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The contribution of Knowledge Building  
to Human Transformative Education

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*Maria Beatrice Ligorio, Donatella Cesareni,  
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*Publisher*

Progedit, via De Cesare, 15

70122, Bari (Italy)

tel. 080.5230627

fax 080.5237648

info@progedit.com

www.progedit.com

qwerty.ckbg@gmail.com

www.ckbg.org/qwerty

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# Knowledge Building in the artificial intelligence age: Exploring the role of large language models as students' consultant

*Stefano Cacciamani\**, *Ahmad Khanlari\*\**


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## Abstract

Knowledge Building has long theorized the need of rethinking K-12 and higher education systems by orienting their activity toward the co-construction of knowledge, to solve community's authentic problems. This shift in perspective is today enriched by a new question: how can Artificial Intelligence (AI), and particularly Large Language Models (LLMs), be leveraged to support these systems in functioning as genuine knowledge-building communities? This contribution centers on this question, first revisiting the key elements of the Knowledge Building theory, exploring the opportunities offered by AI tools based on LLMs, identifying the role of LLM to support knowledge-building activities, and examining future directions of inquiry

**Keywords:** Knowledge Building, Artificial Intelligence, Large Language Models, Epistemic Agency, Chatbot

\* University of Valle d'Aosta, Italy,  0000-0003-4455-3988.

\*\* University of Toronto, Canada,  0000-0001-6390-0629.

Corresponding author: [s.cacciamani@univda.it](mailto:s.cacciamani@univda.it)

## Introduction

Since its launch in November 2022, ChatGPT has sparked a pivotal shift in public focus toward Artificial Intelligence (AI), particularly in the realm of Natural Language Processing, now empowered by Large Language Models (LLMs). The advanced capabilities of LLMs in understanding and generating text have, in fact, fascinated a large audience and have favored their massive use in everyday life activities. In this contribution, we define AI as a technology that constructs systems capable of thinking and acting in ways that mimic human cognition and behavior, with the ability to achieve specific goals (Akgun & Greenhow, 2022). Thanks to Natural Language Processing techniques, artificial intelligence tools can interact with human subjects using language. LLMs, such as ChatGPT or Copilot, are AI models trained on vast datasets, allowing them to generate human-like texts, answer questions, and perform many linguistic tasks accurately (e.g., translating texts into different languages, summarizing texts, providing feedback, etc.) (Kasneji et al., 2023).

The availability of such powerful tools has also sparked a broad debate in education, exploring how they can serve as a resource for building innovative learning environments in schools. Recent works have examined the possible applications of LLMs in learning contexts, highlighting opportunities and challenges associated with the use of such tools to support student activity (Joksimovic, et al. 2023; Kamalov et al., 2023; Kasneji et al., 2023).

However, it should be considered that this historical turning point, linked to the advent of AI based on LLMs, aligns with the evolving needs of the “Knowledge Society”. The origin of this expression can be traced back to the 1960s, when Drucker (1969) introduced the concept of the “Knowledge Society” to characterize a new type of economy in which knowledge emerged as a fundamental resource, marking a clear break from the societal structures of earlier historical periods. More recently, the White Paper of the European Commission used this concept to describe a new type of society that recognizes knowledge as a fundamental resource and is characterized by continuous transformation driven by the rapid development of new

digital technologies (Commission Européenne, 1995). Moreover, UNESCO has coined the expression “Inclusive Knowledge Society” to emphasize “societies in which people have the capabilities not only to acquire information but also to transform it into knowledge and understanding, which empowers them to enhance their livelihoods and contribute to the social and economic development of their communities” (Souter, 2014, p.18). In this way, UNESCO highlights a key perspective for fostering sustainable human and economic development. In the digital era of AI-powered LLMs, this calls for a transformation of current education systems to incorporate activities in schools that not only cultivate lifelong learning skills but also foster the competence for collaborative knowledge building that contributes to the advancement of one’s community. As highlighted by Tan et al. (2021) classroom designs and teaching practices are often misaligned with the purpose of educating students for knowledge work, because “creative knowledge work requires open ended inquiry, but many classroom designs focus on teacher-directed inquiry, scripted activities, initiate-response-evaluate discourse patterns, fixed groups and role membership, which lack emergence, integration and adaptive designs” (p. 2252). It is necessary, then, to shift from instructionist and teacher centered approaches toward a new paradigm. Knowledge Building (KB) (Scardamalia & Bereiter, 1999; 2010) has long theorized the need for this shift in perspective, which today is enriched by a new question: how can AI, and particularly LLMs, be leveraged to support a classroom in functioning as a genuine KB Community? This contribution centers on this question, first revisiting the key elements of the Knowledge Building theory, exploring the opportunities offered by AI tools based on LLMs, identifying the role of LLM ways to support KB activities, and examining future directions of inquiry.

