The Influence of ChatGPT-Assisted Heutagogy and Prior Knowledge on Students' Conceptual Understanding and Application in a Learning Strategies Course

Towelna Tarumasely

Department of Christian Religious Education, Faculty of Christian Education, Institut Agama Kristen Negeri Ambon, Ambon, Indonesia

Corresponding author: yowelnatarumasely@gmail.com

Abstract. This quasi-experimental study examined the effects of ChatGPT-assisted heutagogy, prior knowledge, and their interaction on students' conceptual understanding and utilization skills. The study included 85 fourth-semester students enrolled in a learning strategies course at IAKN Ambon. Using a 2×2 factorial design, participants were divided into an experimental group (heutagogy with ChatGPT assistance, n = 42) and a control group (heutagogy without AI support, n = 43), which were further grouped based on their prior knowledge (high/low). Data were collected through validated multiple-choice and essays and analyzed using MANOVA. The results showed that the ChatGPT-supported group showed significantly higher conceptual understanding and usage ($p < 0.05$). Students with a high level of prior knowledge performed better than those with little prior knowledge ($p < 0.05$). In particular, no significant interaction was found between learning intent and prior knowledge ($p > 0.05$), suggesting that AI-assisted heutagogy consistently benefits students at all knowledge levels. These findings confirm that integrating generative AI, such as ChatGPT, within a heutagogic framework can enhance learning quality and promote equitable outcomes.

Keywords: AI; ChatGPT; concept understanding; concept utilization; heutagogy; prior knowledge

INTRODUCTION

21st-century education is an effective way to achieve success. Literacy requires students to develop complex skills that include not only cognitive power but also practical application skills (Griffin, McGaw, & Care, 2012). The framework of 4C (Critical Thinking, Collaboration, Communication, and Creativity) has emerged as crucial to modern education (Trilling & Fadel, 2009). For aspiring teachers of Christian religious education in Indonesia, mastery of conceptual understanding and its application represents a fundamental skill directly linked to their ability to design effective learning experiences (Darling-Hammond, 2017; Korthagen, 2017).

Research in Indonesian educational contexts has shown persistent challenges in students' conceptual understanding and application skills. Studies have shown that only about 50% of students achieve satisfactory proficiency in pedagogical conceptual mastery, while the rest demonstrate inadequate comprehension (Salmila & Erita, 2023; Suhyanto & Musyrifah, 2016). This gap between theoretical knowledge and practical application skills presents significant challenges for teacher preparation programs, especially in religious education contexts where contextual application is critical (Jeyaraj, 2021; Tarumasely, 2020).

The Learning Strategies course plays a crucial role in developing pedagogical skills for prospective teachers. This course provides both a theoretical basis and practical skills for designing, implementing, and evaluating learning experiences (Nurdyansyah & Riananda, 2016; Wena, 2014). Students with a strong conceptual understanding can better analyze learning theories, connect theory and practice, and develop creative teaching designs.

Heutagogy, or self-determined learning, provides a suitable approach for addressing these challenges. This pedagogical framework places students as primary agents in their learning process, with autonomy to determine goals, intentions, and reflections (Hase & Kenyon, 2013; Blaschke, 2012). Research indicates that heutagogy fosters critical thinking and problem-solving skills by promoting proactive and reflective engagement (Canning, 2010; Tricahyono, 2021). However, exposure often faces limitations, including limited access for instructors to intensive guidance and insufficient resources for the needs of individual students (Agnello et al., 2021; Blaschke, 2019).

Integration of AI is a viable solution to increase heutagogic efficiency. AI topics include learning analytics, personalized content recommendations, and real-time feedback (Manongga, Rahardja, & Sembiring, 2022; Putri et al., 2023). Generative AI tools, such as ChatGPT, can act as a metacognitive partner, providing instant answers to students' questions, stimulating critical thinking through probing questions, and offering explanations tailored to individual learning paths (Baskara, 2023; Kasneci et al., 2023). This responsive support enables students to pursue self-determined learning paths more effectively by bridging the gap between theoretical autonomy and practical resource limitations (Chen et al., 2020; Rashel et al., 2024).

