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# Three inseparable facets and five new knowledge domains: An extended GenAI-TPACK proposal

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**ABSTRACT**

With the emergence of generative artificial intelligence (GenAI) in the field of education, the ability of the traditional Technological Pedagogical Content Knowledge (TPACK) framework to explain teacher competencies in the AI era has come under study. In this conceptual study, a new model aimed at explaining teacher competencies in the AI era has been proposed. The proposed Extended GenAI-TPACK framework draws its fundamental theoretical foundation from Demir's model, which positions technology and theoretical framework as two inseparable facets in technology integration programs; it adapts this model to the AI era by transforming it into a tripartite core (Technology + Theoretical Framework + AI Agency). The proposed framework includes five new knowledge domains surrounding this tripartite core (Critical Evaluation, Prompt Engineering, Human-AI Role Sharing, Ethics and Social Judgment, Student-AI Interaction Management) and a Phronesis axis that anchors the entire system within the classroom context. Additionally, Hughes' three-level technology integration model has been reframed through the Co-Agency axis to create a six-cell application matrix. The framework was developed to address the structural limitations of classical TPACK in the GenAI context and offers educational technology literature a conceptual tool that is both theoretical and operationally applicable.

**Keywords:** GenAI-TPACK, generative artificial intelligence, teacher competence, curriculum development, Hughes levels, co-agency, Phronesis

## INTRODUCTION

The rapid dissemination of generative artificial intelligence (GenAI) into the field of education has taken discussions about teacher competence to a new level. The widespread adoption of AI-supported tools in the classroom has raised important questions about whether these tools have transformed the challenges of technology integration that were discussed in the past, or whether they have simply reproduced them in a more intense form. It can be argued that the answers to these questions demand a serious reevaluation of whether traditional conceptual frameworks are sufficient.

The Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006), which has formed the conceptual backbone of the educational technology field for over fifteen years, conceptualizes teacher knowledge as the interaction of content, pedagogy, and technology components. This framework adds a technology dimension to Shulman's (1986, 1987) concept of Pedagogical Content Knowledge (PCK) and addresses the teacher's competence in technology integration within a multi-layered structure. The framework has found a broad range of implementations, from science education to mathematics instruction, from language education to professional development, and has served as the conceptual backbone of empirical studies in the field for over a decade (Koehler & Mishra, 2009; Tseng et al., 2022; Valtonen et al., 2019).

However, with the introduction of GenAI into the classroom, warnings are increasing that the explanatory power of classical TPACK is limited. Mishra et al. (2023) argued that the protean, opaque, unstable, generative, and social qualities of GenAI do not find a full counterpart within TPACK's current components. According to Feldman-Maggor et al. (2025), prompt engineering is partially based on TPACK. But AI-related competencies such as hallucinations, bias, and discrimination do not belong to any dimension of the TPACK framework. Similarly, according to Lan et al. (2025), ethical awareness should be an independent component within the GenAI-TPACK framework. Ríos Gonzales et al. (2025) note that while TPACK provides a solid foundation in a higher education sample, it does not fully explain faculty members' adoption of GenAI. Therefore, the framework must be extended to include AI-specific competencies. Meanwhile, noting the shortcomings of the TPACK framework, Prilop et al. (2025)

argue for its extension to cover the triple construct of AI literacy. According to Zou et al. (2025), TPACK does not fully represent the new functions, risks, and skill levels that AI brings to education.

The starting point of this study is a previous conceptual model that argues technology and the theoretical framework must be treated as two inseparable facets in technology integration programs (Demir, 2011). In this model, the four core components of program development (purpose, content, teaching-learning situations, and assessment) are presented as a dynamic system shaped by both technology and the theoretical framework. Over the past fourteen years, the technology landscape has undergone a fundamental transformation. Unlike traditional technologies, GenAI does not appear as a passive tool but as an active component of the interaction process, engaging both teachers and students. The aim of this study is not to revise the 2011 model but to build upon its theoretical continuity and propose a new model for teacher competencies in the AI era. This new model has been developed to address the shortcomings of existing theoretical frameworks in education within the context of GenAI.

Three metaphors for understanding GenAI's pedagogical capacity can summarize the various facets of the discussions in the field. In the first metaphor, an AI-supported classroom can be envisioned as an environment with as many assistant teachers as there are students. This metaphor points to AI's capacity for personalized feedback and differentiated support. According to the second metaphor, the teacher occupies the role of a maestro in the AI era, coordinating multiple actors rather than performing alone. The third metaphor expresses a more cautious observation: GenAI has limited contextual memory and, much like an actor who learns quickly but forgets, requires re-contextualization with every interaction. When considered together, these three metaphors reveal that the pedagogical integration of GenAI is a process rather than a purely technical issue or an unlimited opportunity; it elevates the teacher's abilities in coordination, contextualization, and critical evaluation to a more critical position.

However, the introduction of GenAI into the educational field does not, by itself, produce positive outcomes. The historical experience of educational technology shows that while every new technology is initially met with exaggerated hopes, it produces limited impact when not contextualized within a pedagogical framework. The expectation that placing students in front of screens upon the computer's introduction to schools would automatically improve learning was later proven incorrect. As Cuban (2001) demonstrated in his classic analysis, there is no direct relationship between the frequency of technology use and pedagogical transformation. The risk of this same historical pattern repeating with GenAI is evident; Yan et al. (2024) and Bower et al. (2024) emphasize that GenAI's impact on education depends more on pedagogical integration than on technological capacity. As in Maslow's frequently cited observation, those who have only a hammer tend to see every problem as a nail; this tendency perpetuates the risk of a technology-centric interpretation in the GenAI era.

A distinction must be clarified from the outset when defining the scope of this study. AI-supported tools are also widely used in school administration, bureaucratic processes, reporting, and data management. While these uses are valuable, the focus of this study is on in-class pedagogical interaction and the role structure within the teacher-student-AI triangle. Bureaucratic uses of AI are not directly within the scope of this framework; however, they remain in the background as part of the school ecosystem.

Within this framework, the study has three primary objectives. First, to identify the structural limitations that classical TPACK faces in the context of GenAI and to propose new knowledge domains that overcome these limitations. Second, to construct a new model specific to the AI era by drawing on the theoretical legacy of Demir's (2011) two inseparable facets model. Third, to produce an operational matrix by reframing Hughes' (2005) three-level technology integration model through the lens of AI. The proposed Extended GenAI-TPACK framework is situated at the intersection of these three objectives.

## THEORETICAL FOUNDATIONS

### The Classical Structure of the TPACK Framework

The TPACK framework, developed by Mishra and Koehler (2006), conceptualizes teacher knowledge as the interaction of content (CK), pedagogy (PK), and technology (TK) components. The framework adds a technology dimension to Shulman's (1986, 1987) concept of Pedagogical Content Knowledge (PCK) and addresses the teacher's competence in technology integration within a multi-layered structure. Pedagogical Content Knowledge (PCK), Technological Pedagogical Knowledge (TPK), and Technological Content Knowledge (TCK) emerge from the dual intersections of these three main knowledge domains. At the center of this triple intersection lies TPACK. This dimension refers to a teacher's competence in selecting and applying pedagogically appropriate technology while teaching a specific content area. This entire structure is embedded within contextual variables such as the classroom, school, and educational system. A visual representation of the framework is presented in **Figure 1**.

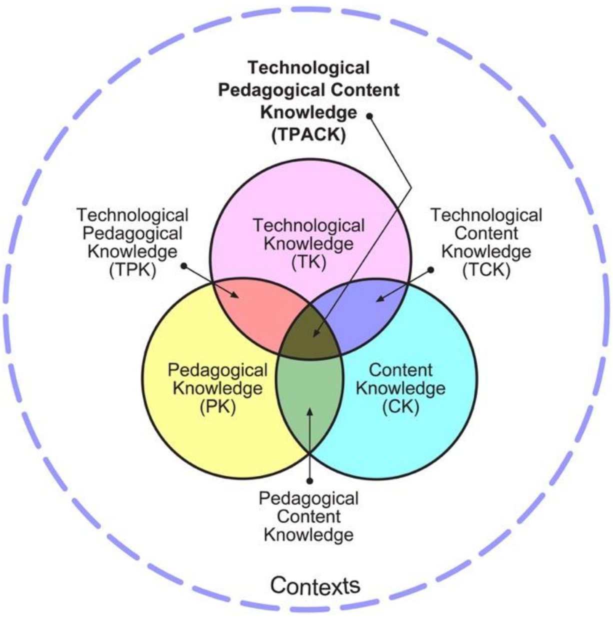


**Figure 1.** Three main knowledge domains and their intersections in the classical TPACK framework (Mishra & Koehler, 2006)

For more than a decade, the seven components of TPACK have functioned as a central conceptual tool in educational technology research. The framework has been applied across a wide range of disciplinary contexts.

