**Journal of Social, Humanity, and Education (JSHE)**
*ISSN: 2746-623X, Vol 6, No 4, 2026, 505-521* https://doi.org/10.35912/jshe.v6.n4.p505-521.2026

# Personalization of Heutagogical Learning through LLMs: A Thematic Study of Opportunities and Challenges

**Fatiyatul Muawanah Amdar[1], Arismunandar Arismunandar[2*], Arnidah Arnidah[3], Sapto Haryoko[4], Ansar Ansar[5], Nurhikmah H[6]**
Universitas Negeri Makassar, Makassar, Indonesia[1,2,3,4,5,6]
fatiyatul.muawanah.amdar@gmail.com[1], arismunandar@unm.ac.id[2*], arnidah@unm.ac.id[3], sapto.haryoko@unm.ac.id[4], ansar@unm.ac.id[5], nurhikmah.h@unm.ac.id[6]

**Article History**
Received on 17 April 2026
1st Revision on 21 April 2026
2nd Revision on 21 June 2026
3rd Revision on 4 July 2026
Accepted on 8 July 2026

**Abstract**
**Purpose:** This study explores how university students use Large Language Models (LLMs) to personalize learning within a heutagogical framework, with particular attention to the opportunities and challenges that emerge in their learning experiences..
**Methodology:** A qualitative exploratory design was employed involving 21 undergraduate students from science, social science, STEM, and education programs. Data were collected through semi-structured in-depth interviews, chat log analysis, and learning documentation, and analyzed using thematic analysis and trustworthiness criteria.
**Results:** Four major themes emerged: LLM as a metacognitive scaffold, LLM as a learning partner, cognitive offloading, and autonomy versus dependency of the learning process. The findings show that while LLMs can stimulate reflection, critical questioning, and idea exploration, they also create the risk of shortcut thinking and reduced cognitive engagement.
**Conclusions:** LLMs play a dual role in heutagogical learning, functioning as both cognitive catalysts and cognitive crutches. Their educational value depends on how they are designed and used to preserve productive struggles and learner autonomy.
**Limitations:** This study was limited to a qualitative exploration of higher education and did not quantitatively measure learning outcomes.
**Contributions:** This study contributes to the growing literature on AI in education by offering a nuanced understanding of LLMs as metacognitive scaffolds and informing pedagogical design for AI-scaffolded autonomy.

**Keywords:** *Artificial Intelligence (AI), Cognitive Offloading, Heutagogy, Large Language Models, Learner Agency, Metacognitive Scaffolding*

**How to Cite:** Amdar, F. M., Arismunandar, A., Arnidah, A., Haryoko, S., Ansar, A., & H, N. (2026). Personalization of Heutagogical Learning through LLMs: A Thematic Study of Opportunities and Challenges. *Journal of Social, Humanity, and Education*, 6(4), 505-521.

## 1. Introduction

In the rapidly evolving digital era, education faces new demands to prepare students to become lifelong learners, adapt flexibly, and respond effectively to continuous changes in knowledge and technology (Hardianto, Mahanal, Zubaidah, & Setiawan, 2024). The advancement of digital

technologies, particularly artificial intelligence, has transformed how individuals' access, produce, and interpret information (Alqahtani, Badreldin, Alrashed, Alshaya, & Alghamdi, 2023; Schwendicke, Samek, & Krois, 2020). Learning is no longer confined to formal classroom settings; instead, it occurs dynamically, openly, and continuously across diverse digital environments (Wang, & Zheng, 2020; Dzulfikry, Bundu, & Saud, 2025). Traditional teacher-centered learning models are increasingly viewed as insufficient to meet these demands, as they tend to position students as passive information recipients (Mundia, 2026). Such approaches often fail to foster critical thinking, reflective capacity, and learner autonomy, which are essential competencies in the 21st century (Suteja, Saifuddin, Farihin, Aris, & Winarso, 2022). Therefore, a transformation toward more personalized, interactive, and student-centered approaches is required to enable students to effectively manage, evaluate, and direct their own learning processes (Bae, & Kwon, 2021; Kuiper, 2002).

Heutagogy emerges as a response to the need for more autonomous, flexible, and adaptive learning in addressing the complexities of the digital era (Andriani, Ulfatin, Imron, & Sumarsono, 2023). In contrast to pedagogy, which positions the teacher as the primary driver of the learning process, and andragogy, which still involves shared control between educators and students, heutagogy provides substantially greater space for students to determine their own learning goals, strategies, resources, and evaluation processes (Brown & Foster, 2023). Students are viewed as active agents who possess the capacity to construct knowledge autonomously while taking responsibility for the direction and quality of their learning. This shift toward heutagogy is crucial, as 21st-century learning extends beyond mere content mastery to encompass the ability to think reflectively, adapt, and make decisions in dynamic and unstructured contexts. Heutagogy fosters the development of learner agency, metacognition, and double-loop learning, the capacity not only to solve problems but also to critically examine underlying assumptions, strategies, and cognitive frameworks (Danial, 2010; Ismirawati, Corebima, Zubaidah, Ristanto, & Nuddin, 2020). Therefore, heutagogy provides a relevant foundation for cultivating learners who are more autonomous, critical, and well prepared to navigate ongoing changes in the contemporary era.

The rapid development of Large Language Models (LLMs) as a component of generative artificial intelligence has opened new opportunities in education, particularly in supporting more personalized and adaptive learning (Abadal, 2024; Al, Abdulmuhsin, Rehman, & Mjlae, 2025). Unlike earlier educational technologies that tended to be static and based on predetermined learning pathways, LLMs enable dynamic, responsive, and contextual dialogic interactions tailored to users' needs (Nadel, Maloney, & Monahan, 2024; Yigci, Eryilmaz, Yetisen, Tasoglu, & Ozcan, 2025). This capability allows students to receive real-time feedback, explore multiple perspectives, and develop a deeper understanding through conversations that resemble human interactions. In the context of self-directed learning, LLMs function not only as sources of information but also as potential learning partners that can facilitate thinking processes, reflection, and idea exploration (Jackson, 2025). Through effective prompting strategies, LLMs can assist students in generating critical questions, testing their understanding, and actively constructing their knowledge. However, the integration of LLMs in education raises important questions regarding whether this technology genuinely supports learner autonomy or fosters dependency. Therefore, it is essential to examine the use of LLMs within a heutagogical framework to better understand their role in promoting independent learning (Kirwan, 2024). Recent evidence indicates a rapid increase in the adoption of artificial intelligence in higher education, with most university students reporting the use of AI-powered tools to support their learning. This trend highlights the growing relevance of Large Language Models (LLMs) as personalized learning tools that align with heutagogical principles emphasizing learner autonomy, self-direction, and independent knowledge construction.

From a heutagogical perspective, Large Language Models (LLMs) hold significant potential as metacognitive scaffolds that can support higher-order thinking and deep reflection (Nikolovski, Trajanov, & Chorbev, 2025). Through dialogic interaction, LLMs can function as question prompts, feedback providers, and facilitators of idea exploration, encouraging students to not only understand information but also reflect on how they think. Approaches such as Socratic scaffolding enable LLMs to pose critical questions that challenge students' initial assumptions, thereby promoting double-loop

learning and strengthening their metacognition. Moreover, the adaptive capabilities of LLMs allow for personalized learning experiences aligned with individual needs, interests, and levels of understanding (Gavali, Jadhav, Chougule, Jadhav, Pise, & Patil, 2026; Gao, Wang, Wang, & Quan, 2025). LLMs can adjust the level of explanatory complexity, offer alternative perspectives, and facilitate self-regulated learning more effectively (Zdravkova, Dalipi, & Ahlgren, 2023). In this context, LLMs are no longer merely supportive tools but function as thinking partners that assist students in developing intellectual autonomy (Laato, Morschheuser, Hamari, & Bjorne, 2023). The use of LLMs as metacognitive scaffolds thus presents substantial opportunities to strengthen student-centered learning and foster the development of reflective thinking skills (Vendrell & Johnston, 2026).

