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From Large Language Models to Human-Centred Learning: Rethinking Learner Agency in Education 5.0

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Shruti Dwivedi[1] & Prof. Tripta Trivedi[2]

1, Senior Research Scholar, Department of Education, University of Lucknow.

2, Professor, Department of Education, University of Lucknow

Abstract— Education 5.0 is about the usage of advanced technologies to help people grow, learn in ways that suit them, stay well connected and take part responsibly. In other words it incorporates personalisation and adaptation according to the needs of the learner. Now there are Large language models (LLMs) which can explain topics, give feedback, which can have a conversation and respond to individual learner needs. But these same capabilities may also cause cognitive offloading, over-reliance on automated responses, less reflection, and feeling less ownership of learning. This leads to the main question of this paper which is to understand under what pedagogical conditions can learning with help of LLMs make learners stronger and more independent or make them weaker.

This paper presents integrative conceptual review as it brings five existing ideas which are Self-Determination Theory (motivation), Cognitive Load Theory (mental effort), the Zone of Proximal Development (the right level of help), Human-Centred Artificial Intelligence (people stay in control) and research on cognitive engagement (cognitive engagement). This paper argues that the educational impact of LLMs is not determined by technology alone but the LLM affordances does not act on the student directly but the lesson design of the lesson decides how they are used. Learner agency is not one skill but it is conceptualized as a multi-dimensional skill involving making real choices, taking an active part, self-regulation, evaluative judgment and taking responsibility for learning. An integrative mediation architecture is proposed where the pedagogical design conditions influence learners' psychological needs, satisfaction, productive cognitive engagement and calibrated boundary conditions are considered prior knowledge, task type, AI literacy, and learning context. In this paper five propositions are developed on learner choices, calibrated scaffolding, productive cognitive engagement, transparency and human control, and pedagogical alignment. The paper builds a mechanism-oriented view, showing how identical LLM capabilities may lead to different agency outcomes under different pedagogical conditions, and it provides a basis for future research.

Keywords: Education 5.0; large language models; learner agency; generative artificial intelligence; human-centred learning; Self-Determination Theory; Cognitive Load Theory; Human-Centred Artificial Intelligence

1. Introduction

Artificial intelligence (AI) is no longer just a specialized educational technology but rather it is becoming part of our everyday educational activity. Large language models (LLMs) such as Perplexity, ChatGPT, Gemini, Claude, etc., can explain concepts, generate examples, provide feedback, reformulate text, answer the questions the way wanted, support brainstorming, and adapt interactions to individual user needs. Recent reviews identify the major educational applications of LLMs which are student assistance, adaptive learning, personalization, and teacher support (Kasneci et al., 2023; Wang et al., 2025). But at the same time, researchers have raised the concerns about inaccurate information, bias, inappropriate reliance, academic integrity, cognitive offloading and the potential for learners to outsource activities that education is meant to foster (Giannakos et al., 2025).

All these developments are of particular interest for Education 5.0 as the literature generally labels Education 5.0 under the concept of education based on the learner, personalization, technological integration, wellbeing, human development, and responsible use of emerging technologies (Ahmad et al., 2023). Some literature also highlights the need to understand

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Education 5.0 as a relationship between technological development and human purposes rather than as technological advancement (Komló, 2025). LLMs appear to fit naturally within this vision of education 5.0. Personalization means the AI adapts to the student whereas Agency means the student stays in control of their own learning (Gupta et al., 2024; Hauk & Groschner, 2022). This distinction becomes important because emerging empirical evidence presents a mixed picture. Fan et al. (2025), for example, found that ChatGPT-supported learners could achieve better essay performance while showing concerns related to metacognitive engagement and knowledge transfer. Bastani et al. (2025) similarly showed that unrestricted access to GenAI (generative AI) during mathematics practice by the high school students could improve immediate practice performance while leaving them unprepared to solve such problems in exams or in future. On the other hand the AI tutor which gives hints to solve the problem helps the learners to solve similar problems in future also. These findings do not show that LLMs are harmful. It depends how we use it. This is not the main problem addressed in this paper. The question is, 'Under what pedagogical circumstances in which personalization with the support of LLMs can enhance and not undermine learner agency?' This question is important because the literature contains several partially connected perspectives. The Self-Determination Theory (SDT) explains why autonomy and competence-supportive learning environments matter, the Cognitive Load Theory (CLT) explains the importance of managing cognitive demands, the Zone of Proximal Development (ZPD) helps to understand the important role of calibrated assistance, human-Centred AI shows an approach to making AI helpful, transparent, reliable and responsible for the learner (Deci & Ryan, 2000; Sweller, 1988; Vygotsky, 1978; Shneiderman, 2020). Typically these ideas are presented individually.

