Generative AI and Knowledge Mapping in Programming Education: Student Learning and Engagement

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Abstract: This study examines how Generative AI and knowledge-mapping tools support student learning and engagement in programming education. A quasi-experimental design was conducted with 30 undergraduate students enrolled in an object-oriented programming course, where participants used both tools across a four-week intervention. Data were collected through task performance and learner perception surveys. The results indicate that students reported higher ease of use and immediate support when using Generative AI, while knowledge mapping was associated with stronger support for conceptual understanding and reflective learning in later stages. These findings suggest that the two approaches support different aspects of learning, with Generative AI facilitating rapid clarification and knowledge-mapping tools encouraging structured conceptual engagement. The study contributes to the e-learning field by providing empirical insight into how different forms of learning support function within the same instructional context. Rather than positioning the tools as direct alternatives, the findings highlight their complementary pedagogical roles and offer guidance for integrating adaptive AI support with structured learning approaches in programming education.

Keywords: Generative AI, Knowledge mapping, Mytelemap, Programming education, Student learning outcomes

1. Introduction

Artificial intelligence (AI) continues to reshape the educational landscape by offering tools that enhance both teaching and learning experiences. Among these innovations, Generative AI technologies have emerged as powerful agents of change, capable of generating personalized content and supporting self-directed learning. Tools such as OpenAI's ChatGPT exemplify this trend by offering real-time interaction, instant feedback, and tailored study materials, which make them particularly useful in accommodating diverse learner needs. Complementing these advances, knowledge mapping tools like Mytelemap provide structured and visual approaches to learning. By enabling learners to map out concepts and relationships between topics, Mytelemap supports competence-based learning and encourages deeper engagement with content. Its design aligns well with educational goals that prioritize conceptual understanding, self-regulated learning, and critical thinking. Mytelemap is considered in this study as an example of a knowledge-mapping approach rather than as a standalone tool for evaluation. Knowledge mapping has been widely used in educational research to support conceptual understanding, schema development, and reflective learning. The inclusion of Mytelemap therefore represents a broader category of visualization-based learning support, enabling a comparison with AI-based approaches within the same instructional context. Despite their promise, both Generative AI and Mytelemap face challenges. Generative AI raises concerns about content reliability, ethical use, and academic integrity, while Mytelemap requires users to invest time and effort to master its mapping techniques. Understanding the pedagogical differences between these tools is important for educators seeking to integrate them effectively into programming instruction. As the two tools serve different pedagogical functions, this study does not treat them as directly equivalent. Instead, the comparison focuses on how different forms of learning support—Generative AI and knowledge mapping—are associated with differences in student learning processes and experiences within the same instructional context.

This study investigates how different forms of learning support—Generative AI and knowledge mapping—are associated with differences in student performance and perceptions in programming learning. It examines their perceptions of each tool's usability, learning support, and overall effectiveness. The research also investigates how each tool is associated with differences in learning performance and student satisfaction. By analyzing these outcomes, the study aims to provide practical insights into the role of emerging technologies in education and offers recommendations for integrating them into hybrid learning environments. Also, the present study is

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theoretically informed by Cognitive Load Theory (Sweller, 1994) and Constructivist learning principles. From a Cognitive Load perspective, Generative AI may reduce extraneous load by offering immediate, simplified explanations that help novices progress quickly through early programming tasks. In contrast, Mytelemap's knowledge-mapping processes align with constructivist theory, which emphasizes active meaning-making, integration of new information with prior knowledge, and the construction of conceptual structures. Mapping requires learners to externalize relationships among programming concepts, thereby promoting cognitive load and deeper schema formation. Framing the comparison through these theories provides explanatory power for understanding why AI-driven tools accelerate comprehension while visualization-based tools enhance conceptual depth.

This study contributes empirical insight by examining how a Generative AI tool and a visualization-based knowledge-mapping tool (Mytelemap) support learning within the same programming course context. Whereas prior studies examined each tool independently, relatively few studies have examined how their differing learning mechanisms—AI-mediated adaptive feedback and competence-based visual structuring—may shape student outcomes within the same instructional context. The findings contribute to ongoing discussions in technology-enhanced learning by providing insight into when each tool may be pedagogically advantageous, thereby informing the design of hybrid learning models that integrate AI-driven personalization with structured conceptual mapping.

Despite the increasing use of both Generative AI and knowledge-mapping tools in education, the research problem remains insufficiently articulated in existing literature. Prior studies have typically examined these technologies separately, with limited attention to how they function within the same learning context. As a result, there is still a lack of clarity regarding how different forms of learning support—AI-driven adaptive feedback and visualization-based knowledge structuring—affect student learning processes and outcomes in programming education.

Based on the above considerations, this study addresses the following research questions:

RQ1: *How does the use of Generative AI compare with Mytelemap in supporting students' programming task performance?*

RQ2: *How do students perceive the usability and learning support provided by Generative AI and Mytelemap?*

RQ3: *In what ways do the two tools differ in supporting conceptual understanding and engagement in programming learning?*

The analytical focus of this study is to examine how these two forms of learning support differ in their underlying learning mechanisms and how these differences are reflected in student performance and perceptions.

Section 2 provides an overview of Generative AI and Mytelemap, examining their roles in education and summarizing previous comparative studies that highlight their respective advantages and limitations. Section 3 describes the research methodology employed in this study, including the design of the experiment, data collection procedures, and the evaluation criteria used to assess the tools' effectiveness. Section 4 presents the results and discusses key findings, focusing on how each tool impacted students' learning outcomes and user satisfaction. Finally, Section 5 concludes the study by summarizing the main contributions, addressing the limitations, and offering recommendations for future research, particularly on the integration of Generative AI with knowledge mapping technologies to create more effective hybrid learning solutions.

2. Generative AI and Mytelemap

2.1 Generative AI and its Uses in Education

Generative Artificial Intelligence (Generative AI) is an emerging technology that is increasingly influencing educational practices. Its capabilities are influencing how learning content is created and delivered to students, and in turn how students process and respond to learning tasks, offering new opportunities for engagement and efficiency. Generative AI refers to systems that leverage machine learning techniques, particularly deep learning models such as large language models (LLMs), to produce original content in response to user inputs (Bender et al., 2021). These outputs can include natural language text, images, audio, video, or even software code, and are typically generated in a way that closely mimics human reasoning and creativity (Bender et al., 2021). In the educational context, Generative AI offers several potential benefits for both learners and educators, although its adoption comes with challenges that require careful consideration.

One of the most significant contributions of Generative AI in education is its ability to support personalized learning. Traditional educational models often struggle to accommodate diverse learner needs, particularly in large classrooms where individual attention is limited. Generative AI tools can provide customized learning experiences aligned with students' knowledge level and pace (Khreisat et al., 2024). These tools are capable of generating personalized quizzes, flashcards, study guides, and summaries that align with individual learner goals. For instance, Xodabande, Atai and Hashemi (2024) found that university students who used AI-generated digital flashcards demonstrated significantly higher retention of technical vocabulary compared to those relying on conventional learning materials. Such adaptive learning support facilitates differentiated instruction, ensuring that learners with varying capabilities and backgrounds can receive content that meets their specific needs.

