Surfacing Tacit Reasoning: A Methodological Approach to Tracing Teacher–AI Complementarity Through PID, TPACK, and SRL

Alice Aaviksoo[1,*], Reet Kasepalu[1], Jörgen Ivar Sikk[1] and Kairit Tammets[1]

[1]*Tallinn University, Estonia*

Abstract

Generative artificial intelligence is increasingly used in education, yet little is known about how teachers' professional knowledge and self-regulatory processes unfold when working with these tools. This pilot study introduces an analytical approach for tracing how teacher competence intersects with the generative capabilities of artificial intelligence during lesson design. The approach combines situation-specific perception–interpretation–decision skills, self-regulated learning processes and technological pedagogical content knowledge to observe teachers' real-time reasoning. Analysing interactions through this approach made teachers' underlying reasoning processes visible, revealing how pedagogical reasoning, contextual awareness and ethical judgement shaped the way AI-generated ideas were adapted or constrained. Findings suggest that the integration of teacher expertise and AI capabilities was more apparent when teachers engaged in critical and ethical regulation of the design process. These insights may inform future work on Learning Analytics approaches that recognise teachers' reasoning patterns and support more balanced forms of human–AI collaboration in lesson design.

Keywords

Generative AI, Lesson Design, Teacher Expertise, Self-Regulated Learning, Situation-specific skills, TPACK, Human-AI Complementarity

1. Introduction

Generative AI tools are increasingly capable of producing learning materials and lesson structures, yet how they are integrated into teachers' professional design practices remains poorly understood. Prior research has focused mainly on student personalization and task automation [1–3], offering limited insight into teachers' cognitive processes when working with AI during lesson planning. As AI becomes embedded in everyday teaching, supporting instructional design and decision-making [5], understanding teachers' professional reasoning, rather than mere tool use, becomes critical. This pilot study addresses the gap by examining teachers' professional reasoning while planning lessons with generative AI. Rather than introducing a new theory, we refine an analytical approach that captures how teachers activate professional knowledge (TPACK), situation-specific skills, and self-regulatory processes, and how these interact with AI's generative capacities. Teachers were asked to plan a lesson with GenAI while thinking aloud, allowing us to examine lesson planning as a collaborative process in which teachers' professional pedagogical judgments guide AI output. Drawing on the PID (perception–interpretation–decision) model as the primary analytical lens, and informed by TPACK and self-regulated learning (SRL), the study addresses two research questions: (1) What knowledge, self-regulatory processes, and situation-specific skills do teachers activate when planning with AI? and (2) How do teacher actions and AI functions complement each other during this process? PID structures the analysis by tracing how teachers perceive, interpret, and decide upon AI-generated information in lesson design. TPACK and SRL are not parallel models but explanatory layers that specify the knowledge base and regulatory mechanisms operating within PID processes.

Joint Proceedings of LAK 2026 Workshops, co-located with the 16th International Conference on Learning Analytics and Knowledge (LAK 2026), Bergen, Norway, April 27 – May 1, 2026.

*Corresponding author.
aliceaav@tlu.ee (A. Aaviksoo); reetkase@tlu.ee (R. Kasepalu); ivarsikk@tlu.ee (J. I. Sikk); kairit@tlu.ee (K. Tammets)
0009-0008-1322-0818 (A. Aaviksoo); 0000-0003-3389-8673 (R. Kasepalu); 0009-0001-9262-0711 (J. I. Sikk); 0000-0003-2065-6552 (K. Tammets)

2. Theoretical background

2.1. Teacher competence: dispositions and situation-specific skills

Teacher competence is a complex construct that integrates cognitive, motivational, and affective capacities with context-dependent professional actions. Following Blömeke et al. [6] and Roth et al. [7], competence develops along a continuum linking teachers' underlying dispositions to their situation-specific skills and results in observable pedagogical actions. These relatively stable dispositions - knowledge, beliefs, motivation - shape how teachers perceive and interpret professional situations and provide the latent capacities for action. Situation-specific skills are conceptualised as perception, interpretation, and decision-making (PID) processes [6]. Perception involves noticing relevant cues, interpretation links these cues to pedagogical or theoretical knowledge, and decision-making entails selecting actions based on this understanding. PID thus explains how teachers' underlying professional knowledge becomes visible in their instructional decisions. In lesson planning, PID traces how teachers recognise curricular demands, interpret AI-generated ideas, and decide how to integrate or adapt technological options into coherent instruction. This makes PID a critical lens for understanding how pedagogical intentions are aligned with technological means and for identifying the types of cognitive processes that learning analytics systems should capture to support effective teacher–AI complementarity. Dispositions provide the foundational basis for perception, interpretation, and decision-making.