## **Knowledge Building**

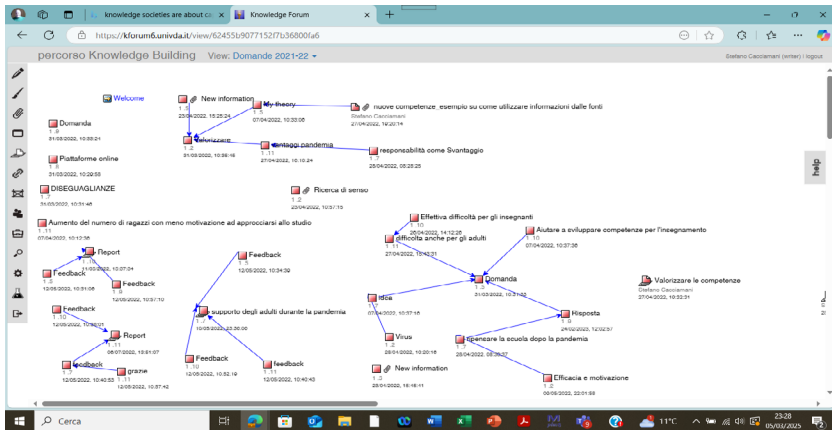
Knowledge Building (KB) developed by Carl Bereiter and Marlene Scardamalia from the University of Toronto in the late 1980s, introduces a “Copernican revolution” in the vision of education, from

K-12 to higher education systems, by orienting their activity to build knowledge to solve the community's authentic problems (Scardamalia et al., 1994). From KB's perspective, then, learning is no longer considered the ultimate purpose of education; rather, it is an activity through which students acquire knowledge to build new knowledge. KB is a theory and a practice guided by 12 principles rather than rigid procedures. The principles work together in a systemic way to globally ensure the conditions for knowledge building (Scardamalia, 2002; Scardamalia & Bereiter, 2010). As described by Scardamalia and Bereiter (2006), KB turns a high level of agency to students by involving them in high levels of knowledge work. They are, indeed, engaged in defining goals of inquiry, planning, monitoring, and assessing their work (Epistemic Agency principle). Diversity of ideas proposed by students plays an important role in advancing community knowledge (Idea Diversity principle), and the ability to build knowledge highly depends on recognizing and respecting the ideas of others, by considering that all ideas can be potentially improved (Improvable Ideas principles). Also, students can work with diverse ideas in complex problem spaces to advance the current levels of explanation and create higher level syntheses on knowledge advancements (Rise Above' principle). To make idea improvement and rise above happen, KB engages students in social interactions in which they create community knowledge through discursive practices (Knowledge Building Discourse principle). Additionally, students are encouraged to use authoritative sources in a constructive and critical way to support and refine their ideas (Constructive Use of Authoritative Sources principle). Expertise is distributed within the community and between groups and therefore, the advancement of knowledge happens symmetrically, through a joint effort between more or less knowledgeable groups (Symmetric Knowledge Advancement principle). In fact, in such a community, knowledge is democratized, and all participants are legitimate contributors to the advancement of community knowledge (Democratizing Knowledge principle). Contribution to the community is not only a right, but a responsibility; community and individual achievement go hand in hand (Community Knowledge principle). To follow sustained creative work with ideas, students need the space and opportunity to