Generative AI also enhances the interactivity of the learning experience. AI-powered virtual tutors can simulate personalized, one-on-one instruction by responding to learners' questions in real time. These systems, designed to emulate the guidance of a human teacher, provide detailed explanations, step-by-step problem-solving assistance, and contextually relevant examples to reinforce comprehension. Were (2022) highlights the potential of these AI-driven tutoring systems to bridge educational gaps, particularly in under-resourced environments where access to qualified instructors is limited. By providing immediate, adaptive feedback, Generative AI enables students to clarify doubts without delay, promoting continuous learning and reducing dependence on external instruction.

In addition to enhancing learner engagement, Generative AI streamlines various administrative and instructional processes for educators. One of its practical applications is automating the generation and grading of assessments. By leveraging natural language processing and machine learning algorithms, AI systems can automatically generate exam questions, assignments, and project guidelines tailored to specific course objectives (Eden, Chisom and Adeniyi, 2024). Furthermore, AI-powered grading systems offer immediate and consistent feedback on student submissions, freeing educators from time-intensive evaluation tasks and allowing them to focus on more meaningful interactions with students (Saqr, Al-Somali and Sarhan, 2024). Automated feedback systems also enable students to track their performance in real time, identifying areas for improvement and adapting their learning strategies accordingly.

Beyond classroom applications, Generative AI contributes to developing educational resources and materials. Tools like ChatGPT can assist instructors in designing lesson plans, writing lecture notes, and creating instructional videos or interactive modules (Hutson et al., 2023). This capacity to generate high-quality educational content reduces the preparation time required by educators, allowing them to dedicate more attention to facilitating discussions, mentoring students, and fostering collaborative learning environments.

Despite these benefits, the integration of Generative AI into education raises several challenges and ethical concerns. One of the most pressing issues relates to the accuracy and reliability of AI-generated content. While Generative AI models are capable of producing plausible and fluent text, they are also prone to generating factually incorrect or misleading information, a phenomenon commonly referred to as "hallucination" (Bender et al., 2021). This can have serious consequences in educational settings, where students may unknowingly rely on erroneous explanations or data. Ensuring that AI-generated materials are accurate and verifiable is a significant challenge that requires the development of robust validation frameworks and critical media literacy skills among learners (Singh et al., 2025).

Academic integrity is another area of concern. The ease with which Generative AI tools can produce essays, reports, computer code, and other academic work has led to increased instances of plagiarism and unauthorized assistance (Hutson et al., 2023). As students gain access to tools capable of completing assignments with minimal effort, educators face difficulties in assessing authentic student learning and ensuring fair evaluation practices. To address these challenges, institutions are adopting AI-detection tools, revising assessment methods, and encouraging the development of original, process-based assignments that emphasize critical thinking and personal reflection (Singh et al., 2025).

Data privacy and security are additional ethical considerations associated with the use of Generative AI in education. Many AI-powered platforms require access to user data to personalize learning experiences and improve model performance. However, this data collection raises concerns about user consent, data protection, and potential breaches (Khreisat et al., 2024). Ensuring compliance with data privacy regulations such as the General Data Protection Regulation (GDPR) and establishing transparent data governance policies are essential for protecting learners' sensitive information and building trust in AI systems.

Furthermore, Generative AI systems may inadvertently perpetuate biases present in their training data. Because LLMs are trained on vast datasets collected from the internet, they can reproduce and amplify existing social, cultural, and ideological biases (Bender et al., 2021). This can lead to discriminatory or biased outputs, which undermine inclusivity and equity in education. Addressing these issues requires careful curation of training datasets, regular auditing of AI systems, and the implementation of fairness-aware algorithms designed to minimize biased outcomes (Eden, Chisom and Adeniyi, 2024).

Despite these challenges, proponents argue that Generative AI has the potential to advance inclusive and equitable education when implemented responsibly. AI's ability to deliver scalable, personalized instruction can help close educational gaps, particularly for marginalized and underserved populations (Were, 2022). For example, AI-powered translation services and multilingual learning resources can support students who speak different languages, while adaptive learning tools can assist students with disabilities by offering customized content and accessibility features (Strielkowski et al., 2024). These inclusive capabilities highlight the transformative potential of Generative AI in addressing long-standing disparities in educational access and quality.

Another important consideration is the role of Generative AI in fostering lifelong learning. In today's rapidly evolving knowledge economy, learners must continuously update their skills and knowledge to remain competitive. Generative AI supports lifelong learning by providing on-demand access to up-to-date information, personalized learning pathways, and micro-learning opportunities tailored to individual interests and career goals (Saqr, Al-Somali and Sarhan, 2024). This flexibility empowers learners to take control of their educational journeys and engage in self-directed learning at their own pace.

Generative AI offers a range of applications in education. Its ability to personalize learning, facilitate engagement, automate instructional tasks, and provide scalable support holds promise for enhancing learning outcomes and improving educational access. However, the successful integration of Generative AI into education requires a balanced approach that addresses concerns related to content accuracy, academic integrity, data privacy, bias, and ethical use. As institutions and educators explore the adoption of Generative AI tools, it is essential to develop guidelines and best practices that ensure these technologies are used responsibly and effectively to support meaningful learning experiences.

Future research should focus on evaluating the long-term impacts of Generative AI in education, particularly in terms of student learning outcomes, teacher roles, and curriculum design. Studies exploring hybrid approaches that combine AI-driven personalization with human-centered instruction may offer insights into creating balanced and effective learning environments. Additionally, interdisciplinary collaboration among educators, technologists, ethicists, and policymakers is needed to establish comprehensive frameworks for the ethical and pedagogical use of Generative AI in education.

2.2 Overview of Mytelemap in Education

Mytelemap, a digital tool designed for knowledge mapping, has gained traction in educational contexts for its ability to visually organize and connect learners' knowledge (Nitchot, Wettayaprasit and Gilbert, 2019). Knowledge mapping, a pedagogical technique, helps students visualize the knowledge "landscape" of their learning. Mytelemap's intuitive interface and dynamic visualization capabilities make it a valuable asset in both traditional and online learning environments. The Mytelemap prototype application (www.mytelemap.com) is a web-based tool that allows for the display of knowledge mapping. Clicking on the visualization allows viewers to interact with it, and the screenshot shown illustrates how the mapping overview is arranged (Figure 1). The algorithm finds the connections based on the subject matter keywords when students click on a mapping node. Mytelemap filters the potential web links by selecting mapping node that corresponds to each subject area. Learners can discover their competencies, spot inconsistencies, integrate and adapt as needed, and test their new knowledge through additional map development and traversal through the traversal of a pedagogical knowledge mapping.

