as major concerns, suggesting that metrics such as pacing variability, completion trajectories, early or late engagement, and help-session use are particularly meaningful. Since instructors also reference motivation and self-regulation, learning-analytics systems may need to rely on behavioral proxies such as login patterns, resource revisits, or time-to-resubmission to represent these internal processes.

Human and LLM agreement, such as *virtual help sessions*, show automated coding can reliably scale explicit instructional supports, while divergences in implicitly expressed constructs such as motivation and self-pacing highlight the continued need for human interpretation.

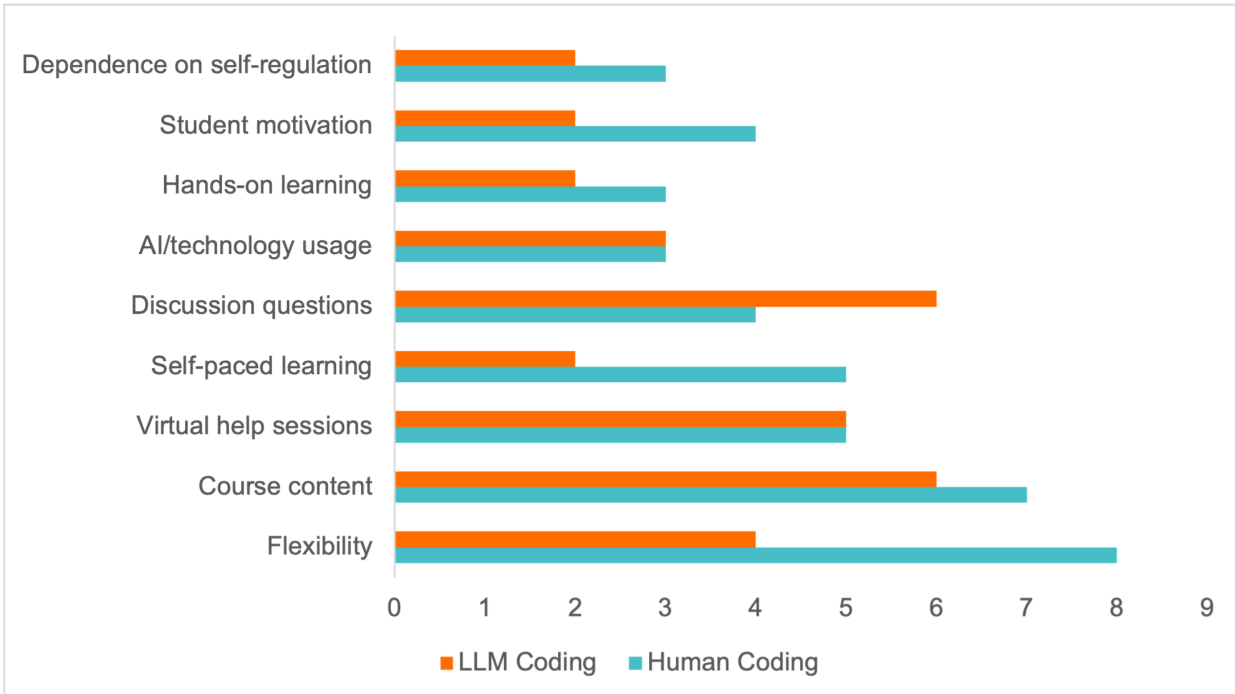

Figure 1: Frequency of codes that affect Cognitive Presence

Social Presence

Faculty highlighted several factors that influence how students connect with one another and with instructors in online STEM courses. Figure 2 shows the frequency of codes associated with social presence across human and LLM-generated analyses. As with cognitive presence, areas of alignment particularly emerged around discrete, explicitly named tools.

Across both methods, *discussion boards* was one of the most frequently identified indicators of social presence (7 human vs. 6 LLM). This suggests that well-defined, commonly referenced platforms for peer interaction are reliably recognized in both human and LLM analysis. Similar alignment appeared in codes related to interactions with students and *asking/answering questions*, though human coders identified these more often, indicating a greater sensitivity to indirect references to interpersonal exchange. Larger discrepancies emerged in areas where social presence was implied rather than named directly. *Optional meeting times* showed the greatest divergence (6 human vs. 3 LLM), suggesting that humans more readily interpret flexible synchronous opportunities as inherently relational even when they are embedded within broader descriptions of course logistics. Smaller differences surfaced in *feedback* (5 human vs. 3 LLM) and *email communication* (2 human vs. 6 LLM), reflecting subtle distinctions in how each method interprets comments related to instructor responsiveness or communication channels.