The use of Large Language Models (LLMs) in learning also presents several challenges that require critical attention. One major risk is cognitive offloading, in which students tend to delegate their thinking processes to AI without engaging in deep reflection or analysis (Otsuka, Hajdu, & Kovacs, 2025; Weber, Neda, Juarez, Wong-Ma, Gago-Masague, & Ziv, 2024). The possibility of AI hallucination, where systems generate inaccurate or misleading information, can further affect the quality of students' understanding (Xiang, Zhang, Luo, Yang, & Song, 2025). Excessive reliance on LLMs may also diminish critical thinking skills and learner autonomy, particularly when the technology is used merely as a tool for obtaining instant answers (Huangsuwan, Cooharojananone, Punyabukkana, Suchato, Puangngam, & Bunram, 2026; Rücker, Büchting, & Kosch, 2025). In addition, the use of LLMs introduces tension between technological support and learner autonomy, often referred to as the autonomy–control tradeoff. On the one hand, LLMs can provide highly personalized and responsive assistance; on the other hand, excessive AI intervention may limit students' opportunities for intellectual exploration (Mavroudi & Torgersen, 2024). This raises important questions about how to design the use of LLMs to preserve productive struggle and the active cognitive engagement essential for meaningful learning (Ngo, Vo, & Phan, 2025). Therefore, a more in-depth investigation is needed to comprehensively understand how these opportunities and challenges manifest in heutagogy-based learning practices.

Although research on the use of artificial intelligence in education continues to grow, most studies still focus on effectiveness-related aspects, such as improvements in learning outcomes, learning efficiency, or user satisfaction (Wang and Zheng, 2020; Aguilera, 2016; Jin, Sun, Pan, & Lin, 2025). Such approaches tend to position LLMs as output-oriented instructional tools and therefore do not fully capture how this technology influences learners' internal processes, including the development of metacognition, reflection, and decision-making in learning. The dynamics of students' learning experiences when interacting with LLMs remain a “black box” that has not been extensively explored (Aguila, Ngoc, Nguyen, Huynh, Mai, Le, & Tuyen, 2024; Nagy, Nagy-Toth, & Nagy, 2026). Furthermore, research specifically examining the use of LLMs within a heutagogical framework, particularly in understanding how this technology shapes learner agency and self-determined learning pathways, is limited. Some studies have yet to integrate both opportunities and challenges simultaneously within the context of authentic learner experiences. Therefore, a qualitative research approach is needed to comprehensively explore the meanings, experiences, and interaction patterns of students engaging with LLMs. This is essential for developing a more holistic understanding of the role of LLMs in personalizing heutagogical learning while also identifying their conceptual and practical implications.

The phenomenon of LLM use in learning represents a complex and contextual reality that is strongly shaped by students' subjective experiences (Al-Dokhny, Alismaiel, Youssif, Nasr, Drwish, & Samir, 2024). Interactions between learners and AI do not merely produce answers; they also involve processes of interpretation, reflection, and decision-making that are internal in nature and not always observable through quantitative measures (Rachmat, Riza, & Abidin, 2024). A qualitative approach is therefore considered more appropriate for exploring in depth how students make meaning of LLM use within heutagogical learning and how this technology influences the way they think, learn, and develop autonomy. In this context, thematic analysis was employed as an analytical approach that enabled researchers to identify, analyze, and interpret patterns of meaning (themes) emerging from students' experiences (Andriani et al., 2023). Through this analysis, this study seeks to describe the

phenomenon and uncover the dynamics of the opportunities and challenges associated with LLM use in shaping learner agency, metacognition, and self-determined learning processes. This approach is expected to provide a more comprehensive and contextualized understanding of the integration of LLMs into heutagogical learning.

Based on the foregoing, this study aims to explore and interpret students' experiences using Large Language Models (LLMs) to personalize learning within a heutagogical framework. Specifically, this study seeks to identify key themes that represent both the opportunities and challenges of LLM use, as well as examine how interactions with this technology influence learner agency, metacognitive processes, and self-determined learning pathways. Accordingly, this study is expected to contribute theoretically by enriching the discourse on the integration of artificial intelligence in heutagogy-based learning, particularly in understanding the role of LLMs as metacognitive scaffolding. In addition, it offers practical implications for educators in designing learning strategies that optimally leverage LLMs without diminishing students' autonomy and critical thinking skills, thereby fostering a balance between technological support and the development of human capacities.

## 2. Literature Review

### *2.1 Heutagogy as Self-Determined Learning*

Heutagogy, or self-determined learning, is an educational approach that positions students as the primary agents in determining the direction, goals, and strategies of their own learning (Andriani et al., 2023; Hairi, Mohamad, Saad, & Ahmad, 2023). In contrast to pedagogy, which is teacher-centered, and andragogy, which involves shared control between educators and learners, heutagogy grants full autonomy to students in managing their learning processes. Within this approach, students are not only expected to understand content but also to develop the ability to learn how to learn, enabling them to adapt to dynamic and unstructured learning situations (Hogan, Dwyer, Harney, Noone, & Conway, 2015; Livingston, 2011). Heutagogy emphasizes the development of learner agency, metacognition, and double-loop learning, which is the ability to reflect on and evaluate the assumptions, strategies, and cognitive frameworks employed in the learning process. Its focus on the capability to apply knowledge in novel contexts distinguishes it from traditional learning approaches that primarily emphasize competency. In the context of 21st-century education, heutagogy has become increasingly relevant, as it fosters students to become lifelong learners who are autonomous, reflective, and adaptable to rapid changes, particularly within continuously evolving digital environments (Marthaliakirana, Suwono, Saefi, & Gofur, 2022).

### *2.2 Large Language Models in Education*

Large Language Models (LLMs) represent one of the most recent advancements in generative artificial intelligence, with the capability to understand, generate, and respond to human language in a contextual manner (Kisić et al., 2024). In the context of education, LLMs offer a more interactive and adaptive approach compared to earlier learning technologies, which tended to be static and based on predetermined learning pathways (Elshaer, Kooli, Azazz, & Alyahya, 2026). LLMs enable dynamic two-way interactions, allowing students to receive explanations, feedback, and clarifications in real time according to their needs and levels of understanding. Beyond serving as mere sources of information, LLMs function as learning agents that can personalize students' learning experiences. These technologies can adjust content complexity, provide alternative perspectives, and support independent idea exploration through conversations that resemble interactions with human tutors (Aguila et al., 2024; Zdravkova et al., 2023). Thus, LLMs act not only as instructional tools but also as conversational partners that can enrich knowledge construction. This role makes LLMs highly relevant for supporting more flexible, responsive, and individualized learning in the digital era. Recent studies have reported a substantial increase in the adoption of generative AI and Large Language Models in higher education, particularly for personalized learning, academic support, and self-regulated learning activities. Furthermore, emerging evidence suggests that LLMs can function as adaptive learning partners that facilitate metacognitive reflection, feedback generation, and learner autonomy in AI-enhanced educational environments (Xiang, Zhang, Luo, Yang, & Song, 2025).