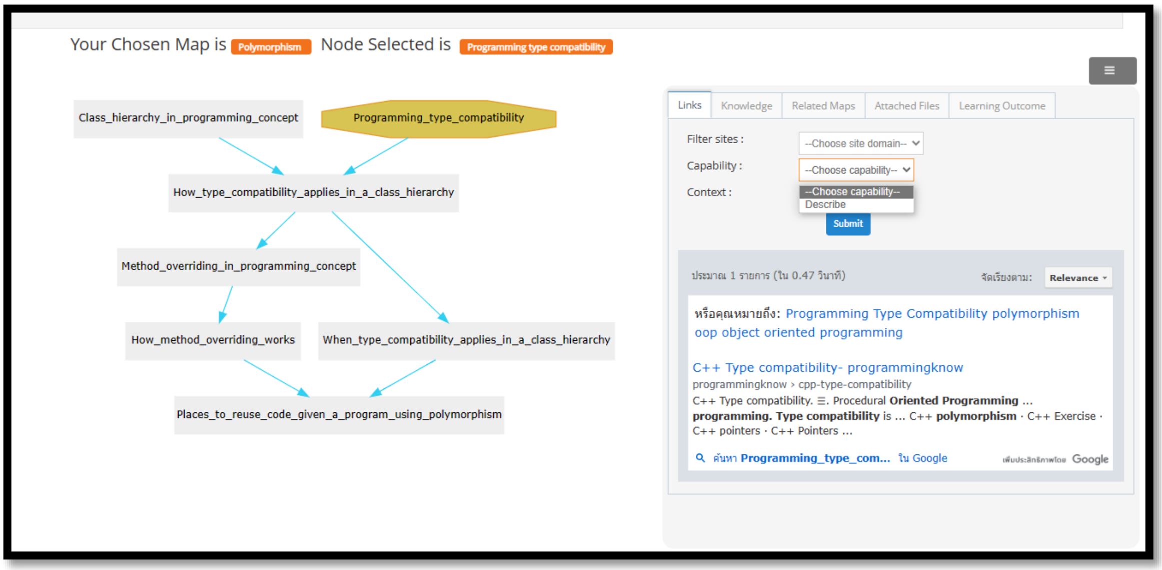

Figure 1: Mytelemap Prototype Showing the Knowledge Map of the Topic 'Polymorphism'

One of the tool's primary innovations lies in its support for competence mapping. Competence-based education requires learners to develop and demonstrate specific skills and knowledge in a structured, transparent manner. Mytelemap enables users to create maps that reflect their competencies, explicitly outlining the knowledge and skills they have acquired as well as those they still need to develop. In the studies related to the uses of Mytelemap, Nitchot and Gilbert (2024a) demonstrated that Mytelemap effectively supports competence articulation, offering learners a clearer picture of their learning trajectories and providing them with personalized recommendations for further study. The ability to track one's competencies over time fosters self-regulated learning, as learners are empowered to take responsibility for their educational progress. Moreover, Mytelemap enhances motivation and learner engagement. In a recent study on programming courses, Nitchot and Gilbert (2024b) found that students using Mytelemap reported increased motivation and satisfaction. By visualizing complex programming concepts, such as inheritance and polymorphism, students gained greater clarity and confidence in their understanding. The competence mapping functionality allowed them to see their learning progress in real time, which fostered a sense of achievement and encouraged continued engagement with the material.

Another significant advantage of Mytelemap is its facilitation of collaborative learning. The platform allows multiple users to co-create and share knowledge maps, promoting peer collaboration and collective knowledge construction. As Rahayu, Ferdiana and Kusumawardani (2022) observed, collaborative knowledge mapping fosters critical thinking and deepens conceptual understanding by encouraging learners to negotiate meanings and integrate diverse perspectives into a unified map. Mytelemap's collaborative features support synchronous and asynchronous learning, making it a valuable tool for group projects and blended learning environments. In addition to supporting individual and collaborative learning, Mytelemap also plays a crucial role in reflective practice. Nitchot and Gilbert (2025) conducted a case study in which students used Mytelemap to map out competencies required for constructing a holographic projector. The study found that learners benefited from the opportunity to reflect on their existing competencies and identify areas for improvement. By explicitly visualizing the links between acquired and required skills, Mytelemap encouraged metacognitive awareness and self-directed learning, enabling students to make informed decisions about their learning priorities.

Mytelemap represents a significant advancement in knowledge mapping tools for education. Its pedagogically informed design, emphasis on competence-based learning, and support for personalized and collaborative learning make it a valuable asset for both learners and educators. The growing body of research, particularly by (Nitchot and Gilbert, 2024a; Nitchot and Gilbert, 2024b; Nitchot and Gilbert, 2025), demonstrates Mytelemap's effectiveness in promoting critical thinking, motivation, and self-regulated learning. As educational institutions seek to harness the power of knowledge mapping, Mytelemap offers a promising solution that aligns with contemporary educational goals. Nevertheless, its future development—especially with the integration of AI—must address challenges related to usability, accessibility, and ethical considerations to ensure its impact remains positive and equitable across diverse learning environments.

2.3 Comparative Studies between Generative AI and Non-AI Tools

The rapid development of educational technology has introduced a variety of tools aimed at improving learning experiences and outcomes. Among these, Generative Artificial Intelligence (Generative AI) systems and Non-AI knowledge mapping tools such as Mytelemap represent two distinct learning support mechanisms with different pedagogical roles. While both aim to support learning and knowledge acquisition, they operate on fundamentally different principles. Generative AI leverages machine learning algorithms to generate adaptive content and provide personalized feedback, whereas Mytelemap focuses on helping students visually structure and organize knowledge. Although existing research explores the individual use of Generative AI and knowledge mapping tools in education, no prior studies have directly compared Generative AI and Mytelemap in terms of their educational effectiveness. This section synthesizes available literature on each tool type and presents comparative insights based on recent experimental findings.

Generative AI tools such as ChatGPT and similar systems have been widely recognized for their ability to deliver personalized learning experiences. These tools can generate instant explanations, summaries, quizzes, and examples tailored to individual learners' needs (Khreisat et al., 2024). Their interactive, conversational nature allows learners to ask questions and receive immediate responses, which can help clarify complex concepts and support self-paced learning (Saqr, Al-Somali and Sarhan, 2024). Studies have shown that students who use Generative AI tools often experience increased motivation and engagement due to the immediacy and personalization of the feedback they receive (Ward et al., 2025). Furthermore, Generative AI has been noted for its potential to support inclusive learning by adapting content to accommodate diverse learning styles (Eden, Chisom and Adeniyi, 2024).

In contrast, Mytelemap is a Non-AI knowledge mapping tool that assists learners in visually organizing and connecting ideas within a given domain. Knowledge mapping, as a pedagogical strategy, encourages students to structure information hierarchically and explore the relationships between concepts (Nitchot, Wettayaprasit and Gilbert, 2019). Mytelemap facilitates this process through an intuitive interface that allows users to create nodes and links, enabling them to develop a comprehensive representation of their understanding of a subject. This process promotes deeper learning by requiring students to actively engage with the material, evaluate connections, and reflect on how new information fits within their existing knowledge structures (Rahayu, Ferdiana and Kusumawardani, 2022). By fostering this metacognitive engagement, tools like Mytelemap support long-term retention and conceptual understanding.