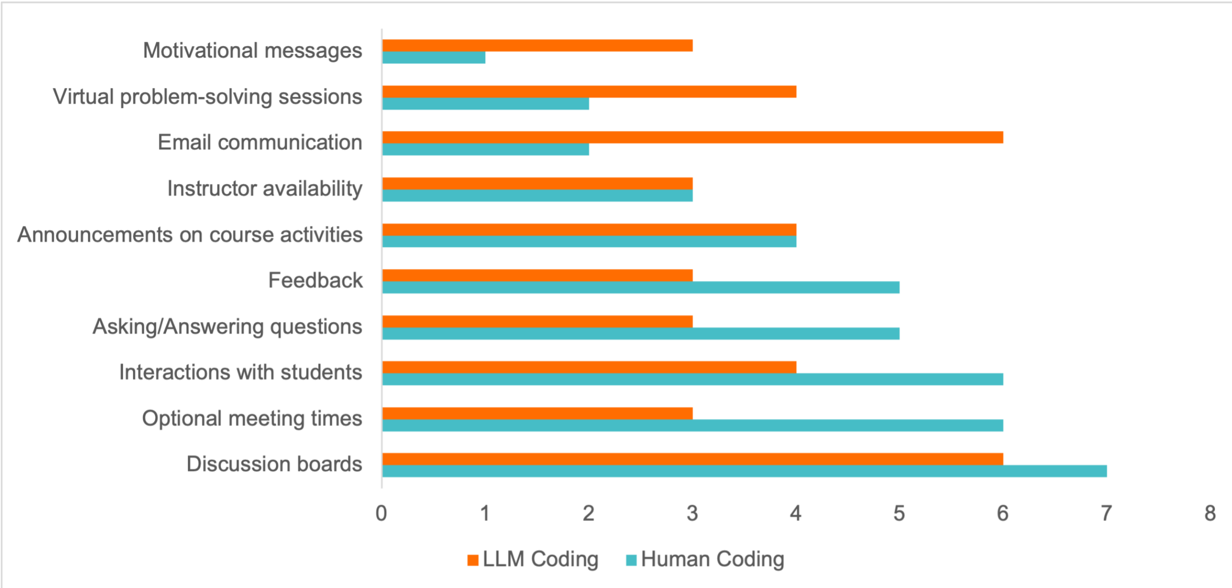

Figure 2: Frequency of codes that affect Social Presence

Both approaches also identified additional themes. Human coder highlighted interpersonal dynamics situated within broader instructional contexts such as feedback on assignments or attendance during live sessions that signal relational presence even when not labeled as such. In contrast, the LLM identified concrete instructional elements linked to collaborative engagement, including mentoring, collaborative projects, hands-on activities, weekly meetings, and flexibility in communication. These patterns mirror those observed in cognitive presence that human analysis is more attuned to nuances and implicit relational cues, whereas the LLM excels at extracting explicit, structured references. As with cognitive presence, differences in detecting subtle or contextually embedded relational cues imply the continued need for human interpretation.

The above findings also suggest that LA systems aiming to represent social presence may benefit from combining direct indicators (e.g., discussion posts, email threads, optional meeting attendance) with behavioral proxies (e.g., response times, consistency of communication, patterns of synchronous participation) to fully capture the interpersonal dynamics.

Teaching Presence

Figure 3 summarizes the frequency of codes related to teaching presence across human and LLM-generated analyses. As in the other presences, several areas of alignment appeared alongside some divergences that highlight differences in how each method detects instructional practices.

Both approaches showed good agreement on *curated external resources*, the most frequently identified indicator of teaching presence (9 human vs. 8 LLM). This suggests that faculty place significant emphasis on selecting, organizing, and integrating supplementary materials to support student learning. Similar alignment occurred for *structured weekly approach* though human

