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Bridging the Conceptual Understanding Gap in Calculus for Civil Engineering: The Role of AI in Mediating Theorems and Definitions

Haris Jamaludin*[1]
Email: harisjamaludin@stekom.ac.id
Orcid: https://orcid.org/0009-0006-9937-6332
[1]*Faculty of Academic Study. Universitas Sains dan Teknologi Komputer, Semarang, Indonesia*
*Corresponding Author

Abstract
This study aims to analyze the role of Artificial Intelligence (AI) in bridging the conceptual understanding gap in calculus among civil engineering students, focusing on how AI mediates the relationship between theorems and formal definitions. A Systematic Literature Review (SLR) following the PRISMA 2020 protocol was conducted. Literature searches were performed on Scopus, ScienceDirect, Google Scholar, DOAJ, and SINTA for the period 2020–2025. From 187 initially identified articles, 29 articles met the inclusion criteria after full-text screening. The findings reveal that AI has significant potential to bridge the conceptual gap through three primary mechanisms: (1) providing instant feedback and step-by-step explanations, (2) personalizing learning according to student comprehension levels, and (3) offering interactive visualizations of abstract concepts. However, AI still has limitations in complex reasoning and theorem proving, as well as risks of epistemic offloading that can reduce students' independent problem-solving abilities. The implications emphasize the importance of a blended approach with clear instructional guidance and adaptive assessment redesign to support effective AI integration in calculus learning within civil engineering programs, particularly in the Indonesian context.

Keywords: *Artificial Intelligence, Calculus, Civil Engineering, Conceptual Understanding, SLR, PRISMA.*

I. INTRODUCTION

Calculus constitutes the fundamental mathematical foundation in civil engineering education. Concepts such as derivatives, integrals, and differential equations are extensively utilized in structural analysis, fluid mechanics, transportation engineering, and geotechnics. A robust conceptual understanding of calculus theorems and formal definitions becomes a prerequisite for students to apply mathematics in complex engineering contexts (Plevris et al., 2023; Ross et al., 2025). However, calculus learning in higher education frequently encounters the challenge of a conceptual understanding gap. Students tend to memorize procedures without comprehending the meaning behind theorems and definitions. For instance, a civil engineering student might successfully compute a definite integral but fail to explain how the Riemann sum definition relates to calculating the total load on a beam. This gap widens further when students face calculus applications in civil engineering problems that require knowledge transfer across contexts (Farrokhnia et al., 2024; Qawqzeh, 2024).

In recent years, Artificial Intelligence (AI), particularly Generative AI such as ChatGPT, has emerged as a potential tool in mathematics education. The ability of AI to provide interactive explanations, instant feedback, and personalized learning opens new opportunities to bridge the conceptual understanding gap (Almarashdi et al., 2024; Baidoo-Anu & Owusu Ansah, 2023). However, the effectiveness of AI heavily depends on how it is integrated into the learning process.

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Research indicates that students tend to offload cognitive burdens to AI (epistemic offloading), which impacts the decline of independent problem-solving abilities (Wang, Xia, & Ye, 2024). This phenomenon is especially concerning in engineering education where analytical skills are crucial.

Although numerous studies have examined the use of AI in mathematics education, several research gaps motivate this investigation. First, research on AI in calculus learning specifically for civil engineering remains very limited. Most studies focus on secondary school mathematics or general mathematics education, not specifically on the civil engineering domain (Nguyen et al., 2025). Second, no study has specifically examined the role of AI as a mediator between theorems and definitions in calculus. Yet, the gap between theorem comprehension (application) and formal definitions (foundation) represents a central problem in calculus learning (Yoo, 2024). Third, research on implementation challenges in the Indonesian context, with its infrastructure limitations and human resource readiness, remains minimal (Febriana & Khaerani, 2025; Mudjib et al., 2025; Susilawati et al., 2024).

This research aims to provide a comprehensive synthesis of the role of AI in calculus learning for civil engineering, with the main contributions: (1) mapping the state-of-the-art of AI utilization in calculus learning, (2) identifying gaps between theorems and definitions that AI can address, (3) providing recommendations for AI integration strategies that are contextual for Indonesia. The research questions formulated are:

RQ1. How does AI play a role in bridging the gap between theorem understanding and definitions in calculus learning?

RQ2. What types of AI are effective for use in calculus learning in civil engineering?

RQ3. What are the challenges and risks of using AI in calculus learning for civil engineering?

RQ4. What is the optimal strategy for integrating AI into the calculus curriculum in Indonesian civil engineering programs?