In mathematics education, Niess (2005) viewed TPACK as a technique of representing mathematics teachers' understanding of instruction. Further work has followed this line of inquiry in several directions: the pedagogical reasoning exhibited by teachers when designing technology-supported lessons (Priyanda et al., 2025), the conceptualization of the integration of dynamic geometry environments such as GeoGebra (Bueno et al., 2021), and the analysis of the urban-rural digital divide through a TPACK lens (Li, 2025a). In the field of language, according to the results of the review study conducted by Tseng et al. (2022), the articles had different practices as (a) exploring TPACK, (b) assessing TPACK, (c) developing TPACK and (d) applying TPACK. In this field, TPACK was used effectively to scale teachers' competencies. In the field of social studies, TPACK can be used to assess preservice teachers' 21st century skills (Miguel-Revilla et al., 2019) as well as to measure their pedagogical skills in different cultures and contexts (Aksin, 2023). In STEM and STEAM contexts, the framework is often articulated as an interdisciplinary core (Karampelas, 2023; Meletiou-Mavrotheris et al., 2024).

Evidence on the framework's pedagogical contribution has also gathered. In a meta-analysis of teacher education interventions targeting TPACK, Ning et al. (2022) reported a large effect size ($d = .839$), and Jiménez Sierra et al. (2023) mapped patterns of TPACK development based on Lesson Study. Drawing on a three-year longitudinal study with Finnish teacher candidates, Valtonen et al. (2019) followed the developmental trajectory of TPACK components and observed that the most pronounced gains were in PCK. Taken together, this body of work indicates that the components of TPACK do not constitute a fixed or closed set; they appear to require periodic re-examination considering technological change.

## The Theoretical Foundation of Demir's (2011) Model

The model proposed by Demir (2011) argues that technology integration cannot be designed solely based on curriculum development principles or subject-area perspectives; rather, technology itself and the theoretical framework guiding its use must be considered as two inseparable facets. In this model, the four curriculum components (purpose, content, teaching-learning situations, and assessment) are shaped by the central dual core (technology and theoretical framework). The model's unique contribution lies in emphasizing that, during the evaluation process of technology integration, each of these two dimensions must be examined separately.

Demir (2011) also positioned Hughes' (2005) levels of technology integration as a program evaluation tool in the same study. Hughes' three-level model categorizes the qualitative level of technology use into Replacement (media substitution), Amplification (acceleration of the process), and Transformation (reorganization of classroom routines). Demir (2011) also added a "Level 0" category for situations where technology is not used or is used without a specific purpose. These levels have functioned as an applicable analytical tool in both teaching-learning contexts and the evaluation phase.

In the intervening years, the technology ontology underlying the 2011 model has undergone a fundamental transformation. The model conceived of technology as a tool; the teacher and student were the sole active agents in the classroom, while technology served as a passive component facilitating their objectives. However, GenAI, challenges this assumption. As will be demonstrated in the following sections, GenAI is no longer a passive tool but is positioned as an active component of the interaction process. This demands the development of a new model proposal that builds upon the theoretical legacy of the 2011 model.

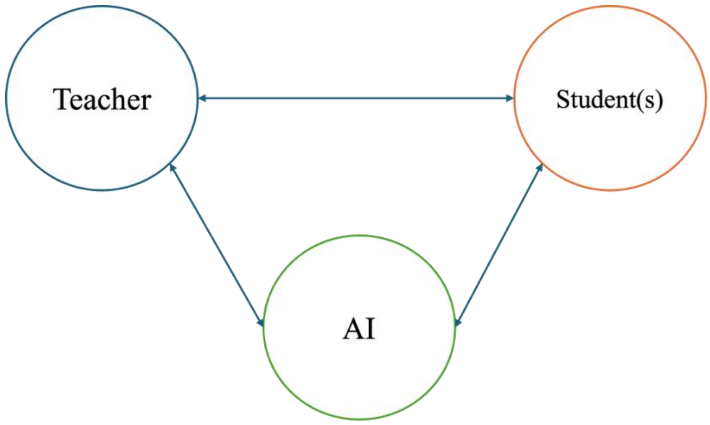


**Figure 2.** Teacher, student and AI interaction (Source: Authors' own elaboration)

## THE DISTINCTIVE NATURE OF GenAI

The limitations of classical TPACK become clearer once the distinctive features of GenAI are specified. Mishra et al. (2023) identified five such features: protean, opaque, unstable, generative, and social. Each feature marks a departure from earlier educational technologies. GenAI is multiform and context-dependent (protean); its internal workings remain largely invisible (opaque); it produces different outputs for the same input (unstable); it generates new content (generative); and it interacts with users (social). These features form the basis for the limitations discussed below.

The opaque and unstable nature of GenAI is most clearly observed in what the literature calls "hallucination." Huang et al. (2025) describe how large language models generate content that deviates from user input, contradicts prior context, or conflicts with established world knowledge. The authors propose a structural taxonomy of these errors. Several empirical studies show similar results. Athaluri et al. (2023) analyzed 178 scientific references generated by ChatGPT. A valid DOI number could not be found in 69 of these references and 28 references could not be found in Google searches. Magesh et al. (2025) found that 17-33% of the content produced by the specific AI, which was trained with RAG specifically for the field of law and was stated not to produce hallucinations, was hallucinatory.

The social and generative features of GenAI also change the structure of classroom interaction. Traditional classrooms are built around two main actors (teachers and students). Technology has the role of a mediating factor. In classrooms where GenAI is active, a triple factor emerges. The interaction is not unidimensional, but the three factors interact among themselves (**Figure 2**). Kim (2024a) conducted interviews with teachers in leadership positions and identified a three-stage development process in teacher-AI collaboration. In the first stage, the teacher is positioned as a passive recipient of AI. In the second stage, the teacher becomes an active user. In the third stage, the teacher and AI establish a constructive partnership. According to Katsenou et al (2025), the AI acts as a collaborator rather than a tool. This will create a dialectical interaction between the student and the teacher. Turvey and Pachler (2026) point to the tension between human-mediated and algorithmic-mediated pedagogy and argue that teacher agency needs to be reconceptualized within this tension.

This reconceptualization is supported by empirical work on AI's active agency. Frøsig and Romero (2024) argue that GenAI requires a hybrid intelligence approach to support teacher agency. Without this orientation, the teacher's capacity for decision-making, influence, and positioning may be narrowed by the system. Mouta et al. (2025b) studied educators and reported that AI systems reshape teacher agency at three levels: subjective, intersubjective, and collective. Practitioners tend to underestimate the intersubjective dimension. These findings indicate that the active agency of AI cannot be accommodated within the ontology of classical TPACK, where technology is positioned as a tool.

The challenges raised by GenAI extend beyond the pedagogical level. Templin et al. (2024) identify six fundamental challenges. These include bias generation, threats to data privacy, the misinterpretation of hostile inputs, and hallucination. The authors argue that none of these are directly addressed within the classical TPACK framework. Yan et al. (2024) examine both the promises GenAI offers for human learning and a set of accompanying concerns: model flaws, ethical dilemmas, and the disruption of traditional assessment structures. This cautious stance motivates the dimension developed as the Phronesis axis in the following sections.

## EXISTING AI-TPACK VARIANTS AND LIMITATIONS

The integration of GenAI into the TPACK framework has been the subject of several conceptual and empirical studies in the last few years. Ning et al. (2024) developed a seven-component and thirty-nine-item AI-TPACK scale to measure AI-supported pedagogical content knowledge. In the aforementioned study, teachers' AI-related pedagogical competencies were considered in a parallel structure with the classical TPACK components. In other words, the AI component was added to existing domains such as TK, TPK, TCK. This approach is based on the assumption that AI can be added to the TPACK framework, but it cannot fully reflect the distinctive qualities of GenAI.

Karataş and Ataç (2024) examined the AI-TPACK framework with structural equation modeling and reported that the ethical dimension stands out as the lowest rated component. This finding suggests that the ethical dimension is either inadequately conceptualized in existing frameworks or teachers have difficulty in internalizing this dimension. Lan et al. (2025) suggest that ethics knowledge should be positioned as a separate dimension in the GenAI-TPACK framework and criticize the current frameworks for treating ethics as a secondary element. Zulianti et al. (2024) empirically examined the AI-TPACK relationship in the context of novice EFL teachers' professional development. In the study, TPACK was structured as a usable professional development framework for the integration of AI-assisted tools into teaching and a program consisting of CKAI, TCKAI, PCKAI, TPKAI and TPACKAI components was developed. The framework treats AI tools not only as an addition to the field of technological knowledge, but as a teacher competency that is repositioned at the intersection of content, pedagogy and technology knowledge. Within the scope of the program, teachers are provided with content on the basic concepts of AI-supported tools, their applications in language teaching and ethical considerations. In addition, topics such as AI-supported assessment, personalized learning, lesson plan preparation and AI-based project development were also covered. The findings of the study showed that teachers who participated in the program had significantly higher knowledge of AI tools, AI-supported teaching skills and self-efficacy towards teaching with AI than the control group. These results point to the importance of hands-on professional development processes where teachers can relate AI tools to pedagogical goals, content area content, student needs and classroom context. However, this study focuses on the functional use of AI-supported tools within TPACK components rather than discussing the specific qualities of GenAI such as productivity, autonomy, data-driven adaptability and ethical risks at the theoretical level in depth. Therefore, the contribution of Zulianti et al. (2024) should be sought in showing how TPACK can be operationalized for AI-supported teacher education rather than the question of whether GenAI transforms the TPACK construct.