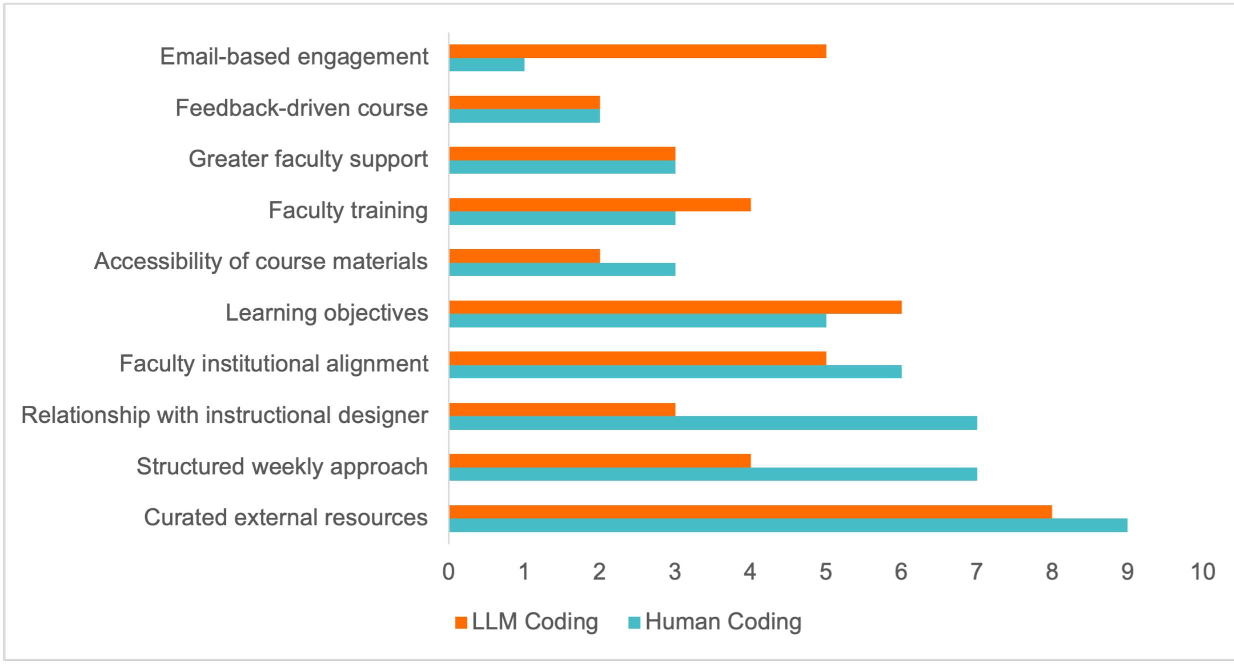

Figure 3: Frequency of codes that affect teaching Presence

coders tended to identify this organizational element more often. This pattern echoes earlier findings that humans are more sensitive to references such as course organization and goal-setting embedded within broader narrative descriptions of instructional planning.

Inconsistencies between the two coding approaches is also observed. *Email-based engagement* showed the largest divergence (1 human vs. 5 LLM). In contrast, *relationships with instructional designers* and *faculty institutional alignment* appeared far more frequently in human coding (7 and 6 counts) than in LLM coding (3 and 5 counts). Smaller differences emerged in *faculty training*, *learning objectives*, and *accessibility of course materials*, with the LLM slightly more likely to tag general references to professional development or support structures as elements of teaching presence.

Additionally, the human coder identified course rigidity, inclusive user interface design, course process streamlining, working around instructor's needs, targeted resource suggestions, faculty misconceptions, recruiting considerations, addressing student weaknesses, and expanding online course offerings as codes for teaching presence. These reflect a more holistic view of teaching presence as shaped by institutional roles, design constraints, and support structures. However, the LLM extracted lecture videos, addressing student confusion in real time, assigning team activities, accessibility to students, supporting reasoning abilities and skill development and weekly availability for students as teaching presence. This mirrors patterns observed in the other presences that humans capture implicitly embedded or context-heavy elements, whereas the LLM prioritizes clearly named instructional components.

The above analysis also suggests that instructors see teaching presence as driven primarily by course design decisions and clear organizational structures. Faculty places high value on the intentional setup of course materials and pathways such as curated external resources, structured weekly approaches, and explicit learning objectives. At the same time, the presence of codes such as faculty support and faculty training indicates that instructors also view teaching presence as dependent on the infrastructure and support surrounding course delivery.

As a whole, the patterns observed across cognitive, social, and teaching presence suggest several actionable insights. Faculty consistently emphasized constructs such as flexibility, pacing, motivation, and relational engagement, which were frequently identified by human coders but only partially captured by the LLM. This could suggest that analytics systems and dashboards may be more effective when used as interpretive support rather than as primary indicators, with instructors using contextualized behavioral indicators such as pacing, communication, or participation, drawing on their experiential knowledge of course conduct and student needs. The alignment between human and LLM coding around explicitly structured instructional elements further suggests that automated approaches can reliably surface components of teaching presence, such as resources, activities, and communication channels, while humans remain essential for interpreting and understanding how these elements function in relation to pedagogy. These findings imply that actionable use of learning analytics depends on qualitative, human-centered interpretations that account for pedagogical intent, course structure, and institutional conditions that shape learning outcomes.

