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Epistemic Network Analysis of Pre-Service Teachers' Generative AI interactions for Lesson Design: The Role of AI Competency and Digital Literacy

Gayathri POTHANCHERI[a*], Shashi Kant SHANKAR[b], Rwitajit MAJUMDAR[c] & Pankaj CHAVAN[d]
[a]Department of Cognitive Sciences and Psychology, School of Social and Behavioural Sciences, Amrita Vishwa Vidyapeetham, India
[b]Mathematical and Physical Science Division, School of Arts and Sciences, Ahmedabad University, India
[c]Research and Education Institute for Semiconductors and Informatics, Graduate School of Social and Cultural Sciences, Kumamoto University, Japan
[d]Center For Education Technology, Indian Institute of Technology Jodhpur, India
*gayathri.p@ammachilabs.org

Abstract: Artificial Intelligence, particularly Generative AI is increasingly used by teachers for instructional design, making the prompt design an essential competency. Effective prompt design requires competencies beyond digital literacy, including AI-related knowledge and competencies. However, existing assessments rely mostly on self-reported skills, which may fail to capture how these competencies are being reflected in lesson design tasks. This study applied Epistemic Network Analysis to examine how Pre-service teachers' prompt design competencies differ across levels of AI competency and Digital literacy. 43 participants completed an activity to design prompts to explain the concept of momentum to Grade 9 students. Based on median split approach on AI competency and Digital literacy, participants were grouped as High-High, High-Low, Low-High and Low-Low. Prompts were coded using the COSTAR rubric, across six dimensions - Context, Objective, Style, Tone, Audience, and Response. ENA modeled co-occurrence relationships among these elements across groups. Results showed different epistemic structures across competency levels, with high digital literacy groups demonstrating strong centralization around the objective, while high AI competency groups showing more centralization towards Audience and Tone dimensions. These results shows how AI competency and digital literacy shapes reasoning for prompt design, emphasizing the need for training the teachers to develop AI competency.

Keywords: Generative AI competency, Prompt Design in Teacher Education, Epistemic Network analysis, Pedagogical reasoning of Prompt Design

1. Introduction

Artificial Intelligence (AI), particularly Generative AI (GenAI), is transforming the traditional way of developing lesson Design for the teachers in daily teaching practice (Ruiz-Rojas et al., 2023). For example, teachers are increasingly interacting with GenAI using prompts to generate explanations and prepare teaching materials (Celik et al.,2025). However, to designing effective prompts in contexts involving multiple factors (like learning objectives, learner characteristics, and context) requires more than typical digital competencies. Thus, the teachers need to develop competencies that extend beyond the basic digital literacy to (Gen) AI-related competencies, to interact with AI systems in a TPACK-informed way (Koehler & Mishra, 2009).

In teacher education, developing these competencies is particularly significant for pre-service teachers (PSTs), as they will be the future practitioners in everyday teaching across diverse classrooms (Celik et al.,2025). PSTs may have varying levels of digital literacy and AI competency, making it important to understand how these competencies influence prompt design as part of teacher preparation.

Despite the growing importance of AI competency, existing assessment approaches rely more on self-reported measures such as surveys and questionnaires derived from standard frameworks like DigiCompEdu and UNESCO AI Competency Framework for teachers (Caena et al., 2019; Cukurova et al., 2024). These measures might not capture how competencies translate into classroom tasks due to potential bias and reporting limitations.This highlights the need for empirical approaches that can collect process-related data to understand competencies with performance-based learning activity data. Multimodal Learning Analytics (MMLA) as an empirical approach provides such opportunities by enabling the collection of multimodal datasets including instructional artifacts, textual inputs, system interaction traces, and design outputs (Cukurova et al., 2024). However, extracting and modelling the relationships between competency constructs and multimodal empirical data from such digital systems still remains a challenge.

Network-based analytical approaches provide a framework for addressing this challenge. Epistemic Network Analysis (ENA), a quantitative ethnographic method, models relationships among coded epistemic elements as networks of connections (Shaffer et al., 2016). ENA captures co-occurrence patterns and examines network structures providing insight into how competency differences reflect in observable behaviour. By comparing network structures across groups, ENA enables interpretation of structural patterns linked to competency differences. In AI-mediated teaching contexts, prompt design serves as a valuable source of multimodal empirical data. However, limited research has examined how competency differences shape the structural organization of prompt design through network-based approaches.