It is not the claim that any one of these propositions is completely novel, but this paper shows an integration of these perspectives in the context of learner agency in Education 5.0 by developing a mechanism. It suggests that there is a disjuncture between LLM affordances and learner agency. Rather, pedagogical design affects the manner in which those affordances are experienced by learners and can support or act to diminish agency in psychological, cognitive and epistemic ways.

The paper focuses on three objectives:

1. To conceptualize learner agency in LLM-supported learning;
2. To integrate motivational, cognitive, developmental, and human-centred perspectives into an explanatory architecture
3. To develop propositions that can be empirically tested in future educational research.

2. Methodology: Integrative Conceptual Literature Review

2.1 Review Approach

The paper is based on an integrative literature review. It is not a systematic literature review or meta-analysis. The purpose is not to assess the overall impact of LLMs on learning. The aim is to bring together ideas across five areas: Education 5.0, LLMs in education, learner agency and self-regulated learning, theories of learning support and human-centred AI .

2.2 Literature Identification and Selection

The literature base was built through a systematic exploration of peer-reviewed literature and potentially influential theory-based sources through the use of terms like "Education 5.0", "large language models", "generative AI", "learner agency", "learner control", "AI-assisted learning", "self-determination theory", "cognitive load", "scaffolding", "human-centred AI" and "human control". Priority was given to recent studies on generative AI (2023 onward) and old theory papers were included to support the framework. A source was kept if it made clear how LLMs can be understood, how Education 5.0 and human-centred AI may inform responsible use. The sources were grouped by theme and compared and connected to each other. The gaps identified in this process informed the model proposed in this paper.

2.3 Analytical Logic

The analysis followed a three-stage logic:

Technology affordances → pedagogical conditions → learner mechanisms → learner agency

This difference is the key to the article. An LLM can give an answer right away, but the student can be asked to first try the problem and ask for a hint, evaluate the hint and defend the final answer. It's the same technology, but the pedagogical

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environment is different. In this way the architecture acknowledges that the pedagogical design is the key mediator between the technological capacity and the learner experience.

3. Education 5.0 and the LLM Turn

3.1 Education 5.0 as a Human-Centred Educational Orientation

Education 5.0 is the product of the fifth industrial revolution. It is also the result of the increasing integration of advanced technologies into education. Ahmad et al. (2023) describe Education 5.0 as learner-centred education, technological integration, personalization, engagement, access, and wellbeing. Komló (2025) shows the relationship between technological development and human purposes in Education 5.0. For this paper, Education 5.0 is treated as a **human-centred educational orientation** instead of a fixed technological model. Four dimensions are particularly relevant:

- learner-centredness;
- meaningful personalization;
- human wellbeing and development; and
- responsible integration of advanced technology.

This interpretation makes learner agency especially important.

3.2 Why LLMs Matter

LLMs differ from many earlier educational technologies because they can participate in open-ended dialogue. If a learner is confused about a thing, it can explain an idea in a new way. It can give easier or harder examples. It can give feedback and compare different approaches. Student support, adaptive learning, personalized educational assistance, and teacher support are among the applications found in recent surveys (Wang et al., 2025). But this creates a pedagogical problem also. If learners can obtain complete solutions immediately, they may bypass the learning activity. The important distinction is therefore, personalization asks, "How can the system adapt to this learner?" Agency asks, "How much does the learner remain an active decision-maker in that adaptation?" This distinction is central to the present conceptual argument.

4. Conceptualising Learner Agency

Learner agency is related to the concepts like autonomy of the learner, control of learning, independence, engagement, and self-regulated learning. But it is bigger than any single one of them. According to Bandura (2001) human agency as setting goals, planning ahead, guiding your actions and reflection over the progress. Reeve and Tseng (2011) showed agency means student actively shape how they are being taught rather than just passively listening. Another research highlights that agency requires learners to take full charge of planning, checking and evaluating their own learning process (Zimmerman, 2002). These papers define learner agency as the learner's capacity to make meaningful choices, to participate actively in learning, regulate the learning process, evaluating information and assistance. It is also about assuming responsibility for learning-related decisions. This definition is broader than autonomy. For example, consider a student solving a chemistry problem. A low-agency interaction might involve, "Give me the answer." The student copies the response without attempting the problem or evaluating the explanation. A potentially higher-agency interaction might involve: "I attempted the problem. I think the limiting reagent is X, but I am uncertain about step three. Give me a hint rather than the answer." The learner then checks the hint, then revises the solution and reasons why the final answer is correct. The second interaction does not eliminate AI assistance. Instead, it positions AI assistance within an active learner-controlled process. This difference suggests that LLM use should not itself be treated as evidence of learner agency.