### *2.3 LLM as a Metacognitive Scaffold*

The concept of scaffolding refers to the temporary support provided to help students achieve higher levels of understanding, ultimately enabling them to learn independently. With technological advancement, the role of scaffolding is no longer limited to interactions between teachers and students but can also be facilitated by artificial intelligence-based systems, including Large Language Models (LLMs) (Dubljević, 2024; Guizani et al., 2025). LLMs have the potential to function as metacognitive scaffolds that not only provide information but also encourage students to reflect on their own thinking processes (Varaliya, Kanojia, & Nabajja, 2025). Through strategies such as prompting, reflective questioning, and Socratic questioning, LLMs can facilitate dialogic interactions that stimulate critical thinking and metacognitive awareness. These interactions enable students to test their understanding, identify misconceptions and develop more effective learning strategies. In this capacity, LLMs act as thinking partners or probing interlocutors that challenge assumptions and broaden students' perspectives (Elshaer & Azazz, 2025). Thus, LLMs not only support self-regulated learning but also contribute to fostering double-loop learning, which involves deep reflection on the thinking processes and conceptual frameworks that underlie learning.

## 3. Methodology

### *3.1 Research Design*

This study employed a qualitative approach with an exploratory design to gain an in-depth understanding of students' experiences, meanings, and interpretations of utilizing Large Language Models (LLMs) within heutagogical learning. This approach was chosen because the phenomenon under investigation is complex, contextual, and cannot be adequately understood solely through numerical measurements (Creswell, 2012). Through this design, the study aims to uncover how students make meaning of LLMs as learning tools, how these technologies influence their thinking processes and learning autonomy, and the key themes that emerge regarding the opportunities and challenges of their use in supporting self-determined learning.

### *3.2 Participants*

The participants in this study were university students who had experience using Large Language Models (LLMs) as part of their self-directed learning processes. Participants were selected using purposive sampling, with the criterion that they actively utilized LLMs in learning activities such as seeking information, engaging in discussions, and reflecting on their understanding of the material. Specifically, participants were required to have used LLMs for at least six months and to regularly engage with these tools for academic learning activities such as information seeking, problem-solving, or reflective learning. This criterion ensured that the participants possessed sufficient experience to provide rich and meaningful insights into LLM-supported learning.

The number of participants was determined flexibly until data saturation was reached, that is, when no new information or themes emerged from the collected data (Wu, Mossé, Goodman, & Piech, 2019). Data saturation was achieved when consecutive interviews no longer generated new codes, categories, or themes related to the learners' experiences with LLMs. Saturation was observed after the nineteenth interview and confirmed through two additional interviews. This study was conducted in the context of higher education, allowing for a more in-depth exploration of complex, reflective, and autonomous learning experiences. Ethical considerations were also treated as fundamental aspects of the data collection and management processes. Each participant was informed of the purpose of the study and was required to provide informed consent prior to participation. Participant confidentiality was ensured through the use of codes or anonymity, and all collected data were used only for academic purposes. Furthermore, the use of data in the form of chat logs with LLMs was conducted ethically, ensuring that no personal information was included or disclosed. This study upholds scientific integrity while respecting the rights and privacy of all participants.

### *3.3 Data Collection*

Data for this study were collected using multiple complementary techniques to obtain a comprehensive understanding of students' learning experiences. The primary method employed was semi-structured in-depth interviews, aimed at exploring students' experiences, perceptions, and

reflections on using Large Language Models (LLMs) during self-directed learning processes. In addition, this study utilized interaction analysis in the form of chat log records of conversations between students and LLMs to identify patterns of thinking, prompting strategies, and the dynamics of dialogue occurring throughout the learning process. As a supplementary source, documentation such as students' learning notes and reflective journals were also used to strengthen data interpretation. This combination of techniques enables researchers to generate rich and in-depth data on how LLMs are utilized within the context of heutagogical learning.

### *3.4 Data Analysis*

The collected data were analyzed using thematic analysis following the stages proposed by Braun and Clarke (Hammarberg, Kirkman, & De Lacey, 2016). The analysis process began with the familiarization stage, which involved reading and comprehensively understanding the data, followed by generating initial codes to identify relevant units of meaning. These codes were then organized in the search for themes stage to identify patterns emerging from the data, which were subsequently reviewed in the reviewing themes phase. In the next stage, the identified themes were clearly defined and named (defining and naming themes) before being presented in a systematic narrative (producing the report). The analysis focused on uncovering key themes related to the opportunities and challenges of LLM use, as well as how this technology influences learner agency and metacognitive processes in heutagogical learning.

To ensure data trustworthiness, this study applied credibility, transferability, dependability, and confirmability criteria. Credibility was established through the triangulation of data sources and methods, such as comparing interview findings with chat log data and learning documentation. Transferability was achieved by providing detailed descriptions of the research context, which enabled readers to assess the applicability of the findings to other contexts. Dependability was maintained through systematic documentation of the research process (audit trail), while confirmability was ensured by grounding the findings in the data rather than researcher bias, supported by reflexivity and transparency throughout the analysis. Thus, the findings of this study are expected to demonstrate high trustworthiness and scientific rigor.

## 4. Results and Discussions

### *4.1 Result*

The participants in this study consisted of 21 undergraduate students from diverse academic disciplines, including science, social science, STEM, and education fields. This heterogeneous composition was intentionally selected to capture a wide range of experiences in using Large Language Models (LLMs) within self-determined learning contexts. The participants were in their second to fourth years of study, with ages ranging from 20 to 23 years, reflecting a relatively mature stage of academic engagement where independent learning practices are more prominent. In terms of experience, all participants had prior exposure to LLMs, ranging from six months to two years, with varying frequencies of use, from weekly to daily engagement. This variation allowed for a richer exploration of how different levels of familiarity and intensity of use influenced learners' experiences, perceptions, and interactions with LLMs. The diversity in academic backgrounds, combined with varying levels of LLM experience, provides a robust foundation for identifying patterns and themes related to the opportunities and challenges in heutagogical learning environments. The participants' detailed demographic characteristics are presented in Table 1.

Table 1. Demographics data

| Participant ID | Gender | Age | Study Program | Field | Year of Study | Experience with LLM | Frequency of Use |
|---|---|---|---|---|---|---|---|
| $P_1$ | Female | 20 | Biology Education | Science | 2nd Year | 1 year | Daily |
| $P_2$ | Male | 21 | Economics | Social Science | 3rd Year | 1.5 years | Daily |
| $P_3$ | Female | 22 | Biology Education | Science | 4th Year | 2 years | Several times a week |
| $P_4$ | Male | 20 | Engineering | STEM | 2nd Year | 6 months | Several times a week |

| Participant ID | Gender | Age | Study Program | Field | Year of Study | Experience with LLM | Frequency of Use |
|---|---|---|---|---|---|---|---|
| $P_5$ | Female | 23 | Mathematics Education | Science | 4th Year | 2 years | Daily |
| $P_6$ | Male | 21 | Management | Social Science | 3rd Year | 1 year | Weekly |
| $P_7$ | Female | 22 | Physics Education | Science | 4th Year | 1.5 years | Several times a week |
| $P_8$ | Male | 20 | Informatics | STEM | 2nd Year | 8 months | Weekly |
| $P_9$ | Female | 21 | Biology Education | Science | 3rd Year | 1 year | Daily |
| $P_{10}$ | Male | 23 | Accounting | Social Science | 4th Year | 2 years | Several times a week |
| $P_{11}$ | Female | 22 | Chemistry Education | Science | 4th Year | 1.5 years | Daily |
| $P_{12}$ | Male | 21 | Civil Engineering | STEM | 3rd Year | 1 year | Several times a week |
| $P_{13}$ | Female | 20 | Primary Education | Education | 2nd Year | 6 months | Weekly |
| $P_{14}$ | Male | 22 | Law | Social Science | 4th Year | 1.5 years | Several times a week |
| $P_{15}$ | Female | 21 | Biology Education | Science | 3rd Year | 1 year | Daily |
| $P_{16}$ | Male | 23 | Information Systems | STEM | 4th Year | 2 years | Daily |
| $P_{17}$ | Female | 20 | English Education | Education | 2nd Year | 8 months | Weekly |
| $P_{18}$ | Male | 22 | Public Administration | Social Science | 4th Year | 1.5 years | Several times a week |
| $P_{19}$ | Female | 21 | Mathematics | Science | 3rd Year | 1 year | Daily |
| $P_{20}$ | Male | 20 | Mechanical Engineering | STEM | 2nd Year | 6 months | Weekly |
| $P_{21}$ | Female | 23 | Biology Education | Science | 4th Year | 2 years | Daily |