A common feature of these studies is that they merely add the AI component to the existing TPACK framework. This approach fails to internalize the social and generative qualities of GenAI, i.e. the active agency dimension, at the conceptual level. Feldman-Maggor et al. (2025) find that prompt engineering is a separate competency area that has no parallel in the current components of TPACK. Sperling et al. (2024) argue that teacher knowledge in the context of GenAI needs to be reappraised in three different domains: episteme (theoretical-scientific knowledge), techne (practical-productive knowledge) and phronesis (professional judgment). This Aristotelian tripartite distinction illustrates that the teacher's competence cannot be reduced to the cognitive-technical dimension and that professional judgment (phronesis) should be placed in a separate category.

Cukurova et al. (2025) proposed a taxonomy of teacher-AI cooperation in five layers, the bottom being transactional use and the highest being synergistic partnership. In contrast to traditional TPACK models, this model considers AI as an active element of interaction, not a passive tool. Mouta et al. (2025a) developed a framework for addressing difficulties in AI ethics for teacher professional development, discussing the ethical dimension of teacher agency particularly. Prilop et al. (2025) argue in a Danish case study that the AI literacy possesses a triadic nature (teaching tool, teaching content and learning tool) and that this triadic nature asks for the extension of TPACK within ethical, cultural and democratic frameworks.

## STRUCTURAL LIMITATIONS OF THE CLASSICAL TPACK

The literature summarized above highlights the structural limitations of the classical TPACK framework in the context of GenAI. These limitations can be considered not as independent shortcomings but as a continuum that extends from the ontological position of technology to the relationship that teachers and students establish with AI.

The first shortcoming relates to the ontological status of technology. The TPACK framework conceptualizes technology as a passive component that mediates the teacher's objectives. GenAI, however, functions as an active actor rather than a passive tool. Its ability to make suggestions, ask questions, and generate content are clear indicators of this shift (Katsenou et al., 2025; Mishra et al., 2023). This transformation requires a redefinition of the concept of "technological knowledge."

This ontological shift reveals a second shortcoming: the absence of a critical evaluation dimension. GenAI systems tend to generate hallucinations (Athaluri et al., 2023; Huang et al., 2025; Magesh et al., 2025). This tendency places the ability to check outputs and to engage in critical evaluation at the core of teacher competency. This dimension has no direct analog in the standard TPACK framework.

Beyond evaluation competence, it is obvious that dealing with AI needs a different kind of communication. Prompt engineering is not just a technical talent, but a communication competence interwoven with topic understanding and pedagogical judgment, as Feldman-Maggor et al. (2025) describe. Walter (2024) presents this ability as one of the essential components of AI literacy, while Federiakin et al. (2024) include this same competency among the 21st-century competencies. This dimension, which could be termed "prompt engineering," does not fit within the existing components of TPACK.

Beyond the issue of interaction, the question of how work done with AI should be shared also requires conceptualization. The five-level collaboration taxonomy proposed by Cukurova et al. (2025) and Kim's (2024a, 2024b) three-stage teacher-AI collaboration model indicate that role sharing should be addressed as a separate category within TPACK.

The issue of role sharing brings ethical and social judgment dimensions to the forefront. Alzahrani (2024) lists the "gray areas" in AI's integration into education as human connection, data privacy, algorithmic bias, transparency, critical thinking, access equity, and ethical issues. He also emphasizes that these issues are not separate from each other but form an interconnected whole. Farheen et al. (2025) have empirically shown statistically significant positive associations between teachers' beliefs about AI bias and their perceived concerns about educational justice. But Karakuş et al. (2025) compared the responses of teachers and

AI systems to ethical dilemmas. It has been shown that teachers are situated along axes of empathy and commitment to values whereas AI systems are situated along a more analytical and outcome-oriented axis. When we look at them together, we see the necessity for the ethical judgment to be made by human instructors and the necessity for the ethical dimension to be treated not as a component, but as an axis that runs through the whole framework.

Finally, managing the use of AI in the classroom goes beyond the scope of the traditional role of the teacher. Gerlich (2025) revealed that the alleviation of cognitive load creates a significant negative correlation between the use of AI technologies and critical thinking. Fan et al. (2025) suggested that the support provided by ChatGPT may lead to metacognitive complacency among students. This support seems to enhance short-term performance rather than knowledge acquisition and transfer. Zhang et al. (2024) associate dependence on AI with increased lethargy, the spread of disinformation, decreased creativity, and impaired critical thinking skills. In his comprehensive review, Zhai (2025) concluded that over-reliance on AI conversational systems negatively affects decision-making and analytical reasoning abilities. The findings suggest that educators are taking on a new management role in AI-enabled environments.

Taken together, these limitations demonstrate that the classical TPACK cannot be transferred to the GenAI context without being expanded. The Extended GenAI-TPACK framework presented in the next section proposes a conceptual response to each of these limitations.

## THE PROPOSED EXTENDED GenAI-TPACK FRAMEWORK

The proposed framework is presented as a new model designed for the GenAI era, drawing on the theoretical continuity of Demir's (2011) two inseparable facets model. This structure consists of four layers, each addressing one or more of the structural limitations identified in the previous section.

### Tripartite Core: Technology, Theoretical Framework, and AI Agency

In the first layer, the binary structure of the 2011 model was transformed into a tripartite structure. In the 2011 model, there is the technology and the theoretical framework, while in the proposed model, the AI agency is added here. AI Agency refers to teachers' competence to recognize, anticipate and pedagogically integrate GenAI's capacity to act as an interactive participant that generates content, asks questions, offers suggestions and influences classroom interaction. The rationale for the AI Agency dimension is drawn from many sources. Mishra et al. (2023) argue that the social and generative qualities of GenAI qualitatively distinguish it from previous technologies and that these characteristics have no counterpart in the existing components of the TPACK framework. Runge et al. (2025) state that AI-TPACK should be conceptualized not only as a simple extension of classical TPACK, but as a teacher competency domain that responds to the unique capabilities of AI technologies. According to the authors, AI-TPACK refers to teachers' competence in pedagogically using AI-specific features such as human-machine dialogues, automated assessment, and constructive feedback.

This emphasis supports treating GenAI not merely as a new tool added to the existing body of technological knowledge, but as an interactive and pedagogical form of technology that requires rethinking at the core of teacher knowledge. Katsenou et al. (2025) observe that AI has evolved from a "helper" to a "co-agent." Frøsig and Romero (2024) argue that this evolution should be modeled within the framework of the concept of hybrid intelligence. Turvey and Pachler (2026) note that the tension between human-mediated and algorithmic-mediated pedagogy requires a new theoretical tool. The AI Agency dimension transforms the common conclusion of the relevant literature into a structural component of the framework. Within this framework, Celik's (2023) Intelligent-TPACK model can be considered an important intermediate step. Celik argues that while TPACK can be used to explain AI-based instruction, teachers' knowledge must be expanded to include AI's pedagogical possibilities and ethical decision-making processes.

The model defines the components Intelligent-TK, Intelligent-TPK, Intelligent-TCK, and Intelligent-TPACK; thus, AI is treated not merely as a tool within the scope of technological knowledge, but as an instructional system that influences pedagogical decisions, discipline-specific applications, and ethical evaluations. This tripartite core is situated at the center of the model and serves as the theoretical foundation upon which all other knowledge domains are built.

### Five New Knowledge Domains

In the second layer, five new knowledge domains surround the tripartite core. These knowledge domains are designed to directly address the structural limitations of classical TPACK identified in the previous section. The theoretical foundation of each knowledge domain will be examined separately.

#### *Critical evaluation*

The Critical Evaluation knowledge domain refers to the competence to address the risks that GenAI outputs may contain hallucinations, biases, and false information. Huang et al. (2025) demonstrate that hallucination is a structural feature of large language models, making the user's verification competence critical. Athaluri et al. (2023) found that a significant portion of AI-generated references cannot be verified, which is particularly concerning in an educational context. Magesh et al. (2025) document that even advanced AI tools marketed as "hallucination-free" produce hallucinations at significant rates. In the field of education, Lee et al. (2024) report that teacher candidates' lesson plans prepared using ChatGPT contained hallucinated sources. Li (2025b) suggests that, in addition to basic literacy skills, students must be taught specific verification strategies—such as lateral reading, the SIFT method, and Socratic questioning—to cope with AI hallucinations. van den Berg and du Plessis (2023) emphasize that

ChatGPT should be intentionally incorporated into teacher education to develop critical evaluation skills. This dimension is positioned as a component of teacher competence not only at the knowledge level but also at the skill and disciplinary levels.

### *Prompt communication*

The Prompt Communication knowledge domain covers the competencies of iterative dialog with GenAI, context structuring and persona design. The view that these competencies cannot be explained by the technical knowledge (TK) component in the classical TPACK framework is becoming increasingly evident in recent literature. Feldman-Maggor et al. (2025) explicitly define prompt engineering as an uncommon competency with no equivalent among the current TPACK components. Walter (2024) considers AI literacy, prompt engineering and critical thinking as three inseparable core competencies. Knoth et al. (2024) empirically show that AI literacy is a predictor of prompt engineering competence and directly affects the quality of LLM output.

