TUTORING MODELS IN ARTIFICIAL INTELLIGENCE AND KNOWLEDGE SKILLS IN THE CONTEXT OF INDUSTRY 5.0

MODELOS DE TUTORIA EM INTELIGÊNCIA ARTIFICIAL E HABILIDADES DE CONHECIMENTOS NO CONTEXTO DA INDÚSTRIA 5.0

MODELOS DE TUTORÍA EN INTELIGENCIA ARTIFICIAL Y HABILIDADES DE CONOCIMIENTO EN EL CONTEXTO DE LA INDUSTRIA 5.0

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ABSTRACT
The expansion of generative artificial intelligence has increased the presence of digital tutoring systems in educational and corporate environments, enhancing the capacity for personalization, scalability, and availability of learning support. At the same time, Industry 5.0 repositions human beings at the center of technological transformation, reinforcing the relevance of knowledge skills for continuous learning, adaptability, and value creation. This article analyzes how artificial intelligence tutoring models relate to the development of knowledge skills in the context of Industry 5.0. The study adopts a theoretical conceptual approach, developed through an integrative literature review based on the authors' doctoral qualification texts and the project's authorized sources. The findings indicate that human, artificial, and hybrid tutoring models produce distinct effects on autonomy, motivation, engagement, self-regulated learning, and the development of cognitive, digital, and adaptive competencies. It concludes that AI-based tutoring can serve as a support infrastructure for the development of knowledge skills, provided it operates within a human-centered logic, articulated with pedagogical principles, human curation, knowledge-creation, and circulation processes.

Keywords: Artificial Intelligence (AI). Tutoring Models. Knowledge Skills. Industry 5.0. Generative AI.

RESUMO
A expansão da inteligência artificial generativa ampliou a presença de sistemas de tutoria digital em ambientes educacionais e corporativos, elevando a capacidade de

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personalização, a escalabilidade e a disponibilidade do suporte à aprendizagem. Em paralelo, a Indústria 5.0 reposiciona o ser humano no centro da transformação tecnológica, reforçando a relevância das habilidades de conhecimento para a aprendizagem contínua, a adaptabilidade e a criação de valor. Este artigo analisa como modelos de tutoria em inteligência artificial se relacionam ao desenvolvimento de habilidades de conhecimento no contexto da Indústria 5.0. O estudo adota uma abordagem teórico-conceitual, desenvolvida por meio de revisão integrativa da literatura, com base nas produções de qualificação dos autores e nas fontes autorizadas do projeto. Os achados indicam que modelos de tutoria humana, artificial e híbrida produzem efeitos distintos sobre a autonomia, a motivação, o engajamento, a aprendizagem autorregulada e o desenvolvimento de competências cognitivas, digitais e adaptativas. Conclui-se que a tutoria baseada em IA pode atuar como infraestrutura de apoio ao desenvolvimento de habilidades de conhecimento, desde que operada com lógica human-centered, articulada a princípios pedagógicos, à curadoria humana e a processos de criação e de circulação do conhecimento.

Palavras-chave: Inteligência Artificial (IA). Modelos de Tutoria. Habilidades de Conhecimentos. Indústria 5.0. IA Generativa.

RESUMEN

La expansión de la inteligencia artificial generativa ha ampliado la presencia de sistemas de tutoría digital en entornos educativos y corporativos, elevando la capacidad de personalización, la escalabilidad y la disponibilidad del apoyo al aprendizaje. Al mismo tiempo, la Industria 5.0 reposiciona al ser humano en el centro de la transformación tecnológica, reforzando la relevancia de las habilidades de conocimiento para el aprendizaje continuo, la adaptabilidad y la creación de valor. Este artículo analiza cómo los modelos de tutoría basados en inteligencia artificial se relacionan con el desarrollo de habilidades de conocimiento en el contexto de la Industria 5.0. El estudio adopta un enfoque teórico-conceptual, desarrollado mediante una revisión integradora de la literatura, con base en las producciones de calificación de los autores y en las fuentes autorizadas del proyecto. Los hallazgos indican que los modelos de tutoría humana, artificial e híbrida producen efectos distintos sobre la autonomía, la motivación, el compromiso, el aprendizaje autorregulado y el desarrollo de competencias cognitivas, digitales y adaptativas. Se concluye que la tutoría basada en IA puede actuar como infraestructura de apoyo al desarrollo de habilidades de conocimiento, siempre que opere bajo una lógica human-centered, articulada con principios pedagógicos, la curaduría humana, los procesos de creación y circulación del conocimiento.