The thematic analysis revealed four major themes that illustrate how learners experience the use of Large Language Models (LLMs) in heutagogical learning contexts, encompassing both opportunities and challenges. The first theme, LLM as a Metacognitive Scaffold, highlights the role of LLMs in supporting learners' metacognitive processes. Participants reported that their interactions with LLMs encouraged reflective thinking, enabling them to evaluate and reconsider their understanding and responses. For instance, one participant noted, “I realized my way of answering was not entirely correct,” indicating a process of self-evaluation. Additionally, LLMs were found to stimulate critical questioning, prompting learners to reassess their initial assumptions through dialogic interaction, as reflected in the statement, “The AI often asks back, which makes me think again.” This suggests that LLMs can function as catalysts for metacognitive awareness and deeper cognitive engagement in the learning process.

The second theme, LLM as Learning Partner, reflects how learners perceive LLMs as interactive and supportive companions in the learning process. Participants described their interactions with LLMs as resembling meaningful discussions rather than mere information retrieval, which facilitated the exploration of ideas and conceptual understanding. One participant expressed, “It feels like a discussion, not just searching for answers,” emphasizing the dialogic nature of the interaction. Furthermore, LLMs enabled learners to explore multiple perspectives, contributing to more flexible and non-linear learning pathways, as illustrated by the comment, “I can see different points of view.” These findings indicate that LLMs play a significant role in enriching personalized and self-directed learning experiences of students.

However, the analysis also identified challenges associated with LLM use, particularly under the theme of Cognitive Offloading. Some participants reported a tendency to rely on LLMs for immediate answers without engaging in deeper cognitive processing of the questions. This dependency was

evident in statements such as, “Sometimes I just ask without thinking first,”suggesting a shift away from active thinking. Additionally, the convenience of LLMs was associated with shortcut thinking, where learning becomes faster but less reflective, as one participant stated, “It quicker, but I don't really think deeply.” These findings highlight the potential risk of reduced metacognitive engagement when LLMs are used without critical awareness

The final theme, Autonomy vs. Dependency, captures the tension between the empowering and constraining effects of LLM use on learner agency. On one hand, LLMs were perceived as tools that enhance independent learning, allowing learners to study autonomously without constant reliance on instructors, as reflected in the statement, “I can learn on my own without a lecturer.” On the other hand, excessive reliance on LLMs was found to diminish learners' motivation to independently seek information, as expressed by a participant who stated, “With AI, I feel less motivated to search by myself.” This duality underscores the complex role of LLMs in heutagogical learning, where they can simultaneously act as enablers of autonomy and as sources of dependency. Table 2 shows the thematic analysis, which revealed four major themes that illustrate how learners experience the use of Large Language Models (LLMs) in heutagogical learning contexts, encompassing both opportunities and challenges.

Table 2. Main findings

| No | Main Theme | Subtheme | Analytical Aspect | Description of Findings | Participant Quote |
|---|---|---|---|---|---|
| 1 | LLM as Metacognitive Scaffold | Reflective thinking | Metacognitive process | LLM supports learners in evaluating their understanding and thinking strategies | “I realized my way of answering was not entirely correct” |
| 1 | LLM as Metacognitive Scaffold | Critical questioning | Metacognition | LLM prompts learners to reassess their initial assumptions | “The AI often asks back, which makes me think again” |
| 2 | LLM as Learning Partner | Interactive dialogue | Learning experience | Interaction with LLM resembles a discussion that supports idea exploration | “It feels like a discussion, not just searching for answers” |
| 2 | LLM as Learning Partner | Idea exploration | Learning pathways | LLM enables learners to explore multiple perspectives | “I can see different points of view” |
| 3 | Cognitive Offloading | Dependency | Learner agency | Learners tend to rely on AI for answers without deep thinking | “Sometimes I just ask without thinking first” |
| 3 | Cognitive Offloading | Shortcut thinking | Metacognition | Learning becomes faster but less reflective | “It quicker, but I don't really think deeply” |
| 4 | Autonomy vs Dependency | Increased autonomy | Learner agency | LLM supports independent learning | “I can learn on my own without a lecturer” |
| 4 | Autonomy vs Dependency | Increased dependency | Agency | Overuse reduces independent exploration | “With AI, I feel less motivated to search by myself” |

Although the four themes were evident across all disciplines, some differences emerged. Students from STEM and science programs more frequently described using LLMs for problem solving, concept clarification, and analytical reasoning, whereas students from social science and education programs tended to emphasize idea exploration, discussion, and reflective learning. These differences suggest that

academic background may shape learners' engagement with LLMs in heutagogical learning environments.

### *4.2 Discussions*

*4.2.1 LLM as Metacognitive Scaffold: Between Cognitive Activation and Theoretical Alignment*

The findings of this study indicate that Large Language Models (LLMs) function as metacognitive scaffolds that encourage students to engage in reflective and critical thinking processes. Participants reported that interactions with LLMs increased students' awareness of their thinking processes and motivated them to re-evaluate their responses and understanding. This condition reflects what can be described as metacognitive disruption, a moment in which students do not merely receive information but instead pause to reconsider, refine, and deepen their thinking processes (Jaleel & P., 2016; Shen & Liu, 2011).

The core principles of heutagogy emphasize the importance of learner autonomy, self-reflection, and the development of metacognitive capabilities (Andriani et al., 2023). The reflective processes emerging from interactions with LLMs are also closely related to the concept of double-loop learning, in which students not only solve problems but also question the underlying assumptions and strategies they employ (Ahmad, Alhejali, Chaffar, & Koubaa, 2025). Furthermore, the role of LLMs in triggering reflection aligns with self-regulated learning theory, which highlights the importance of students' ability to monitor, evaluate, and regulate their learning processes (Kisić et al., 2024).

These findings are consistent with previous studies indicating that AI-based technologies can enhance metacognitive awareness through dialogic interaction (Syukur, Maghfurin, Marhamah, & Jehwae, 2024; Wang & Zheng, 2020). Prior research has shown that AI can facilitate reflection by encouraging students to articulate their reasoning and thinking processes (Rai, Ngaw, & Nannas, 2025). This study extends existing literature by demonstrating that LLMs can function as probing interlocutors dialogic partners that actively challenge students' thinking in real time (Abadal, 2024). Accordingly, LLMs can serve as effective tools for fostering higher-order thinking skills within heutagogical learning frameworks.

*4.2.2 LLM as Learning Partner: Redefining the Nature of Learning Interaction*

The findings of this study indicate that LLMs function not only as sources of information but are also perceived by students as learning partners who support the learning process through dialogic interaction. Participants described their interactions with LLMs as dynamic discussions in which they could ask questions, explore ideas and receive immediate responses. This enables more active and deeper learning processes, as students do not merely seek answers but engage in conversations that foster conceptual exploration and a broader understanding.

From a constructivist perspective, knowledge is developed through active interaction and dialogue (Kim, 2024; Yakar, Sulu, Porgali, & Çalis, 2020). LLMs function as facilitators that support knowledge construction through continuous exchange of ideas (Milano, McGrane, & Leonelli, 2023). Dialogic interaction with LLMs can be understood as a form of mediation that enables students to operate within their zone of proximal development, where they can achieve higher levels of understanding with the support of an adaptive system. Thus, LLMs function as both tools and agents that mediate the learning process.