5. Theoretical Foundations

5.1 Self-Determination Theory

Self-Determination Theory (SDT) proposes that autonomy of learning, competence, and relatedness are fundamental psychological needs associated with motivation and wellbeing (Deci & Ryan, 2000; Ryan & Deci, 2017). Researches applying SDT to education indicates that autonomy-supportive environments can help in autonomous motivation and engagement (Niemiec & Ryan, 2009). Within LLM-supported learning, autonomy means using AI as tool guiding and controlling rather than just passively following whatever it gives you. Competence means using AI to build one's own knowledge and confidence instead of relying on it to do the work. The outcomes is not that learners should always have unlimited choice. It is actually that AI-supported learning should provide **meaningful and pedagogically bounded choices**.

5.2 Cognitive Load Theory

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Cognitive Load Theory emphasizes the limited capacity of working memory and the importance of managing cognitive demands during learning (Sweller, 1988; Sweller et al., 2011). LLMs can potentially reduce unnecessary cognitive demands by explaining difficult concepts, organizing information, or providing examples. However, reducing effort is not necessarily equivalent to improving learning. If an LLM provides the complete solution to a problem before the learner has attempted meaningful reasoning, it may reduce the very cognitive activity the task was designed to develop. Cognitive offloading research similarly demonstrates that people can use external resources to reduce cognitive demands, although the consequences depend on what is being offloaded (Risko & Gilbert, 2016).

Recent GenAI research reinforces the importance of this distinction. Fan et al. (2025) identified concerns about reduced metacognitive engagement under certain conditions of ChatGPT-supported learning. Bastani et al. (2025) found that unrestricted AI assistance could create short-term performance benefits alongside poorer later unaided performance, while a more learning-oriented tutor reduced this problem. Thus, the key question is not whether AI reduces cognitive effort, but **which cognitive effort is reduced and which cognitive activity remains with the learner**.

5.3 Zone of Proximal Development and Scaffolding

Vygotsky's (1978) Zone of Proximal Development (ZPD) emphasizes the importance of assistance in enabling learners to perform beyond what they can currently accomplish independently. The scaffolding tradition similarly emphasizes support that responds to learners' needs and can gradually be withdrawn (Wood et al., 1976).

LLMs can potentially provide scalable scaffolding. They can offer hints, examples, explanations, questions, or feedback. However, scaffolding becomes problematic when assistance is excessive, permanent, or unrelated to the learner's actual needs. The central principle is therefore **calibration**. A novice learner may require structured examples and explicit guidance, whereas a more experienced learner may benefit from prompts that require independent reasoning. The expertise-reversal literature suggests that instructional support that benefits novices may become redundant or counterproductive for more knowledgeable learners (Kalyuga et al., 2003).

5.4 Human-Centred Artificial Intelligence

Human-Centred AI shifts attention from what AI can accomplish to how AI affects human capabilities, decision-making, wellbeing, and control. Yang et al. (2021) argue that educational AI should be considered in relation to human conditions and contexts rather than technological performance alone.

Shneiderman (2020) similarly emphasizes reliable, safe, trustworthy AI with meaningful human control. Human-centred AI does not require rejecting automation. Instead, high levels of automation can coexist with high levels of human control when systems are appropriately designed. This principle is particularly relevant to education. Learners should be able to understand when AI is influencing their learning, question its output, verify information, and reject or override suggestions when appropriate.

5.5 Integrating the Perspectives

TABLE 1 : The theories above address different parts of the same problem

Perspective	Main question	Relevance to LLM-supported learning
Self-Determination Theory	Who controls the learning process?	Choice, autonomy and competence
Cognitive Load Theory	How much cognitive effort should remain with the learner?	Managing assistance and cognitive offloading
ZPD/scaffolding	What assistance is appropriate at this point?	Calibrating and withdrawing support
Human-Centred AI	Who remains in control of AI-supported decisions?	Transparency, verification and override
Learner-agency literature	What does active learner	Choice, regulation,

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	participation involve?	judgement and responsibility

The value of integration lies in showing that these principles can sometimes conflict. For example, SDT may support greater learner choice, but a novice learner may not know what level of assistance is productive. Conversely, highly structured AI guidance may support immediate performance but reduce perceived autonomy. The proposed architecture therefore treats **bounded choice and calibrated assistance as complementary rather than competing principles**.