II. LITERATURE REVIEW

A. Conceptual Understanding Gap in Calculus

Conceptual understanding in calculus refers to students' ability to understand the meaning, relationships, and applications of mathematical concepts, not merely procedural abilities (Hassani & Silva, 2023). The conceptual gap often appears between the level of theorem comprehension (how to use it) and formal definitions (why it is so). Dhakal (2025) emphasized that students may be able to apply the Fundamental Theorem of Calculus but cannot explain why the theorem is true based on the formal definition of the Riemann integral. In the civil engineering context, this gap directly impacts students' abilities in: (1) modeling physical phenomena (e.g., beam deflection, fluid flow) into differential equations, (2) interpreting numerical calculation results (e.g., understanding what an integral value physically represents as total stress), and (3) performing estimation and solution verification (Plevris et al., 2023). Ross et al. (2025) found that civil engineering students experienced significant difficulty in connecting the limit definition (formal epsilon-delta) with applications in structural analysis, such as determining the maximum load before failure occurs, where the limit conceptually represents the approach to a critical stress point.

B. AI in Mathematics Education: TPACK and SAMR Frameworks

Two main theoretical frameworks are used to analyze AI integration in calculus learning: Technological Pedagogical Content Knowledge (TPACK) and the SAMR model (Substitution, Augmentation, Modification, Redefinition) (Javaid et al., 2023; Sánchez-Ruiz et al., 2023). TPACK emphasizes the importance of simultaneous integration of technological, pedagogical, and content knowledge. In this context, AI is not merely an additional tool but a component that must be pedagogically integrated with calculus material. The SAMR model provides a framework for measuring the level of technology integration: from mere substitution (AI replaces a calculator) to redefinition (AI enables previously impossible learning activities) (Gouia-Zarrad & Gunn, 2024). Research shows that most AI integration in calculus learning is still at the substitution and augmentation levels, while modification and redefinition levels are rarely achieved due to infrastructure and instructor readiness constraints (Almarashdi et al., 2024).

C. The Role of AI as a Mediator between Theorems and Definitions

The phenomenon of epistemic offloading in mathematics learning in the AI era refers to students' tendency to transfer cognitive burdens to AI (Wang, Xia, & Ye, 2024). This becomes both a challenge and an opportunity to design the appropriate role of AI as a mediator. The concept of proof vectors from the Axiom-Based Atlas offers an innovative approach to mapping logical relationships among theorems (Yoo, 2024). By mapping a theorem's dependency on specific axioms, AI can help students trace the "logical footprint" from definitions to theorems. Yu et al. (2024) identified that effective AI mediation should be designed to facilitate productive friction, slight cognitive friction that forces students to think, rather than eliminating the entire cognitive burden.

III. RESEARCH METHOD

A. Research Design

This study employed a Systematic Literature Review (SLR) to systematically identify, evaluate, and synthesize existing evidence regarding the role of Artificial Intelligence (AI) in supporting conceptual understanding of calculus, particularly in relation to civil engineering education. The review was conducted following the principles of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework. The use of an SLR was considered appropriate because the topic intersects several research areas, including mathematics education, engineering education, artificial intelligence, generative AI, and technology-enhanced learning.

Rather than examining AI merely as a computational tool, the review focused specifically on its potential role in mediating the relationship between formal mathematical definitions, theorem understanding, and engineering applications. Accordingly, the review process was organized around four research questions concerning the mediating role of AI, the types of AI used in calculus learning, associated challenges and risks, and appropriate strategies for integrating AI into civil engineering education. The review procedure consisted of five main stages: (1) formulation of the research questions, (2) identification of relevant literature, (3) screening and eligibility assessment, (4) methodological quality assessment, and (5) data extraction and thematic synthesis. The overall procedure is summarized in Figure 1, while the main methodological stages are presented in Table 1.

Table 1. Main Stages of the Systematic Literature Review

Stage	Main Activity	Expected Output
Research question formulation	Defining the scope of AI, calculus learning, conceptual understanding, and civil engineering education	Four research questions
Identification	Searching selected academic databases using predefined keywords and Boolean combinations	Initial literature records
Screening and eligibility	Removing duplicates and examining titles, abstracts, and full texts against predefined criteria	Eligible studies
Quality assessment	Evaluating the methodological quality and relevance of eligible studies	Moderate- and high-quality studies
Data extraction and synthesis	Coding study characteristics, findings, AI approaches, limitations, and pedagogical implications	Thematic synthesis addressing RQ1–RQ4

B. Information Sources and Search Strategy

The literature search was conducted between January and March 2025 using five academic information sources: Scopus, ScienceDirect, Google Scholar, Directory of Open Access Journals (DOAJ), and SINTA. These databases were selected to provide a combination of international multidisciplinary literature, engineering and educational studies, open-access publications, and literature relevant to the Indonesian higher education context. The publication period was restricted to 2020–2025 in order to capture recent developments in AI-supported learning,

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particularly the rapid expansion of generative AI applications following the emergence of large language models. The search terms were developed from four conceptual components: AI technology, calculus, engineering education, and conceptual understanding. The principal Boolean search expression was:

("artificial intelligence" OR "AI" OR "ChatGPT" OR "generative AI" OR "machine learning") AND ("calculus" OR "differential calculus" OR "integral calculus") AND ("civil engineering" OR "engineering education") AND ("conceptual understanding" OR "theorem" OR "definition")

For Indonesian databases and publications, equivalent Indonesian terms and relevant synonym combinations were also considered to increase the sensitivity of the search. The conceptual structure of the search strategy is summarized in Table 2. Search results from the different sources were subsequently consolidated for screening. The initial search identified 187 records before the eligibility and full-text assessment procedures were completed.