These findings are consistent with previous research indicating that conversational AI can enhance learning engagement and support more personalized learning experiences (Ayanwale, Sanusi, Adelana, Aruleba, & Oyelere, 2022). Prior studies have also demonstrated that LLMs can function as conversational agents that provide adaptive feedback and assist students in exploring different perspectives. This study reinforces these findings by showing that LLMs not only enhance interaction but also contribute to the development of more flexible and non-linear learning pathways (Nadel et al., 2024; Xie, Tan, & Zhang, 2023; Jh, Annas, & Saud, 2025). In this regard, LLMs play a significant role in supporting heutagogical learning, which emphasizes learner autonomy and independent exploration.

*4.2.3 Cognitive Offloading: When AI Becomes a Cognitive Crutch*

The findings of this study also reveal the phenomenon of cognitive offloading, in which students tend to delegate part of their thinking processes to Large Language Models (LLMs). Participants tended to directly request answers without engaging in in-depth analysis, resulting in more immediate and pragmatic cognitive engagement. While this practice may enhance efficiency in completing tasks, some participants acknowledged that their learning processes became less reflective and involved a reduced cognitive effort. This indicates a shift from active learning to a growing reliance on technology.

This phenomenon aligns with the concept of cognitive offloading, which refers to individuals' tendency to transfer cognitive load to external tools, including digital technologies (Heinik, 2022; Karim et al., 2019). In the context of learning, this may lead to reduced metacognitive engagement and diminished critical thinking skills if not balanced with appropriate usage strategies (Dabarera, Renandya, & Zhang, 2014). From a self-regulated learning perspective, excessive reliance on LLMs has the potential to disrupt self-regulation processes, as students become less actively involved in planning, monitoring, and evaluating their own learning (English & Kitsantas, 2013). Therefore, the use of LLMs should be directed toward supporting rather than replacing students' internal cognitive processes.

The use of AI-based technologies may pose a risk of diminishing the quality of thinking when utilized passively (Schwendicke, 2020). Several previous studies have also highlighted that the ease of accessing instant answers can reduce students' motivation to engage in independent exploration and in-depth analyses. The findings of this study reinforce this perspective by demonstrating that LLMs can function as cognitive crutches which, if not properly regulated, may hinder the development of higher-order thinking skills (Milano et al., 2023). Therefore, pedagogical strategies are needed to maintain a balance between the use of technology and students' cognitive engagement (Gao, Wang, Wang, & Quan, 2025).

*4.2.4 Autonomy vs Dependency: The Central Tension in AI-Augmented Heutagogy*

The findings related to the theme of autonomy versus dependency reveal a complex dynamic in the use of Large Language Models (LLMs) in heutagogical learning. On the one hand, LLMs provide substantial support for learner autonomy, as students feel more capable of accessing information, understanding content, and managing their learning processes independently, without relying fully on instructors (Ahmad et al., 2025). However, the intensive use of LLMs also gives rise to tendencies toward dependency, where students become less motivated to seek information independently or explore sources beyond AI (Gao et al., 2025). This reflects the inherent tension between enhanced autonomy and the risk of dependency on the use of such technologies.

Theoretically, these findings are closely related to the core principles of heutagogy, which position learner agency as the central element in the learning process. Ideal learning occurs when students can independently direct, control, and evaluate their learning processes (Ni et al., 2024). The presence of LLMs introduces the phenomenon of an autonomy–control tradeoff, in which excessive technological support may reduce opportunities for independent exploration and decision-making (Ferro, Sapio, Terracina, Temperini, & Mecella, 2021). Therefore, the role of LLMs should be positioned as facilitative rather than dominant, ensuring a balance between external support and internal autonomy (Abadal, 2024).

AI technologies can exert a dual effect on learner agency. On the one hand, AI can enhance accessibility and flexibility in learning, thereby strengthening students' autonomy (Demir & Güraksin, 2022; Al-Azzawi, 2026; Ramdani, 2025). However, the ease and speed it offers may reduce motivation for independent thinking and deeper exploration. The findings of this study support the argument that LLMs can function as cognitive catalysts that promote autonomy and as cognitive crutches that may foster dependency. Therefore, pedagogical approaches are needed to maintain productive struggle and ensure that students remain cognitively engaged throughout the learning process.

*4.2.5 Conceptual Integration: From Cognitive Catalyst to Cognitive Crutch*

The integration of the four themes identified in this study indicates that the use of Large Language Models (LLMs) in heutagogical learning is inherently ambivalent, functioning both as cognitive catalysts and crutches. LLMs have been shown to promote reflection, expand idea exploration, and support learner autonomy through their roles as metacognitive and learning partners. However, the ease of access and instant responses they provide may also weaken students' cognitive engagement through phenomena such as cognitive offloading and increased dependency on AI. These findings highlight that the impact of LLMs is not singular but highly contingent on how the technology is utilized within the learning context.

These findings extend the discourse on AI integration within a heutagogical framework by demonstrating that technology functions not merely as a supportive tool but also as an agent that shapes learners' cognitive and metacognitive dynamics (Kabashkin, Misnevs, & Zervina, 2023). The results point toward the reinforce the concept of AI-Scaffolded Autonomy, defined as a condition in which LLMs are utilized to support learner autonomy without diminishing students' active engagement in thinking and reflection. Within this framework, the key to effective implementation lies not in the mere presence of technology but in how human and AI interactions are designed to sustain productive struggle as an essential component of the learning process as can be seen in Figure 1.

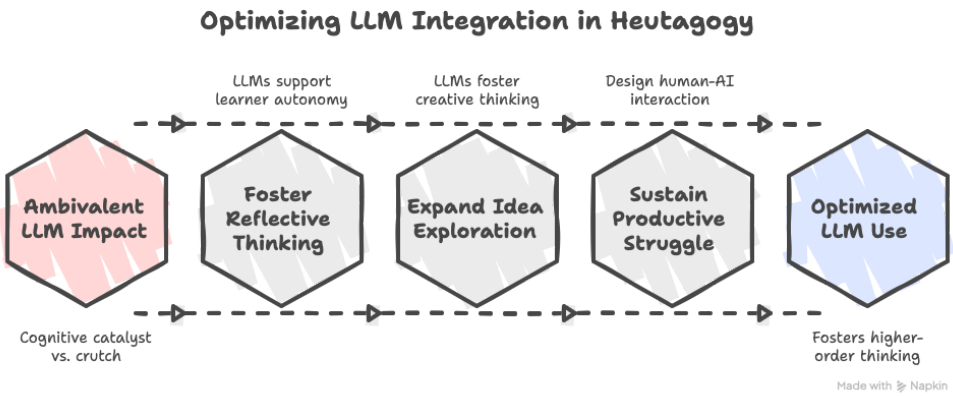


Figure 1. Conceptual Integration

This study contributes to the literature by integrating previous findings on the role of AI in learning while offering a more holistic perspective. While prior research has tended to separate the benefits and risks of AI use, the results of this study demonstrate that both emerge simultaneously within students' learning experiences. Therefore, a key implication of these findings is the need for instructional designs that balance the efficiency afforded by LLMs with the necessity of maintaining depth in thinking. In this way, LLMs can be optimized as tools for developing higher-order thinking skills without compromising students' autonomy or the quality of their learning processes.

## 5. Conclusions

### *5.1 Conclusion*

This study demonstrates that the integration of Large Language Models (LLMs) in heutagogical learning presents a fundamentally dualistic role, functioning both as a cognitive catalyst that enhances reflection, learner agency, and personalized knowledge construction, and as a cognitive crutch that may lead to cognitive offloading and increased dependency. The findings highlight that when positioned as metacognitive scaffolds and learning partners, LLMs can effectively support higher-order thinking and self-determined learning processes. However, their benefits are contingent upon intentional and well-designed pedagogical use that preserves productive struggles and active cognitive engagement. Therefore, this study underscores the importance of designing human–AI interactions that balance technological support with the development of learner autonomy,

contributing to a more nuanced understanding of AI-Scaffolded Autonomy in contemporary education.