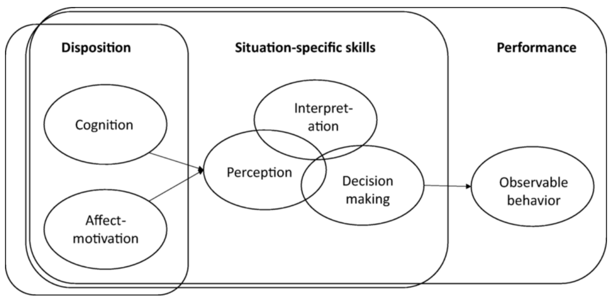

Figure 1: Competence framework, Blömeke et al., 2015

In AI-supported lesson design, self-regulation and teachers' dispositions on professional knowledge are especially relevant. Knowledge-based dispositions are captured through TPACK [8], which in AI contexts includes teachers' ability to critically evaluate AI outputs and decide which suggestions to adopt, adapt, or reject [4]. Self-regulation refers to teachers' capacity to plan, monitor, and evaluate their engagement during complex design tasks [9,10] shaping whether they critically engage with AI suggestions or rely on them without reflecting. Professional action is viewed as cyclical: teachers perceive AI suggestions, interpret them using professional knowledge, and make design decisions, while self-regulation supports evaluation, prompt refinement, and alignment with pedagogical and ethical goals.

2.2. Teacher-AI learning design

Learning design refers to planning how people learn through activities and resources that support the development of knowledge and skills [11]. In this study, we focus on lesson planning as teachers' situated design decisions for a single lesson, directly preceding classroom enactment and shaped through collaboration with AI. GenAI can support teachers continuously adapting their practices by offering ideas, drafting materials, suggesting alternatives, and serving as a reference point for decision-making, while pedagogical and contextual judgement remains with the teacher. Prior studies show that teachers use GenAI to create lesson materials, structure lessons and courses, give feedback, and deepen their understanding of content [12–15]. At the same time, risks such as bias, over-reliance, and reduced pedagogical reflection have been noted [16–18]. These risks underline that effective AI integration depends on teachers' professional competence and their ability to critically evaluate and adapt AI-generated ideas. This motivates our analytical focus on teachers' moment-to-moment PID and SRL processes, through which such critical filtering occurs and human–AI complementarity can emerge during lesson planning.

2.3. Teacher-AI complementarity

The growing use of generative AI in education is reshaping teachers' work, positioning AI not only as an automation tool but as a collaborator within hybrid intelligence systems. Teacher–AI complementarity refers to collaboration where AI and teachers contribute different but complementary strengths to lesson design [2,19]. AI can generate ideas, alternatives, and information quickly, while teachers provide the contextual, pedagogical, and ethical judgment needed to evaluate and adapt these outputs [20]. From a situation-specific skills perspective [6], complementarity emerges through teachers' perception, interpretation, and decision-making. AI may surface goals, resources, or learner-related suggestions, but teachers decide what to attend to, how to interpret it, and whether and how to use it in a given context. Lesson design therefore results from a distributed process in which teachers' professional knowledge guides the use of AI-generated suggestions. Productive teacher–AI interaction depends on the integration of teachers' professional knowledge (TPACK), self-regulation, and PID skills. This can be described across three dimensions: cognitive complementarity, where teachers contextualise and transform AI-generated ideas; procedural complementarity, where teachers regulate when to rely on or revise AI suggestions; and ethical complementarity, where teachers ensure accuracy, inclusivity, and fairness in AI-assisted materials [4,13,21]. Understanding how these processes unfold during real-time lesson planning remains an important focus for research on teacher–AI collaboration.