There are different approaches on how to conceptualize prompt engineering. Federiakin et al. (2024) consider it as a 21st century skill and propose an assessment framework. Oreški et al. (2025) offer a more comprehensive reading, redefining prompt engineering not only as a technical skill but as a form of literacy. This redefinition implies that the field is evolving from a purely operational competence to a conceptual and critical one. Empirical evidence from the educational context is in line with this theoretical discussion. Elsayary et al. (2025) show that efficient use of prompts improves teachers' effectiveness using GenAI tools and the relevancy of the materials they create in lesson planning. Al-Abdullatif (2024) describes AI literacy as the capability of an individual to utilize AI applications, to evaluate the capacity and limitations of these apps, to respect ethical standards and to be conscious about privacy and security issues.

Based on this definition, interacting with GenAI extends beyond the ability to give technical commands and requires the user to evaluate the limits of the tool, the reliability of its outputs, and the context of use. In this respect, Prompt Communication is closely related to AI literacy, but is considered as a more specialized area of interactional competence. As a whole, it defines Prompt Communication as a unique area of competence that cannot be fit into technical knowledge (TK).

### *Human-AI role sharing*

The field of Human-AI Role Sharing refers to the determination of the division of labor between teachers and AI based on pedagogical principles. Celik (2023) highlights the aspects that distinguish AI-based technologies from traditional instructional technologies. These technologies can interact with teachers, generate alerts regarding student progress, and assume decision-support functions in the instructional process. Therefore, a teacher's knowledge should not be limited to merely operating the AI tool or understanding its technical functions; it must also include the ability to interpret notifications from AI in a pedagogical context, monitor students' learning processes, and translate feedback provided by AI into instructional decisions. This finding supports the view that the division of roles between humans and AI should be approached not as a technical task distribution but as a form of collaboration grounded in the teacher's pedagogical judgment.

The subject of how to structure this collaboration is approached from several perspectives in taxonomic investigations from the field. Kim (2024a) observed that teacher-AI collaboration progresses via a three-stage developmental trajectory with the expectation that instructors will have TPACK knowledge and skills in conflict resolution related to AI. Cukurova et al. (2025) propose a five-level taxonomy of cooperation, proposing a developmental trajectory from transactional to synergistic teaming. Moreover, Al-Abdullatif's (2024) Intelligent TPACK items also measure the instructional character of human-AI role sharing. According to the report, teachers need the ability to adapt diverse GenAI tools for real-time feedback, support personalized learning, and employ GenAI in the development of tests and assessments. The ability to integrate instructional content, GenAI tools, and teaching methodologies and pick relevant tools to measure student learning is also highlighted. This paradigm shows that GenAI is not perceived as a replacement of the teacher element but a system that forms a functional role-sharing connection with the instructor in feedback, personalization, evaluation, and monitoring activities. Typologies of role sharing are being elaborated from many angles as well. Zhai (2025) suggests four roles of teachers; Observer, Adopter, Collaborator, and Innovator to evaluate the level of their connection with GenAI. Frøsig and Romero (2024) believe that AI can assist teacher agency through hybrid intelligence. On the other hand, Mouta et al. (2025b) differentiate between the subjective, intersubjective and collective dimensions of agency; they underline that finding a balance between these dimensions is vital for teachers.

Mohebi and ElSayary's (2026) mixed-methods study empirically supports that human-AI role sharing should be established through pedagogical judgment rather than technical competence. In the research conducted with 325 in-service teachers from 26 countries, it was demonstrated that the most critical mechanism explaining teachers' GenAI competencies is the transformation of technological knowledge into pedagogical knowledge. In particular, it was reported that Technological Pedagogical Knowledge mediates the relationship between Technological Knowledge and overall TPACK-GenAI competence. The impact of Technological Knowledge on TPACK also largely occurs through Technological Pedagogical Knowledge. Qualitative findings also support this pattern. Teachers position tools such as ChatGPT, MagicSchool, Gamma AI, and similar platforms as "smart assistants" or "co-teachers" in processes such as lesson planning, material creation, assessment preparation, monitoring student performance, and providing feedback. When these findings are evaluated together, it becomes evident that the relationship between GenAI and teachers should be conceptualized at the level of pedagogical task sharing rather than tool usage. Role sharing should therefore be addressed as a matter of pedagogical judgment rather than a technical preference, and within the proposed framework it should be positioned as a distinct domain of knowledge.

### *Student-AI interaction management*

Student-AI Interaction Management refers to the knowledge required to structure students' engagement with GenAI tools pedagogically. It also concerns the prevention of dependency and the protection of critical thinking. The need for this field is becoming increasingly clear in the empirical literature. Unsupervised use of GenAI tools may weaken students' cognitive processes.

Gerlich (2025) found a negative relationship between AI tool use and critical thinking skills. This relationship was mediated by cognitive offloading and was especially visible among younger individuals. Fan et al. (2025) reported a similar pattern in an experimental study. Chat-based AI support improved short-term performance, yet it led to metacognitive sloth. It also failed to support knowledge acquisition and transfer.

Zhang et al. (2024) further explained this tendency through the negative consequences of AI addiction. These consequences include sloth, misinformation dissemination, reduced creativity, and the loss of autonomous thinking. Zhai's (2025) comprehensive review reached a similar conclusion. The review showed that over-reliance on AI dialogue systems can affect decision making, critical thinking, and analytical reasoning. This concern is also supported by Georgiou's (2025) experimental finding. In that study, cognitive involvement was substantially reduced in academic work produced with AI assistance.

The literature indicates that it is not sufficient to just put GenAI technologies in the classroom, but pedagogical design is needed for the interaction between student and AI. The results of Mohebi and ElSayary (2026) are important in showing how this obligation of structuring is conceptualized as a new area of teacher competency. In the interview data, teachers mentioned pedagogical uses of GenAI tools including real-time monitoring of student performance, identification of learning challenges, content organization according to individual pace of learning, and quick feedback. Participants argued that adaptive AI systems can provide individualized support by analyzing students' learning styles and needs, which can help students advance at their own learning rate, especially in mixed-level classes. However, the same study also reveals that the use of AI carries risks such as inequality of access, dependency on paid tools, lack of infrastructure, lack of teacher training, and students becoming overly dependent on AI. Thus, the contribution of GenAI in the classroom seems to depend on how the teacher structures the interaction.

This bidirectional picture also informs the definition of Student-AI Interaction Management. This competence covers both the capacity to increase opportunities for AI-supported learning and the capacity to regulate the boundaries, quality, and pedagogical safety of students' engagement with AI. The risks of cognitive offloading and dependency and the opportunities for personalization and instant feedback are located in the same pedagogical decision space, where the role of the teacher is to set up configurations that make the opportunities visible while avoiding the risks. In this respect, Student-AI Interaction Management is emerging as a new axis of pedagogical responsibility for teaching in the GenAI era.

#### *Ethics and social judgment*

Ethics and Social Judgment is positioned as a dimension that cross-cuts other knowledge areas in the framework. This positioning is based on the view that ethics cannot be treated as an isolated subtopic in the integration of GenAI into education. This position is sustained by Alzahrani's (2024) critical synthesis, which reports that aspects such as human connection, data privacy, algorithmic bias, transparency, critical thinking, and equality of access are inseparable from each other, and ethics functions as a cross-cutting axis. This transverse nature requires that ethics be approached as a coordinate that impacts the operation of other fields of knowledge rather than as a partition added to the framework.

This conceptual orientation is derived from empirical literature. Farheen et al. (2025) identified a significant positive relationship between teacher perceived algorithmic bias and their concerns about educational equity. Exposure to AI technologies among teachers heightened their awareness of bias. Karataş and Ataç (2024) demonstrated the lack of ethics in the present frameworks: The ethical component is the least rated dimension of AI-TPACK, which can be explained by the placing of ethics as a subsidiary factor. Celik's (2023) research empirically addressesed this gap by showing how ethical evaluation is a complimentary component of the TPACK framework. It was found that ethical evaluation conceptualized through transparency, justice, accountability and inclusiveness produced significant effects on Intelligent-TPK, Intelligent-TCK and Intelligent-TPACK. This finding suggests that for teachers to use GenAI tools pedagogically, they need not only technological and pedagogical knowledge but also the capacity to ethically evaluate AI decisions.

Two approaches to how to position ethics become evident in the literature. Lan et al. (2025) argue that ethical knowledge should be considered a separate dimension in the GenAI-TPACK framework, although Al-Abdullatif's (2024) discussion indicates that ethical knowledge is more diffusely positioned. The study finds that trust in GenAI is affected not just by the technical reliability of the tools, but also by ethical problems such as privacy, bias, accountability and transparency that directly impact teachers' acceptance and usage decisions. The author points out that trainings for AI literacy should cover the capacities and limitations of GenAI, its ethical application, possible biases, and pedagogical integration tactics. Mouta et al. (2025a) also strengthen this diffuse stance by thematizing the problems associated to AI ethics in teacher professional development in conjunction with the ethical dimension of teacher agency. When these three lines are considered together, Ethics and Social Judgment in the proposed framework is treated as a competence axis that spans across AI literacy, Intelligent TPACK, trust and acceptance processes and cuts horizontally across all knowledge domains.