### *5.2 Research Limitations*

This study has several limitations that should be considered when interpreting the findings. First, the use of a qualitative exploratory design with a relatively limited number of participants from a higher-education context may restrict the generalizability of the results to other educational levels or settings. Second, reliance on self-reported data and chat log analysis may not fully capture the complexity of students' cognitive processes during interactions with LLMs. Third, this study did not quantitatively measure the impact of LLM use on learning outcomes or metacognitive development, which could provide additional empirical validation. Based on these limitations, future research should involve larger and more diverse samples across different educational contexts, integrate mixed-methods approaches to combine in-depth insights with measurable outcomes, and examine the longitudinal effects of LLM use on learner agency, critical thinking, and self-regulated learning. Additionally, further studies should explore the design of pedagogical strategies that effectively balance technological support with productive struggle, ensuring that LLMs enhance, rather than diminish, students' cognitive engagement.

### *5.3 Suggestions and Directions for Future Research*

Future research should expand the scope of participants by involving more diverse samples across educational levels, disciplines, and cultural contexts to enhance the generalizability of the findings. In addition, employing mixed methods or longitudinal designs would provide a more comprehensive understanding of how interactions with Large Language Models (LLMs) influence learner agency, metacognition, and learning outcomes over time. Further studies should explore instructional design interventions that intentionally integrate LLMs within heutagogical frameworks, particularly in maintaining productive struggle while leveraging AI support. Moreover, investigating additional factors such as digital literacy, prompting skills, and learners' epistemic beliefs may offer deeper insights into students' engagement with LLMs. Finally, future research should examine the ethical, cognitive, and pedagogical implications of LLM use, including strategies to mitigate cognitive offloading and dependency, thereby contributing to the more effective and responsible integration of AI in education. Educators are encouraged to integrate LLMs through reflective prompting and guided inquiry activities that stimulate critical thinking and self-regulated learning. Positioning LLMs as metacognitive scaffolds rather than answer providers may help preserve learner autonomy while maximizing the benefits of AI-supported learning. The integration of LLMs should be accompanied by careful attention to ethical issues, including data privacy, transparency, and responsible AI usage. In addition, educators should implement strategies that minimize AI over-reliance and encourage students to maintain critical thinking and independent learning behaviors

## Acknowledgement

The authors would like to express their sincere gratitude to all the participants who generously contributed their time, experiences, and insights to this study. We also appreciate the valuable feedback and support of our colleagues and academic peers throughout the research process. The authors declare that this research was conducted without any specific funding from public, commercial, or not-for-profit funding agency.

## Author Contributions

FMA contributed to the conceptualization and design of the study, data collection and analysis, and drafting of the manuscript. AA contributed to the study design, supervision, and critical revisions of the manuscript. AA contributed to the data collection and analysis. SH provided methodological guidance and manuscript editing. AA contributed to the data validation and interpretation. NH contributed to the manuscript review and final approval. All authors have read and approved the final version of the manuscript and agree to be held accountable for all aspects of the work.

## References


Abadal, L. M. (2024). Ensuring genuine assessment in philosophy education: Strategies for scaffolding writing assessment in an LLM Era. *Teaching Philosophy*, *47*(2), 255-277. https://doi.org/10.5840/teachphil2024422195

Aguila, A., Ngoc, N. T., Nguyen, N. A. D., Huynh, K.-T., Mai, A., Le, T. D., & Tuyen, N. T. V. (2024). Large language model in higher education: Leveraging llama2 for effective academic advising. Paper presented at In V. N. Q. Bao & D. T. Anh (Eds.), International Conference on Advanced Technologies for Communications (pp. 590–595). IEEE Computer Society.

Aguilera, M. (2016). Artificial breakwaters as garbage bins: Structural complexity enhances anthropogenic litter accumulation in marine intertidal habitats. *Environmental Pollution, 214, 737–747*. https://doi.org/10.1016/j.envpol.2016.04.058

Ahmad, A., Alhejali, W., Chaffar, S., & Koubaa, A. (2025). University Chatbot system using generative AI with large language models. In A. Koubaa, W. Boulila, A. B. Mnaouer, & S. Raghay (Eds.), (pp. 235-242). Lecture Notes in Networks and Systems: Vol.

Al Atraqchi, O. M. A., Abdulmuhsin, A. A., Rehman, S. U., & Mjlae, S. A. (2025). Developing a knowledge management-large language model (KM-LLM) application in higher education: A UTAUT2 perspective. *VINE Journal of Information and Knowledge Management Systems, 1–27*. https://doi.org/10.1108/VJIKMS-08-2024-0309

Al-Azzawi, A. A. A. (2026). The effectiveness of e-learning in Iraqi Universities during the COVID-19 pandemic: A case study of selected Iraqi Universities and Institutes. *Universal Teaching and Learning Journal*, *2*(2), 71-82. https://doi.org/10.35912/utlj.v2i2.4308

Al-Dokhny, A., Alismaiel, O., Youssif, S., Nasr, N., Drwish, A., & Samir, A. (2024). Can multimodal large language models enhance performance benefits among higher education students? An investigation based on the task–technology fit theory and the artificial intelligence device use acceptance model. *Sustainability (Switzerland)*, *16*(23). https://doi.org/10.3390/su162310780

Alqahtani, T., Badreldin, H. A., Alrashed, M., Alshaya, A. I., Alghamdi, S. S., Bin Saleh, K., . . . Al Yami, M. S. (2023). The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research. *Research in social and administrative pharmacy*, *19*(8), 1236-1242.

Andriani, N., Ulfatin, N., Imron, A., & Sumarsono, R. B. (2023). Heutagogy and indigenous knowledge in integrated thematic instruction and character education. *Revista de Gestao Social e Ambiental*, *17*(7). https://doi.org/10.24857/rgsa.v17n7-030

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence, 3, 100099*. https://doi.org/10.1016/j.caeai.2022.100099

Bae, H., & Kwon, K. (2021). Developing metacognitive skills through class activities: What makes students use metacognitive skills? Educational Studies, 47(4), 456-471 2019.1707068. https://doi.org/10.1080/03055698

Brown, G., & Foster, C. (2023). The use of virtual learning environments in higher education: Content, community and connectivism, learning from student users. *In Advanced Sciences and Technologies for Security Applications: Vol. Part F15 (pp. 125–142)*. https://doi.org/10.1007/978-3-031-33627-0_6

Creswell, J. W. (2012). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research*. USA: Pearson Education.

Dabarera, C., Renandya, W. A., & Zhang, L. J. (2014). The impact of metacognitive scaffolding and monitoring on reading comprehension. *System*, *42*(1), 462-473. https://doi.org/10.1016/j.system.2013.12.020

Danial, M. (2010). Pengaruh strategi PBL terhadap keterampilan metakognisi dan respon mahasiswa the effects of pbl strategy to students metacognition skill and respon. *Chemica, 11, 1–10*.