Palabras clave: Inteligencia Artificial (IA). Modelos de Tutoría. Habilidades de Conocimiento. Industria 5.0. IA Generativa.

1 INTRODUCTION

The incorporation of Artificial Intelligence (AI) in educational environments has ceased to occupy a peripheral position and has become part of broader strategies for learning mediation, especially with the dissemination of generative models and conversational interfaces. In parallel, Industry 5.0 has consolidated an agenda that combines technological transformation, sustainability, resilience, and human centricity, shifting the debate from the mere use of technology to the ability to develop skills and transform knowledge into organizational value (European Commission, 2025; Ghobakhloo et al., 2022; Xu et al., 2021).

In the educational field, this movement manifests in the expansion of digital tutors, academic assistants, and systems that answer questions, organize content, offer feedback, and support self-regulated learning. Recent studies indicate that AI-based tutors can improve the learning experience when they combine technical responsiveness with consistent pedagogical foundations, especially in higher education and distance education contexts (Baillifard et al., 2025; Ding et al., 2023; Reicher et al., 2025).

The effectiveness of this type of solution, however, does not depend only on technical availability. The literature shows that perceived utility, ease of use, enabling conditions, motivation, autonomy, and quality of mediation continue to be decisive factors for engagement and sustained use of technology-mediated educational systems (Davis, 1989; Ryan & Deci, 2000; Tbaishat et al., 2026; Venkatesh & Bala, 2008).

This debate gains density when connected to Industry 5.0-driven environments, as the central issue is no longer just the adoption of AI but its ability to support the development of knowledge skills, understood as capacities to learn, interpret, combine, apply, and share knowledge in complex, digital, and intensively changing contexts (Alavi & Leidner, 2001; Leon, 2023; Nonaka, 1994; World Economic Forum, 2025). In this context, cognitive, digital, relational, and adaptive competencies become critical assets for the creation and circulation of organizational knowledge (Nonaka & Takeuchi, 1995; Rikala et al., 2024).

The theoretical gap lies precisely in the intersection between these two agendas. Literature has advanced the analysis of intelligent tutors, AI-mediated learning, technological acceptance, and motivation. It also advanced the discussion on competencies, skills gaps, knowledge management, and Industry 5.0. Even so, an integrative reading that explains how AI tutoring models can contribute to the formation and mobilization of knowledge skills required in environments of accelerated digital transformation and continuous learning remains less developed (Anshari & Hamdan, 2022; Cerchione et al., 2024; Shen et al., 2025).

Therefore, this article aims to analyze, from a theoretical-conceptual perspective, how different models of tutoring (human, artificial, and hybrid) relate to the development of knowledge skills in the context of Industry 5.0. The relevance of the study is both theoretical, as it integrates two fields that usually run in parallel, and practical, as it offers a useful basis for designing more effective tutoring solutions in educational and organizational contexts.

2 THEORETICAL FOUNDATIONS

2.1 TUTORING MODELS IN ARTIFICIAL INTELLIGENCE

Tutoring, in its classic formulation, serves a mediating function among the student, the content, and the learning process. In digital environments, this function has expanded to include automated support, recommendation, feedback, and follow-up mechanisms (Massuga et al., 2021; Peel et al., 2023). Currently, three main tutoring arrangements can be found in educational and corporate settings: human tutoring, artificial tutoring, and hybrid tutoring.