Prior knowledge remains a crucial factor in determining learning outcomes. Students' current knowledge strategies facilitate contact with new information, speed up understanding, and reduce misunderstandings (Halilkari, Katajavuori, & Lindblom-Ylänne, 2008; Dochy, Segers, & Buehl, 2002). Those with limited prior knowledge often struggle with new material, whereas students with a strong foundation more easily grasp concepts, recognize patterns, and develop analytical thinking skills (Maulidya & Saputri, 2016; Vosniadou, 2013). Early assessments on IAKN Ambon often reveal limited prior knowledge among students, resulting in suboptimal learning outcomes, as noted in previous studies (Tarumasely, 2020; Payung et al., 2016).

Theoretical Gap and Novelty

While heutagogic principles (Hase & Kenyon, 2013; Blaschke, 2012) and the importance of prior knowledge (Halilkari et al., 2008; Dochy et al., 2002) are well recognized, their intersection with generative AI represents a new area of research. Previous studies have examined AI in education (Zawacki-Richter et al., 2019; Chen et al., 2020) and the implementation of heutagogy (Blaschke, 2019; Agnello et al., 2021) separately, but empirical studies integrating generative AI tools like ChatGPT within heutagogic frameworks remain rare (Kasneci et al., 2023; Baskara, 2023). This gap is particularly evident in specific contexts such as teacher education in religious education in Indonesia (Jeyaraj, 2021).

This study builds on previous research on heutagogy and expands on it by examining the integration of AI technologies within heutagogic frameworks. The study makes three different contributions: (1) integration of novelty through empirical investigation of Generative AI (ChatGPT) coupled with self-determined learning rules (Heutagogy); (2) contextual novelty in the utilization within Christian religious education teacher preparation in the Indonesian context; and (3) analytical novelty through the investigation of the interplay effects between the AI-Heutagogy approach and previous knowledge.

Research Objectives

This study aimed to: (1) examine differences in learning outcomes (understanding and use of learning strategy concepts) between students who use AI-assisted heutagogy versus those who use heutagogy without AI-assistance; (2) analyze differences in conceptual understanding among students with high and low prior knowledge; and (3) examine interactions between learning strategies (AI-assisted vs. non-AI) and prior knowledge of conceptual understanding and utilization outcomes.

METHODOLOGY

Research Design

This study used a quasi-experimental 2×2 factorial mismatch comparison group model (Creswell, 2014; Setyosari, 2015). The design followed established methodological approaches used in previous education technology research (Tarumasely, 2020; Cohen, Manion, & Morrison, 2018). Undefined classes were used for experimental and control groups, with random allocation of classes according to circumstances. Two classes implemented AI-assisted heutagogy (experimental group), while two classes implemented heutagogy without AI support (comparison group).

Participants

Participants were 85 fourth-semester students from the Christian Religious Education School at IAKN Ambon for the 2023/2024 academic year. The experimental group consisted of 42 students, while the control group consisted of 43 students. Participants were further grouped into two categories based on their prior knowledge, as determined by a prior knowledge test, following the classification methodology used in previous studies (Tarumasely, 2020; Dochy et al., 2002).

TABLE 1. Distribution of research participants

Group	High prior knowledge (n)	Low prior knowledge (n)	Total
Experimentation (AI-Supported)	23	19	42
Control (Non-AI)	22	21	43
Total	**45**	**40**	**85**

Variables

The independent variable in this study is the learning strategy, specifically comparing AI-assisted heutagogy with non-AI heutagogy. Prior knowledge, categorized as high or low, serves as the moderating variable. The dependent variables are conceptual understanding and conceptual application, which are measured to assess the outcomes of the learning strategies. Additionally, several control parameters are maintained throughout the study, including the instructional materials, learning tools, implementation time, and the instructor, to ensure consistency and reliability of results.

Research Instruments

The research instruments employed in this study consisted of three main components. First, the Prior Knowledge Test was a 25-item multiple-choice assessment, developed based on prerequisite materials for the Learning Strategies course. This test was validated by experts and demonstrated a reliability coefficient (Cronbach's Alpha) of 0.78. Second, the Conceptual Understanding Test consisted of 15 essay questions designed to evaluate students' ability to explain concepts related to learning strategies. This instrument achieved a validity coefficient of 0.85 and a reliability of 0.81. Third, the Concept Application Test included 10 scenario-based problems that assessed students' capability to apply learning strategies within a classroom context. This tool reported a validity coefficient of 0.82 and a reliability of 0.79.