Conclusion

This study examined how qualitative insights from faculty and instructional designers can complement LA to provide a comprehensive understanding of online learning. Faculty described online learning environments in ways that traditional learning management system (LMS)-based analytics could not capture, highlighting how quantitative indicators such as clicks, logins, or page views often miss the motivations, constraints, and interpretations that shape student behavior. These findings support the need for human-centered LA that prioritize context, interpretability, and stakeholder perspectives.

Across the cognitive presence data, faculty emphasized flexibility and self-regulation. While asynchronous structures support personalized pacing, they can also inhibit the triggering events needed for deeper cognitive engagement. Faculty attributed these challenges not only to student motivation but also to limitations in course design and LMS structures. Incorporating qualitative data can help distinguish between these sources and support more accurate interpretations of learning patterns.

In terms of social presence, faculty reiterated that common engagement tools such as discussion boards often generate interaction but not meaningful connection. Analytics that focus on participation frequency therefore risk overstating actual engagement. Instructors emphasized that delayed feedback, superficial discussion prompts, and rigid communication tools constrain opportunities for genuine social presence. LA needs to address the quality, purpose, and relational dimensions of interaction rather than solely counting contributions.

Teaching presence emerged as the presence most tied to institutional structures, resources, and collaboration. Faculty noted that their ability to design high-quality courses, provide timely feedback, and act on analytics depends heavily on instructional design support, professional development, and alignment across institutional units. Participants also described difficulty translating LMS data into meaningful instructional decisions. This highlights the value of collaborative approaches to LA and course design, where instructors co-develop dashboards, indicators, and interpretations to ensure analytic outputs align with pedagogical frameworks.

This study also used an LLM to generate parallel qualitative coding. Comparing LLM-based themes with human-coded themes revealed that LLMs are effective at detecting explicit instructional elements such as structured activities, resources, and communication channels. However, they are less sensitive to implicit, contextual, or relational nuances that human coders identify. Rather than replacing human analysis, these findings illustrate how LLMs may serve as an initial layer of scalable categorization, with human interpretation providing the necessary nuance. This hybrid approach incorporates both automated and human-interpreted qualitative data to better represent the complexity of online learning environments.

This study is limited by its small sample size and single-institution context, which may restrict the transferability of the findings to other online learning environments. The perspectives analyzed were primarily those of faculty and instructional designers, providing only part of the broader learning ecosystem. Future work should incorporate insights from instructors, students, and system-level data across multiple institutions and larger sample sizes to build a more holistic understanding of online learning activity and how analytics are interpreted by different stakeholder groups. In addition, although the comparison between human and LLM coding offered useful insights into the potential role of automated qualitative analysis, the LLM results were shaped by the prompts and coding framework used. As such, they should not be interpreted as fully generalizable indicators of automated analysis performance.

Acknowledgments

The faculty who participated in this study are greatly appreciated for sharing their perspectives on online learning, making this research possible.

References

[1] T. Elias, "Learning analytics," *Learning*, vol. 1, p. 22, 2011.

[2] B. Sherin, N. Kersting, and M. Berland, "Learning analytics in support of qualitative analysis." International Society of the Learning Sciences, Inc.[ISLS]., 2018.

[3] S. Johnson, P. Nath, and S. Bakrania, "Deepening insights from learning analytics through student perspectives," in *2025 ASEE Annual Conference & Exposition*, 2025.

[4] E. J. C. Amaya, F. Restrepo-Calle, and J. J. Ramírez-Echeverry, "Discovering insights in learning analytics through a mixed-methods framework: application to computer programming education," *Journal of Information Technology Education: Research*, vol. 22, pp. 339–372, 2023.

[5] C. Lenhart and J. Bouwma-Gearhart, "STEM faculty instructional data-use practices: Informing teaching practice and students' reflection on students' learning," *Education Sciences*, vol. 11, no. 6, p. 291, 2021.

[6] C. Klein, J. Lester, T. Nguyen, A. Justen, H. Rangwala, and A. Johri, “Student sensemaking of learning analytics dashboard interventions in higher education,” *Journal of Educational Technology Systems*, vol. 48, no. 1, pp. 130–154, 2019.

[7] I. Rets, C. Herodotou, V. Bayer, M. Hlosta, and B. Rienties, “Exploring critical factors of the perceived usefulness of a learning analytics dashboard for distance university students,” *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, p. 46, 2021.

[8] H. L. Herriott and M. A. McNulty, “Virtual learning impacts communication and teamwork,” *The Clinical Teacher*, vol. 19, no. 5, p. e13514, 2022.