To address this gap, this study applies ENA to multimodal prompt design data generated by PSTs. By modelling co-occurrence relationships among prompt design components and comparing the epistemic structures across competency groups, this study aims to extract and interpret the structural relationships between PSTs' AI competency, digital literacy, and their initial prompt design behaviour, addressing the following research question: How do the complex structural relationships among pre-service teachers (PSTs) in prompt design components differ across levels of digital literacy and AI competency?

2. Methodology

This study employs an ENA design to examine differences in epistemic structures across participant groups with varying levels of AI competency and digital literacy. Data were collected through a structured prompt-improvement activity conducted on the LA-ReflecT learning analytics platform (Majumdar et al., 2022). PSTs were tasked with designing instructional prompts for GenAI to explain the concept of momentum to Grade 9 students, given the context that "Imagine that you are teaching the concept of momentum to Grade 9 students. During your lesson, you realize that many students are still confused about the concept of momentum. To address this, you decide to use AI to generate explanations to address your students' learning difficulties. You realize that better prompts could help the AI produce clearer explanations." The activity was structured in three sequential phases: Design (Initial Prompt): Participants created an instructional prompt from scratch, ReDesign_1: Participants revised their prompt after reflecting on learner constraints, and ReDesign_2: Participants further refined their prompt to address specific learning difficulties or misconceptions.

2.1 Participants and grouping

Participants completed validated survey instruments measuring AI Competency and Digital Literacy. A median split approach was applied to categorize participants into High and

Low categories for each construct, resulting in four distinct groups as follows HH (High AI Competency, High Digital Literacy; n = 9), HL (High AI Competency, Low Digital Literacy; n = 8), LH (Low AI Competency, High Digital Literacy; n = 12), and LL (Low AI Competency, Low Digital Literacy; n = 14).

2.2 Coding Scheme

The Initial prompts were then rated based on the COSTAR evaluation rubric for Prompt analysis to capture the epistemic elements (Ohalete et al., 2025). Each prompt was coded binarily (1 = Element present; 0 = Element absent) across the following codes: Context, Objective, Style, Tone, Audience and Response.To establish reliability, inter-rater reliability was calculated using Cohen's kappa. Across 258 coding decisions (43 participants, 6 dimensions, 2 raters), substantial agreement was observed (k = 0.71), indicating strong consistency between raters. Discrepancies were resolved through discussion, and consensus ratings were used for final analysis.

2.3 Pre-processing of Epistemic Network Analysis

The ENA online tool was used to model the structural relationships among the elements. Examples of matrix construction are given in the table below (see Table 1).

Table 1. Example of Data Matrix Construction Used for ENA Analysis

Participant ID	Group	Context	Objective	Style	Tone	Audience	Response
P9	HH	1	1	1	1	1	1
P30	LL	0	0	0	0	0	0
P7	HL	1	1	1	0	1	0
P37	LH	0	1	1	0	1	0

In ENA webtool, Participant ID is the Unit, Group (HH, HL, LH, LL) are the Conversation, and COSTAR Context, Objective, Style, Tone, Audience, Response is the Code. So, each participant becomes a network, participants are grouped into HH, HL, LH, and LL, and the codes become the network nodes. For each participant, ENA computes active nodes and the edges formed.

3. Findings

According to the ENA of the first-stage prompt design, all four groups of prompts exhibit distinct epistemic structures. These four networks exhibit variations in density levels and co-occurrence patterns, which indicate the qualitative variations in the structural integration of the prompt components across varying performance levels.

3.1 HH

The HH group shows a network with a strong and dominant connection between Audience and Objective (see Figure 1). It indicates that the participants with high levels of AI competency and digital literacy make a connection between who is learning and what is being learned. The network also shows connections branching from the center toward Context, Response, Style and Tone. It indicates a broad approach in which the objective lies in the centre, similar to the classroom context. The other prompt elements are centered on the Objective rather than being peripherally interconnected.

3.2 HL

The HL network has a square-like structure, with edges connecting Tone, Response, Audience, and Objective, indicating a multidimensional integration of the elements that extends beyond audience and objective alignment (see Figure 2). The weight of the edges is relatively uniform. The strong reciprocal connections among these four components indicate that participants in this group strive to balance all the elements necessary for effective prompt design. However, the absence of explicit centralization suggests an inclusive yet less hierarchical design.