### Axis of Phronesis

The third layer is the axis of Phronesis, which surrounds all the inner layers. This term, borrowed from Aristotle's concept of practical wisdom, refers to the context-sensitive, deliberative and normative dimension of professional judgment. In existing AI literacy frameworks, however, this dimension has been largely relegated to the background. Sperling et al. (2024) mapped AI literacy in teacher education with three Aristotelian concepts, namely episteme, techne and phronesis, and reported that existing frameworks concentrate on episteme and techne dimensions, while largely neglecting the phronesis dimension. This neglect necessitates modeling the normative dimension of professional judgment, which cannot be reduced to cognitive-technical knowledge alone, as a separate axis.

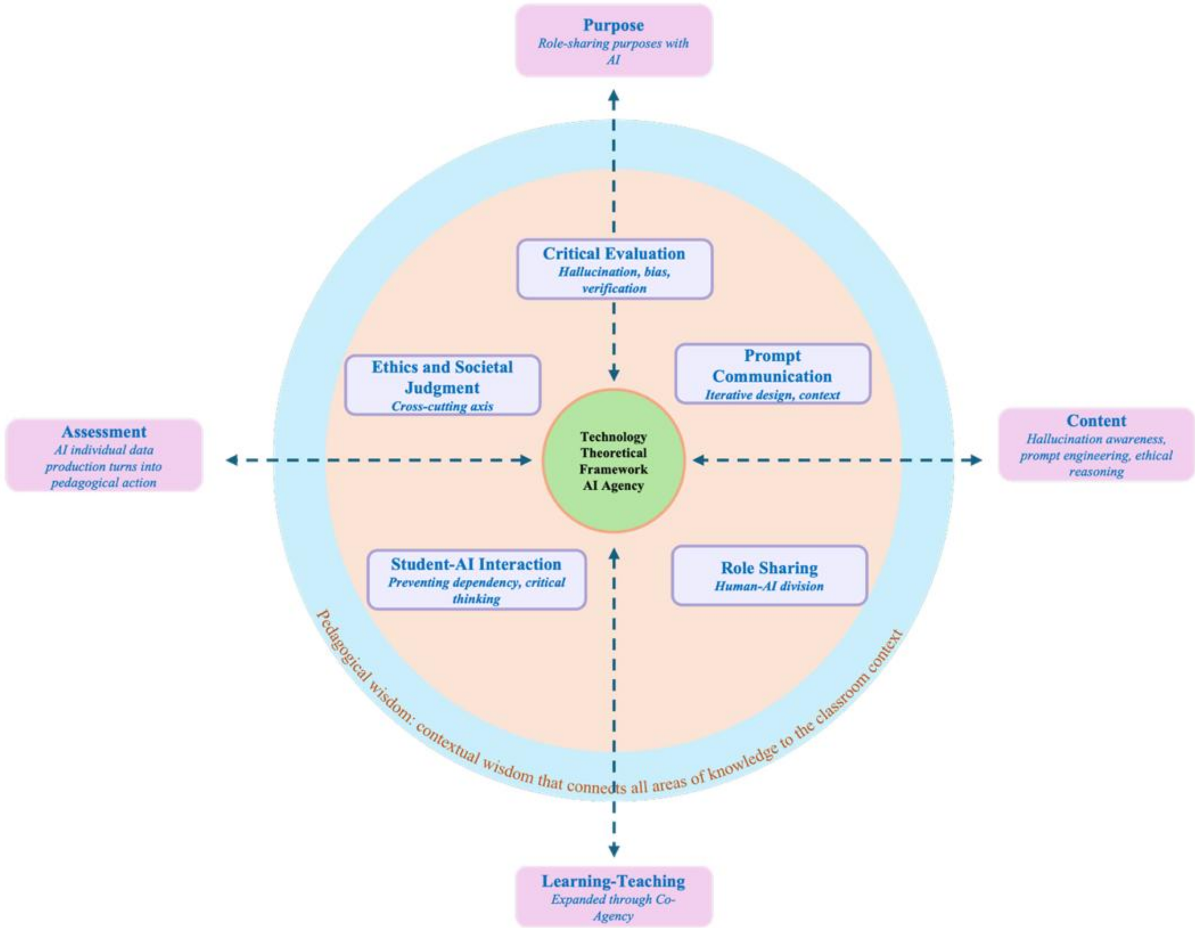


**Figure 3.** Extended GenAI-TPACK framework: Three integral facets, five new knowledge (Source: Authors' own elaboration)

The literature on the construction of the phronesis axis points to several complementary dimensions of the concept. Ribers et al. (2024) examine pedagogical phronesis through four dimensions: the existential-phenomenological dimension, the life-historical dimension, relational competence, and the social dimension of learning. Kristjánsson (2024) argues that Aristotelian phronesis should occupy a central place in the teaching of professional ethics. In this view, professional decisions depend not only on formal norms but also on context-sensitive judgment. Yacek and Jonas (2025) take up the subject of how this judgment might be developed and argue that ethical habituation and "epiphany" experiences should be encouraged by phronesis-based teacher education. Heilbronn (2025), on the other hand, considers phronesis together with the concept of kairos and states that the "when" dimension is as decisive as the "how" dimension.

In the proposed framework, phronesis is positioned as an axis that operates above all fields of knowledge rather than as a separate field of knowledge. This positioning makes it visible that professional judgment functions as a meta-determinant in the transformation of cognitive and technical knowledge into practice. For example, a teacher's competence in hallucination detection (Critical Evaluation) or effective prompt writing skills (Prompt Communication) is not enough on its own; when, how and for what pedagogical purpose these competencies will be put into practice in the classroom is the domain of phronetic judgment. In this respect, the axis of Phronesis functions as the contextual layer of judgment that makes the other knowledge domains of teaching meaningful in the GenAI era. This positioning distinguishes Phronesis from the Ethics and Social Judgment domain. Whereas Ethics and Social Judgment supplies the normative content of pedagogical reasoning (bias, fairness, transparency, equity), Phronesis governs the situational application of that content, namely when, how, and in what configuration ethical and other knowledge domains should be enacted in a given classroom context.

### Program Components Layer

In the fourth and outermost layer, the theoretical continuum from Demir (2011) model includes four curriculum components: purpose, content, teaching-learning situations and assessment. These components are no longer directly connected to the inner core but interact with the inner layers through the axis of Phronesis. This structural arrangement visually illustrates the mediating function of pedagogical judgment in transforming knowledge domains into programmed practices. The integrated structure of the framework is presented in **Figure 3**.

Domains and Program Components As can be read in **Figure 3**, the frame is organized in four layers from the inside out. In the center, there is a tripartite nucleus in a coral-colored circle. Surrounding it, within the coral area, are five new fields of knowledge. These two layers are surrounded by the amber Phronesis ring; at the outermost, the four program components are connected to the inner layers by bidirectional arrows. The direction of the bidirectional arrows emphasizes that the interaction is reciprocal rather than unilateral; as the teacher's programming judgment transforms the knowledge domains, developments in the knowledge domains require redesign of the curriculum components.

## THE HUGHES LEVELS × CO-AGENCY MATRIX

### Rethinking the Hughes Model in the Context of AI

The three-level model proposed by Hughes (2005) has served as a useful analytical tool in technology integration research for many years. The levels of Replacement, Amplification, and Transformation are used to determine whether a classroom activity merely involves a change in media, whether it accelerates an existing process, or whether it reorganizes classroom routines. The conceptual clarity of the Hughes model accounts for its sustained use in educational technology research. In the literature where the Hughes model is compared with SAMR, it is noted that Hughes's three levels offer greater conceptual clarity (Blundell et al., 2022). Although SAMR's four levels (Substitution, Augmentation, Modification, Redefinition) align with practical categories, the model has been criticized for inadequately representing teacher agency and pedagogical context (Bicalho et al., 2022; Blundell et al., 2022).

With the entry of GenAI into the classroom, a structural limitation of both the Hughes and the SAMR frameworks becomes apparent. Both models rest on the assumption that technology is a passive component. The concepts of Replacement and Substitution describe the swapping of technology as a tool; they do not conceptually accommodate the possibility that technology itself may function as an interacting agent. This assumption remained workable for conventional digital tools. GenAI, however, disrupts this assumption. Generative AI offers suggestions in the classroom, raises questions, and produces content (Mishra et al., 2023; Yan et al., 2024). Kim (2024a, 2024b) shows that the active role of AI transforms the teacher's position and that classical technology integration models fall short in explaining this transformation.

The solution proposed in the present study is not to add a fourth level to the Hughes model. Adding a fourth level would compromise the conceptual simplicity of the existing three. It would also confine AI's active role to a single cell. Instead, this study proposes crossing the Hughes levels with a new axis termed Co-Agency. This structural arrangement positions AI's agency as a dimension applicable to all levels. Teacher-AI partnership may emerge even at the Replacement level; the teacher may remain the sole active agent even at the Transformation level. Treating Co-Agency as a separate axis is therefore a conceptual necessity.