3. Methodology

3.1. Research design

This exploratory qualitative design study used a think-aloud observational approach to capture teachers' real-time reasoning during lesson planning with generative AI. As a pilot study, the focus was on tracing teachers' perception, interpretation, and decision-making cycles and associated self-regulatory processes. While the think-aloud method may potentially influence participants' behaviour by prompting more deliberate reflection than would occur naturally [23], this was acceptable given the aim to trace and make visible the moment-to-moment, context-dependent cognitive and regulatory processes that usually remain tacit in lesson design. To enhance interpretive depth, we triangulated teachers' verbal reasoning with observable design actions, including screen activity, prompt iterations, and artifact production. Participants were asked to design a genuine lesson they would actually teach, using their preferred GenAI tools and typical (classroom) resources to strengthen authentic validity. Although this reduced experimental control, it produced rich, situated interaction data necessary to refine the complementary analytical approach and capture real complexities of teacher–AI co-design.

3.2. Context and sampling

Participants were recruited through an open call distributed by the Estonian Association of Educational Technologists to teachers' institutional email addresses. Twelve teachers initially responded. Two school board members and two teachers who reported no prior use of generative AI in lesson planning were excluded from the study. The remaining eight participants represented diverse subject areas, educational levels and degrees of AI experience. All eight teachers took part in the think-aloud sessions; however, detailed qualitative analysis was conducted on the data from three participants (see Table 1). The purpose of the pilot study was to explore how teachers integrate generative AI into lesson planning and to develop and refine an analytical approach for tracing the steps to teacher–AI complementarity in design processes. Given this aim, we prioritised analytical depth over breadth by examining a small number of information-rich cases to enable in-depth analysis of teachers' reasoning and regulatory processes. The three focal cases were purposefully selected to stress-test the analytical approach by representing contrasting approaches to lesson design and differing dispositions toward the use of AI. All participants provided informed consent before data collection. Data was anonymized and all identifiers were removed from recordings and artifacts prior to analysis to ensure confidentiality.

Table 1
Overview of the three focal teacher cases

Case	Subject / Grade	Lesson topic	AI exp.	Tools	Session	Utter.
T1	Informatics / G5	Cyberbullying	Regular	ChatGPT, Gamma	60	170
T2	BritLit / G10	George III and his era	Regular	ChatGPT, Copilot, Gemini	40	130
T3	Maths / G10	Exponents	Regular	ChatGPT, Gemini, Mathpix	70	320

Across all three cases, teachers mainly worked with general-purpose conversational GenAI agents thus human–AI interaction was broadly comparable across cases and could be characterised as iterative input-output exchanges. All participants self-reported regular prior use of GenAI tools which was also supported by observational evidence: teachers interacted confidently, formulated and revised prompts, uploaded and adapted their materials, and recovered smoothly from minor technical disruptions. In all cases, teachers were designing a lesson within their primary subject area, had articulated learning goals and intended outcomes in advance and entered the session with an initial lesson structure in mind.

3.3. Data collection

Each teacher participated in an individual online session (60-90 minutes) conducted via Zoom with at least two researchers present. Sessions were recorded in full, from the initial setup to the post-session interview. The main task was to plan a lesson and create related materials as teachers would normally do for their own teaching. To support consistency, participants received standardized task instructions and a brief think-aloud guide containing prompts aligned with the perceive–interpret–decide sequence and task episodes (defining lesson context, articulating pedagogical frameworks, creating materials).

Teachers shared their screens while working on the task, allowing researchers to observe their design actions (tool switching, prompt writing, AI output modifications). Researcher intervention was minimal – limited to brief reminders or clarifications. All sessions captured audio, video and screen activity, while artifacts (prompts, AI outputs, lesson plans/material) were exported where possible to supplement verbal data.

3.4. Data analysis

After the sessions, one researcher manually transcribed the recordings in Google Sheets, including timestamps and key on-screen actions (e.g., tool switching, prompt formulation). Transcripts were segmented into meaningful utterances, each representing a complete idea or decision [24] and aligned with the research questions.