In human tutoring, a pedagogical representative offers support through welcome, guidance, feedback, and relationship building. This model tends to offer greater interpretive density, greater contextual sensitivity, and a stronger ability to address the subjective dimensions of learning, such as insecurity, belonging, and motivation. On the other hand, it faces limitations in scale, availability, and standardization (Massuga et al., 2021; Peel et al., 2023).

In artificial tutoring, support is provided by AI-based systems, often supported by natural language processing, generative models, and knowledge retrieval mechanisms. These systems increase availability, reduce response time, personalize interactions, and expand the capacity for continuous support, especially for operational questions, conceptual reinforcement, and study organization (Ding et al., 2023; Hobert & Berens, 2024; Lee, 2025; Reicher et al., 2025).

And, hybrid tutoring combines the advantages of both models, in which AI tends to operate as the first layer of support, absorbing recurring demands and structuring initial guidance, while the human tutor remains responsible for more complex mediations, welcoming, conceptual deepening, and pedagogical judgment. Literature has indicated that this format tends to be more robust in contexts in which speed and scale need to coexist with relational quality and pedagogical consistency (Alfirević et al., 2025; Seo et al., 2021).

In addition to the delivery format, AI tutoring models vary in their interaction architecture, with some systems limited to on-demand responses and others incorporating proactive elements such as reminders, study recommendations, encouragement of engagement, and support for self-regulation. This point is relevant because it shifts tutoring from a merely reactive function to a broader formative function (He, 2025; L. Liu et al., 2024; Yin et al., 2026).

Still, the limits are clear to artificial tutors, which can increase the efficiency of support, but they do not, by themselves, guarantee cognitive depth, pedagogical quality, or criticality - without curation, instructional design, and validation mechanisms, there is a risk of superficiality, inaccurate answers, and excessive dependence of the student on the system (Đerić et al., 2025; Kasneci et al., 2023; Tharapos et al., 2025).

2.1.1 The artificial tutor: definition, architecture, and application contexts

An artificial tutor based on generative AI is a computer system that interacts with users in natural language, offering personalized support, answering questions, providing feedback, and automatically guiding learning processes. Unlike classical tutoring systems based on fixed rules, tutors in generative AI, especially those supported by Large Language Models (LLMs), operate through probabilistic models trained on large volumes of text, which allows them to generate contextually relevant responses, adapt to the user's interaction style, and handle ambiguity (Kasneci et al., 2023; Lee, 2025; Reicher et al., 2025).

The most common architecture includes three main layers: the conversational interface, which enables natural-language interaction; the processing layer, which combines generative models with Retrieval-Augmented Generation (RAG) techniques; and the curated knowledge base, which guides the system's responses with institutionally validated content. This framework allows the artificial tutor to offer immediate responses, personalize study paths, monitor the user's progress, and, in more advanced settings, identify learning gaps and suggest pedagogical interventions (Ding et al., 2023; Lee, 2025; Yin et al., 2026).

In the academic context, artificial tutors can be used to clarify concepts, support the resolution of exercises, guide reviews, stimulate self-regulation of learning, and offer adaptive simulations. Its application is especially relevant in disciplines with high demand for support, in distance education environments, and in contexts where the ratio of students to available human tutors is unfavorable (Baillifard et al., 2025; Hobert & Berens, 2024).

In the business context, AI mentoring can support upskilling and reskilling programs, technical training trails, onboarding new employees, professional certification support, and the dissemination of organizational knowledge. In this scenario, the tutor acts as a facilitator of access to corporate knowledge, reducing the response time to operational questions and expanding the scalability of development programs (Anshari & Hamdan, 2022; Leon, 2023; World Economic Forum, 2025).