Demir, K., & Güraksin, G. E. (2022). Determining middle school students' perceptions of the concept of artificial intelligence: A metaphor analysis. *Participatory Educational Research*, *9*(2), 297-312. https://doi.org/10.17275/per.22.41.9.2

Dubljević, V. (2024). Colleges and universities are important stakeholders for regulating large language models and other emerging AI. *Technology in Society, 76*. https://doi.org/10.1016/j.techsoc.2024.102480

Dzulfikry, R. ., Bundu, P., & Saud, S. (2025). Interactive biology media learning development to the student learning style (audio-visual-kinesthetic) based on Google Site. *Universal Teaching and Learning Journal*, *1*(1), 47-59. https://doi.org/10.35912/utlj.v1i1.3367

Elshaer, I. A., & Azazz, A. M. S. A. (2025). The impacts of large language model addiction on university students' mental health: Gender as a moderator. *Algorithms*, *18*(12). https://doi.org/10.3390/a18120789

Elshaer, I. A., Kooli, C., Azazz, A. M. S., & Alyahya, M. (2026). Large Language models and innovative work behavior in higher education curriculum development. *Administrative Sciences*, *16*(1). https://doi.org/10.3390/admsci16010056

English, M. C., & Kitsantas, A. (2013). Supporting student self-regulated learning in problem- and project-based learning. *Interdisciplinary Journal of Problem-Based Learning*, *7*(2). https://doi.org/10.7771/1541-5015.1339

Ferro, L. S., Sapio, F., Terracina, A., Temperini, M., & Mecella, M. (2021). Gea2: A serious game for technology-enhanced learning in STEM. *IEEE Transactions on Learning Technologies*, *14*(6), 723-739. https://doi.org/10.1109/TLT.2022.3143519

Gao, Y., Wang, Q., Wang, X., & Quan, Q. (2025). Chinese EFL university teachers' beliefs on large language models in language education: A latent profile analysis. *SAGE Open*, *15*(3). https://doi.org/10.1177/21582440251382580

Gavali, P., Jadhav, R., Chougule, V., Jadhav, A., Pise, S., & Patil, S. (2026). A review of retrieval-augmented generation-based large language model chatbots for enhanced academic and administrative support in universities. In M. Saraswat, A. Rajan, & A. Chakravorty (Eds.), (pp. 571-585). Systems and Technologies: Vol.

Guizani, S., Mazhar, T., Shahzad, T., Ahmad, W., Bibi, A., & Hamam, H. (2025). A systematic literature review to implement large language model in higher education: Issues and solutions. *Discover Education*, *4*(1). https://doi.org/10.1007/s44217-025-00424-7

Hairi, F., Mohamad, S. N. M., Saad, S., & Ahmad, I. (2023). Determining heutagogy design elements for online learning model using fuzzy delphi methods. *Journal of Theoretical and Applied Information Technology*. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85172442273&partnerID=40&md5=9f16f43e20f383a3060f3e6a7540b5fb

Hammarberg, K., Kirkman, M., & De Lacey, S. (2016). Qualitative research methods: When to use them and how to judge them. *Human Reproduction*, *31*(3), 498-501. https://doi.org/10.1093/humrep/dev334

Hardianto, H., Mahanal, S., Zubaidah, S., & Setiawan, D. (2024). The effectiveness of RICOSRE-flipped classroom in improving students' digital literacy. Paper presented at Paper presented at the AIP Conference Proceedings.

Heinik, J. (2022). Age-and education-related values for the hebrew version of the Cambridge Cognitive Examination – Revised (CAMCOG-R) in Cognitively Intact Elderlies. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85165601171&partnerID=40&md5=db7455714379649b0806f80cfbf9edd0

Hogan, M. J., Dwyer, C. P., Harney, O. M., Noone, C., & Conway, R. J. (2015). Metacognitive skill development and applied systems science: A framework of metacognitive skills, self-regulatory functions and real-world applications. *Metacognition: Fundaments, Applications, and Trends, 75–106*.

Huangsuwan, K., Cooharojananone, N., Punyabukkana, P., Suchato, A., Puangngam, Y., & Bunram, P. (2026). Enhancing learner engagement in Chulalongkorn University MOOC computing courses: Insights from Behavioral trends and analyses of multiple large language models. In W. W.-S., L. C.-F., H. Y.-M., F. E. Sandnes, & T. A. Sandtrø (Eds.), (pp. 403-411). Lecture Notes in Computer Science: Vol.

Ismirawati, N., Corebima, A. D., Zubaidah, S., Ristanto, R. H., & Nuddin, A. (2020). Implementing ercore in learning: Will metacognitive skills correlate to cognitive learning result?. *Universal Journal of Educational Research*, *8*(4), 51–58. https://doi.org/10.13189/ujer.2020.081808

Jackson, J. (2025). *"Who's Doing the Thinking Here?": A Pedagogy-First Approach to Integrating Large Language Models in Higher Education*.

Jaleel, S., & P., P. (2016). A study on the metacognitive awareness of secondary school students. *Universal Journal of Educational Research*, *4*(1), 165-172. https://doi.org/10.13189/ujer.2016.040121

Jh, T. S. ., Annas, S. ., & Saud, S. (2025). Development of a web-based Multimedia Learning Management System (MLMS) in High School physics learning. *Universal Teaching and Learning Journal*, *1*(1), 1-18. https://doi.org/10.35912/utlj.v1i1.3355

Jin, F., Sun, L., Pan, Y., & Lin, C.-H. (2025). High heels, compass, spider-man, or drug? Metaphor analysis of generative artificial intelligence in academic writing. *Computers and Education, 228*. https://doi.org/10.1016/j.compedu.2025.105248

Kabashkin, I., Misnevs, B., & Zervina, O. (2023). Artificial intelligence in aviation: New Professionals for new technologies. *Applied Sciences (Switzerland)*, *13*(21). https://doi.org/10.3390/app132111660

Karim, H. T., Tudorascu, D. L., Cohen, A., Price, J. C., Lopresti, B., Mathis, C., … Aizenstein, H. J. (2019). Relationships between executive control circuit activity, amyloid burden, and education in cognitively healthy older adults. *American Journal of Geriatric Psychiatry*, *27*(12), 1360-1371. https://doi.org/10.1016/j.jagp.2019.07.008

Kim, Y. (2024). Application of social constructivism in medical education. *Korean Medical Education Review, 26(Suppl 1), S31–S39*. https://doi.org/10.17496/kmer.23.044

Kirwan, A. (2024). ChatGPT and university teaching, learning and assessment: Some initial reflections on teaching academic integrity in the age of Large Language Models. *Irish Educational Studies*, *43*(4), 1389-1406. https://doi.org/10.1080/03323315.2023.2284901

Kisić, E., Milić, M. R., Saqr, M., López-Pernas, S., Conde, M. Á., & Pavlović, O. (2024). Large language models in higher education - perspectives, opportunities and limitations. *In M. Saqr, S. of C. University of Eastern Finland Yliopistokatu 2 Joensuu, S. Lopez-Pernas, S. of C. University of Eastern Finland Yliopistokatu 2 Joensuu, M. A. Conde, E. de I. University of Leon Campus de Vegazana S/N Leon, … F. of I. T. Belgrade Metropolitan University Tadeusa Koscuska 63 Belgrade (Eds.), CEUR Workshop Proceedings (Vol. 3938). CEUR-WS*. Retrieved from https://www.scopus.com/pages/publications/105000380007?origin=resultslist

Kuiper, R. (2002). Enhancing metacognition through the reflective use of self-regulated learning strategies. *The Journal of Continuing Education in Nursing*, *33*(2), 78-87. https://doi.org/10.3928/0022-0124-20020301-11

Laato, S., Morschheuser, B., Hamari, J., & Bjorne, J. (2023). AI-assisted learning with ChatGPT and large language models: Implications for higher education. Paper presented at In M. Chang, C. N.-S., R. Kuo, G. Rudolph, D. G. Sampson, & A. Tlili (Eds.), Proceedings - 2023 IEEE International Conference on Advanced Learning Technologies, ICALT 2023 (pp. 226–230). Institute of Electrical and Electronics Engineers Inc.

Livingston, J. A. (2011). *Metacognition: An overview*. USA: Department of Education.