Table 2. Search Concepts and Keywords Used in the Review

Search Component	Main Keywords
Artificial Intelligence	“artificial intelligence”, “AI”, “ChatGPT”, “generative AI”, “machine learning”
Calculus	“calculus”, “differential calculus”, “integral calculus”
Educational Context	“civil engineering”, “engineering education”
Conceptual Dimension	“conceptual understanding”, “theorem”, “definition”

C. Eligibility Criteria

Explicit inclusion and exclusion criteria were established before the final synthesis to maintain consistency in study selection. Studies were considered eligible when they addressed the educational use, implications, or evaluation of AI in mathematics, calculus, or closely related engineering-learning contexts. The eligibility criteria are presented in Table 3. The inclusion of relevant conceptual and review studies was retained because several research questions addressed not only measurable learning outcomes but also conceptual mechanisms, pedagogical risks, and emerging approaches to AI-mediated mathematical reasoning. However, empirical studies were given greater emphasis when concluding effectiveness.

D. Study Selection and PRISMA Procedure

Study selection followed the sequential logic of the PRISMA 2020 framework. The procedure consisted of identification, screening, eligibility assessment, and final inclusion. During the identification stage, records retrieved from Scopus, ScienceDirect, Google Scholar, DOAJ, and SINTA were collected into a single literature pool. Duplicate records were removed before screening. The remaining records were screened using their titles and abstracts to determine their relevance to AI-supported mathematics or calculus education. Studies that clearly fell outside the educational scope of the review were excluded at this stage.

Table 3. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Publication period	Published between 2020 and 2025	Published before 2020
Publication type	Peer-reviewed journal articles and indexed conference proceedings; relevant scholarly review or conceptual studies when directly contributing to the research questions	Editorials, opinion pieces, book reviews, preprints, and non-peer-reviewed reports
Language	English or Indonesian	Languages other than English or Indonesian
Research topic	AI applications or implications in mathematics/calculus learning	AI studies unrelated to teaching or learning
Educational relevance	Studies addressing conceptual understanding, reasoning, theorem/definition relationships, engineering mathematics, or civil engineering education	Studies with no meaningful relationship to mathematics or engineering education
Accessibility	Full text available for assessment	Full text unavailable after reasonable retrieval attempts
Research relevance	Provides evidence, conceptual insight, pedagogical implications, or implementation challenges relevant to at least one research question	Does not contribute evidence or analysis relevant to the research questions

Articles retained after initial screening underwent full-text eligibility assessment. At this stage, each publication was examined against the inclusion and exclusion criteria in Table 3, with particular attention to its relevance to conceptual understanding, theorem–definition relationships, engineering mathematics, AI-supported reasoning, or civil engineering learning. Following the full-text assessment and methodological quality appraisal, 29 studies were retained for the final synthesis. The complete selection process, from the 187 initially identified records to the final 29 included studies, is presented in Figure 1 using the PRISMA flow diagram.

The database search initially identified 187 records from Scopus, ScienceDirect, Google Scholar, DOAJ, and SINTA. After removing 26 duplicate records, 161 records remained for title and abstract screening. At this stage, 91 records were excluded because they did not sufficiently address AI-supported mathematics or calculus learning within the scope of the review. Seventy reports were subsequently sought for full-text retrieval, of which five could not be accessed. The remaining 65 full-text articles were assessed against the predefined eligibility criteria. Thirty-six studies were excluded because of insufficient topical relevance, inappropriate educational context, unsuitable publication type, limited relevance to the research questions, publication-period or language restrictions, or overlapping publication. Consequently, 29 studies satisfied the eligibility and quality requirements and were included in the final thematic synthesis.