Although no previous studies have directly compared Generative AI tools and Mytelemap, recent experimental research provides insight into how these tools perform relative to one another in specific educational contexts. In an object-oriented programming course, students used both tools to support their learning. Generative AI was found to be more effective in terms of ease of use and providing quick, adaptive responses. Many students appreciated the AI tool’s ability to generate immediate answers and examples, which they found particularly helpful during early-stage learning when familiarity with programming concepts was still developing. These findings are consistent with the broader literature, which highlights Generative AI’s ability to facilitate quick access to information and provide tailored support (Saqr, Al-Somali and Sarhan, 2024; Khreisat et al., 2024).

However, as students progressed through more complex topics such as polymorphism and inheritance, they encountered limitations in Generative AI’s content accuracy and reliability. While Generative AI tools like ChatGPT can generate helpful explanations, they are not immune to producing incorrect or oversimplified information (Bender et al., 2021). Some students in the study expressed concerns about the need to cross-check AI-generated content with authoritative sources, which could hinder independent learning if not managed carefully.

On the other hand, Mytelemap was found to be more effective in promoting deep conceptual understanding, particularly as students engaged with advanced programming topics. Students using Mytelemap demonstrated improved abilities to visualize relationships between concepts, such as how inheritance relates to encapsulation and polymorphism. The knowledge mapping process required them to actively organize information and make decisions about concept relationships, leading to a more comprehensive understanding of object-oriented programming. These findings align with existing research on the effectiveness of knowledge mapping tools in fostering critical thinking and deep learning (Rahayu, Ferdiana and Kusumawardani, 2022; Nitchot, Wettayaprasit and Gilbert, 2019).

One of the primary differences observed between Generative AI and Mytelemap was in the level of cognitive engagement required from learners. Generative AI tools offered convenience and efficiency, which made them attractive for quick reference and immediate feedback. However, this convenience sometimes led to passive consumption of information rather than active learning. Some students became overly reliant on AI-generated answers without critically evaluating them, a concern echoed in the literature regarding potential over-reliance on AI (Strielkowski et al., 2024; Singh et al., 2025). In contrast, Mytelemap demanded more active involvement from students, as they had to build their knowledge maps manually. This process was initially perceived as more time-consuming and complex, but over time, students reported gaining a deeper understanding of the material. The need to explicitly identify and connect concepts encouraged reflective learning and a more nuanced understanding of the course content. While the tool presented an initial learning curve, particularly for students unfamiliar with knowledge mapping strategies, many participants expressed satisfaction with Mytelemap's ability to enhance their conceptual clarity once they became comfortable with its use.

Usability and accessibility were also key areas of comparison. Generative AI tools generally require little to no training, making them highly accessible to learners at all levels of technical proficiency (Eden, Chisom and Adeniyi, 2024). Their natural language interfaces allow users to interact with the system easily, reducing the cognitive load associated with learning how to use the tool itself. In contrast, Mytelemap's interface, while designed to be intuitive, still requires users to invest time in learning how to create effective knowledge maps. This additional effort can act as a barrier for some learners, though it also provides opportunities for skill development in information organization and critical thinking. Ethical considerations further distinguish these two tools. Generative AI tools typically rely on large datasets and user interactions to refine their outputs, raising concerns about data privacy and informed consent (Khreisat et al., 2024). Additionally, the ease with which students can generate essays, code, or other assignments using AI increases the risk of academic dishonesty (Hutson et al., 2023). In contrast, Non-AI tools like Mytelemap generally operate within controlled educational environments where data privacy concerns are easier to manage. Because Mytelemap emphasizes active participation, it also reduces opportunities for students to engage in plagiarism or passive learning.

Despite the differences between Generative AI and Mytelemap, there is potential for these tools to complement each other when integrated thoughtfully into educational settings. For instance, Generative AI could assist in generating preliminary content or suggesting resources that students could then organize and refine within a knowledge mapping tool like Mytelemap. Such hybrid approaches have been proposed in the literature as a way to balance the efficiency and personalization of AI with the deep learning and critical thinking encouraged by traditional educational tools (Hutson et al., 2023; Eden, Chisom and Adeniyi, 2024).

Although prior research has examined Generative AI and knowledge-mapping tools separately, there is still limited empirical evidence on how these approaches operate within the same learning environment. In particular, existing studies do not sufficiently explain how their different learning mechanisms influence student performance and conceptual understanding when applied to the same instructional tasks. Generative AI tools offer ease of use, immediate feedback, and personalized learning experiences, making them suitable for introductory learning and quick content generation. However, their potential for inaccuracy and over-reliance must be carefully managed. Mytelemap, on the other hand, promotes deep conceptual understanding and critical thinking through active knowledge organization, though it requires a greater investment of time and effort from learners. Based on recent experimental findings, educators may consider using both tools in tandem to leverage their complementary strengths and provide a balanced, effective learning experience.

Taken together, the literature suggests that Generative AI and knowledge-mapping tools support learning through fundamentally different mechanisms. Generative AI primarily facilitates rapid access to information, adaptive feedback, and task-oriented assistance, which can reduce cognitive load during early learning stages. In contrast, knowledge-mapping tools emphasize active knowledge construction, conceptual organization, and metacognitive engagement. However, existing studies have largely examined these approaches independently, focusing either on AI-supported learning or visualization-based tools. As a result, there remains limited empirical understanding of how these different forms of learning support function within the same instructional context, particularly in programming education where both procedural skills and conceptual understanding are critical.

This gap motivates the present study, which examines how Generative AI and knowledge-mapping approaches support programming learning when used within the same course context. By focusing on both performance and learner perceptions, the study aims to provide a more integrated understanding of how these complementary learning supports function in practice.

3. Methodology

3.1 Data Collection

The experiment was designed to examine differences in how Generative AI and Mytelemap support student learning in helping students learn through knowledge mapping. The study involved 30 first-year undergraduate students from the "Object Oriented Programming" course at Prince of Songkhla University International College, Thailand. An a priori power analysis was conducted using GPower 3.1 (Buchner, Faul and Erdfelder, 2024) to ensure an adequate sample size of N = 30, which was deemed sufficient for detecting large effect sizes with 95% power at the 5% level of significance. The sample size (N = 30) and the focus on a single course context should be considered when interpreting the findings. These factors may limit the generalizability of the results to other disciplines, institutions, or learner populations. The study was granted ethical approval by the University’s Ethics Institutional Review Board under reference PSU IRB 2024-LL-Uic-019 (Internal).

The overview of experimental design is shown in Figure 2. The study took place over the final four weeks of the course, with students participating in one hour-long session per week. Each week, the students sketched their own knowledge mapping and used Generative AI or Mytelemap to learn and complete the assigned tasks. The learners were divided into two cohorts: Cohort A used Generative AI, while Cohort B used Mytelemap. The students were assigned specific tasks to complete using the respective tool, with one of the tasks being to complete "C# Methods" assignments. Mytelemap is a research-based knowledge-mapping environment developed to support structured conceptual learning through visualization. While its deployment is currently limited to the study context, it represents a class of knowledge-mapping tools designed to facilitate active knowledge construction. The purpose of including Mytelemap in this study is not to evaluate its general adoption, but to examine how this type of learning support functions in comparison with AI-based approaches within the same instructional setting.