Marthaliakirana, A. D., Suwono, H., Saefi, M., & Gofur, A. (2022). Problem-based learning with metacognitive prompts for enhancing argumentation and critical thinking of secondary school students. *Eurasia Journal of Mathematics, Science and Technology Education*, *18*(9). https://doi.org/10.29333/ejmste/12304

Mavroudi, A., & Torgersen, G. (2024). A Large Language Model Implementing an AI Assistant in a Higher Education Setting. *In B. R. Barricelli, G. Fischer, D. Fogli, A. Morch, A. Piccinno, & S. Valtolina (Eds.), CEUR Workshop Proceedings (Vol. 3685). CEUR-WS*. Retrieved from https://www.scopus.com/pages/publications/85194176016?origin=resultslist

Milano, S., McGrane, J. A., & Leonelli, S. (2023). Large language models challenge the future of higher education. *Nature Machine Intelligence*, *5*(4), 333-334. https://doi.org/10.1038/s42256-023-00644-2

Mundia, M. (2026). A comparative study of synchronous vs asynchronous technology tools in developing oral communication skills. *Universal Teaching and Learning Journal*, *2*(1), 11-22. https://doi.org/10.35912/utlj.v2i1.3925

Nadel, P., Maloney, D., & Monahan, K. (2024). Enabling access to large-language models (LLMs) at scale for higher education. *PEARC 2024 - Practice and Experience in Advanced Research Computing 2024: Human Powered Computing. Association for Computing Machinery, Inc*. https://doi.org/10.1145/3626203.3670577

Nagy, P., Nagy-Toth, B., & Nagy, A. S. (2026). Areas of use of ChatGPT and other Large Language Models among Hungrian universities, focusing on the Generation Z and the business world. Paper presented at ICEME 2025 - Proceedings of the 2025 16th International Conference on E-Business, Management and Economics, 216–229. Association for Computing Machinery, Inc.

Ngo, T. T. A., Vo, T. T. A., & Phan, M. T. (2025). The psychology of AI adoption in education: University students' intentions to use Large Language Models for learning from a TAM and TPB perspective. *Acta Psychologica, 261*. https://doi.org/10.1016/j.actpsy.2025.105789

Ni, R., Pan, J., Ni, Y., Zhong, Y., Wang, Z., & Jia, X. (2024). Exploration of Large language model application in university information service systems. Paper presented at Proceedings of the IEEE International Conference on Computer and Communications, ICCC, (2024), 281–286. Institute of Electrical and Electronics Engineers Inc.

Nikolovski, V., Trajanov, D., & Chorbev, I. (2025). Advancing AI in higher education: A comparative study of large language model-based agents for exam question generation, improvement, and evaluation. *Algorithms*, *18*(3). https://doi.org/10.3390/a18030144

Otsuka, A., Hajdu, C., & Kovacs, K. (2025). Chatbot assistant based on Large-Language Models for University students. Paper presented at INES 2025 - 29th IEEE International Conference on Intelligent Engineering Systems 2025, Proceedings, 77–82. Institute of Electrical and Electronics Engineers Inc.

Rachmat, H., Riza, H., & Abidin, T. F. (2024). Fine-tuning Large Language Model (LLM) to answer basic questions for prospective new students at syiah kuala university using the Retrieval-Augmented Generation (RAG) method. Paper presented at 2024 9th International Conference on Informatics and Computing, ICIC 2024. Institute of Electrical and Electronics Engineers Inc.

Rai, M. E., Ngaw, M., & Nannas, N. J. (2025). Artificial intelligence performance in introductory Biology: Passing grades but poor performance at high cognitive complexity. *Education Sciences*, *15*(10). https://doi.org/10.3390/educsci15101400

Ramdani , D. M. (2025). Developing an islamic adab-based teacher leadership model to improve teacher performance in Islamic boarding schools. *Universal Teaching and Learning Journal*, *1*(1), 31-45. https://doi.org/10.35912/utlj.v1i1.3360

Rücker, M. T., Büchting, C., & Kosch, T. (2025). Understanding the effect of risk perception on the acceptance and use of large language models among university students. Paper presented at Proceedings of the ACM on Human-Computer Interaction.

Schwendicke, F. a., Samek, W., & Krois, J. (2020). Artificial intelligence in dentistry: Chances and challenges. *Journal of dental research*, *99*(7), 769-774.

Shen, C. Y., & Liu, H. C. (2011). Metacognitive skills development: A web-based approach in higher education. *Turkish Online Journal of Educational Technology*, *10*(2), 140-150.

Suteja, Saifuddin, Farihin, Aris, & Winarso, W. (2022). A traditional game-based parenting model as a cultural-inheritance medium in early childhood education. *International Journal of Learning, Teaching and Educational Research*, *21*(3), 143-165. https://doi.org/10.26803/ijlter

Syukur, F., Maghfurin, A., Marhamah, U., & Jehwae, P. (2024). Integration of artificial intelligence in islamic higher education: Comparative responses between Indonesia and Thailand. *Nazhruna: Jurnal Pendidikan Islam*, *7*(3), 531-553. https://doi.org/10.31538/nzh.v7i3.13

Varaliya, M., Kanojia, M., & Nabajja, S. (2025). Revolutionizing higher education institute query system by linking custom knowledge base with large language models. In A. Bajaj, A. M. Madureira, & A. Abraham (Eds.), (pp. 86-94). Lecture Notes in Networks and Systems: Vol.

Vendrell, M., & Johnston, S.-K. (2026). Scaffolding critical thinking with generative AI: Design principles for integrating large language models in higher education. *Computers and Education: Artificial Intelligence, 10*. https://doi.org/10.1016/j.caeai.2026.100572

Wang, Y., & Zheng, G. (2020). Application of artificial intelligence in college dance teaching and its performance analysis. *International Journal of Emerging Technologies in Learning (iJET)*, *15*(16), 178-190.

Weber, J. L., Neda, B. M., Juarez, K. C., Wong-Ma, J., Gago-Masague, S., & Ziv, H. (2024). Beyond the Hype: Perceptions and realities of using large language models in computer science education at an R1 University. *IEEE Global Engineering Education Conference, EDUCON. IEEE Computer Society*. https://doi.org/10.1109/EDUCON60312.2024.10578596

Wu, M., Mossé, M., Goodman, N., & Piech, C. (2019). Zero shot learning for code education: Rubric sampling with deep learning inference. *782–790. AAAI Press*. https://doi.org/10.1609/aaai.v33i01.3301782

Xiang, L., Zhang, P., Luo, H., Yang, Y., & Song, Z. (2025). A study on task-based english teaching design in higher education based on large language models. Paper presented at Proceedings of 2025 International Conference on AI-Enabled Education, AIEE 2025, 171–175. Association for Computing Machinery, Inc.

Xie, J., Tan, B., & Zhang, Y. (2023). A large-scale study into protist-animal interactions based on public genomic data using DNA barcodes. *Animals*, *13*(14), 1-12. https://doi.org/10.3390/ani13142243

Yakar, U., Sulu, A., Porgali, M., & Çalis, N. (2020). From constructivist educational technology to mobile constructivism: How mobile learning serves constructivism?. *International Journal of Academic Research in Education*, *6*(1), 56–75. https://doi.org/10.17985/ijare.818487

Yigci, D., Eryilmaz, M., Yetisen, A. K., Tasoglu, S., & Ozcan, A. (2025). Large language model-based chatbots in higher education. *Advanced Intelligent Systems*, *7*(3). https://doi.org/10.1002/aisy.202400429

Zdravkova, K., Dalipi, F., & Ahlgren, F. (2023). Integration of large language models into higher education: A perspective from learners. Paper presented at In do R. R. M, M. Figueiredo, & J. Torres (Eds.), 25th International Symposium on Computers in Education, SIIE 2023. Institute of Electrical and Electronics Engineers Inc.