### Theoretical Foundations of the Co-Agency Construct

The idea of co-agency has become a prominent construct in the current literature on teacher-AI interaction. Cukurova and Luckin (2025) provide a five-level taxonomy for teacher-AI collaboration, from transactional use (AI as a tool, with pedagogical authority held by the instructor) to synergistic teaming (pedagogical decisions made together). A similar structural concern is visible in Kim (2024b), who identifies six configurations of teacher-AI collaboration ranging from a single-teacher / single-observer arrangement to team teaching.

An earlier study by Kim (2024a) traces a three-stage developmental trajectory in which the teacher moves from a passive recipient of AI, to an active user of it, and finally to a constructive partner. Structurally, however, the first two stages share the same feature: the teacher remains the sole active agent and AI continues to function as a tool. Only the partnership stage introduces a categorical shift in agency, which suggests that the trajectory can be reduced to a binary distinction between single-agent use and genuine partnership without loss of analytical content. Such a binary axis also tends to support more reliable coding in classroom observation work (Blundell et al., 2022).

Comparable grounds for treating Co-Agency as a structural axis can be found in the hybrid intelligence literature. Frøsig and Romero (2024) claim that AI can only assist teacher agency if it is included in a hybrid intelligence architecture, otherwise the system may limit the teacher’s ability to decide, influence and adopt a position. Mouta et al. (2025a, 2025b), who have worked with practicing educators, report that the influence of AI on teacher agency is at the subjective, intersubjective and collective levels but these levels seem to converge on the same underlying question of pedagogical judgment, which is what a single Co-Agency axis is meant to capture.

Complementarity is a core idea of human-AI collaboration, conceptualized by Hemmer et al. (2024). They argue that collaboration structures can allow performance levels neither partner can achieve alone. This view is consistent with empirical evidence from Kong et al. (2025), whose human-AI synergy model in hybrid intelligence learning environments suggests that synergy remains at low to moderate levels and that Co-Agency does not spontaneously arise in classroom practice, but depends on intentional pedagogical design.

### The Structural Logic of the Matrix and the Six Cells

The matrix is to be read in such a way that the two axes are to be defined as structurally independent of each other. The Hughes axis evaluates the amount of change that occurs in classroom procedures. At the L1 level the teacher adheres to conventional classroom practices. These routines comprise of structures such as lecture, sequential work, and direct teaching. At Level L2, the process is accelerated, but the class’s basic routine remains unchanged. At Level L3, the teacher has transitioned to innovative teaching approaches. These approaches include structures such as the flipped classroom, project-based learning, problem-based learning, the workshop model, and inquiry-based teaching.

The Co-Agency axis measures AI’s role as an actor within the classroom. On the Single Actor side, there is no direct interaction between AI and students in the classroom. AI can provide significant assistance to the teacher during the preparation phase. For example, it can generate content, provide support in designing assessment tools, and develop alternative materials. However,

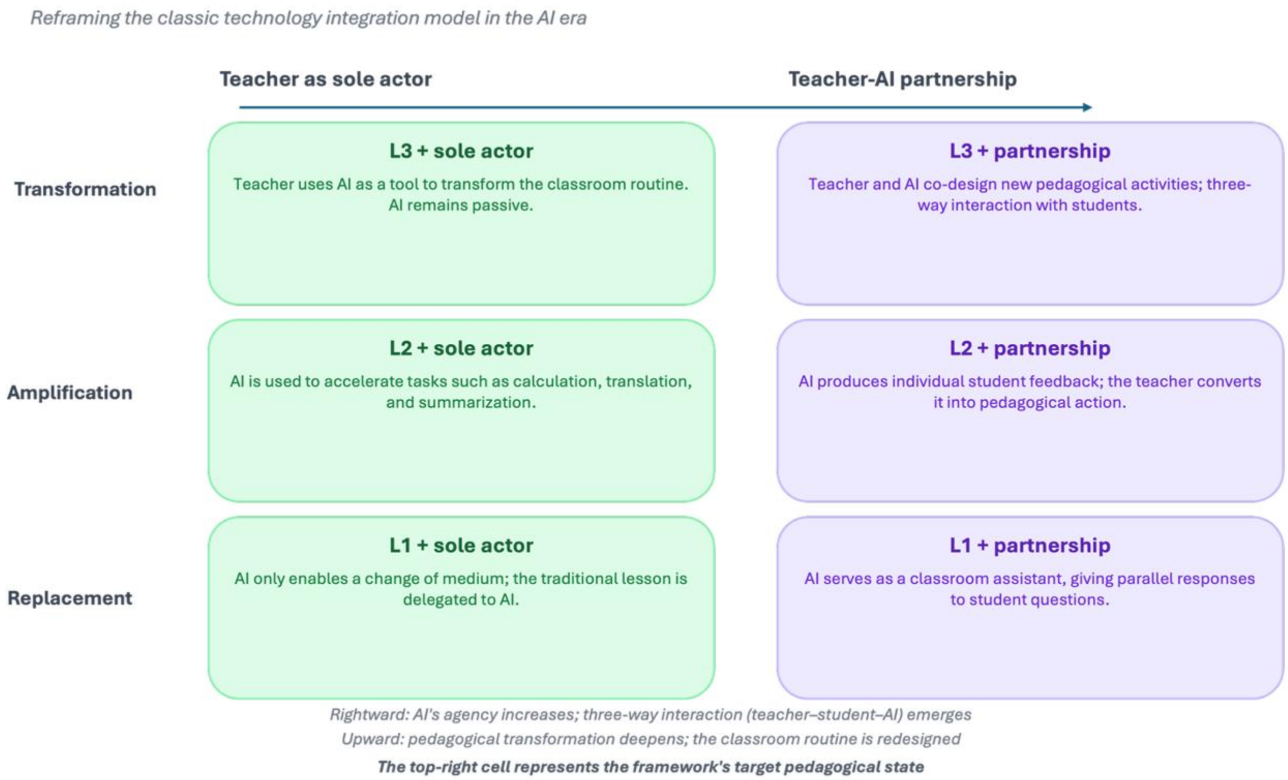


**Figure 4.** Hughes Levels × Co-Agency Axis (Source: Authors' own elaboration)

there is no student-AI interaction during the classroom process. On the Partnership side, AI is active within the classroom. Students interact directly with AI, which functions as an actor that makes suggestions, generates questions, or provides feedback.

The independence of these two axes ensures that each of the six cells is structurally distinguishable. A teacher can transform classroom routines and make extensive use of AI in this transformation; however, they may choose not to have AI interact directly with students in the classroom. Similarly, a teacher can maintain traditional classroom routines while assigning AI an active role in the classroom. The transformation of classroom routines and AI's role as an actor within the classroom are two separate pedagogical decisions. A teacher can adopt one independently of the other. This distinction structurally grounds why the six cells of the matrix are distinguishable. The matrix is presented in **Figure 4**.

**L1 + Sole Actor: Substitution, Passive AI.** In this scenario, AI functions solely as an instrumental element that facilitates limited change within the instructional environment. The traditional teacher's presentation is transferred to a digital platform; however, the pedagogical structure remains fundamentally unchanged. While the teacher remains the sole active actor in the classroom, the AI does not play a direct role in classroom interaction. In a typical example, the teacher employs AI tools to create visualizations, presentations or concept maps to use in the classroom. In this case, the interaction is only between the teacher and AI. The study by Galindo-Domínguez et al. (2024) with 445 instructors from elementary, middle and higher education schools in Spain shows that the usage of AI technologies is mostly focused on content creation, especially among teachers of basic and middle school.This usage is concentrated in functions such as presentation, text, and video generation; students' direct interaction with AI tools, however, does not stand out prominently. This pattern corresponds to a structure where AI is used solely by the teacher and there is no student-AI interaction within the classroom. Therefore, this usage pattern directly represents the L1 + Single Actor cell.

**L1 + Partnership: Substitution, Active AI.** In this cell, AI provides supplementary explanations in the classroom and can generate responses to student questions in parallel with the teacher. The classroom routine generally remains unchanged; however, AI is no longer merely a passive preparation tool and becomes visible in classroom interactions. Kim's (2024b) "One Teach, One Assist" typology aligns with this cell. In this structure, there are two presentation actors: the teacher and the AI. The presence of AI does not weaken the teacher's pedagogical role. On the contrary, the teacher positions themselves as the primary pedagogical agent who monitors, evaluates, and, when necessary, guides the supplementary content generated by the AI. For example, in an eighth-grade science class, while the teacher is explaining the structure of an atom, they draw the electron shells on the board and explain them to the students. At the same time, the ChatGPT screen is open on the classroom projector. When a student asks, "Why are electrons found in different shells?" the teacher first provides their own explanation. Then they pose the same question to ChatGPT. ChatGPT's response appears on the projection screen. The teacher evaluates this response, corrects any missing or incorrect points, and explains how students should interpret the answer. Within this structure, while AI assumes the role of an assistant, the teacher maintains their position as the pedagogical supervisor.