In addition to using the tools, the students were also asked to complete surveys at the end of each session. These surveys gathered their opinions on the use of knowledge mapping in both tools, focusing on factors such as effectiveness, engagement, ease of use, learning enhancement, motivation, overall satisfaction, relevance, clarity, organization, comprehensiveness, usability, and whether the tools were up to date. The surveys helped measure the overall effectiveness of Generative AI and Mytelemap in supporting the learning process.

Furthermore, participants were assigned to complete learning tasks each week after using both tools. These tasks were designed to evaluate their understanding and application of the knowledge mapping tools. The students' task performance was assessed and compared between the two tools to determine their impact on learning outcomes. Task scores were recorded for each cohort to assess how effectively each tool supported the students' learning.

At the end of the study, the learners were provided with a URL to access the study findings and see how their data was used in the research. The study aimed to gather both quantitative data from task scores and qualitative data from student surveys, offering a comprehensive evaluation of the tools' effectiveness in enhancing learning outcomes. Through this design, the experiment compared both the performance and satisfaction of students using Generative AI and Mytelemap.

Experimental Design Doc7

	E1 **Generative AI**	**E2** **Mytelemap**	**Duration (mins)**
Pre-activities			
Session 0. Introduction to the experiment.	N = 30 Purpose, duration, etc.		5
Introduction to the ideas.	N = 30 Mapping and getting study links activites		15
Explain tools.	N = 30 MyTeleMap & Generative AI		15
Treatment activities			
Session 1. Undertake task: "**C# Methods**".	N = 15 Cohort A	N = 15 Cohort B	60
Measure opinion	N = 30 Resulting task scores		10
Session 2. Undertake task: "**C# Arrays**".	N = 15 Cohort B	N = 15 Cohort A	60
Measure opinion	N = 30 Resulting task scores		10
Session 3. Undertake task: "**C# Lists**".	N = 15 Cohort B	N = 15 Cohort A	60
Measure opinion	N = 30 Resulting task scores		10
Session 4. Undertake task: "**C# Strings**".	N = 15 Cohort A	N = 15 Cohort B	60
Measure opinion	N = 30 Resulting task scores		10
Post-activities			
Session 5. Debrief	N = 30 Opinions on Tools Thanks, etc.		5
Options			
Score paper.			
Score products.			

Figure 2: Experimental Design: Overview of the Four-week Alternating Tool Use and Survey Timeline

After using the assigned tool each week, participants were asked to evaluate their satisfaction based on a series of statements related to their experience with the tools. The statements for Mytelemap and Generative AI were as follows, where the tool name was inserted at the position indicated:

- Eu: [Tool name] was easy to use for generating knowledge mappings.
- Ev: [Tool name] effectively helped in visualizing knowledge mappings.
- Ar: The knowledge mappings generated by [Tool name] were accurate and reliable.
- Al: The study materials links suggested by [Tool name] aligned well with my learning objectives.
- Ud: The study materials suggested by [Tool name] were current and up to date.
- Cc: [Tool name] allowed me to customize the criteria for suggesting study materials links.

The statements for Generative AI were:

- Ahs: Generative AI provided high quality of study contents.
- Ars: The study contents suggested by Generative AI were highly relevant to my study topics.
- Ats: I trusted the study contents suggested by Generative AI.

Participants rated each of the above statements on a Likert scale, from 1 (Strongly Disagree) to 5 (Strongly Agree). This evaluation assessed the learners' overall satisfaction with both tools in various aspects such as ease of use, visualization effectiveness, alignment with learning objectives, and content relevance. Although no single pre-existing validated instrument fully captured the constructs relevant to both Generative AI usage and knowledge-mapping tools, the questionnaire was adapted from scales previously used in technology acceptance and learning environment studies (e.g., usefulness, clarity, relevance, and satisfaction). At the end of the study some limited evidence was gathered to examine the reliability of the questionnaire. Participants encountered the questionnaire four times, twice in the context of using Generative AI, and twice in the context of using Mytelemap. These encounters were treated as data for calculating Cronbach's Alpha by analogy with the calculation of test-retest reliability. The resulting Cronbach's Alpha value (α = 0.23) indicates low internal consistency according to conventional methodological standards. This suggests that the questionnaire items do not measure a single coherent construct. This result should be interpreted in light of the study design, as the "retest" second encounter involved a different programming task, and the questionnaire was intentionally designed to capture multiple dimensions of learner perception (e.g., usability, engagement, and content relevance) rather than a single underlying construct. As such, Cronbach's Alpha may not be an appropriate measure of reliability for this instrument. Accordingly, the questionnaire results are interpreted as descriptive indicators of different aspects of learner experience rather than as a unified scale.

The questionnaires, class exercises and mapping scores criteria were reviewed by 2 independent experts to confirm face validity, clarity, and content relevance and were found to be clear and relevant measures. The experts included one from an external organization who had a research background similar to the investigator, and another was the head of curriculum, who was responsible for curriculum development and management. The experts used a 5-point Likert scale (1 = Not at all, 2 = Slightly, 3 = Moderately, 4 = Very, and 5 = Completely) in making 117 ratings, summarized in Table 1. All ratings were 4, 4.5, or 5; 89% of Expert 1 ratings were "5", 83% for Expert 2. All items rated less than 5 were revised before deployment.

Table 1: Expert 1 × Expert 2 Crosstabulation of 117 Ratings of Face Validity, Clarity, And Content Relevance

		Expert 2 ratings			**Total**
		4	4.5	5	
Expert 1 ratings	4	0	0	2	2
	4.5	0	0	11	11
	5	14	6	84	104
Total		14	6	97	117

Chi-squared (4) = 3.02, p = .55 for the crosstabulation. Some of the expected frequencies were less than 5, but because the Chi-square was not significant, no correction for continuity was made. This finding suggests that Expert 1's pattern of ratings was not significantly different from that of Expert 2.

This expert review procedure aligns with common validation practices in exploratory educational technology research, providing justification for using a customized questionnaire tailored to the unique features of the two tools.The learning tasks were based on weekly topics related to key programming concepts covered in the course, including programming classes, objects, encapsulation, and inheritance. In completing these tasks, students applied their knowledge of programming and object-oriented design.