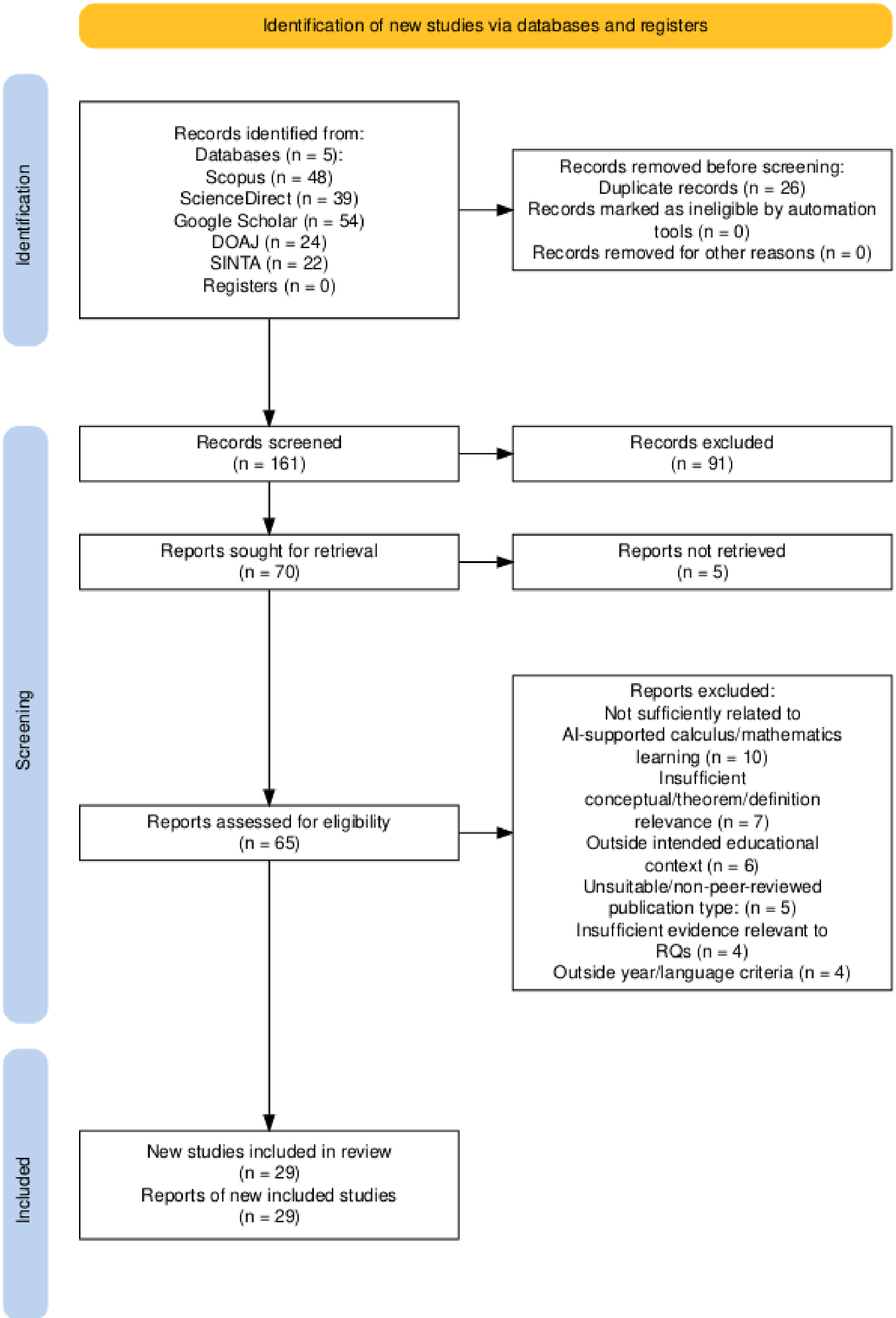

Figure 1. PRISMA Flow Diagram of the Literature Identification and Selection Process

E. Methodological Quality Assessment

A methodological quality assessment was conducted to reduce the influence of weak or insufficiently supported evidence on the review findings. Because the included literature involved different methodological designs, quality assessment was adjusted to the type of study being evaluated. The Critical Appraisal Skills Programme (CASP) checklist was used to examine qualitative studies, whereas the Joanna Briggs Institute (JBI) critical appraisal tools were used for quantitative studies. The appraisal focused on aspects such as clarity of research objectives, appropriateness of the methodological design, adequacy of the data collection and analysis procedures, transparency of the reported findings, and correspondence between evidence and conclusions.

Based on the appraisal, studies were classified into three general quality categories: high, moderate, or low quality. Only publications considered to provide moderate or high-quality evidence were retained for the main synthesis. Peer-reviewed journal articles were prioritized when evidence from different source types addressed the same issue. Indexed conference proceedings were considered when they reported original research or provided substantial evidence directly related to the research questions. Conceptual and review studies were used primarily to support theoretical interpretation, identify emerging themes, or contextualize empirical evidence rather than being treated as equivalent to direct empirical evaluations.

F. Data Extraction

A structured data extraction procedure was applied to the 29 included studies. Information was extracted consistently in order to support comparison across different technological, educational, and geographical contexts. The extraction framework covered six principal dimensions, as presented in Table 4. The extracted information was subsequently organized according to its relevance to the four research questions. This procedure allowed studies with different research designs to be compared without assuming that they provided identical forms of evidence.