However, the effectiveness of the artificial tutor depends on structural conditions. The first is the curation of the knowledge base, which must be accurate, up-to-date, and expert-validated. The second is clarity about the scope of the system's actions, avoiding unrealistic expectations that it can replace complex human mediation. The third is training users to interact productively with the tutor, formulating clear questions, validating answers, and using the system as support rather than a substitute for critical thinking. Without these conditions, the tutor can expand access, but compromise the quality of learning (Đerić et al., 2025; Kasneci et al., 2023; Tharapos et al., 2025).

2.2 TECHNOLOGICAL ACCEPTANCE, MOTIVATION, AND USE OF AI TUTORING

Understanding the effective use of AI tutoring systems requires more than a mere functional description of the technology. It is necessary to understand how users perceive, accept, and incorporate these systems into their learning routines. In this field, the Technology Acceptance Model (TAM), proposed by Davis (1989) continues to be one of the most influential frameworks for explaining technology adoption.

According to the TAM, the intention to use is strongly influenced by two core beliefs: perceived utility and perceived ease of use. In AI-mediated educational contexts, these two variables remain particularly relevant, as the perception of practical value and the absence of technical barriers directly affect engagement with digital tutors and learning platforms (Davis, 1989; Davis et al., 1989; Ngo et al., 2025). The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) expands this analysis by incorporating contextual and social factors, such as performance and effort expectations, social influence, and enabling conditions. This expansion is important because the decision to use an AI tutor depends not only on the interface but also on infrastructure, institutional support, the culture of use, and prior experience with digital tools (Acikgul & Sad, 2026).

In the case of the artificial tutorial, recent research shows that students strongly value attributes such as speed, continuous availability, accessible language, consistency of answers, and concrete usefulness for tasks and assessments - when these elements are present, technology tends to be perceived as an ally, when they are not, it is seen as operational noise or a low-confidence solution (Al-Abri, 2025; Ding et al., 2023; Hobert & Berens, 2024).

But the adoption of artificial tutors cannot be explained by instrumental factors alone. Self-Determination Theory (SDT) adds a decisive layer to the debate by showing that sustained engagement depends on the satisfaction of three basic psychological needs: autonomy, competence, and relationship (Niemiec & Ryan, 2009; Ryan & Deci, 2000).

In technology-mediated environments, this means that a tutoring solution tends to be more effective when, in addition to being functional, it reinforces the student's sense of autonomy, expands their perception of competence, and sustains some level of bonding or welcoming. This point helps explain why some technically efficient systems don't necessarily produce deep engagement or lasting learning (Chiu, 2024; Li et al., 2024; Puderbach et al., 2025).

Recent research has made progress by combining technological acceptance with motivation, and these integrated models suggest that understanding the adoption of generative AI in education is clearer when cognitive, contextual, and motivational factors are considered together. In educational terms, users do not engage with a tutor just because it is available, but because they see its value, feel capable of using it, find it supportive, and believe that the technology helps them to progress and become more autonomous (Tbaishat et al., 2026).

2.3 KNOWLEDGE SKILLS AND KNOWLEDGE CREATION

In the context of Industry 5.0, the discussion of competencies needs to go beyond the traditional technical repertoire, as the contemporary agenda values skills that integrate technology, cognition, adaptation, judgment, collaboration, and knowledge creation. Therefore, the expression knowledge skills is useful in this article, as it refers not only to the mastery of information, but to the ability to transform knowledge into action, learning, and value (European Commission, 2025; Sheikh et al., 2025; World Economic Forum, 2025).

Accelerated transformation scenarios and skill gaps are no longer merely operational problems; they are beginning to pose a direct risk to competitiveness, innovation, and organizational learning capacity. Therefore, cognitive, digital, adaptive, and relational skills should be treated as strategic assets and as inputs for broader processes of knowledge creation and circulation (Leon, 2023; Rikala et al., 2024).