The learning tasks were assessed using a set of criteria to evaluate the quality and effectiveness of the work produced by the participants:

- Rrw (Relevance to Real World): This criterion assessed how well the chosen scenario or problem related to the participants' daily life or interests. The criterion mark was based on how applicable and realistic the problem was in the context of real-world situations.
- Cor (Correctness): This evaluated whether inheritance was correctly implemented and functioned as intended. The participants' code was examined and marked according to the proper application of core programming concepts, especially inheritance.
- Cqu (Code Quality): This criterion focused on whether the code was clean, well-organized, and well-documented. The mark was based on clear and maintainable code that followed good programming practices and included adequate comments to explain their design choices.
- Ref (Reflection): The participants were assessed on how well they articulated their design choices and learning experiences. The mark was based on their explanation of the decisions they made during the task and reflection on how the concepts learned were applied in their solution.
- Tes (Testing): on the criterion assessed the thoroughness of the test cases provided. The mark was based on adequate and comprehensive testing of the correctness of the implementation.

This approach ensures that each participant's task was evaluated comprehensively, considering both the technical aspects of programming and the depth of their understanding and reflection on the learning process. A total mark was calculated as Tot (Total mark), weighted 20% Rrw, 30% Cor, 20% Cqu, 10% Ref, and 20% Tes.

Assessment and marking was carried out by an investigator blind to the identity of the participant and their experimental treatment, and used a detailed scoring rubric to keep scoring as consistent as possible.

Students were assigned to Cohort A (Generative AI first) and Cohort B (Mytelemap first) based on class attendance order during the first week; no pre-existing academic criteria were used for assignment. The counterbalanced ABBA and BAAB design mitigated order effects by ensuring that every student used both tools and allowed a within-subjects analysis of their data. Pre-tests and post-tests were not administered in this short four-week intervention; instead, weekly learning tasks served as performance indicators. Pre-tests and post-tests were not administered in this study; instead, learning outcomes were inferred from weekly task performance. This limits the ability to draw strong causal conclusions regarding learning gains attributable to each tool.

As the study was conducted within a natural classroom setting and did not include full experimental controls, the findings should be interpreted as indicative of relationships rather than definitive causal effects.

3.2 Data Analysis

As illustrated in Figure 2, each student used Mytelemap and Generative AI twice, termed their First Encounter in Week 1 or 2, and Second Encounter in week 3 or 4. Four sets of analyses of variance were conducted using IBM SPSS version 29. The first set examined the Total mark in a univariate repeated measures design; the second set investigated the five components of the Total mark (Rrw, Cor, Cqu, Ref, Tes) in a multivariate repeated measures design; the third set investigated the six opinion variables (Eu, Ev, Ar, Al, Ud, Cc) in a multivariate repeated measures design; the fourth set investigated the three Generative AI opinion variables (Ahs, Ars, Ats). Effect sizes for significant effects are shown as Cohen's d.

3.2.1 Total mark

Table 2 shows the interaction effect of Tool (Generative AI vs. Mytelemap) by Encounter (First or Second) was not significant, while the main effects of Tool and of Encounter were significant.

Table 2: Anova summary table for Total mark

Source	SSs	df	MS	F	p	d
Encounter	480.00	1	480.00	9.97	0.004	0.58
Error(Encounter)	1396.00	29	48.14			
Tool	433.20	1	433.20	17.77	<0.001	0.77
Error(Tool)	706.80	29	24.37			
Encounter * Tool	38.53	1	38.53	0.85	0.37	
Error(Encounter*Tool)	1321.47	29	45.57			

Where a factor comprises two levels, a significant main effect may be directly interpreted by inspection of the mean values of the variable concerned. The main effect of Tool showed that the Generative AI mean Total Mark (80.6) was significantly larger than that for Mytelemap (76.8), and the main effect of Encounter showed that the Second Encounter mean Total Mark (80.7) was significantly larger than that at First Encounter (76.7). These findings suggest that both tools contributed to improved learning with their second use, and that Generative AI contributed more to the participants' marks on the learning tasks than Mytelemap.

3.2.2 Components of total mark

The five components of the Total mark (Rrw, Cor, Cqu, Ref, and Tes) were investigated to explore if the significant differences between Tools, and between Encounters, on Total Mark were associated with any particular component of that mark. Table 3 provides the multivariate analysis of the five components, where it is seen that the overall interaction effect of Tool * Encounter was not significant, while the overall main effects of Tool and Encounter were significant.

Table 3: Multivariate anova summary table for Rrw, Cor, Cqu, Ref, and Tes

Source	F	Hypothesis df	Error df	p
Encounter	6.24c	5	25	<0.001
Tool	3.84c	5	25	0.01
Encounter * Tool	1.60	5	25	0.20

Following the multivariate tests, univariate analyses were conducted on the main effects (only) of Tool and Encounter for the five components, as summarized in Table 4. It may be seen that the Tool main effect was significant for Cqu and Ref, and not significant for Rrw, Cor, and Tes. The Encounter main effect was significant for Ref and Tes, and not significant for Rrw, Cor, and Cqu.

Table 4: Univariate anova summary table for Rrw, Cor, Cqu, Ref, and Tes

Source	Measure	SS	df	MS	F	p	d
Tool	Rrw	0.68	1	0.68	3.51	0.07	
	Cor	0.41	1	0.41	2.22	0.15	
	Cqu	2.13	1	2.13	6.27	0.02	0.46
	Ref	3.68	1	3.68	5.59	0.03	0.43
	Tes	1.01	1	1.01	3.00	0.09	
Error(Tool)	Rrw	5.57	29	0.19			
	Cor	5.34	29	0.18			
	Cqu	9.87	29	0.34			
	Ref	19.07	29	0.66			
	Tes	9.74	29	0.34			
Encounter	Rrw	1.01	1	1.01	2.39	0.13	
	Cor	0.21	1	0.21	0.45	0.51	
	Cqu	0.13	1	0.13	0.28	0.60	
	Ref	2.41	1	2.41	6.75	0.01	0.47
	Tes	7.01	1	7.01	20.86	<.001	0.83
Error(Encounter)	Rrw	12.24	29	0.42			
	Cor	13.54	29	0.47			
	Cqu	13.87	29	0.48			
	Ref	10.34	29	0.36			
	Tes	9.74	29	0.34			

The main effect of Tool on Cqu showed that the Generative AI mean (3.98) was significantly larger than for Mytelemap (3.72), and on Ref showed that the Generative AI mean (4.02) was significantly larger than for Mytelemap (3.67). This suggests that the larger mean Total Mark for Generative AI than for Mytelemap was attributable to better code quality (Cqu) and to better reflection on the design choices (Ref), and that there was no significant difference between the tools on real world relevance (Rrw), correctness (Cor), or testing (Tes).

The main effect of Encounter on Ref showed that the Second Encounter mean (3.98) was significantly larger than that at First Encounter (3.70), and on Tes showed that the Second Encounter mean (3.95) was significantly larger than that at First (3.47). This suggests that the larger mean Total Mark at Second Encounter was attributable to better reflection on the design choices (Ref) and to better testing (Tes), and that there was no significant gain at Second Encounter attributable to code quality (Cqu), real world relevance (Rrw), or correctness (Cor).

3.2.3 Opinions on Tools

The six opinion variables (Eu, Ev, Ar, Al, Ud, Cc) were investigated to explore if they showed significant differences between Tools or Encounters. Table 5 provides the multivariate analysis of the six opinions, where it is seen that the overall interaction effect of Tool * Encounter was significant.