pursue their real ideas and authentic problems that arise from their efforts to understand the world and the concepts they are working with (Real Ideas, Authentic Problems principle). Rather than solving given problems, they learn to mine the world around them for interesting issues and challenges, discovering opportunities for knowledge advancement also across different contexts (Pervasive Knowledge Building principle). Assessment becomes integral to the process and students themselves monitor community knowledge advances, rather than simply waiting for external evaluation (Concurrent, Embedded and Transformative Assessment principle) (Scardamalia & Bereiter, 2006). KB, with these 12 principles, has the potential to “set a knowledge building classroom off as profoundly different from even the best of traditional and modern classrooms” (Scardamalia 2002, p. 77).

Considering the importance of discourse for knowledge building, an online discussion space called Knowledge Forum (KF) has been developed to support the production of knowledge (Scardamalia, 2004). Three specific features of KF are “notes,” “build-on” and “views.” Students can share their ideas and questions using notes (written messages). They can also build ideas onto other students’ ideas contained in other notes, or answer questions posted by the instructor/other students using the build-on function (linking contributions to foster dialogue). Notes and build-ons are posted on views, which are collaborative spaces created to discuss a specific topic (Scardamalia, 2004). Within KF, students can also use scaffolds that support the KB discourse. These scaffolds that support discourse (Soliman et al., 2021) and “help shape discourse to knowledge building purposes” (Scardamalia & Bereiter, 2006, p. 22) include, but are not limited to “I need to understand” (to indicate a problem of understanding) or “My theory” (to formulate a possible explanation of a problem). These scaffolds act as epistemic markers, operating at a meta-discourse level, explicitly focused on knowledge building. Additionally, the “Rise above” function allows students to synthesize ideas, collectively advancing the community’s knowledge. This collaborative platform thus facilitates a unique and essential form of discourse for KB.

**Figure 1.**  
*A view of Knowledge Forum.*



Based on the 12 KB principles and supported by KF, in a KB Community, the activity typically starts with the teacher introducing a topic, who creates the conditions for students to pose their authentic questions. The most promising questions are identified—those that deepen understanding of the topic and serve as catalysts for collaborative knowledge building. Students, often working in research groups, generate their initial theories—provisional explanations or solutions to their inquiry problems. These theories are then continuously refined through engagement with authoritative sources, empirical data collection, and, where applicable, experimentation. The investigation process is accompanied by collaborative discourse within Knowledge Forum (KF), where students share information and iteratively refine their initial theories. Under the guidance of the teacher, research groups engage in periodic KB Talks, where they assess knowledge progress, identify emerging challenges, refine inquiry directions, and advance collective understanding. These discussions foster improvement and epistemic agency, ensuring that students take responsibility for deepening their inquiry. By the end of the investigative process, students collaboratively formulate progressive, high-quality theories that provide well-founded explanations and potential solutions to the

problems addressed. In this contribution, we focus on how a large language model (LLM) can support key actions that typically occur in a KB activity: (1) asking questions; (2) formulating and refining theories; (3) finding and critically analysing relevant information and references; (4) discussing and critiquing ideas; and (5) synthesizing contributions and identifying knowledge advances.

### **Large Language Models (LLMs) and Knowledge Building: some challenges**

LLMs represent a transformative breakthrough in artificial intelligence, particularly within the realm of natural language processing. At their core, transformer-based models—exemplified by systems such as GPT (Generative Pre-trained Transformer) or Copilot—are designed to process and generate human-like text (Hadi et al., 2023; Raiaan et al., 2024). These models work by analyzing enormous datasets to detect patterns and relationships among words and phrases. Their self-attention mechanism enables them to assess the relevance of each word in a given context, thereby producing coherent and contextually appropriate responses (Liu, 2025). This capability underpins several core functions: generating text, synthesizing information from diverse sources, and providing immediate, on-demand feedback, all of which have contributed to their rapid adoption in educational technology (Liu, 2025).