6. Research Gaps

6.1 The Conditionality Gap

A substantial portion of discussion about generative AI focuses on whether AI improves or harms learning. This framing can obscure an important possibility: the same technology may produce different outcomes under different pedagogical conditions. Recent evidence already points toward conditionality. Bastani et al. (2025) demonstrated different consequences depending on whether students used an unrestricted LLM or a learning-oriented tutor. Vendrell and Johnston (2026) similarly argue for pedagogical designs that preserve cognitive engagement and combine AI-mediated and AI-free learning phases. What remains unclear is the mechanism that links AI features to learner agency.

6.2 The Integration Gap

Existing literature provides important insights into motivation, cognition, scaffolding, AI ethics, and learner control. However, these perspectives are often investigated separately. The unresolved issue is how these conditions interact. The present paper addresses this integration gap by placing learner agency at the centre of these relationships.

6.3 The Education 5.0 Translation Gap

Education 5.0 literature establishes a human-centred and learner-centred aspiration, while LLM research increasingly describes technological capabilities and educational applications. Yet the translation between these two levels remains underdeveloped. In other words:

- Education 5.0 tells us what education should value.
- LLM research tells us what technology can do.
- Pedagogical design determines how these two can be reconciled.

TABLE 2 : Comparison of Existing Approaches and the Present Study

Existing Approach	**Main Focus**	**Gap Addressed by the Present Study**
Generative AI in education	Personalization and learning support	Explains how AI support may influence learner agency
Self-regulated learning	Learner planning and monitoring	Connect self-regulation with LLM-supported learning
Self-determination Theory	Autonomy, competence and relatedness	Explains the role of learner choice and motivation
Cognitive Load Theory	Managing cognitive demands	Highlights productive cognitive engagement
Human-centered AI	Human control, trust and ethical use	Connects human control with pedagogical design
Education 5.0 frameworks	Human-centered and responsible education	Integrates Education 5.0 with learner-agency mechanisms
Present Study	**LLM- supported learner agency**	**Integrates AI affordances, pedagogical design and learner mechanisms**

As shown in Table 2, the contribution of this study lies in integrating existing perspectives into a coherent conceptual explanation of how pedagogical design may shape the influence

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of LLMs on learner agency. Building on this comparison, the integrative architecture is proposed.

7. Proposed Mediation Architecture

The proposed architecture is conceptual rather than empirically established. It begins with **LLM affordances**, such as explanation, personalization, feedback, dialogue and generation of content. These affordances do not directly determine learner agency. But, they are arranged through **pedagogical design conditions**, including:

- learner choice over AI use
- calibrated scaffolding
- opportunities for cognitive engagement
- transparency and human control
- alignment between task, learner expertise and AI support.

These design conditions influence three learner-level mechanisms:

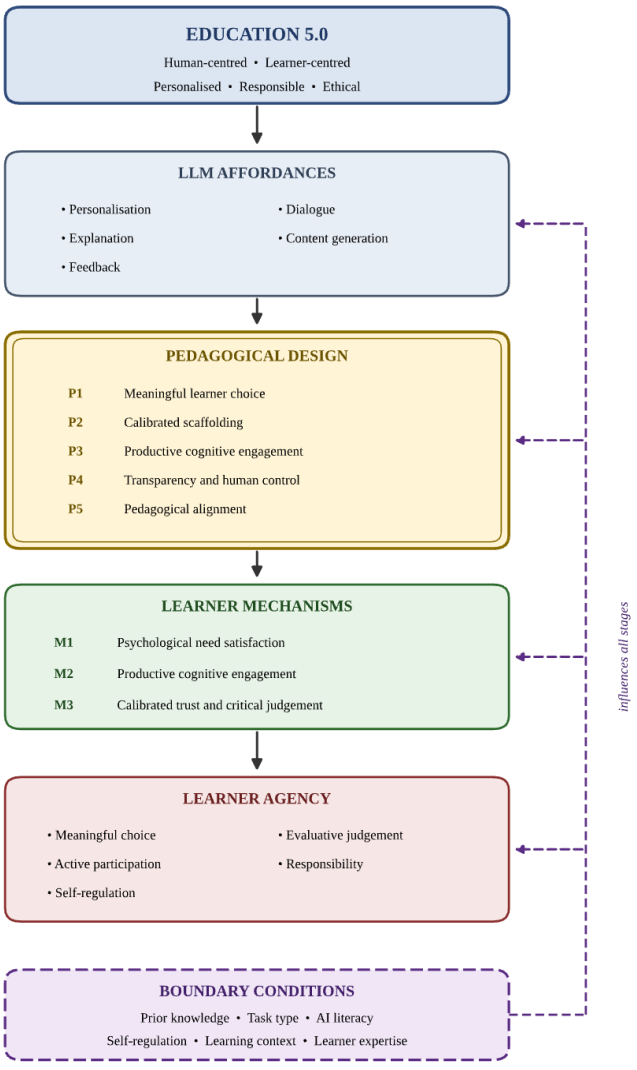
M1: Psychological need satisfaction	Whether learners experience autonomy and competence.
M2: Productive cognitive engagement	Whether learners interpret, evaluate, transform and reason with AI-generated material.
M3: Calibrated trust in AI	Whether learners neither blindly trust nor unnecessarily reject AI output.

These mechanisms are expected to influence **learner agency**, expressed through meaningful choice, active participation, self-regulation, evaluative judgement, and responsibility. The relationship can therefore be expressed as:

LLM affordances → pedagogical design → learner mechanisms → learner agency

with **prior knowledge, task type, AI literacy, self-regulation, and learning context** acting as boundary conditions. This architecture differs from a simple technology-effects model because it does not assume: more AI means better learning or less AI → less learning**.** Instead, it proposes:

AI capability + pedagogical conditions → learner processes → agency outcomes.



8. Conceptual Propositions

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Proposition 1: Learner Choice

LLM-supported learning is more likely to strengthen learner agency when learners have meaningful and bounded choices regarding when, why, and how AI assistance is used. The proposition comes from SDT. Students feel more motivated and in control when they can make their own decisions and understand the purpose of what they are doing. However, unrestricted choice may not always be productive. Therefore, the proposed model emphasizes **bounded choice** rather than unlimited choice. For Example,In an English lesson, a teacher allows students to choose whether to use AI to brainstorm ideas for a story or to improve the grammar of their own draft. Students decide which type of help they need.

Proposition 2: Calibrated Scaffolding

LLM-supported learning is more likely to strengthen learner agency when AI assistance is calibrated to learners' prior knowledge and gradually reduced as competence develops. A hint may support learning without replacing the learner's reasoning. For Example,A student is learning how to balance chemical equations. The AI first gives a small hint about counting atoms on each side. If the student still struggles, it provides another hint and then a step-by-step explanation.

Proposition 3: Productive Cognitive Engagement

LLM use is to strengthen learner agency. The learners are required to interpret, evaluate, compare, justify, or transform AI-generated output rather than merely consume it. Asking learners to critique an AI explanation, identify unsupported claims, compare multiple solutions. This requires greater cognitive participation. For Example,In a history lesson, students ask AI to explain the causes of the Revolt of 1857. They then compare its explanation with their textbook and write their own summary of the main causes. It means that students process and evaluate information and create their own understanding instead of merely reproducing AI generated text.

Proposition 4: Transparency and Human Control

LLM-supported learning strengthens learner agency only when it acts as a helpful tool that students can inspect, double check, question and overrule. Thus, keeping the learning in control of their own learning (Shneiderman, 2020). In education, this means learners should not be passive recipients of AI decisions. Research on human-centred AI in education also indicates that human control and stakeholder involvement remain important areas requiring further development (Alfredo et al., 2024). For example, In a biology lesson, AI suggests that a particular animal is a mammal. A student checks the animal's characteristics using a reliable reference, finds that the AI is incorrect, and rejects its answer with an explanation. Meaning that the student does not treat the LLM as the final authority but uses independent judgement to decide whether its answer is reliable or not.

Proposition 5: Pedagogical Alignment

The extent to which LLM assistance influences learner agency depends on the alignment of the learning task, the learner's expertise, and the level of AI support. For example, a novice learner confronted with a new mathematical concept may benefit from worked examples and structured hints, whereas an advanced learner may benefit more from prompts that require independent reasoning. Therefore, the same amount of AI assistance will not be equally beneficial for all learners. This proposition does not depend on learning style matching. It is related to the relation between task demands, learner expertise, and intensity of the support.