Table 5: Multivariate anova summary table for Eu, Ev, Ar, Al, Ud, Cc

Source	F	Hypothesis df	Error df	p
Encounter	1.50c	6	24	0.22
Tool	42.83c	6	24	<0.001
Encounter * Tool	5.40c	6	24	0.001

Univariate analyses were conducted on the six opinion variables, as summarized in Table 6. It may be seen that the interaction effect of Tool * Encounter was significant for Ev and Ud, hence their main effects are not interpreted for these variables. The Tool effect was significant for Eu, Ar, and Al, and not for Cc. The Encounter effect was significant for Eu, and not for Ar, Al, or Cc.

Table 6: Univariate anova summary table for Eu, Ev, Ar, Al, Ud, Cc

Source	Opinion	SS	df	MS	F	p	d
Encounter	Eu	1.20	1	1.20	6.00	0.02	0.45
	Ev	0.08	1	0.08	0.24	0.63	
	Ar	0.07	1	0.07	0.38	0.54	
	Al	0.03	1	0.03	0.16	0.69	
	Ud	0.30	1	0.30	0.54	0.47	
	Cc	0.30	1	0.30	0.57	0.46	
Error(Encounter)	Eu	5.80	29	0.20			
	Ev	9.17	29	0.32			
	Ar	5.67	29	0.20			
	Al	5.97	29	0.21			
	Ud	16.20	29	0.56			
	Cc	15.20	29	0.52			
Tool	Eu	22.53	1	22.53	56.99	<0.001	1.38
	Ev	46.87	1	46.87	109.85	<0.001	1.91
	Ar	35.21	1	35.21	156.08	<0.001	2.28
	Al	2.70	1	2.70	4.53	0.04	0.39
	Ud	0.83	1	0.83	1.77	0.19	
	Cc	0.03	1	0.03	0.08	0.77	
Error(Tool)	Eu	11.47	29	0.40			
	Ev	12.38	29	0.43			
	Ar	6.54	29	0.23			
	Al	17.30	29	0.60			
	Ud	13.67	29	0.47			
	Cc	11.47	29	0.40			
Encounter * Tool	Eu	0.53	1	0.53	2.07	0.16	
	Ev	3.01	1	3.01	16.64	<0.001	0.74
	Ar	0.07	1	0.07	0.59	0.45	
	Al	1.20	1	1.20	3.22	0.08	
	Ud	4.03	1	4.03	12.36	0.001	0.64

Source	Opinion	SS	df	MS	F	p	d
	Cc	0.30	1	0.30	0.61	0.44	
Error(Encounter*Tool)	Eu	7.47	29	0.26			
	Ev	5.24	29	0.18			
	Ar	3.67	29	0.13			
	Al	10.80	29	0.37			
	Ud	9.47	29	0.33			
	Cc	14.20	29	0.49			

A significant interaction effect requires the investigation of the simple main effects of a factor at each level of the other factor. Where each factor comprises two levels, simple main effects may be directly tested by pairwise comparisons. Table 7 provides the pairwise comparisons between First and Second Encounters for mean Ev and Ud opinions of participants when they used Generative AI and when they used Mytelemap, and Table 8 provides the pairwise comparisons between Generative AI and Mytelemap for mean Ev and Ud opinions of participants at First and Second Encounters.

While it can be seen that the Second Encounter using Generative AI was rated significantly higher on help with visualizing knowledge mappings than First Encounter, and Second Encounter was rated significantly lower than First Encounter using Mytelemap, it is clear that visualizing knowledge mappings using Mytelemap was rated significantly higher than Generative AI at both First and Second Encounter.

It can be seen that the Second Encounter using Generative AI was rated not significantly different on up-to-date study materials compared with First Encounter, while Second Encounter was rated significantly higher than First Encounter on up-to-date materials using Mytelemap. Study materials were rated as more up to date on First Encounter when using Generative AI than Mytelemap, and the difference between the tools was rated as not significant at Second Encounter.

Table 7: Pairwise comparisons between First and Second Encounters for mean Ev and Ud

Opinion	Tool	First Encounter	Second Encounter	Mean Diff	p	d
Ev	Generative AI	3.23	3.60	-0.37	0.01	0.65
	Mytelemap	4.80	4.53	0.27	0.04	0.48
Ud	Generative AI	4.60	4.33	0.27	0.07	0.36
	Mytelemap	4.07	4.53	-0.47	0.02	0.63

Table 8: Pairwise comparisons between Generative AI and Mytelemap for mean Ev and Ud

Opinion	Encounter	Generative AI	Mytelemap	Mean Difference	p	d
Ev	First	3.23	4.80	-1.57	<0.001	2.78
	Second	3.60	4.53	-0.93	<0.001	1.64
Ud	First	4.60	4.07	0.53	0.01	0.71
	Second	4.33	4.53	-0.20	0.18	

The main effect of Encounter showed a significantly higher mean rating on Second Encounter of ease of use (4.13) than on First Encounter (3.93). There was no significant difference between First and Second Encounter mean opinion ratings for accuracy and reliability (Ar), alignment with learning objectives (Al), or customizable criteria (Cc) (overall means 4.11, 4.40, 4.42 respectively).

The main effect of Tool showed a significantly higher mean rating of ease of use (Eu) for Mytelemap (4.47) than for Generative AI (3.60) and a significantly higher rating for accuracy and reliability (Ar) (4.65 vs 3.57), but a significantly lower rating for alignment with learning objectives (Al) (4.25 vs 4.55). There was no significant difference between Generative AI and Mytelemap mean opinion ratings for customizable criteria (Cc) (overall mean 4.42).

The mean opinion ratings all showed positive agreement, and were significantly higher than a "Neither agree nor disagree" rating. The results suggest that, in general, Mytelemap provided significantly higher ratings than

Generative AI, if not at First Encounter then at the Second Encounter, on visualizing knowledge mappings, ease of use, accuracy and reliability, and up-to-date materials. The exceptions were that Generative AI rated more highly for alignment with learning objectives, and that both tools were rated as equally customizable.

3.2.4 *Opinions on Generative AI*

The three Generative AI opinion variables (Ahs, Ars, Ats) were investigated to explore if they showed significant differences between Encounters. Table 9 provides the multivariate analysis of the opinions, where it is seen that the Encounter effect was significant.

Table 9: Multivariate anova summary table for Ahs, Ars, Ats

Source	F	Hypothesis df	Error df	p
Encounter	3.06	3	27	0.05

Univariate analyses were conducted on the three opinion variables, as summarized in Table 10. It may be seen that the Encounter effect was significant for Ats, but not for Ahs or Ars.