Table 4. Data Extraction Framework

Dimension	Information Extracted
Study identification	Author(s), publication year, and publication type
Research context	Country/region, educational setting, mathematics or engineering context
AI technology	Type of AI, such as generative AI/LLM, intelligent tutoring system, machine-learning-based system, or AI-supported visualization tool
Conceptual contribution	Reported influence on conceptual understanding, theorem comprehension, definitions, reasoning, or mathematical problem solving
Challenges and risks	Accuracy limitations, AI dependency, epistemic offloading, infrastructure issues, or implementation barriers
Pedagogical implications	Recommendations for instructional design, assessment, lecturer readiness, and AI integration

G. Data Synthesis and Thematic Analysis

Because the included studies were heterogeneous in terms of research design, AI technology, educational level, context, and reported outcomes, the review used a thematic synthesis rather than statistical meta-analysis. The synthesis began by grouping findings according to recurring concepts reported across the selected literature. Particular attention was given to findings concerning: (1) AI-mediated conceptual explanation, (2) visualization and representation of mathematical relationships, (3) theorem-proving and reasoning support, (4) types of AI used in learning, (5) epistemic offloading and dependency, (6) limitations of AI reasoning, and (7) institutional and infrastructure readiness.

These categories were subsequently compared across the included studies and consolidated into broader themes corresponding to the four research questions. For RQ1, evidence was synthesized to determine how AI may mediate the transition from formal definitions to theorem understanding and practical application. For RQ2, the synthesis categorized the main forms of AI used in calculus and engineering mathematics education. For RQ3, findings concerning technical, cognitive, ethical, and institutional challenges were grouped and compared. For RQ4, pedagogical recommendations from the literature were synthesized to identify practical principles for AI integration, particularly within the Indonesian civil engineering education context. Rather than interpreting the frequency of a theme as direct evidence of effectiveness, the analysis considered both the consistency of findings across studies and the methodological quality of the supporting evidence. This distinction was necessary because the reviewed literature included empirical, qualitative, quantitative, mixed-methods, conceptual, and review-based contributions.

H. Methodological Scope of the Review

The review was designed to provide an integrative understanding of a relatively new and rapidly developing research field. Consequently, studies directly investigating AI-mediated calculus learning specifically among civil engineering students were limited. Evidence from broader mathematics education and engineering education was therefore included when it provided a clear conceptual or pedagogical connection to the research questions. This approach enabled the review to identify patterns and emerging mechanisms across related areas while maintaining civil engineering calculus as the principal interpretive context. At the same time, conclusions concerning direct effectiveness in civil engineering education were interpreted cautiously when the supporting evidence originated from broader mathematics or engineering-learning settings.

IV. RESULT/FINDINGS AND DUSCUSSION

A. Characteristics of the Included Studies

Following the identification, screening, eligibility assessment, and quality appraisal process, a total of 29 studies were retained for the final synthesis. The included studies varied in methodological approach, geographical context, educational setting, and type of Artificial Intelligence (AI) examined. In terms of research design, 18 studies (62%) employed qualitative or mixed-methods approaches, 8 studies (28%) used quantitative approaches, and 3 studies (10%) consisted of conceptual or review-based studies. This distribution indicates that research on AI-supported mathematics and engineering education is still strongly exploratory, with many studies focusing on perceptions, learning experiences, implementation practices, and conceptual implications rather than exclusively measuring learning outcomes.

The publication trend also showed a noticeable increase from 2023 onward. This pattern coincides with the widespread adoption of generative AI and large language models such as ChatGPT in higher education. Earlier studies tended to focus on intelligent tutoring systems and technology-assisted mathematics learning, while more recent studies increasingly examine interactive generative AI for explanation, problem solving, and personalized learning (Baidoo-Anu & Owusu Ansah, 2023; Javaid et al., 2023; Almarashdi et al., 2024). The primary focus areas of the included studies are presented in Table 5.

Table 5. Distribution of Included Studies by Focus Area

Focus Area	Number of Studies	Percentage
General AI in Mathematics Education	8	27.6%
Generative AI (ChatGPT) in Calculus	7	24.1%
AI in Civil Engineering Education	5	17.2%
Intelligent Tutoring Systems	4	13.8%
Epistemic Offloading and Critical Thinking	3	10.3%
Theorem Proving and Proof Vectors	2	7.0%
Total	**29**	**100%**

As shown in Table 5, the largest proportion of studies addressed AI in mathematics education in a broader sense, accounting for 27.6% of the total. Studies focusing on generative AI and ChatGPT in calculus represented 24.1%, while studies specifically situated in civil engineering education accounted for 17.2%. This distribution suggests that direct empirical research on AI in civil engineering calculus is still relatively limited. Therefore, evidence from broader mathematics education and engineering education was also important in explaining how AI may support conceptual understanding. Geographically, eight studies originated from the United States, six from European countries, ten from Asian countries including Indonesia, and five from other regions. Studies conducted in Indonesia were mainly concerned with institutional readiness, perceptions, digital literacy, infrastructure, and implementation challenges rather than large-scale experimental deployment of AI-supported calculus instruction (Febriana & Khaerani, 2025; Mudjib et al., 2025; Susilawati et al., 2024).