9. From AI Assistance to Learner Agency: Two Pathways

The same AI tool can either help students become independent learners or make them dependent on AI. The difference depends on how teachers design learning activities and how students use AI.

1) Agency-supportive pathway

LLMs support learner agency when they are used to extend, challenge, or refine learner thinking. The learner attempts the task, uses AI strategically, evaluates the output, verifies consequential claims, and remains responsible for the final judgement.

2)Agency-eroding pathway

LLMs may weaken learner agency when they replace instead of supporting the essential cognitive and evaluative activity. This happens when learners often command complete solutions and accept the outputs without verification. But cannot perform effectively when AI support is unavailable. The difference is pedagogical rather than technological.

Similar LLM capabilities can support either pathway depending on how the tasks, prompts, assessments,

feedbacks and accountability of the learner are designed. Recent work on GenAI-supported critical thinking similarly focuses on preserving cognitive engagement, embedding evaluation, treating LLMs as provisional thinking partners, and sequencing AI-mediated and AI-free learning activities (Vendrell & Johnston, 2026).

10. Implications for Educational Practice

The proposed architecture suggests several practical implications.

1 Design AI Use Around Learning Goals - Teachers should begin with the learning objective rather than the technological capability. If the objective is factual retrieval, direct AI assistance may be relatively unproblematic. If the objective is reasoning, evaluation, argumentation, or problem solving, AI use should be designed so that these processes remain with the learner.

2 Use Progressive Scaffolding - AI assistance can be sequenced from:

question → prompt → hint → explanation → worked example → complete solution

rather than immediately providing the final answer.

3 Require Verification - Learners can be asked to verify the claims, compare AI responses with textbooks or the reliable sources (Long & Magerko, 2020; Shneiderman 2020).

4 Preserve AI-Free Learning Phases - Some activities should deliberately require independent reasoning before AI assistance. This can help teachers to differentiate between learning supported by AI and learning that learners can demonstrate independently.

5 Develop AI Literacy as Critical Judgement - AI literacy should be beyond prompt writing. Learners must understand limitations of the model, uncertainty, bias, verification of source, privacy, and its responsible use (Long & Magerko, 2020).

6 Treat Personalization as Learner Support, Not Learner Replacement - Education 5.0 should not equate personalization with full automation. Personalization is human-centred when it expands the learner's ability to understand, decide, participate, and improve.

11. Limitations

First, this paper is conceptual and does not test the proposed relationships empirically. The propositions should therefore be interpreted as theoretically grounded expectations rather than established causal effects. Second, the framework does not assume that all LLM systems, educational settings, or learners are equivalent. The relationships proposed here may vary across age groups, disciplines, languages, levels of prior knowledge, and assessment contexts. Third, learner agency is not a fixed trait. A learner may exercise substantial agency in one task or institutional context while having limited opportunities to do so in another. Fourth, the framework concentrates on LLMs and does not fully address other forms of educational AI, including learning analytics, adaptive systems, robotics, and immersive technologies.

Finally, issues such as equity, privacy, bias, accessibility, teacher workload, data governance, and school policy are mentioned as only background conditions. Each needs deeper study. Human-centred educational AI requires not only learner-level agency but also institutional arrangements that make meaningful learner participation possible.

12. Conclusion

The real question for education 5.0 is not whether we should use AI tools (LLMs) in education, but how we should use them so that education still serves people. Learning can be made more accessible, understandable and interactive with AI. It can give examples, it can talk with the students, give feedback. But this will have to do until the students surrender their thinking to it. And then they will lose their ability to think for themselves.This paper has argued that LLM affordances do not have a direct effect on learner agency. It is contingent upon how the teacher sets up the lesson. There are five things that help students to keep control of their learning: bounded learner choice, calibrated scaffolding, productive cognitive engagement, transparency and human control and pedagogical alignment. These conditions foster learners' ability of thinking, choosing, evaluating, regulating while using LLMs. But overall

LLMs work best when they add to a student's thinking and don't replace it.

It is when it is to decide whether to use LLMs. One should look at more than personalized lessons, speed or good scores and the learner actively takes part and takes responsibility for their own learning. Future research needs to test which pedagogical designs best support this outcome across learners, disciplines, and educational contexts.

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