[9] S. R. Cellini, “How does virtual learning impact students in higher education?” Brookings, 2021. [Online]. Available: https://www.brookings.edu/articles/how-does-virtual-learning-impact-students-in-higher-education/

[10] M. Van Wart, A. Ni, P. Medina, J. Canelon, M. Kordrostami, J. Zhang, and Y. Liu, “Integrating students’ perspectives about online learning: A hierarchy of factors,” *International Journal of Educational Technology in Higher Education*, vol. 17, no. 1, p. 53, 2020.

[11] Z. Xiao, X. Yuan, Q. V. Liao, R. Abdelghani, and P.-Y. Oudeyer, “Supporting qualitative analysis with large language models: Combining codebook with GPT-3 for deductive coding,” in *Companion Proceedings of the 28th International Conference on Intelligent User Interfaces*, 2023, pp. 75–78.

[12] Z. Taylor, “Using ChatGPT to clean interview transcriptions: a usability and feasibility analysis,” *SSRN*, 2023. [Online]. Available: http://dx.doi.org/10.2139/ssrn.4437272

[13] E. Kasneci, K. Seßler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier *et al.*, “ChatGPT for good? On opportunities and challenges of large language models for education,” *Learning and Individual Differences*, vol. 103, p. 102274, 2023.

[14] C. Wu, S. Zipf, N. Li, and D. B. Hellar, “Data-informed instruction: pedagogical responses and obstacles in using learning analytics,” in *2025 ASEE Annual Conference & Exposition*, 2025.

[15] W. Symes, R. Lazarides, and I. Hußner, “The development of student teachers’ teacher self-efficacy before and during the covid-19 pandemic,” *Teaching and Teacher Education*, vol. 122, p. 103941, 2023.

[16] S. K. Ahmed, R. A. Mohammed, A. J. Nashwan, R. H. Ibrahim, A. Q. Abdalla, B. M. M. Ameen, and R. M. Khdhir, “Using thematic analysis in qualitative research,” *Journal of Medicine, Surgery, and Public Health*, vol. 6, p. 100198, 2025.

[17] H. M. Dai, T. Teo, N. A. Rappa, and F. Huang, “Explaining Chinese university students’ continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective,” *Computers & Education*, vol. 150, p. 103850, 2020.

[18] V. Braun and V. Clarke, “Using thematic analysis in qualitative research,” *Qualitative Research in Psychology*, vol. 3, no. 2, pp. 77–101, 2006.

[19] J. Fereday and E. Muir-Cochrane, “Demonstrating rigor using thematic analysis: A hybrid approach of inductive and deductive coding and theme development,” *International Journal of Qualitative Methods*, vol. 5, no. 1, pp. 80–92, 2006.

[20] D. R. Garrison, T. Anderson, and W. Archer, “Critical inquiry in a text-based environment: Computer conferencing in higher education,” *The Internet and Higher Education*, vol. 2, no. 2-3, pp. 87–105, 1999.

[21] D. R. Garrison and J. B. Arbaugh, “Researching the community of inquiry framework: Review, issues, and future directions,” *The Internet and Higher education*, vol. 10, no. 3, pp. 157–172, 2007.

Appendix A: Faculty Survey Questions

Background and Experience

(i) Can you identify the online courses and the number of times you have taught each course?

(ii) How would you categorize these courses in terms of the type of content and delivery?

Course Design and Delivery

(iii) What are the salient components of your online course (videos, readings, other activities) that support learning?

(iv) Briefly describe what engagement in an online course means to you?

(v) Describe the key mechanisms you frequently deployed to maintain or enhance engagement in your course?

Effective Practices and Barriers

(vi) What do you see as the strongest or most effective aspects of online teaching at Rowan University?

(vii) What are the biggest challenges or limitations you have observed in online teaching at Rowan University?

Opportunities and Challenges Ahead

(viii) What opportunities do you see for improving or expanding online teaching at Rowan University?

(ix) What factors might undermine the effectiveness of online teaching at Rowan University?

Appendix B: Instructional Designer Survey Questions

Background and Experience

(i) How long have you worked in instructional design or online course support?
(ii) How many online courses have you designed or supported at Rowan University?
(iii) What types of courses or disciplines do you usually work with?

Course Design and Engagement

(iv) How do you structure your course content (videos, readings, activities) to support learning?
(v) How do you ensure courses are accessible, inclusive, and effective in supporting learning outcomes?
(vi) What challenges do you encounter when designing courses to engage students effectively?

Collaboration with Instructors

(vii) How do you collaborate with instructors during course design?
(viii) How much emphasis is placed on the quality and content of the lecture videos?
(ix) How effective is your collaboration in shaping course design, structure, content, and assessments?

Evaluation and Recommendations

(x) How do you assess whether a course is successful in supporting student learning outcomes?
(xi) What improvements or best practices would you recommend for online course design at Rowan University?