Another significant advantage of LLMs is their potential to serve as scaffolding tools in educational settings (Attard & Dingli, 2024; Malik et al., 2024). By assisting students in structuring their thoughts, organizing their research, and even mapping out the evolution of their ideas, these models help bridge the gap between initial understanding and deeper conceptual insight. They can guide learners to identify knowledge gaps in their reasoning and suggest resources or questions that drive further exploration (Murtaza et al., 2025). This scaffolding role is especially important in complex subjects where the pathway from problem identification to solution development is non-linear and iterative. Mollick and Mollick (2023) analyze a practical approach to using AI to help students learn, outlining seven approaches that can serve as a complement to classroom teaching: AI-tutor, for increasing knowledge,

AI-coach for increasing metacognition, AI-mentor to provide balanced, ongoing feedback, AI-teammate to increase collaborative intelligence, AI-tool for extending student performance, AI-simulator to help with practice, and AI-student to check for understanding.

However, integrating LLMs into a classroom that is re-designed as a KB Community requires a different approach, not focused on promoting learning but on supporting the construction of knowledge. We will define this approach through the metaphor of the AI as KB Consultant. The idea of a consultant is chosen to identify an agent with whom students can interact, not only to receive information but to address the progressive problem solving activity that characterizes knowledge building (Scardamalia & Bereiter, 1994). To describe this shift, we will consider several important challenges that must be addressed when introducing a LLM into a KB activity.

The first challenge concerns the practice of questioning and involves finding the right balance between students' epistemic agency and AI support while avoiding overreliance on AI-generated outputs. As Mollick and Mollick (2023) emphasize, students may be tempted to delegate their cognitive responsibilities to AI, which can lead to problematic outcomes. In a KB environment, this may result in students relinquishing their epistemic agency by avoiding the development of deep, meaningful research questions. While LLMs can offer valuable support, it is essential that educators ensure students remain the primary agents of their own inquiry.

A second challenge relates to formulating and improving theories. It concerns the risk that students may be influenced in their work by the persuasive capability of AI. As Denhart and Mongeau (2022) explain, "we define AI-based persuasion as a symbolic process in which a communicative-AI entity generates, augments, or modifies a message—designed to convince people to shape, reinforce, or change their responses – that is transmitted to human receivers" (p. 4). When students are presented with rhetorically sophisticated responses from a Chatbot, they may perceive these answers as definitive or indisputable solutions to their inquiry problems. This can lead them to prematurely accept AI outputs and abandon the effort to critically formulate and refine their own theories.

Another critical challenge involves finding and critically analysing information and results. The key concern is ensuring that AI-generated outputs do not become uncritically accepted as authoritative sources of information. LLMs, despite their impressive capabilities, are not immune to error and may generate content that appears credible but contains factual inaccuracies or underlying biases. As noted by Mollick and Mollick (2023), LLMs are prone to producing incorrect yet plausible information, a phenomenon known as confabulation or hallucination. These models can generate responses that seem insightful and convincing while including fabricated “facts” seamlessly woven into their output. It is essential, therefore, to teach students to critically evaluate AI-generated content: questioning its claims, verifying its accuracy, and situating it within broader academic discourse. Such practices not only protect the integrity of the KB process but also foster the development of critical information literacy.

A fourth challenge concerns the practice of discussing and critiquing ideas. According to the “Community Knowledge” principle of KB, the goal is to create ideas that hold value for the community as a whole (Scardamalia & Bereiter, 2010). The challenge, therefore, is to ensure that the contributions generated with the support of an LLM remain focused on advancing collective understanding, rather than serving individual interests alone. While AI consultation can offer highly personalized support, it is crucial that such assistance also contributes to community knowledge advancement. The ideal scenario is one where the insights generated by the AI are shared and discussed within the broader community, thus reinforcing collective responsibility and mutual advancement of knowledge. In other words, while the model may initially interact with an individual learner, its contributions should eventually feed back into group discussions, supporting a vibrant, collaborative KB environment.