The development of tools followed course materials and expert exams. Validity was assessed using Pearson product-moment correlation (Arikunto, 2014; Ghozali, 2013), while reliability was calculated using Cronbach's absolute coefficient (minimum = 0.70). The tool development followed similar grading methods to those used in previous research on self-directed learning (Tarumasely, 2020; Fraenkel, Wallen, & Hyun, 2012).

Procedure

The study was conducted over 6 weeks using the following method:

1. Pre-test and prior knowledge assessment: All participants completed the prior knowledge test during the first week.
2. Postponement of treatment:
   a. Experimental Group (AI-Assisted Heutagogy): Students were instructed on using ChatGPT as a learning partner. They learned rapid engineering techniques to: (a) ask for concept explanations, (b) ask for examples of applications of learning strategies, (c) create case studies for analysis, and (d) receive feedback on their learning designs. Students used ChatGPT during self-directed learning courses to review course materials and complete assignments.
   b. Control group (Heutagogy without AI): Students implemented self-determined learning without AI support, relying on common resources such as textbooks, lecture notes, and discussions with peers and instructors. They participated in similar self-directed learning activities, but without the aid of AI.
3. Posttest: After the treatment period, all participants completed the concept perception and usability tests.

Ethical Concerns

This study received ethical approval from the Research Ethics Committee of IAKN Ambon. All participants gave informed consent after receiving detailed information about the research processes. Specific instructions were issued regarding the ethical use of ChatGPT, including: (1) verifying information from multiple sources, (2) avoiding plagiarism through proper citation practices, and (3) maintaining academic integrity in all assignments. Anonymity and confidentiality were maintained throughout the research process.

Data Analysis

The Multivariate Analysis of Variance (MANOVA) with SPSS 19 was used to examine the main influences and interactions between learning strategies and prior knowledge. Descriptive analyses identified differences in learning outcomes between groups. Assumption tests included normality (Kolmogorov-Smirnov test) and homogeneity (Box's M and Levene's tests). The analytical approach was consistent with methods used in previous education research (Tarumasely, 2020; Field, 2018).

RESULTS

Descriptive Statistics

TABLE 2. Descriptive statistics for post-test results

Learning Plan	Curiosity	Conceptual understanding		Use of concept	
		M	SD	M	SD
AI-supported	Tall (n=23)	79.48	5.16	76.00	6.93
	Low (n=19)	69.04	5.42	73.57	6.00
	Total (n=42)	74.26	7.43	74.78	6.53
Non-AI	Tall (n=22)	74.96	5.15	74.43	5.36
	Low (n=21)	66.43	4.31	66.83	5.30
	Total (n=43)	70.70	6.37	70.63	6.52
Overall	Tall (n=45)	77.22	5.59	75.22	6.18
	Low (n=40)	67.74	5.02	70.20	6.55
	Total (N=85)	72.48	7.11	72.71	6.82

As shown in Table 2, the analysis revealed that students in the AI-assisted group demonstrated a higher conceptual understanding (M = 74.26, SD = 7.43) compared to the non-AI group (M = 70.70, SD = 6.37). Similarly, the results for concept application were higher in the AI-assisted group (M = 74.78, SD = 6.52) compared to the control group (M = 70.63, SD = 6.52). Students with high prior knowledge consistently performed better than those with little prior knowledge, consistent with results from previous studies (Tarumasely, 2020; Dochy et al., 2002)

Assumption Tests

The data met the prerequisites for parametric testing. Normality tests using the Kolmogorov-Smirnov method showed a significance value of greater than 0.05 for both dependent variables. Homogeneity experiments using Box's M ($p = 0.804$) and Levene's Test (Conceptual Understanding: $p = 0.950$, Concept Application: $p = 0.950$) confirmed the homogeneity of variance, consistent with the prerequisites for parametric testing (Field, 2018; Tabachnick & Fidell, 2019).

Inference Statistics

MANOVA demonstrated significant primary influences for learning strategy (Pillai's Trace = .214, F = 11,327, $p < .001$) and prior knowledge (Pillai's Trace = .362, F = 23,415, $p < .001$). The interaction between learning intent and prior knowledge was not significant (Pillai's Trace = .018, F = 0.754, p = .474).