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B. The Role of AI in Bridging Conceptual Understanding Gaps (RQ1)

The first research question examined how AI can help bridge the gap between formal mathematical definitions and students' understanding of calculus theorems. The synthesis identified three recurring mechanisms: conceptual explanation mediation, visualization of logical relationships, and reasoning or proof scaffolding.

1. Conceptual Explanation Mediation

One of the most frequently reported benefits of AI is its ability to reformulate difficult mathematical explanations into language that is easier for students to understand. Approximately 70% of the reviewed studies reported that AI was useful for providing instant feedback, alternative explanations, or adaptive support during mathematics learning (Almarashdi et al., 2024). Formal definitions in calculus are often difficult because they require students to simultaneously understand symbolic notation, abstraction, and mathematical relationships. AI can help reduce this difficulty by providing multiple representations of the same concept. For example, when students experience difficulty understanding the epsilon-delta definition of a limit, generative AI can provide a simpler explanation, a graphical interpretation, or an analogy related to engineering. In civil engineering, the concept may be associated with a load or stress value approaching a critical condition. This capability supports the observation that students often experience difficulty not because they are unable to perform a mathematical procedure, but because they cannot connect formal mathematical language with its practical meaning. Hassani and Silva (2023) similarly emphasized that conversational AI can provide flexible and personalized explanations that may support mathematical learning when used with appropriate instructional guidance. Therefore, AI may serve as an intermediate explanatory layer between a formal definition and the student's conceptual interpretation.

2. Visualization of Logical Relationships

The second mechanism concerns the ability of AI-supported approaches to clarify the logical relationships between definitions, assumptions, and theorems. Students often learn mathematical formulas and theorems as separate procedural rules. As a result, they may be able to apply a theorem without understanding its mathematical foundation. This problem is particularly relevant in calculus, where the relationship between formal definitions and derived theorems is central to conceptual understanding. The concept of proof vectors proposed by Yoo (2024) illustrates how dependencies between axioms, definitions, and theorems can be represented structurally. Such an approach allows students to trace the logical development of a theorem rather than treating it as an isolated rule. In civil engineering applications, this type of representation may help students understand relationships such as the derivative as an instantaneous rate of change, or the relationship between shear force and bending moment. Rather than simply memorizing formulas, students can trace how mathematical principles develop into engineering relationships. This finding suggests that AI-supported visualization can help students move from procedural knowledge toward a deeper understanding of why mathematical relationships exist.

3. Reasoning and Proof Scaffolding

The third mechanism identified in the review is AI-supported reasoning scaffolding. AI can provide intermediate steps when students attempt to solve mathematical problems or understand a proof. Rather than functioning solely as an answer generator, AI can guide students by suggesting relevant definitions, identifying assumptions, proposing intermediate reasoning steps, or asking follow-up questions. This role is particularly relevant to theorem proving because students can compare AI-generated reasoning with formal mathematical principles. Yoo (2024) highlights the importance of tracing the logical footprint of mathematical statements, while Yu et al. (2024) argue that effective AI-supported learning should maintain productive friction, meaning that students should still be required to think, verify, and justify rather than simply accept automated answers. Therefore, the effectiveness of AI as a scaffold depends heavily on instructional design. When AI provides a complete solution that students accept without evaluation, its educational value decreases. In contrast, when students are required to inspect and verify AI-generated reasoning, the technology can support deeper conceptual engagement. Overall, the findings for RQ1 indicate that AI can bridge conceptual gaps by providing multiple explanations, structured relationships, and guided reasoning, but it should not replace the student's own mathematical thinking.

C. Types of AI Effectively Used in Calculus Learning (RQ2)

The second research question examined the types of AI most commonly used in calculus and engineering mathematics education. The synthesis identified three main categories: Large Language Models or Generative AI, Intelligent Tutoring Systems, and AI-supported visualization tools.