Utterances were coded using a combined deductive–inductive approach. Initial codes were drawn from the PID, TPACK, and SRL frameworks and refined iteratively. Each utterance could receive up to three codes to capture different layers of reasoning: (1) PID codes (perception, interpretation, decision-making) representing situation-specific skills; (2) TPACK components indicating the knowledge base underlying the utterance; and (3) SRL dimensions reflecting regulatory processes shaping the action. This approach allowed us to capture the multidimensional nature of teachers' reasoning rather than forcing utterances into single categories.

The observational study aimed to trace teachers' PID skills and SRL processes during AI-supported lesson planning; a think-aloud approach was used to surface tacit reasoning while interacting with AI. Initial coding approach identified task phases, teacher actions (operations) and activated knowledge domains allowing to describe what occurred during lesson planning with AI. As insufficient for explaining why particular pedagogical decisions were made, PID layers were added to capture teachers' reasoning process: what teachers noticed in the situation, how they interpreted AI outputs regarding context and pedagogical aspects and how these informed decisions. SRL layers were included to capture regulatory processes that guided evaluation, adaptation or rejection of AI suggestions.

Coding was conducted by the first author who iteratively refined the coding framework during analysis. The aim was not to establish a stable taxonomy but to examine whether a combined PID-SRL-TPACK framework could meaningfully explain teachers' reasoning behind observable action. Throughout the analysis, emerging interpretations and coding decisions were discussed with members of the research group who provided alternative perspectives, feedback and clarifications that informed the refinement of the framework.

SRL coding was informed by Karlen et al. [9] and Pintrich [10] and organised into three dimensions: cognitive regulation (task reasoning and content organisation), metacognitive regulation (monitoring, evaluation, and strategy adjustment), and motivational regulation (effort, interest, and task value). PID coding followed Blömeke et al.'s [6] competence model, distinguishing utterances that reflected noticing relevant cues (perception), making sense of them through professional reasoning (interpretation), or selecting and adapting instructional actions (decision-making). To specify the knowledge bases activated within PID, these categories were further elaborated using the TPACK framework [8].

Data analysis proceeded at multiple levels. Frequency analysis identified common PID, SRL, and TPACK activations, while pattern analysis examined co-occurrences across layers. Qualitative analysis then focused on key interaction episodes marked by shifts between teacher actions and AI outputs. These episodes were used to examine teacher–AI complementarity, operationalised through combined PID, SRL, and TPACK traces, and to assess whether interactions reflected augmentation or dependence within hybrid intelligence lesson design.

4. Results

4.1. Knowledge, self-regulatory processes and situation-specific skills activated

To address the first research question – What kinds of knowledge, self-regulatory processes, and situation-specific skills do teachers activate when planning lessons with AI? – the results are presented in two parts. First, frequency counts establish the baseline activation of the observed components (PID, TPACK and SRL) that constitute teacher competence. This baseline is essential for tracing how these components later interact to form complementarity within Hybrid Intelligence systems. Percentages illustrate relative distributions of knowledge activation (TPACK) and regulatory processes (SRL) within and across teachers in this pilot data-set. Not to support statistical generalisation, rather these observed distributions reflect the different forms of reasoning during AI-supported lesson design primarily aiming to test the analytic approach and inform subsequent larger-scale studies. Second, qualitative excerpts from the think-aloud protocols illustrate how teachers' PID cycles of perceiving, interpreting, and deciding reflected the activation of different knowledge and regulatory processes during AI-supported lesson design.

4.1.1. Distribution of TPACK components

Overall, teachers activated a broad range of knowledge domains when designing lessons with AI. However, the frequency patterns varied notably across participants (see Table 2). Teacher 1 and 2 predominantly drew on Pedagogical Knowledge (32.9% and 37.2% respectively of all coded utterances), often reasoning about instructional structure and student engagement when evaluating AI suggestions. Teacher 3, in contrast, showed a more balanced distribution between Technological Knowledge (25.6%) and Pedagogical Content Knowledge (23.1%), reflecting both a focus on exploring AI tools and their affordances and on aligning technological outputs with content-specific instructional aims.