Table 10: Univariate anova summary table for Ahs, Ars, Ats

Source	Opinion	SS	df	MS	F	p	d
Encounter	Ahs	0.02	1	0.02	0.07	0.79	
	Ars	0.27	1	0.27	1.00	0.33	
	Ats	1.35	1	1.35	7.60	0.01	0.50
Error(Encounter)	Ahs	6.48	29	0.22			
	Ars	7.73	29	0.27			
	Ats	5.15	29	0.18			

The mean opinion ratings all showed positive agreement, and were significantly higher than a “Neither agree nor disagree” rating. Mean trust in the study contents (Ats) of the Generative AI tool significantly increased from First Encounter (4.3) to Second (4.6), while there was no significant change in mean opinion on quality (Ahs) or relevance (Ars) of the study contents of the Generative AI tool (overall means 4.7 and 4.7 respectively).

3.2.5 *Grade Point Average (GPA)*

The relationship between GPA and Total Mark was explored by correlating the participants’ GPA with their mean Total Mark for Generative AI and Mytelemap, and with the difference in these two means. As would be expected, GPA correlated highly with both Generative AI and Mytelemap Total Marks ($r(28) = .66$ and .70, both $p < .001$), but more interestingly did not correlate with the difference in mark, $r(28) = 0.04$, $p = .83$, This suggests that whether a participant found one or other tool more useful was not particularly related to their GPA.

4. Results and Discussion

These results align strongly with theoretical expectations from Cognitive Load Theory and Constructivist pedagogy. Generative AI appears to reduce extraneous cognitive load by providing immediate clarification and simplified explanations, which helps novices overcome early programming barriers. This may help explain patterns observed in task performance and ease-of-use ratings. Conversely, Mytelemap requires learners to actively construct conceptual relationships, consistent with constructivist principles of meaning-making and schema integration. The cognitive effort required to build, revise, and navigate mappings appears to foster deeper reflection and conceptual clarity, particularly evident in improvements in the Reflection and Code Quality components during later encounters. This reinforces the pedagogical value of knowledge visualization when learning goals involve abstraction, synthesis, and higher-order understanding.

These findings are consistent with the theoretical perspectives discussed earlier, particularly in relation to Cognitive Load Theory and constructivist learning principles. Generative AI appears to support learning by providing immediate clarification and reducing cognitive effort during early stages, while Mytelemap encourages active knowledge construction and conceptual organization through visual mapping.

The results indicate differences in how students engaged with the two learning environments. Student performance was higher in later encounters with both tools, suggesting increased familiarity over time. However, differences emerged in usability, perceived reliability, and support for conceptual understanding.

Generative AI was associated with higher ratings for ease of use, responsiveness, and alignment with immediate learning needs. Students valued the ability to obtain quick explanations and examples, particularly when encountering new programming concepts. This contributed to higher engagement in early sessions. However, some limitations were observed in terms of content accuracy, particularly in more complex topics, where learners reported inconsistencies and the need to verify information using additional sources.

In contrast, Mytelemap appeared to support deeper conceptual engagement, particularly during later stages of the study. The tool encouraged learners to structure relationships between concepts, which was reflected in stronger performance in tasks involving reflection and code quality. Students also reported increased confidence in the relevance and organization of learning materials over time. However, initial usability challenges were noted, as some learners required time to become familiar with the interface and workflow.

The findings suggest that the two tools support different aspects of learning. Generative AI appears to facilitate rapid task completion and immediate clarification, while Mytelemap encourages more structured knowledge organization and reflection. This indicates that the tools may play complementary roles in programming learning. The two approaches differ in their underlying design and knowledge representation; therefore, the findings should be interpreted in terms of their complementary roles rather than direct equivalence.

While the general distinction between rapid AI-supported assistance and deeper conceptual learning through visualization may appear intuitive, the contribution of this study lies in providing empirical evidence of how these differences manifest within the same instructional context. Rather than simply confirming an assumed difference, the findings show how these learning mechanisms operate under comparable conditions, using both performance data and learner perceptions. In particular, the results indicate that the benefits of each approach vary across stages of learning and types of tasks, offering a more nuanced understanding of how different forms of learning support function in practice. This is particularly relevant given the increasing use of both AI-driven tools and visualization-based approaches in programming education, where understanding how different forms of support influence learning processes remains an open research question.

Overall, these results should be interpreted within the context of the study design. The findings contribute to the e-learning field by providing empirical insight into how different forms of learning support function within the same instructional environment. By highlighting the complementary and context-dependent roles of Generative AI and knowledge mapping, the study offers a more nuanced perspective on integrating adaptive and structured learning approaches in programming education.

5. Conclusion

This study examined how Generative AI and knowledge mapping approaches are associated with differences in student learning within an object-oriented programming course. The findings reveal that while Generative AI excels in providing quick, personalized learning support, it is limited by concerns over content accuracy. Mytelemap, as a knowledge-mapping approach, appears to support deeper conceptual understanding through structured visualization and active knowledge organization, although it presents usability challenges for new users. Framing these findings through Cognitive Load Theory and Constructivist principles suggests that Generative AI is effective for reducing extraneous load and facilitating quick comprehension, whereas Mytelemap supports deeper schema development and reflective learning. This theoretical integration highlights the potential of hybrid instructional approaches that intentionally sequence AI-mediated scaffolding with visualization-based consolidation activities. As the two approaches differ in their underlying pedagogical design and knowledge representation, they are not treated as directly equivalent in this study. Instead, the comparison focuses on how different forms of learning support—Generative AI and knowledge mapping—are associated with variations in student learning processes and experiences within the same instructional context.

Rather than viewing one approach as superior, the findings suggest that each supports different aspects of learning and may be more effective under different conditions. Generative AI appears to support rapid clarification and early-stage learning tasks, while knowledge-mapping approaches appear to support conceptual organization and reflective understanding. This distinction provides a basis for designing instructional strategies that align specific tools with particular learning objectives and stages. These findings provide a foundation for future research by identifying how different forms of learning support function within a shared instructional environment. This enables further investigation into how hybrid learning designs can be structured, sequenced, and evaluated across different contexts and disciplines. However, this study has several limitations. First, student perceptions were measured using self-report surveys, which may be subject to bias. Second, participants were more familiar with conversational interfaces than with knowledge mapping tools, potentially affecting initial usability ratings. Third, the intervention spanned only four weeks, limiting the ability to observe long-term learning gains. Finally, although students experienced both tools, the study design did not include full pre/post testing, which constrains causal interpretations regarding learning improvement. Future research should incorporate longer interventions and triangulated performance measures. Future research should explore other domains and more diverse learner populations. In addition, it should investigate the integration of Generative AI into knowledge mapping platforms like Mytelemap, potentially allowing AI-generated suggestions to enhance map creation. Additionally, expanding the study across diverse disciplines and student populations would help validate these findings and explore broader applications. A hybrid learning model that leverages both tools' strengths may offer a promising path forward in technology-enhanced education.

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Ethical Approval: This study was reviewed and approved by the Prince of Songkla University Ethics Institutional Review Board under reference number PSU IRB 2024-LL-Uic-019 (Internal).

Availability of Data and Materials: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations: Generative AI was used in this study as a subject of investigation and not as a tool for data generation or analysis. AI-assisted tools were used only for minor language editing. All research design, analysis, and conclusions were developed by the authors, who take full responsibility for the content.

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