Finally, another important challenge involves synthesizing and identifying knowledge advances. According to the “Rise Above” principle in KB students are encouraged to work with diversity, complexity, and apparent disorder in order to achieve new syntheses. Importantly, synthesis in this context is not merely about summarizing or organizing ideas that emerged during the inquiry. Rather, it involves

selecting ideas that are supported by evidence—such as reliable sources or experimental results—and integrating them into a coherent explanatory framework (Thagard, 1989) to generate meaningful solutions to the problems under investigation. LLMs not only offer advanced capabilities for text generation, but also open new possibilities for synthesizing scientific content in innovative ways (Babaei Giglou et al., 2023). While these models can help synthesize ideas and track the evolution of ideas, the “black box” nature of their underlying processes raises questions about transparency and accountability (Chen et al., 2023). Educators must support students in understanding the rationale behind proposed syntheses, ensuring that the evaluation of knowledge advancements remains within the students’ cognitive responsibility and is aligned with the learning objectives.

The challenges discussed in relation to integrating LLMs into the KB activity offer a framework for identifying key issues that must be addressed. To explore potential solutions, we will describe the role of the LLM using the metaphor of the *LLM as a KB Consultant*.

### **LLM as a KB Consultant: Stage-by-Stage Support**

LLMs can play a significant role in supporting classroom-based KB communities by taking on what we term the role of a KB Consultant. Recent research highlights that appropriate guidance to support effective use of LLMs for specific tasks, can help students form the correct mental models of tools (Kumar et al., 2023). Using a metaphor to define the role of LLM in the KB activity is important for fostering a clear mental model of how it can function within this context.

This section describes a practical framework for integrating LLMs into the KB activity. The method used to build this framework can be outlined in the following steps:

1. Identification of KB actions that can be supported by AI
2. Defining crucial aspects of these actions based on KB principles;
3. Defining Chatbot functions aligned with KB principles;
4. Testing the defined functions through simulation with the Chatbot.

The following section presents an analysis of the possible Chatbot functions corresponding to the KB actions identified earlier: (1) Questioning; (2) Formulating and improving theories; (3) Finding and critically analysing information and references; (4) Discussing and critiquing ideas; and (5) Synthesizing and identifying knowledge advances (see Table 1).

**Table 1.**

*KB actions, functions of a Chatbot as KB Consultant and KB principles.*

KB actions	KB principles	Functions of a Chatbot as KB Consultant
Questioning	Epistemic Agency	Feedback to improve questions
Formulating and improving Theories	Improvable Ideas	Questions and feedbacks to improve theories
Finding and critically analyzing Information and References	Constructive Uses of Authoritative Sources	Help in summarizing and organizing multiple references and in verifying if the information fills identified research gaps or if further exploration is necessary
Discussing & Critiquing Ideas	Community Knowledge	Help in analyzing different ideas to highlight contradictions or unresolved conflicts among them
Synthesizing & Identifying Knowledge Advances	Rise Above	Help in synthesizing and highlighting emergent insights in KB discourse

As shown in Table 1, for each action we define key aspects based on KB principles that inform the design of specific Chatbot functions in its role as a KB Consultant. We then provide simulated interactions with Copilot created to test these functions and offer a clearer illustration.

## Questioning

At the onset of any inquiry, effective questioning is essential. A relevant aspect regarding the questioning, according to the KB principle of “Epistemic Agency”, is the recognition of the possibility for students to take the initiative in defining the questions on which to activate the inquiry activity of the classroom. LLMs can prompt students to generate additional, deeper questions by suggesting alternative perspectives. For example, a student working with his/her classmates in an inquiry about a scientific phenomenon (e.g. climate change) can ask to a Chatbot such as Copilot, how to better develop his/her initial question, as following: *“May you indicate how can I improve my following question: “Why is there climate change?”*). Considering the question, in our simulation Copilot provided this answer: *“Here are a couple of suggestions: Add a focus on causes: “What are the main causes of climate change?” Include effects: “Why is there climate change and how does it affect our planet?” These versions can help your classmates understand not only why climate change is happening but also its impact*). The model suggests, then, additional perspectives on how this phenomenon might affect related systems by proposing some reformulation of the question that *considers* the causes or the consequences of the phenomenon and explains why the reformulated questions can be useful for the inquiry. This generative support not only can help to improve the possible questions and broaden the inquiry but also sparks creative thinking by showing how to explore different perspectives on the initial formulation. In this perspective, by asking the Chatbot, in the role of Consultant, for improving feedback on the research question, the student maintains his/her epistemic agency. In fact, the student remains the creator of the question that starts the process of KB.