**L2 + Sole Actor: Extension, Passive AI.** In this case, AI is a helpful tool that accelerates activities like calculation, translation, summarization and such. The classroom routine is still substantially the same The students can do the tasks assigned to them without AI, but AI helps speed up the process and makes it more efficient. The collaboration between teachers and AI is limited and AI does not play any direct role in the pedagogical decision making process. In that sense, it's a prototypical illustration of how AI is framed as a productivity aid in the classroom.

For example, in an eleventh-grade mathematics class, while the teacher is covering calculus, they use Symbolab or Wolfram Alpha to calculate the derivative of a complex function. The result is obtained in a matter of seconds. The teacher writes this result on the board and explains the solution process step by step. Within this framework, AI functions more as a tool that accelerates the computational process than as a pedagogical actor. AI performs the computation, the teacher explains the logic behind the solution, and students do not interact directly with the system. Yang et al. (2023) demonstrate that a significant portion of AI-based pedagogical activities still remain at this level.

**L2 + Partnership: Empowerment, Active AI.** In this cell, AI delivers tailored feedback to students, which the teacher then interprets into educational action. Therefore, AI is no longer only a tool that speeds up the process and establishes itself as an active supporting player in the educational process. AI aids teacher feedback in STEM courses via generation of multi-modal timelines (Cohn et al., 2025). A prominent example of this cell is the collaboration of the teacher-AI duo in differentiated learning settings.

For example, in a university academic English course, students are writing article drafts. Each student uploads their draft to ChatGPT and receives feedback on grammar, coherence, and argumentative strength. AI generates personalized comments for each student. The teacher moves around the classroom and works individually with each student, using the feedback generated by the AI as a basis. Within this framework, while the AI produces the initial layer of assessment regarding student performance, the teacher acts as the agent who interprets and validates these outputs and transforms them into pedagogical interventions tailored to the student's learning needs. When the AI tells a student that their "argument is weak," the teacher explains what this means and demonstrates how the argument can be strengthened. If the AI's feedback is incorrect for another student, the teacher notices this and corrects it. Thus, a three-way interaction structure emerges between the student, the AI, and the teacher. Pahi et al. (2024) report that a similar structure enhances the quality of feedback in computer science courses. Yang et al. (2023), meanwhile, emphasize that such dynamic transitions are critical for classroom management.

**L3 + Sole Actor: Transformation, Passive AI.** In this cell, the teacher has adopted innovative teaching approaches and transformed classroom routines. However, the AI does not engage directly with students in the classroom. The AI's role is limited to providing intensive support to the teacher during the pre-class preparation phase. The creation of new lesson content, the design of alternative teaching materials, and the development of assessment tools suitable for new classroom routines are the primary areas of this support. The key feature distinguishing this cell from the L1 + Single Actor cell is that the teacher does not maintain the traditional classroom routine and has established an innovative pedagogical structure. For example, a high school biology teacher has abandoned the traditional lecture model. In the new structure, students learn core concepts by watching videos at home; in class, they participate in problem-solving, discussion, and hands-on activities. Before class, the teacher uses ChatGPT to generate video scripts, concept maps, and in-class discussion questions for each unit. At the same time, they design formative assessment tools suited to the new teaching routine. AI does not interact with students in the classroom; discussions proceed solely along the teacher-student axis. In this scenario, the classroom routine has transformed significantly, yet AI is positioned as the teacher's design partner during the preparation phase. Galindo-Domínguez et al. (2024) demonstrate that while teachers intensively use AI for content creation, they do not explicitly emphasize student-AI interaction. This finding suggests that, even though classroom routines have transformed, limiting AI to the preparation phase remains a common preference.

**L3 + Partnership: Transformation, AI active.** This cell represents the pedagogical situation the framework is designed to target: a setting in which the teacher and AI collaborate to design new pedagogical activities and a tripartite interaction is established with the student. Cukurova and Luckin (2025) describe this configuration as synergistic teamwork, and Kim's (2024a, 2024b) "Team Teaching" typology corresponds to the same cell. For example, instead of explaining Einstein's theory of relativity, a high school physics teacher designs a different scenario. They assign students the task of "conducting a Socratic dialogue on relativity with ChatGPT." Each student discusses a concept of their choice (the relativity of time, the speed of light, the equivalence of mass and energy) with ChatGPT. The AI is not in the role of a teacher; it acts as a co-investigator. The student asks questions of the AI, and the AI asks questions of the student. The dialogue is recorded. The teacher serves as a moderator in the classroom. The teacher observes the dialogues and intervenes when the AI provides incorrect or insufficient explanations. At the end of the lesson, each student analyzes the dialogue recording and reports on where the AI was strong or weak. The three-way interaction has deepened. The classroom routine has been fundamentally transformed.

### Comparing the Matrix with the SAMR Model

The SAMR model (Substitution, Augmentation, Modification, Redefinition) is an alternative framework widely used in educational technology research (Blundell et al., 2022). Conceptual parallels exist between the Hughes levels and SAMR. Hughes's Replacement level overlaps with the Substitution level of SAMR; the Amplification level overlaps with the Augmentation/Modification levels; the Transformation level overlaps with the Redefinition level. There are three reasons for preferring the Hughes levels in the proposed framework.

First, the three-level structure of the Hughes model offers higher conceptual simplicity. Blundell et al. (2022) document that the Modification and Redefinition levels of the SAMR model are difficult to distinguish in classroom observations and that this difficulty reduces inter-rater reliability. The three levels of the Hughes model enable more reliable coding.

Second, the Hughes (2005) model connects directly to the anchor conceptual model of Demir (2011). The 2011 model positioned the Hughes levels as a tool for program evaluation. The theoretical continuity of the proposed framework requires the use of the Hughes model.

Third, the SAMR model has been subject to technology-centric critiques (Bicalho et al., 2022). It has been argued that the model does not adequately represent pedagogical context. The simpler structure of the Hughes model, when combined with the Co-Agency axis, captures pedagogical context more effectively.

### The Operational Value of the Matrix

The six-cell matrix provides a functional analytical tool for both quantitative and qualitative research designs. In quantitative research, classroom observations can be coded across the six cells. The distribution across cells defines a teacher's AI use pattern. In qualitative research, the matrix can be used as a coding framework for video-based reflective practice. In mixed methods designs, the relationships between observation codes and self-report scale scores can be tested.

The binary structure of the Co-Agency dimension in the matrix is a conceptual simplification. In real classroom settings, Co-Agency intensity forms a spectrum. Gomez et al. (2023) propose that human-AI interaction patterns can be categorized into seven sub-categories. It can be considered that the binary structure is sufficient for practical research applications and that finer distinctions can be addressed during interpretation. Subsequent research may test whether measuring the Co-Agency axis as a continuous variable proves functional.

Another operational value of the matrix is that it enables pedagogical analysis of transitions between cells. Over the course of a lesson, a teacher may shift across different cells. Such transition patterns may serve as a dynamic indicator of teacher competence. Yang et al. (2023) document that dynamic transitions are critical for classroom management. In subsequent empirical tests of the framework, the analysis of transition patterns may add a new dimension to the framework.

## OPERATIONALIZATION OF THE FRAMEWORK

The proposed Extended GenAI-TPACK framework is not only a theoretical proposal but also an operational tool for empirical research. This section provides basic guidelines on how the framework can be used in quantitative and qualitative research.

In quantitative research, the eight knowledge domains of the framework (classical TPACK components + five new knowledge domains) can be the conceptual basis of scale development studies. The development of separate subscales for the five new knowledge domains will enable the extension of existing AI-TPACK scales (Karataş & Ataç, 2024; Ning et al., 2024). Measuring the phronesis axis requires special attention from a psychometric perspective. This dimension is difficult to capture with classical Likert-type items; scenario-based situational judgment tests may be more appropriate. Structural equation modeling, especially PLS-SEM approach, is considered as a suitable method for empirical testing of the framework. Hair et al. (2019, 2022) emphasize that PLS-SEM is particularly suitable for analyzing complex models, working with small samples, data where the assumption of normal distribution is not met, and models that include formative constructs. Sarstedt et al. (2021) state that PLS-SEM is an effective tool for estimating path models with latent variables. Specific to the field of educational technology, Ghasemy et al. (2020) and Lin et al. (2020) systematically examined the widespread use of PLS-SEM in higher education and e-learning research and provided implementation guidelines. Testing the proposed framework as a complex model with seven or eight components is in line with the methodological strengths of PLS-SEM.

In qualitative research, the Hughes × Co-Agency matrix provides an analytical coding framework for classroom observations. Moments of AI use in the classroom can be categorized in terms of which of the six cells they fall into. This approach can be functional both in the description of teacher competencies and in the evaluation of professional development programs. In mixed methods research, examining the relationships between quantitative scale scores and observation-based matrix codes can provide evidence for the convergent validity of the framework.

The framework also has the potential for direct use in curriculum development practices. As in Demir's (2011) model, teacher education programs designed through four curriculum components can be organized around a tripartite core and five new knowledge areas. The development of the phronesis axis can be supported by case studies, video-based reflective practices and mentoring processes. These practical suggestions show that the framework is not only an academic tool but also functional in professional development.