This reading dialogues directly with Organizational Knowledge Creation (OKC), developed by Nonaka and collaborators. The SECI model explains that organizational knowledge emerges through the continuous conversion between tacit and explicit knowledge, in four movements: Socialization, Externalization, Combination, and Internalization, with the initials of these words forming the acronym. The central point here is simple but decisive: knowledge is not only stored but also created, shared, structured, and reapplied in dynamic cycles (Nonaka, 1994; Nonaka et al., 2000; Nonaka & Takeuchi, 1995).

From this perspective, knowledge skills can be understood as individual and collective capacities that feed these cycles. The ability to formulate questions, interpret answers, connect concepts, explain experiences, learn from feedback, recombine content, and apply knowledge in new contexts is not peripheral - it is part of the very process of creating organizational knowledge (Alavi & Leidner, 2001; Cerchione et al., 2024; Gold et al., 2001).

The perspective of Knowledge Management Processes (KMP) reinforces this reading. Processes such as the creation, storage, transfer, and application of knowledge depend on competencies distributed among individuals, teams, and systems. When these competencies are fragile, misaligned, or poorly mobilized, the flow of knowledge loses quality. As a consequence, the skills gap can be interpreted not only as individual insufficiency but also as a symptom of limitations in the very mechanisms of knowledge conversion and use (Alavi & Leidner, 2001; Anshari & Hamdan, 2022; C. Liu, 2024).

This argument is especially relevant to Industry 5.0, as this paradigm expands the need for continuous learning and collaboration between humans and intelligent systems. In this environment, value arises not solely from automation but from the integration of technology with human judgment, creativity, contextual interpretation, and adaptive learning (European Commission, 2025; Sheikh et al., 2025; Xu et al., 2021).

2.4 AI TUTORING AND KNOWLEDGE SKILLS IN INDUSTRY 5.0

The link between AI tutoring and knowledge skills becomes clearer when one abandons a merely instrumental view of technology. An AI-based tutor should not be seen as just an autoresponder mechanism; in a more mature design, it operates as a layer of support for learning, reflective practice, study organization, access to knowledge, and the internalization of useful repertoires for decision-making and problem-solving (He, 2025; Lee, 2025; Reicher et al., 2025).

When well-designed, AI tutoring models can strengthen skills such as learning autonomy, question formulation, the ability to search for and validate information, conceptual articulation, adaptation to feedback, content synthesis, and practical use of knowledge. These capabilities speak directly to the demands of Industry 5.0, especially in environments where continuous updating, critical interpretation, and workflow learning become essential (Chiu, 2024; Leon, 2023; World Economic Forum, 2025).

At the same time, the literature suggests that the gain is not in replacing human mediation but in repositioning it. Instead of focusing the human tutor on repetitive, operational responses, AI can absorb some of that volume, freeing up space for higher-density interactions, such as mentoring, interpretation, contextualization, and formative follow-up. This redistribution of roles is consistent with the human-centered logic of Industry 5.0, in which technology should expand, not reduce, human potential (Alfirević et al., 2025; Seo et al., 2021; Shen et al., 2025).

This arrangement also makes sense from a knowledge management perspective. If artificial tutoring can support the externalization of doubts, the combination of contents, the internalization of concepts, and the circulation of useful answers, it can operate as a complementary mechanism to SECI cycles. This does not mean attributing to technology the role of autonomous creator of organizational knowledge, but recognizing it as an infrastructure that supports mediation, sharing, and interaction-based learning (Cerchione et al., 2024; C. Liu, 2024; Nonaka et al., 2000).

In summary, AI tutoring can contribute to the development of knowledge skills when it meets five central conditions: practical relevance for the user, ease of use, integration with motivational principles, pedagogical curation, and articulation with broader processes of knowledge creation and application. Without this, technology may even achieve initial adoption, but it is unlikely to produce a consistent formative impact.