## Formulating and improving Theories

In the KB community students are invited to formulate their theories about the common questions of inquiry. The “Improvable Ideas” KB principle assumes that all ideas proposed by the students are impro-

vable. During the theory formulation stage, LLMs can help students expand their initial ideas. For example, a student might present to a Chatbot his/her initial “theory” about a given phenomenon that is being explored and can ask the Chatbot to formulate some questions that can help explore the “theory” in depth. For instance, if the student asks the Chatbot: *“My theory is that climate change is due to human activities. Can you ask me some questions to help me improve my theory?”* In response to this question, Copilot provides some thought-provoking questions like the following: *“What are the main human activities that contribute to climate change?”* *“How can we measure the impact of human activities on the climate?”* and other useful questions that can be used by the student to decide how to further develop his/her “theory.” LLM can also propose extra angles, or can ask questions to stimulate students’ illustrative examples, or to identify missing connections in the different parts of the “theory”. In this way, the model encourages learners to refine their preliminary theories. Simultaneously, LLMs can provide immediate, real-time feedback by flagging logical gaps or highlighting contradictory evidence, which is crucial for formative assessment. Students benefit from this instant insight as it allows them to adjust the clarity, consistency, or novelty of their ideas before moving further in the inquiry process. This dual function—supporting theory expansion while assessing its soundness—ensures that the developmental process remains both dynamic and critically self-reflective. The Chatbot, in its role of Consultant, by proposing its questions to improve the initial theories, is particularly useful, then in achieving what is indicated by the Improvable Ideas principle of the KB theory, which provides that no idea is excluded without first having made an effort to improve its quality, coherence and usefulness.

## **Finding and critically Analysing Information & References**

A critical stage in the KB cycle involves sourcing and selecting information useful to test the theories formulated. The KB principle “Constructive Uses of Authoritative Sources” invites students to be involved in the analysis of authoritative sources that mark the current state of

knowledge with a critical approach. LLMs can suggest reputable academic sources, peer-reviewed articles, or authoritative websites that align with the inquiry topic and provide URLs for these sources. By summarizing and organizing multiple references, the model helps students contrast different viewpoints and understand the breadth of available knowledge. Furthermore, ongoing transformative assessment can be embedded here; the LLM can indicate whether the newly gathered information effectively fills identified research gaps or if further exploration is necessary. In our simulated example if a student asks Copilot:

*“A classmate of mine claims that climate change is caused by volcanoes. May you indicate some source of information to check this theory?”*

*The Chatbot provides this answer:*

*Your classmate’s claim that volcanoes are the main cause of climate change is a common misconception. While volcanic eruptions do release greenhouse gases like carbon dioxide (CO<sup>2</sup>), their contribution is minor compared to human activities.*

*Here are some authoritative sources you can check:*

*... (the Chatbot indicated a list of sources)*

*Would you like a short summary or infographic to help explain this to your classmate?* It is important that students do not just accept the LLM response but analyze the sources indicated by the Chatbot, appropriately selected by the teacher and with his/her support, to verify whether the theory being analyzed is actually falsified. This interaction between “theories” and data not only streamlines the research process but also reinforces the importance of evidence-based inquiry. This Chatbot support function in the analysis of information enables students to fulfill the expectations of the KB principle Constructive Uses of Authoritative Sources with particular reference to the critical stance toward them.