The distribution of TPACK components indicates how teachers positioned AI within their reasoning. The strong activation of Pedagogical Knowledge across participants suggests that teachers primarily

Table 2
Distribution of TPACK components across three teachers

Teacher	CK	PK	TK	PCK	TPK	TCK	TPACK
Teacher 1	1.3%	32.9%	8.9%	2.5%	15.2%	27.8%	11.4%
Teacher 2	7.0%	37.2%	11.6%	20.9%	7.0%	14.0%	2.3%
Teacher 3	1.3%	11.5%	25.6%	23.1%	9.0%	17.9%	11.5%

used AI as a pedagogical consultant, grounding AI-generated ideas in instructional strategies, learner needs and curricular goals. These dominant areas can be interpreted as knowledge-based dispositions, reflecting where each teacher's reasoning was primarily anchored: pedagogical for Teacher 1, didactic for Teacher 2 and technological for Teacher 3. These dispositions shaped how each teacher evaluated AI outputs, made instructional decisions, and integrated pedagogy, content, and technology into a coherent lesson design.

4.1.2. Distribution of SRL components

While the TPACK analysis revealed the types of knowledge teachers activate when designing lessons with AI, the next step was to explore how teachers regulated these knowledge processes in real time. Understanding SRL during design provides insight into how teachers planned, monitored and evaluated their interactions with AI (see Table 3).

By analyzing metacognitive, cognitive and motivational regulation across all utterances, we aimed to identify dominant regulatory patterns and how these shaped teachers' engagement with AI throughout the lesson planning process. Cognitive and metacognitive regulation dominated overall, though their balance varied across participants. Teacher 2 displayed a more metacognitively driven orientation, while Teachers 1 and 3 relied primarily on cognitive control.

Table 3
Distribution of SRL components across three teachers

Teacher	CR		MR		MoR	
	n	% of Total	n	% of Total	n	% of Total
Teacher 1	50	56.8%	35	39.8%	3	3.4%
Teacher 2	17	37.0%	28	60.9%	1	2.2%
Teacher 3	61	58.7%	41	39.4%	2	1.9%
Total	128	53.8%	104	43.7%	6	2.5%

Across all coded utterances, cognitive regulation (CR) was the most frequent process (53.8%), indicating that teachers worked with AI in a predominantly task-level, goal-oriented manner. CR involved organizing or adapting content to meet instructional aims. For example, Teacher 1 noted "I'll take those first four scenarios and add them to the presentation," Teacher 2 remarked "AI didn't do 3x3 minutes for me, I definitely need to change that," and Teacher 3 stated "These questions should be written," referring to AI-generated content.

Metacognitive regulation (MR) accounted for 43.7% of all instances, reflecting teachers' continuous monitoring and strategic adjustment of their design approach. MR occurred when teachers evaluated AI outputs, assessed fit with lesson aims, or refined their prompting strategies (e.g. Teacher 1: "This movement game at the beginning of the lesson is appropriate because students can use their movements to show whether they remember the topic"; Teacher 2: "Not bad, but I can't spend 10 minutes of the first lesson on an introduction."; Teacher 3: "I have to base my decisions on whether I have students with narrow or broad mathematics – if there is a problem, I should repeat these things."). Motivational regulation (MoR) occurred rarely, emerging only when teachers expressed curiosity, doubt, or frustration (signals of affective engagement rather than major regulatory effort).

Taken together, the dominance of CR and MR indicates that teachers engaged with AI in a largely evaluative, goal-driven manner, focusing on improving design quality rather than managing motivation.

Importantly, the high presence of MR suggests that teachers actively monitored and adjusted their strategies – regulatory actions that shape the quality of human–AI interaction.

4.1.3. Situation-specific skills in action

While earlier sections described which knowledge domains and regulatory processes were activated, this section illustrates how teachers' situation-specific skills unfolded in real time during interaction with AI. Three brief episodes show how PID processes connect teachers' dispositions (TPACK and SRL) to professional action in AI-supported lesson planning. Across cases, teachers perceived situational cues, interpreted them through pedagogical or ethical reasoning, and made design decisions based on professional judgement.