3 METHODOLOGY

This article adopts a qualitative, theoretical-conceptual approach, developed through an integrative literature review. The analytical construction starts from the intersection between two main axes: the literature on AI tutoring in higher education, with an emphasis on technological acceptance, motivation, and AI-mediated learning, and the literature on skills, skill gaps, knowledge creation, and Industry 5.0.

The analysis was conducted through a cross-thematic synthesis. The sources were organized into four analytical blocks: tutoring models; technological acceptance and motivation; knowledge and knowledge-creation skills; and Industry 5.0. From this, we identified convergences, tensions, and conceptual interfaces that could sustain an integrative interpretation of the phenomenon under investigation.

The choice of a theoretical-conceptual article is justified because the objective of this stage is not to test a specific model empirically, but to consolidate an analytical basis of two strands that, until then, have been in parallel. Rather than fragmenting the debate, the article builds an interpretive bridge between intelligent mentoring and the development of knowledge skills, focusing on analytical utility and managerial applicability.

4 RESULTS AND DISCUSSION

4.1 CONTRIBUTIONS OF AI TUTORING MODELS TO THE DEVELOPMENT OF KNOWLEDGE SKILLS

The main contribution of AI tutoring models lies in their ability to reduce friction in accessing support and to increase the availability of mediation. In practical terms, this means that the student or user can resort to the system when in doubt, at their own pace and with greater autonomy. This point is decisive because contemporary learning relies less and less on formal windows of instruction and more and more on timely, contextual, and responsive support (Ding et al., 2023; Hobert & Berens, 2024; Reicher et al., 2025).

This type of support favors the development of skills and knowledge on at least four fronts. The first is autonomy, as well-designed tutoring systems help the user to advance without relying exclusively on immediate human interventions. The second is competence: quick feedback and accessible explanations can strengthen the perception of progress. The third is self-regulated learning, as the tutor's availability encourages planning, monitoring, and reviewing one's own study path. The fourth is cognitive articulation, since the user needs to formulate questions, refine commands, interpret answers, and validate information (Chiu, 2024; He, 2025; Ryan & Deci , 2000).

These gains are in direct adherence to the logic of Industry 5.0. Recent literature shows that contemporary work and learning environments require professionals who can engage in continuous learning, operate in hybrid ecosystems, navigate ambiguity, integrate information and judgment, and develop adaptive repertoires. From this perspective, an AI tutor is not only an academic support tool, but it can also be a mechanism for continuous training of competencies associated with the strategic use of knowledge (Leon, 2023; Sheikh et al., 2025; World Economic Forum, 2025).

4.2 COMPARATIVE SYNTHESIS: MODELS OF TUTORING, MEDIATION AND SKILLS DEVELOPMENT

The theoretical analysis developed in the previous sections allowed us to articulate, in a structured way, the relationships between AI tutoring models, pedagogical mediation mechanisms, developed knowledge skills, and adherence to the principles of Industry 5.0. This synthesis was not limited to describing isolated characteristics of each model, but sought to highlight how the use of AIs, specifically in the different tutoring models, can influence, in a different way, the development of critical skills for continuous learning, adaptability, and the creation of knowledge in digital and organizational environments.

Table 1 summarizes these relationships comparatively, showing that the choice of the tutoring model is not neutral: it directly affects which knowledge skills are favored, which mediation processes are activated, and which logic of human centrality or technological scalability prevails; the latter in adherence to the principles of Industry 5.0.

Table 1

Relationship between AI tutoring models, mediation mechanisms, and knowledge skills development

Tutoring Models	Mediation mechanisms	Favored knowledge skills	Adherence to Industry 5.0
Human tutoring	welcoming, relational bonding, contextual interpretation, pedagogical judgment, qualitative feedback	critical thinking, collaboration, contextual sensitivity, relational competence	human centrality, situated learning, qualitative mediation
Artificial tutoring	continuous availability, fast response, algorithmic personalization, scalable access, and immediate feedback	learning autonomy, digital competence, question formulation, information validation, self-regulated learning	scalability, on-demand learning, digital workflow support
Hybrid tutoring	combination of scale (AI) and depth (human), automated screening, guided deepening, pedagogical curation	autonomy, digital competence, critical thinking, adaptability, human-AI collaboration	human-centered technology, continuous learning, collaborative knowledge creation

Source: Prepared by the authors.