3.3 LH

In the LH group, nearly all dimensions converge toward the Objective in a highly centralized, dense network (see Figure 3). This centralization indicates that the objective functions as the major point of focus around which other prompt design elements are organized. The convergence pattern depicts that other components are primarily being connected to the Objective only. But the high density of the connections shows the strong co-occurrence across the dimensions. The strongest connections are found around Objective and Context.

3.4 LL

The LL network is the most dispersed, with a significant emphasis on the link between Objective and Context, as well as the connections to Tone and Response (see Figure 4). With relatively weaker and fewer connections, this group exhibits a diffused network structure. However, a significant connection is observed in the link between Objective and Context, along with the secondary and weak connections to Tone and Response. This pattern explains that rather than sequentially aligning the design elements, participants of this group rely on the contextual signals to define the learning objectives. The LL group network does not have a centralized structure and a focused alignment, unlike the HH and LH groups. The connection between Context and Objective is the only significant connection within this group.

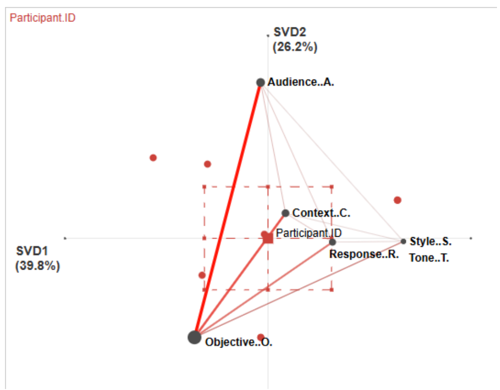

Figure 1. ENA network of relationships among prompt design components in the HH group.

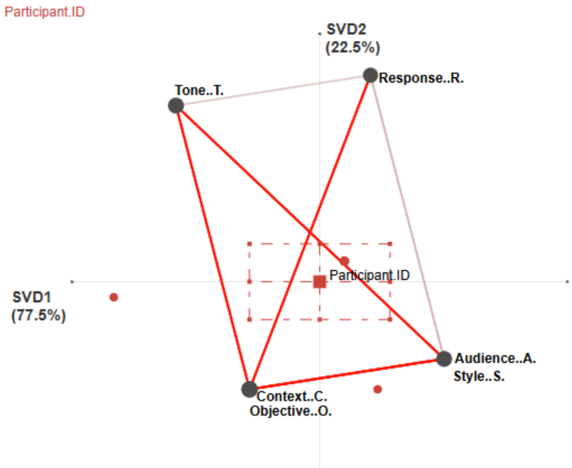

Figure 2. ENA network of relationships among prompt design components in the HL group.

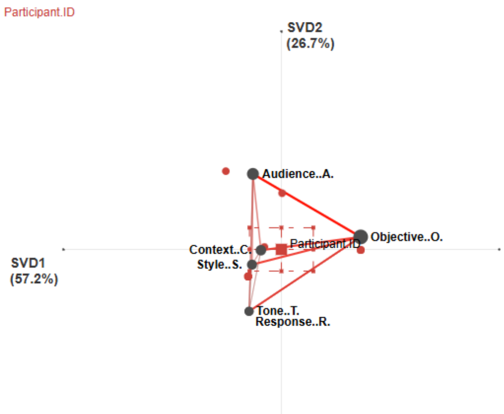

Figure 3. ENA network of relationships among prompt design components in the LH group.

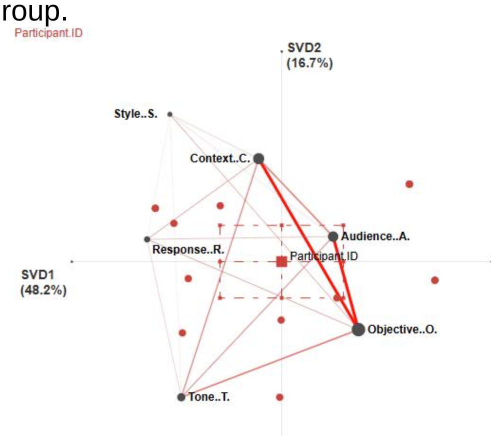

Figure 4. ENA network of relationships among prompt design components in the LL group

The results showed that the groups with higher digital literacy (HH, LH) tend to have centroids or strong connections toward Objective and Context. While groups with high AI competency (HH, HL) show active engagement with the Audience and Tone nodes, resulting in a more expansive network that leverages the AI's generative capabilities.