Example 1: Beginning lesson planning Teacher 1 (Informatics, Grade 5) refined an initial prompt for a cyberbullying lesson by specifying class composition, lesson duration, wellbeing needs, and pedagogical preferences: "Movement breaks are important… I prefer to provide my own material so AI doesn't invent something non-evidence-based." The teacher noticed diverse learner needs (perception), anticipated risks in AI-generated content (interpretation), and constrained the AI by providing materials and requesting active methods (decision). This reflects a theory-driven prompting strategy in which AI is positioned as a controlled assistant.

Example 2: Adapting AI outputs to student interests Teacher 3 (Mathematics, Grade 10) rejected AI-generated examples that felt irrelevant: "These don't interest me or the students… I'll ask for a better context." Here, the teacher noticed a lack of relevance (perception), linked engagement to meaningful contexts (interpretation), and re-prompted the AI to generate a more suitable example (decision). This illustrates a learner-centred prompting strategy.

Example 3: Overriding AI due to pedagogical misalignment Teacher 2 (British Literature, Grade 10) evaluated outputs from different AI tools: "Completing a worksheet is one of the most boring tasks… so I won't do it." The teacher detected low engagement potential (perception), evaluated suggestions against instructional values (interpretation), and rejected them in favour of an active-learning approach (decision). This episode reflects a value-driven prompting strategy. Together, these episodes show how teachers use PID processes to actively shape AI contributions, ensuring that lesson design remains aligned with pedagogical goals, learner needs, and ethical considerations.

4.2. Complementarity episodes

To address the second research question – How teacher actions and AI functions complement each other during lesson planning? – we analysed moments in which teachers' situation-specific skills (PID) shaped how AI contributions were taken up, adapted, or constrained. We conceptualise these moments as complementarity episodes: brief instances where human professional reasoning and AI functions jointly contributed to an instructional decision. Teacher–AI complementarity emerged when teachers engaged in active perception, interpretation, and decision-making, supported by metacognitive regulation. Rather than occurring automatically, hybrid intelligence depended on teachers' metacognitive engagement and pedagogical judgment. In this study, complementarity did not reside in the tools themselves but emerged through teachers' PID processes. AI provided suggestions, while teachers' perception, interpretation, and decision-making guided selection, adaptation, and pedagogical alignment.

Operationally, a segment of teacher-AI interaction was coded as a complementarity episode only if all three minimum criteria were met: (1) an explicit reference to an AI-generated output (e.g., evaluating, quoting, or working with AI-proposed content); (2) enactment of at least one phase of the perception-interpretation-decision (PID) cycle in relation to that output; and (3) a signal of regulation, whereby the teacher actively constrained, adapted, or overrode the AI suggestion (e.g., critique, refinement, rejection, re-sequencing). Interactions involving AI use without PID enactment or regulation were not coded as complementarity episodes.

Complementarity episodes were identified through qualitative analysis of think-aloud protocols by segmenting teacher–AI interactions into decision-relevant episodes and examining whether all three criteria co-occurred within the same segment. Across the three cases, we identified 14 complementarity episodes for Teacher 1, 9 for Teacher 2, and 11 for Teacher 3, occurring at specific decision points rather than continuously throughout AI use. Importantly, not all AI use resulted in complementarity. For instance, during early lesson planning, Teacher 1 reviewed an AI-generated lesson outline and described it as "looking fine" without further interpretation, modification, or instructional decision. Although AI output was referenced, the absence of PID enactment and regulation meant that this interaction functioned as AI-supported automation rather than complementarity.

Cognitive complementarity refers to the interaction between teachers' interpretive reasoning and AI's generative capacity. This was illustrated by Teacher 3 (Mathematics) when attempting to connect exponent rules to roots. Although AI generated suggestions, the teacher identified a conceptual gap, interpreted it using pedagogical content knowledge, and ultimately adjusted the explanation independently. This illustrates partial cognitive complementarity: AI supported idea generation, but conceptual coherence depended on teacher-led interpretation.

Procedural complementarity describes how AI supports lesson structuring while teachers retain control. Teacher 2 (British Literature) used AI to generate an initial lesson outline, which she then refined by adjusting timing, sequencing, and activity types. While AI supported efficiency, the teacher retained control over instructional decisions, guided by pedagogical knowledge and self-regulatory monitoring. Complementarity here was present but asymmetrical, with the teacher directing the process.