Through this relationship, it was possible to identify that the hybrid model presented a greater balance between scalability and pedagogical depth. When comparing these three models, human tutoring favors relational and contextual skills but faces structural limitations in availability; artificial tutoring expands access and speed but can compromise criticality and interpretation; and the hybrid model articulates the two mediation registers in a complementary way. In this configuration, AI takes on operational and first-layer support functions, while the human tutor remains responsible for conceptual deepening, pedagogical validation, and welcoming (Alfirević et al., 2025; Seo et al., 2021).

This division of labor is not only functional. It expresses a design decision about what should be automated and what should remain under human responsibility. When well implemented, this separation allows the human tutor to focus his energy on interactions of greater formative density, freeing up time previously consumed by repetitive responses, operational clarifications, and low-complexity support. At the same time, the AI system becomes more effective by being delimited in its scope, avoiding functional overload or unrealistic expectations regarding its ability to replace complex pedagogical mediation (Hobert & Berens, 2024; Massuga et al., 2021; Shen et al., 2025).

From a knowledge management perspective, it is possible to integrate artificial tutoring into the processes of knowledge creation, sharing, and application. From the perspective of the SECI model, proposed by Nonaka and colleagues, artificial tutoring can especially support three movements in the knowledge conversion cycle: externalization, by encouraging users to formulate questions and articulate doubts explicitly; the combination, by organizing, structuring, and connecting different contents in an accessible and personalized way; and internalization, by facilitating the practical application of concepts through immediate feedback and adaptive exercises (Nonaka, 1994; Nonaka et al., 2000; Nonaka & Takeuchi, 1995).

This positioning does not attribute to AI the role of autonomous creator of organizational knowledge, but recognizes it as an infrastructure to support the mediation, circulation, and application of knowledge in learning contexts. When integrated into broader KMP processes, artificial tutoring can increase the efficiency of knowledge transfer, reduce barriers to access, and strengthen learning cycles in educational organizations and institutions (Alavi & Leidner, 2001; Cerchione et al., 2024; C. Liu, 2024).

However, the effectiveness of this arrangement depends on five structural conditions that must be met simultaneously. The first is the curation of the knowledge base, which ensures the accuracy, updating, and validation of the information accessed by the artificial tutor. Without curation, the system can expand access, but generate inaccurate, outdated, or decontextualized answers, compromising trust and the quality of learning (Kasneci et al., 2023; Tharapos et al., 2025). The second condition is the clarity of scope, which delimits what the artificial tutor can and should do. AI systems are not a substitute for pedagogical judgment, contextual sensitivity, or relational acceptance. When these limits are not made explicit, unrealistic expectations arise, leading to user frustration and distrust of technology (Al-Abri, 2025; Đerić et al., 2025). The third condition is the user's training, which requires developing skills to interact productively with the artificial tutor. This includes formulating clear questions, interpreting answers, validating information, identifying biases or inaccuracies, and using the system to support critical thinking rather than substituting for reflection. Without this training, the use of AI can be superficial, passive, or dependent (Chiu, 2024; He, 2025). The fourth condition is integration with motivational principles, especially those derived from SDT. Artificial tutors who reinforce student autonomy, offer feedback that broadens the perception of competence, and sustain some level of bonding or nurturing tend to promote greater engagement and sustained use. On the other hand, systems that only deliver answers, without formative guidance, can be perceived as cold, instrumental, or disconnected from the real learning process (Li et al., 2024; Ryan & Deci, 2000; Tbaishat et al., 2026). The fifth condition is institutional governance, which defines responsibilities, validation criteria, feedback mechanisms, processes for updating the knowledge base, and forms of articulation between human and artificial tutoring. Without clear governance, the implementation of AI tutors tends to be fragmented, unsustainable, and disconnected from broader formative goals (European Commission, 2025; Shen et al., 2025).