## DISCUSSION

The place of the proposed framework in the literature can be assessed from three perspectives. First, within the classical TPACK extension approaches, this framework presents one of the first attempts to internalize the active agency of AI at a structural level. Ning et al. (2024) and Karataş and Ataç (2024) only add AI to the classical components. The proposed framework, on the other hand, incorporates the distinctive features of GenAI (Mishra et al., 2023) at the structural level and corresponds to them with five new knowledge domains. This distinction is consistent with recent empirical work showing that GenAI cannot be sufficiently understood through classical TPACK or TAM constructs alone. ElSayary et al. (2026), for example, argue that GenAI introduces agency, adaptivity, amplification, and authenticity as dimensions that affect not only instructional practice but also teachers' concerns about pedagogical control, content authenticity, and equitable access. Their integrated TAM-TPACK-GenAI model shows that perceived usefulness is a strong predictor of teachers' attitudes and behavioral intention, while concerns about agency and authenticity moderate positive perceptions of AI use. Therefore, the proposed framework extends the current literature by moving these GenAI-specific dimensions from the level of external variables to the internal architecture of teacher knowledge.

Second, the theoretical continuity of the framework from Demir's (2011) two inseparable facets model emphasizes the cumulative development in the field of educational technology. Most new frameworks emerging in the AI era are constructed without linking to past models. This weakens the cumulative development of the field. The proposed framework argues that the core claim of the 2011 model (the inseparability of technology and theoretical framework) applies more strongly in the AI era, with the addition of AI Agency as a third facet. Recent empirical work on in-service teachers lends support to this argument. Ortiz Colón et al. (2023) point out that technology integration is not a matter of access to digital tools or instrumental skills alone. In a study conducted with 825 in-service teachers, TPACK is reported to function as a diagnostic framework through which teachers' strengths and weaknesses in the technological, pedagogical, and content knowledge domains can be identified. This finding reinforces the central assumption of the proposed framework: technology becomes pedagogically meaningful only when it is interpreted through a theoretical and instructional lens. In the GenAI era, however, this lens must also include the agency of the system, because AI does not merely mediate teaching but can generate content, suggest decisions, and reshape teacher-student interaction.

Third, the framework's dialog with international debates increases its potential to contribute to the global edtech literature. Yan et al.'s (2024) analysis in Nature Human Behaviour shows that the cautious position that AI is both a solution and a source of new problems structurally overlaps with the Phronesis axis of the proposed framework. In the same direction, Cukurova et al.'s (2025) levels of collaboration, Mishra et al.'s (2023) analysis of GenAI attributes, Sperling et al.'s (2024) episteme-techne-phronesis distinction and Lan et al.'s (2025) ethics-based GenAI-TPACK proposal find their counterparts in different layers of the framework.

Fourth, the Hughes × Co-Agency matrix proposes a new conceptual response to the structural limitation that classical models of technology integration face in the GenAI era. Both Hughes (2005) and the SAMR model are built on the assumption that technology is a passive component. GenAI invalidates this assumption (Kim, 2024a, 2024b; Mishra et al., 2023). Instead of adding a fourth level to the Hughes model, the proposed solution is to position the Co-Agency as a separate axis. This move is theoretically important because it prevents AI agency from being treated as a simple intensification of existing technology integration levels. Classical models generally assume that the teacher remains the sole pedagogical agent and that technology functions as an external resource. GenAI systems, however, complicate this assumption. Such systems can provide feedback, generate representations, adapt content, and take part in instructional decision-making. ElSayary et al. (2026) similarly report that GenAI-supported education involves adaptive feedback, co-creation, and instructional personalization, and that this development requires teacher agency to be reconsidered in AI-supported learning environments. On this basis, AI agency can be treated as a dimension that spans all levels of integration. This makes it possible to combine Cukurova and Luckin's (2025) five-level taxonomy of teacher-AI collaboration with Kim's (2024a, 2024b) six structural forms of collaboration into a single, pedagogically functional dual axis. The six-cell matrix allows for systematic coding of classroom observations and pedagogical analysis of transitions between cells, so that a structure proposed at the theoretical level becomes an operational tool for empirical research.

Fifth, the framework is not only a conceptual proposal but also an operational infrastructure for empirical research. Modeling the eight knowledge domains with subscales, measuring the Phronesis axis with scenario-based situational judgment tests, and testing the model with structural equation methods such as PLS-SEM make the framework methodologically testable (Hair et al., 2019, 2022; Sarstedt et al., 2021). In this respect, the framework also provides a structural basis for the extension of existing AI-TPACK scales (Karataş & Ataç, 2024; Ning et al., 2024).

Sixth, the framework offers a systematic reading in terms of the three metaphors of pedagogical capacity. The metaphor of the teacher who is as helpful as the number of students corresponds to the Student-AI Interaction Management knowledge domain; the metaphor of the conductor corresponds to the Human-AI Role Sharing knowledge domain and the Co-Agency axis; and the metaphor of the AI who learns fast but forgets corresponds to the Prompt Communication and Critical Evaluation knowledge domains. The placement of these three metaphors in the sub-dimensions of the framework suggests that the conceptual discussions in the field are actually not independent of each other but show different facets of an integrated structure. A similar tendency is observed in the STEAM-TPACK literature. Karampelas (2023) reports that TPACK and STEAM have gradually converged in recent years, particularly around teacher training, educational technology, and disciplinary integration. This convergence is relevant for the present discussion, because GenAI-supported pedagogy is likely to increase the need for interdisciplinary orchestration in the classroom. In such a context, the teacher's task is not limited to selecting a tool for a given content area; it also involves coordinating AI-supported inquiry, disciplinary knowledge, and ethical reflection. Hence, it can be said that the three metaphors function as pedagogical translations of a broader shift in which tool use is replaced by orchestration, individual competence by distributed classroom agency, and technological integration by judgment-based pedagogical design.

Seventh, the proposed framework tries to avoid a techno-centric reading. The risk of a research community with only an AI hammer at its disposal seeing every pedagogical problem as an AI nail is one of the main challenges of the field. The framework responds to this risk at a conceptual level by positioning AI not at the center but as part of the tripartite core. While the agency of AI is acknowledged, it is emphasized that the pedagogical judgment of the teacher, positioned on the axis of Phronesis, is the supreme determinant.

## LIMITATIONS AND SUGGESTIONS FOR FUTURE RESEARCH

This study provides a conceptual proposal and does not contain empirical data. The validity and usefulness of the proposed framework will have to be tested by subsequent empirical studies. The first recommendation is to conduct scale development studies for five new knowledge domains. These studies should be enriched with validity and reliability analyses, measurement invariance tests, and comparative applications in different cultural contexts.

The second recommendation is to validate the Hughes × Co-Agency matrix through classroom observations. Identifying the empirical correspondence of the six cells, determining which cells are observed in classrooms and how often, and identifying the pedagogical conditions for moving between cells would increase the practical value of the framework.

The third suggestion is the methodological search for measuring the axis of Phronesis. Scenario-based situational judgment tests, video-based reflective practices and professional judgment portfolios can be considered as methodological tools that can capture this dimension. Sperling et al.'s (2024) episteme-techne-phronesis distinction can be used as the conceptual ground for the measurement strategy.

The fourth suggestion is to apply the framework in different disciplines. As shown by Lee et al. (2024) in science education, Priyanda et al. (2025) and Bueno et al. (2021) in mathematics education, and Tseng et al. (2022) in language education, AI transformation takes different forms. Domain-specific adaptations of the framework can capture disciplinary features of the interaction of domain knowledge and AI.

The fifth suggestion concerns the institutional boundary of the framework. The present model concentrates on in-class pedagogical interaction and treats AI's bureaucratic uses (administrative reporting, scheduling, data management) as background features of the school ecosystem rather than as direct objects of analysis. Future research may examine how the tripartite core and the five knowledge domains interact with this institutional layer, particularly where bureaucratic AI use shapes the conditions under which classroom AI use unfolds.

## CONCLUSION

In this study, a new model aiming to explain teacher competencies in the AI era is proposed. The proposed Extended GenAI-TPACK framework takes theoretical continuity from Demir's (2011) two inseparable facets model; transforms the classical binary core into a tripartite structure (Technology + Theoretical Framework + AI Agency); adds five new knowledge domains encompassing this core; proposes a Phronesis axis linking the whole system to the classroom context; and presents a six-cell practice matrix reframing Hughes' (2005) levels with a Co-Agency axis.

The framework emphasizes that AI is not a magic solution in the field of education, but carries the potential for pedagogical transformation when made sense of with the right conceptual tools. As Yan et al. (2024) remind us, GenAI can work as a partner for humanity, but there is also a risk that it can become a crutch that cripples our intellectual faculties. The challenge lies in integrating innovation with pedagogical judgment rather than avoiding it. This framework attempts to make a conceptual contribution to this integration effort.

Finally, in terms of the cumulative development of the field of educational technology, it is crucial that new frameworks are constructed in relation to past theoretical accumulation. This study provides an example of theoretical continuity within the field by constructing a new model specific to the AI era, departing from a conceptual model put forward fourteen years ago. The proposed framework should be read as an opening rather than a closure; it is open to being revisited, transformed, and expanded in the light of empirical research.

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