Ethical complementarity captures teachers' role in ensuring that AI-assisted designs are appropriate and inclusive. This was illustrated by Teacher 1 (Informatics) when adapting AI-generated activities for students with diverse needs. She evaluated suggestions through pedagogical and contextual reasoning and rejected options that posed social or emotional risks. In this case, complementarity relied on the teacher's ethical judgment to constrain and guide the suggestions provided by AI. Across cases, teacher–AI complementarity functioned as distributed reasoning - AI contributed ideas, structure, and alternatives, while teachers provided pedagogical meaning, contextual interpretation, self-regulation, and ethical oversight. Complementarity was strongest when teachers engaged with AI iteratively and reflectively, highlighting that effective Hybrid Intelligence in lesson planning depends on professional competence rather than solely tool capabilities.

5. Discussion and conclusions

Understanding how teachers mobilize technological, pedagogical, and content knowledge together with self-regulatory processes and situation-specific skills is important when planning lessons with GenAI. The findings suggest that GenAI did not interrupt or replace teachers' professional reasoning: teachers actively engaged with AI and weighed its outputs against their instructional needs.

Using PID as the analytical structure, we traced what teachers perceived, how they interpreted AI suggestions in relation to TPACK, and which pedagogical decisions followed, shaped by SRL processes. While teachers worked toward their goals, GenAI provided no diagnostic feedback: it neither highlighted imbalances nor guided teachers toward more coherent integration across TPACK, SRL, and PID, but simply generated responses to prompts. As a result, teachers often remained unaware of how their reasoning patterns shaped the interaction. For example, strong PCK frequently guided prompts, evaluations, and adaptations, yet teachers did not explicitly recognise this influence. Thus, the data reveals not only what teachers know, but what drives their decision-making tacitly.

Teachers relied most often on cognitive regulation (organising and integrating content or tasks) drawing primarily on habitual TPACK domains rather than on metacognitive monitoring of why particular strategies were appropriate. Consequently, they did not always perceive when their reasoning became overly constrained, indicating insufficient metacognitive regulation.

These findings have direct implications for teacher–AI complementarity. Complementarity seemed to emerge when teachers engaged in active monitoring, adjustment, and ethical judgment. GenAI did not correct or balance their reasoning, reinforcing that meaningful AI use requires critical engagement from the human side [4]. Importantly, complementarity remained bounded by teachers' existing knowledge and skills: AI amplified what was already strong but did not extend these boundaries.

This constraint points to an opportunity for Hybrid Intelligence. Because competence lies in orchestrating PID, TPACK and SRL, pedagogically aligned AI systems must be able to detect where breakdowns occur across perception, interpretation and decision-making, and where these components are present or missing. This requires learning analytics capable of analysing teachers' interactions with AI across PID cycles including prompts, revisions, evaluations, and monitoring moments. If systems can infer where attention is limited, for instance accurate perception but narrow interpretation (strong PCK but weak consideration of technological affordances), or minimal metacognitive monitoring during decision-making, systems could respond adaptively through nudges or reflective prompts. In this way, complementarity could be actively supported rather than assumed.

Taken together, the study shows that analysing teacher–AI interaction through PID-TPACK-SRL lenses makes underlying reasoning visible, often more visible to researchers than to teachers themselves. In the analysed cases, teachers predominantly relied on existing professional dispositions, and complementarity was most evident when teachers engaged in critical and ethical regulation of AI outputs. Based on these observations, we propose the following propositions for future testing: Hybrid Intelligence systems may build on this insight by supporting balanced knowledge integration, metacognitive regulation, and reflective, ethically grounded decision-making, provided they are informed by analytics that trace interaction patterns reflecting underlying professional competence.

Acknowledgments

This research was partially funded by the European Union, project TAICo – Teacher AI Complementarity (project number 101177268) and by the European Union and Estonian Ministry of Education and Research via project TEM-TA26.

Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT, Grammarly in order to: Grammar and spelling check, paraphrase and reword. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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