When these five conditions are met, the hybrid tutoring model becomes particularly aligned with the principles of Industry 5.0. This paradigm values not automation for automation's sake, but the ability to combine technology with human centricity, continuous learning, sustainability, and organizational resilience. In this framework, artificial or hybrid tutoring is no longer just an operational support tool but becomes part of the infrastructure for developing knowledge skills, especially those associated with adaptability, critical thinking, digital competence, and the ability to learn autonomously in fast-changing environments (European Commission, 2025; Ghobakhloo et al., 2022; Xu et al., 2021).

Finally, by explaining the relationships between the tutoring model, mediation mechanisms, developed skills, and adherence to Industry 5.0, this research presented criteria for the conscious choice of tutoring configurations, evaluation of educational technologies, and the creation of training trails that combine human development and technological support in a coherent and sustainable way (Leon, 2023; Rikala et al., 2024; World Economic Forum, 2025).

4.3 LIMITS, RISKS AND NECESSARY MEDIATIONS

It would be simplistic to treat AI tutoring as a sufficient solution on its own. The literature shows that the presence of generative systems does not eliminate problems of quality, depth, criticality, or cognitive dependence. In some cases, the fluidity of the response creates a false perception of accuracy; in others, the ease of support encourages passive use, without self-elaboration or without adequate validation of the content (Đerić et al., 2025; Kasneci et al., 2023; Tharapos et al., 2025).

This risk becomes more pronounced when the goal is not only to transmit information but also to develop knowledge skills. Knowing how to access an answer is not the same as knowing how to build knowledge. Real competence development requires interpretation, confrontation of perspectives, reflection, application, and the ability to transfer learning to new contexts. Without these elements, digital tutoring can improve operational efficiency but yield limited formative impact.

Therefore, human mediation remains central. The human tutor, the teacher, the instructional designer, or the manager of the learning process remains essential for defining criteria, validating content, guiding criticality, and sustaining the pedagogical bond. The point, therefore, is not to choose between humans and AI, but to design arrangements in which technology takes over what it does best – speed, scale, availability, and operational support – while humans focus their energy on what requires judgment, context, sensitivity, and depth (Alfirević et al., 2025; Massuga et al., 2021; Seo et al., 2021).

5 CONCLUSION

This article looked at how different mentoring models – human, artificial, and hybrid – relate to the development of knowledge skills in the context of Industry 5.0. The theoretical and conceptual synthesis allowed us to sustain that the AI-mediated tutorial can contribute in a relevant way to autonomy, self-regulated learning, access to knowledge, digital competence, and adaptability, as long as its adoption is articulated with pedagogical, motivational, and organizational criteria, and not only to gains in technological efficiency (Chiu, 2024; Davis, 1989; European Commission, 2025).

The central argument is straightforward: in Industry 5.0, the value of AI in learning environments does not lie only in the ability to respond quickly; it lies in its ability to strengthen human learning, expand the creation and circulation of knowledge, and support the development of competencies that remain critical precisely because the environment has become more technological, not less human. When designed with this logic, AI tutoring is no longer merely an operational accessory but functions as a development infrastructure.

The findings also indicated that the hybrid model tends to offer the best balance between scale, availability, depth, and welcoming. This is not a methodological detail; It's a design decision. And, as is often the case with projects that seem to be resolved too soon, the problem is rarely in the technology alone – it lies in the adopted mediation model.

The article opens the way for empirical studies on the different types of tutoring in Higher Education Institutions (HEIs), corporate environments, and executive training programs. The investigation of metrics that more objectively relate mentoring models to the satisfaction of psychological needs, the development of skills and knowledge, and their effects on academic and organizational performance is also promising.

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