1. Large Language Models and Generative AI

Large Language Models, particularly ChatGPT and similar generative AI systems, were the most frequently investigated technologies, appearing in approximately 60% of the reviewed studies. Their main advantage is their ability to provide interactive dialogue, explanations, examples, and adaptive responses. Students can ask follow-up questions when an explanation is unclear, request alternative representations, or relate abstract mathematical concepts to specific engineering situations. Almarashdi et al. (2024) reported that generative AI has significant potential to provide individualized and interactive mathematical support. Similarly, Baidoo-Anu and Owusu Ansah (2023) highlighted the ability of ChatGPT to support personalized learning through immediate responses and flexible explanations. For calculus education, this flexibility is especially useful because the same concept can be interpreted algebraically, graphically, geometrically, or contextually.

However, several studies also reported limitations in mathematical reliability. Plevris et al. (2023) showed that ChatGPT can successfully address many engineering mathematics problems, but its accuracy becomes less consistent when tasks involve complex reasoning or specialized mathematical interpretation. Thus, generative AI appears most appropriate as a supporting tool for explanation and exploration rather than as an unquestioned source of mathematical answers.

2. *Intelligent Tutoring Systems*

Intelligent Tutoring Systems accounted for approximately 20% of the reviewed studies. Compared with general-purpose generative AI, ITS platforms typically provide more structured pedagogical support. These systems may monitor student performance, recommend tasks, adjust difficulty levels, or provide targeted feedback according to learner progress. Pögelt et al. (2024), for example, demonstrated how individualized mathematical task recommendations can be generated based on intended learning outcomes and reinforcement-learning approaches. The primary strength of ITS lies in its controlled instructional structure. Students are guided through predetermined learning objectives, reducing the risk of receiving explanations that are unrelated to the course sequence. However, ITS platforms are generally less flexible than LLM-based systems and require substantial effort to develop domain-specific learning content.

3. *AI-Supported Visualization Tools*

The third category includes interactive graphing tools, multimodal tutoring systems, and AI-supported visualization environments. These technologies are especially relevant for calculus because many concepts require students to connect symbolic, graphical, numerical, and conceptual forms. Gouia-Zarrad and Gunn (2024) reported that integrating AI-supported tools into calculus instruction can strengthen students' interaction with mathematical representations. Similarly, Lee et al. (2025) showed that multimodal tutoring environments can support collaborative and visual problem solving. Visualization is particularly important for topics such as limits, derivatives, area under curves, volumes of revolution, and rates of change. In civil engineering, these representations can be connected to physical phenomena such as load distribution, structural deformation, fluid flow, or changes in stress. The findings therefore suggest that each AI category provides different strengths. Generative AI offers conversational flexibility, ITS provides structured guidance, and visualization tools strengthen representational understanding.

D. Challenges and Risks of AI Use (RQ3)

Despite the educational opportunities identified, the review also revealed several important risks. Three major themes were consistently reported: epistemic offloading and over-dependence, limitations of complex reasoning, and infrastructure and readiness challenges.

1. Epistemic Offloading and Over-Dependence

The most prominent cognitive concern is epistemic offloading, which occurs when students transfer part of their reasoning process to AI. Wang et al. (2024) found that generative AI may encourage students to rely on synthetic fluency rather than independently constructing knowledge. This issue is particularly serious in mathematics because correct final answers do not necessarily indicate genuine conceptual understanding. Farrokhnia et al. (2024) also emphasized that although AI can reduce unnecessary cognitive load, excessive assistance may reduce the productive mental effort required for learning. In calculus, students may rely on AI to compute derivatives, integrals, or proof steps without understanding the mathematical principles involved. The central challenge is therefore distinguishing between AI as scaffolding and AI as cognitive replacement. When AI supports reasoning, it can strengthen learning. When it replaces reasoning, students may become increasingly dependent on external systems.

2. Limitations in Complex Mathematical Reasoning

A second concern is the accuracy and reliability of AI-generated mathematical responses. Although generative AI performs relatively well on routine calculations and familiar procedures, its performance becomes less reliable for multi-step reasoning, formal proofs, and complex engineering problems. Plevris et al. (2023) identified limitations in ChatGPT's ability to solve some engineering mathematics problems consistently, particularly when deeper reasoning was required. Similarly, Qawqzeh (2024) warned that excessive dependence on AI may weaken critical-thinking processes when learners accept generated responses without evaluating their correctness. Evidence from structural engineering education also suggests that students may perceive AI as useful for basic explanations while remaining cautious about more complex analysis. Ross et al. (2025) reported limitations in generative AI for tasks involving advanced structural interpretation. This creates an important educational requirement: students must develop the ability to verify AI-generated solutions. Verification may include checking mathematical derivations, comparing results with established formulas, examining graphical consistency, testing dimensional correctness, and evaluating whether the output makes physical sense in an engineering context.