## **Discussing & Critiquing Ideas**

Once “theories” and data have been collected, discussion and critique become central to collective knowledge advancement. According to the “Community Knowledge” KB principle, the aim of KB

is to produce knowledge of value to others (Scardamalia & Bereiter, 2010). Theories” are, indeed, the conceptual artifacts to be improved in the KB work to advance community knowledge. LLMs can be invited by the students to analyze students’ discourse to highlight contradictions or unresolved conflicts among competing theories. In our example, for instance, here is the Copilot answer excerpt: “Let’s break down the theories and see how they compare:

1. *Climate change is due to greenhouse effect*

*This theory is widely accepted and supported by scientific evidence. The greenhouse effect is caused by the accumulation of greenhouse gases like CO<sup>2</sup>, methane, and nitrous oxide in the atmosphere, which trap heat and lead to global warming...*

2. *Climate change is caused by volcanoes:*

• *Volcanic eruptions can affect the climate in the short term, primarily through the release of sulfate aerosols that reflect sunlight and cause temporary cooling. However, CO<sup>2</sup> emissions from volcanoes are much lower than those from human activities.....”* and so on.

Copilot provides its feedback on each theory and then presents the comparison like the following:

*“Which theory works best?”*

*The theory that climate change is caused by human activities (theory 3) works best and is supported by extensive scientific evidence. It encompasses the greenhouse effect (theory 1) and includes the impact of agricultural practices (theory 4). Volcanic activity (theory 2) plays a minor role in comparison.”*

By comparing and contrasting overlapping ideas across student contributions, the model fosters a collaborative refinement of collective understanding. Real-time responses and feedback (such as “Have you considered X perspective?”) can further stimulate deeper dialogue. This immediate, formative feedback helps guide group discussions towards more nuanced, critically examined outcomes, ensuring that all contributions are scrutinized and built upon collaboratively. This Chatbot function allows students to “work with the full set of ideas generated by the community, identify weaknesses, engaging in constructive criticism, pursuing better explanations, and defining new problems” (Zhang, et al. 2007, p. 120).

## Synthesizing & Identifying Knowledge Advances

According to the “Rise Above” principle, students work with diversity, complexity and disorder, and to achieve new syntheses. In the final stages of the KB cycle, LLMs can help in synthesizing emergent insights into coherent progress portfolios or conceptual maps that visually represent the evolution of ideas. For example, a student may ask the Chatbot: “Here are some theories that have been formulated in my class about climate change: 1. Climate change is due to the greenhouse effect; 2. Climate change is caused by volcanoes; 3. Climate change is caused by human activities; 4. Climate change is caused by animals. Can you create a synthesis?” Copilot can create a synthesis like the following:

*“The primary cause of current climate change is human activities, which significantly enhance the natural greenhouse effect by increasing the concentration of greenhouse gases in the atmosphere. While volcanic eruptions and animal agriculture do contribute to greenhouse gas emissions, their impact is relatively minor compared to the emissions from burning fossil fuels, deforestation, and industrial processes. Therefore, the most comprehensive understanding of climate change incorporates the role of human activities in driving the enhanced greenhouse effect.”*

The model can flag new, unanswered questions or significant conceptual leaps that emerge during discussions, prompting further inquiry. By regularly providing a transformative assessment of how ideas have shifted over time, LLMs help knowledge builders reflect on their collective progress and determine the next steps for exploration. This continuous, iterative mapping supports a transparent and dynamic learning process where every insight is critically evaluated and integrated into a broader knowledge framework. This Chatbot support function can allow students to create new syntheses from the ideas emerged through the KB discourse, allowing to detect community knowledge advancements, as outlined by the “Rise Above” principle of the KB theory.

## Discussion and Conclusions

The question addressed in the present contribution was: how can AI tools empowered by LLMs be used so that a school class can act as a community that collaboratively builds knowledge?

We have analyzed in detail how the different actions of a KB activity (Questioning, Formulating Initial Theories, Finding Information & References, Discussing & Critiquing, Synthesizing & Identifying Knowledge Advances) could be supported by an Artificial Agent based on LLMs, assuming the role of KB Consultant. To implement this role, we can identify some key conditions concerning the role of the student, the nature of the information provided by the Chatbot and the teacher's role in designing this KB environment powered by AI.