4. Discussion

The findings of the study reveal the systematic differences in how the participants with varying levels of AI competency and digital literacy design the prompt. The findings suggest that the Objective was the major element, which acted as the anchor upon which the prompt design depended.

4.1 Sequential organization of components

The HH group demonstrated a focused network with the strongly co-occurring elements Audience and Objective. It indicates that the PSTs with both high AI competency and digital literacy sequentially organize the prompt components, starting from the pedagogical alignment between learner characteristics and instructional goals. This finding is consistent with an earlier study that found more structured and integrated epistemic networks among experts or high-performing learners (Guo et al.,2023). In particular, Guo et al. (2023) pointed out that higher cognitive engagement groups demonstrated more coherent and organized epistemic networks, leading to deliberate attempts to integrate the key instructional elements rather than keeping it fragmented. The emphasis on Audience and Objective alignment in the HH group aligns with the pedagogical content knowledge (PCK) components of the TPACK framework, indicating that lesson planning begins with a thorough understanding of the learning objectives in relation to the learner characteristics (Koehler & Mishra, 2009; Shulman, 2013). Thus, it is evident that PSTs with high AI competency and digital literacy leverage AI as a pedagogical partner to explicitly align learning objectives with learner needs, thereby maximizing the relevance and effectiveness of AI-generated outputs.

4.2 Multidimensional integration in mixed competency groups

In mixed-competency HL groups, a multi-directional network with significant reciprocal connections shows that the PSTs simultaneously balance the pedagogical and communicative aspects of prompt designing. However, there is a lack of a centroid organizing anchor, indicating a less hierarchical epistemic structure compared to the HH group. It confirms a previous finding that learners with moderate competencies tend to focus on multiple task features simultaneously. But they may lack prioritization strategies that enable efficient integration (Ng, 2008). The LH group showed the most centralized network, with Objective as the dominant anchor for all connections, indicating that high digital literacy alone may help them develop a structured instructional mindset, but this does not necessarily result in effective AI-specific prompt formulation. This result aligns with the recent research emphasizing the need to distinguish between general digital literacy and AI-specific competency (Chiu et al.,2024). While digital literacy enables individuals to understand and structure digital tasks, AI competency involves other skills, such as understanding how AI interprets the instructions and generates outputs.

4.3 AI Competency and Digital Literacy in epistemic structuring

A major contribution of this study is the identification of the different roles AI competency and digital literacy play in shaping epistemic networks. Stronger centralization around Objective and Context was observed in groups having higher levels of digital literacy (HH and LH), suggesting that digital literacy acts as a facilitator for goal-oriented instructional design. This finding is consistent with studies showing that digitally literate students are better able to handle and organize digital information and the instructional process. The groups with higher levels of AI competency (HH and HL) had a stronger connection between Audience and Tone, indicating AI's sensitivity to communicative framing. This finding aligns with a recent study on AI literacy, which found that it involves the ability to strategically formulate instructions that guide AI output generation. The presence of a broader, and integrated network suggests that

AI competency contributes to more sophisticated prompt engineering strategies.

4.4 Implications for Teacher Training and Network-based Analysis

The PSTs with lower competency having fragmented epistemic structures, indicating their difficulty in aligning their instructional need with AI interaction. This underscores the need for structured training in AI-mediated instructional design, with explicit focus on audience, learning objectives, and response specification. Such training can enable PSTs to develop coherent prompt design strategies that effectively align pedagogical reasoning with AI capabilities.

5. Conclusion

This study shows how the competency differences are being reflected in the way PSTs organize the pedagogical and communicative elements in GenAI-interaction, emphasizing the importance of considering Competency as a performance-based construct, emerging through the integration of multiple components. However, this study is limited by its focus on the first level of designing only, which may limit the results from full range of prompt design practices across contexts. Future research would examine the prompt development longitudinally across multiple design phases to understand how the epistemic structures evolve across iterations. By integrating the multimodal interaction data such as time duration, revision patterns and AI response iterations, could provide insights into the development of AI related pedagogical competencies as well. Overall, the findings can contribute to the design of evidence based interventions that better support teachers in integrating AI into their classrooms effectively.

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