Monovariate analyses identified significant differences between categories for conceptual understanding (F = 9,842, p = .002) and conceptual utilization (F = 11,635, p = .001). Prior knowledge significantly affected conceptual perception (F = 45,327, $p < .001$) and usage (F = 18,642, $p < .001$). Non-significant interactions were observed for conceptual perception (F = 2.154, p = .146) and utilization (F = 0.518, p = .474).

DISCUSSION

AI Heutagogy Synergy in Learning Reinforcement

The significantly better performance of the ChatGPT-supported group demonstrates the dynamic interaction between AI technology and heutagogic principles. Heutagogy emphasizes learner autonomy and self-determination (Hase & Kenyon, 2013; Blaschke, 2012), while ChatGPT provides the responsive, personalized support necessary for the effective implementation of these principles (Baskara, 2023; Kasneci et al., 2023). Students were able to engage in instant conversation, receive personalized feedback, and review learning materials adaptively, creating an environment where self-directed learning is both feasible and effective (Ng et al., 2023; Kaçar & Balıkçı, 2023).

This integration addresses a fundamental challenge in the implementation of heutagogy: the gap between theoretical autonomy and practical resource constraints (Agnello et al., 2021; Blaschke, 2019). By providing scaffolds that are always available, ChatGPT enables students to pursue self-determined learning paths without being limited by instructor access or access to resources (Chen et al., 2020; Rashel et al., 2024). AI does not act as a solution provider, but rather as a metacognitive partner that enhances, rather than replaces, the human learning process (Baker, 2016).

The Ongoing Role of Prior Knowledge

The important primary effect of prior knowledge reaffirms the fundamental role of learning processes (Halikari et al., 2008; Dochy et al., 2002). Students with established knowledge programs were able to integrate new information more effectively, experience less cognitive burden, and increase pattern recognition (Sweller, 2011; Vosniadou, 2013). On the other hand, students with limited prior knowledge required more cognitive resources for basic understanding, which limited their ability to engage in higher-order and analytical thinking (Au, Li, & Rao, 2017; Kirschner, Sweller, & Clark, 2006).

The Fair Impact of AI Integration

The non-significant communication effect represents perhaps the most important finding: ChatGPT-assisted heutagogy had no significant effect on students. This suggests that AI integration can help reduce educational disadvantages associated with limited prior knowledge (Baker, 2016; Chen et al., 2020). Technology provides scalable, personalized support that would otherwise require intensive intervention from educators (Rashel et al., 2024; Manongga et al., 2022), may address gender equality issues in educational settings (Darling-Hammond, 2017; Schleicher, 2018).

The absence of a significant communication effect suggests that the benefits of ChatGPT assistance were not limited to students with a high level of prior knowledge. Instead, both students with high and low prior knowledge benefited similarly from the AI support, which suggests that ChatGPT-assisted heutagogy can serve as a balancing tool in different learning environments.

CONCLUSION

This study shows that ChatGPT-assisted heutagogy significantly increases conceptual understanding and usage compared to non-AI approaches. While prior knowledge remains a crucial factor in learning outcomes, AI integration consistently benefits students across all knowledge levels. The unimportant interaction suggests that AI-assisted heutagogy can help address inequities in education by providing scalable, personalized support that makes self-determined learning more accessible and effective for more groups of students (Baskara, 2023; Kasneci et al., 2023).

IMPLICATIONS

The results provide several practical implications for education professionals. Curriculum development suggests that educational institutions should consider integrating AI tools, such as ChatGPT, into self-determined learning frameworks to enhance both conceptual understanding and application skills. In terms of teacher education, professional development programs should include training in AI-assisted pedagogy, with an emphasis on rapid engineering techniques and ethical guidelines for the use of AI. For education policy, institutions should develop clear policies regarding AI integration that strike a balance between innovation and academic integrity, while ensuring equitable access to AI tools across all student groups. However, this study has several limitations. First, it was conducted in a single institution with a relatively small sample size, which may limit the generalizability of the results. Second, the research period was relatively short, so longer-term studies are needed to investigate the lasting effects of AI-assisted heutagogy. Third, the study did not control for potential confounding variables, such as student motivation, digital literacy, and potential Hawthorne effects, in which participants may alter their behavior due to awareness of being observed.

Future research should address these limitations by involving multiple institutions, extending the research period, and examining the role of several factors that may affect the effectiveness of AI integration in heutagogic processes. Studies could also examine the application of this approach in various analytical contexts and assess its long-term impact on students' professional development as teachers.

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