The first condition concerns the *student's role* in the KB process. As previously indicated, Mollick and Mollick (2023) highlight that students may be tempted to delegate their cognitive responsibility to AI, leading to problematic consequences. These authors describe an "Instructional risk", noting that AI can be highly persuasive and present strong, seemingly authoritative viewpoints on facts and theories that the models "believe" to be correct. Due to their convincing nature, they could potentially undercut classroom learning by teaching material that is not correct or is not part of established curricula. To mitigate this risk, it is necessary to preserve students' epistemic agency, as we have seen, in the interaction with the AI. Promoting students' epistemic agency means ensuring they remain active participants in the use of AI, rather than adopting a passive role. The use of LLM as KB Consultant, can preserve the students' epistemic agency, because they are invited to critically question the AI-generated outputs, using metacognitive awareness of their inquiry goals to analyze, evaluate, select, and reorganize the information provided by the tool. Rather than passively accepting AI responses, students should engage in reflective judgment, comparing AI-generated insights with their own evolving ideas and authoritative sources.

A second condition is about *the nature of the information provided by LLMs* and concerns the reliability and the presence of bias in the information produced by the AI agent. This aspect can be con-

nected to the Constructive use of authoritative sources principle of KB that highlights the importance of using authoritative sources in a constructive and critical way to support and refine their ideas. Concerning the reliability of information, as suggested by Kamalov et al. (2023), LLMs are prone to producing incorrect, but plausible facts, a phenomenon known as confabulation or hallucination. While AI can produce results that appear remarkably insightful and helpful, however, it can also make up “facts” that sound entirely plausible and weave those into its output. Therefore, it is crucial that students ask the AI virtual agent to disclose sources when providing information. Also, it is important to raise awareness among students and teachers to verify AI-generated claims with other sources, demand evidence, and remain constructively skeptical in order to use a critical assessment of the information obtained. Furthermore, it is necessary to emphasize that AI output should be a starting point for further discussion and refinement, not the final word. Considering the bias aspect, as highlighted by Kamalov et al. (2023), AI is trained on a vast amount of text, and then receives additional training from humans, providing feedback on the LLMs output. Both processes may introduce biases in the text, concerning gender and racial dimensions or biases against particular viewpoints, approaches, or political affiliations. Strategies must be implemented to make students aware of these risks and to detect, prevent, and mitigate biases and stereotypes in the AI virtual agent’s responses, in the information provided, or in feedback that students can receive.

The third condition concerns *the role of the teacher*. As highlighted by Kamalov et al. (2023) “as AI becomes more embedded in content creation and assessment evaluation, one potential outcome could be the decline in teachers’ authority, as students no longer consider them as the ultimate authority” (p. 21). While this may be a particularly real risk in a learning context, in a KB environment, the use of AI can accelerate an interesting paradigm shift in the role of the teacher. In KB, indeed, the teacher is no longer considered as the authoritative source of information but has a central role in orchestrating KB activities, by facilitating epistemological, cognitive, and socio-cultural aspects of KB (Chen & Hong, 2016). The support of LLMs

can be useful to design KB activities, to simulate possible scenarios of inquiry in classrooms, and to assess the activities. In addition, his /her contribution is essential in modeling critical engagement of the students and in helping them in interpreting AI feedback. It implies the importance of integrating KB training with AI in professional development to help educators in using AI into KB safely and effectively in their classrooms.

This contribution can have important research implications. The metaphor of the LLM as a KB Consultant can promote an advancement in research on the KB at theoretical level by allowing to study how the identified functions can be used by the members of a KB Community, particularly in investigating students' consultation strategies at both individual and small-group levels. It is also useful to study whether there is a prevalence of some functions in some situations, and whether their use entails additional advantages in terms of domain-specific literacies, epistemic literacy and basic literacy, compared to those already acquired by research on the use of the KB (Chen & Hong, 2016). These research directions could also lead to exploring the possibility of rethinking KB principles to consider the new landscape of opportunities provided by the AI age.

On the practical side of the KB, the metaphor of the LLM as a KB Consultant can allow to create training aimed at teachers on how to introduce an LLM in the KB activity in their classrooms, in order to promote the development of an effective mental model by the students of this device to be use effectively on building knowledge of value for the community rather than on learning at an individual level and to preserve students' epistemic agency in the collaborative inquiry.

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