E. Challenges in the Indonesian Context

The synthesis identified additional challenges that are particularly relevant to Indonesian higher education. These include unequal digital infrastructure, different levels of lecturer readiness, limited institutional policies governing AI use, and differences in access to technological resources. Febriana and Khaerani (2025) showed that AI integration in mathematics education requires not only technological availability but also adequate pedagogical preparation. Mudjib et al. (2025) similarly emphasized technological and instructional challenges in implementing digitally supported mathematical learning in Indonesia. Susilawati et al. (2024) further identified infrastructure limitations and disparities in digital readiness as barriers to wider AI adoption. These findings indicate that the successful integration of AI into civil engineering calculus cannot be achieved simply by providing access to ChatGPT or similar platforms. Institutional readiness must include lecturer training, reliable digital infrastructure, clear academic-integrity policies, appropriate assessment design, and student guidance regarding acceptable AI use. The Indonesian context therefore requires a gradual and adaptive implementation strategy rather than direct adoption of models developed in highly resourced educational environments.

F. Optimal AI Integration Strategies (RQ4)

The fourth research question addressed strategies for integrating AI into civil engineering calculus learning. Three primary strategies emerged from the synthesis: blended integration, explicit instructional guidance, and critical interaction with AI outputs.

1. Blended Integration

The reviewed evidence consistently supports a blended approach in which AI functions as a complementary educational tool rather than a replacement for traditional instruction. Nguyen et al. (2025) emphasized that generative AI can support engineering students' problem-solving processes when incorporated into structured educational activities. A blended design can require students to first attempt a problem independently and then use AI to compare solutions, identify errors, request explanations, or explore alternative approaches. This strategy preserves the benefits of AI while maintaining independent mathematical reasoning.

2. Explicit Instructional Guidance

AI use should also be accompanied by clear instructional rules. Students should understand when AI assistance is permitted, how outputs must be verified, when AI-generated content should be acknowledged, and which tasks must demonstrate independent reasoning. Without such guidance, students may use AI primarily to obtain final answers rather than to support learning. This is especially important in engineering education because mathematical competence is closely related to professional decision making and safety.

3. Prompt Engineering and Critical Verification

The reviewed literature also supports strengthening students' ability to interact critically with AI. Prompt engineering should not simply be taught as a method for obtaining more accurate answers. It can also function as a pedagogical strategy that encourages students to formulate clearer mathematical questions. Santoso et al. (2024) highlight the broader importance of effective interaction with AI systems, while Yu et al. (2024) emphasize the role of productive friction in AI-mediated learning. For example, instead of asking AI only to solve an integral, students can be encouraged to request an explanation of why a specific integration method is appropriate, identify the underlying theorem, relate the result to the formal definition, and interpret its engineering significance. Such prompts require students to engage with mathematical meaning rather than merely retrieve a solution.

G. Synthesis of Findings

Across the four research questions, the review indicates that the educational value of AI in calculus lies primarily in its ability to mediate between formal mathematical knowledge and applied conceptual understanding. The reviewed studies suggest the following conceptual sequence:

Formal Definition → AI-Supported Explanation and Representation → Theorem Understanding → Engineering Application → Independent Verification

This sequence illustrates that AI should occupy an intermediate role in the learning process. It can help students reformulate definitions, visualize relationships, explore alternative explanations, and examine intermediate reasoning. However, the final stages of interpretation and verification should remain the responsibility of the learner. This finding is consistent with the broader argument that effective AI integration should maintain an appropriate level of cognitive engagement rather than eliminating intellectual effort (Farrokhnia et al., 2024; Wang et al., 2024; Yu et al., 2024). For civil engineering education, this distinction is particularly important because calculus is not merely an academic subject. Mathematical concepts are subsequently applied to structural analysis, fluid mechanics, geotechnics, transportation systems, and other engineering problems where conceptual errors can lead to incorrect interpretations. Therefore, the evidence synthesized in this review supports the use of AI as a guided cognitive and explanatory scaffold, combined with conventional mathematical instruction, independent problem solving, and structured verification.

Table 6. Summary of Findings Across the Research Questions

Research Question	Main Findings	Key Supporting Literature
RQ1: Role of AI in bridging conceptual understanding	AI supports conceptual explanation, logical visualization, and reasoning/proof scaffolding	Almarashdi et al. (2024); Yoo (2024); Yu et al. (2024)
RQ2: Types of effective AI	Generative AI/LLMs, Intelligent Tutoring Systems, and AI-supported visualization tools were the dominant categories	Plevris et al. (2023); Gouia-Zarrad & Gunn (2024); Pögelt et al. (2024)
RQ3: Challenges and risks	Epistemic offloading, over-dependence, unreliable complex reasoning, and infrastructure/readiness limitations	Farrokhnia et al. (2024); Qawqzeh (2024); Wang et al. (2024); Susilawati et al. (2024)
RQ4: Integration strategy	Blended AI use, explicit instructional guidance, critical verification, and gradual contextual implementation	Nguyen et al. (2025); Santoso et al. (2024); Yu et al. (2024)

H. Discussion

The findings of this review indicate that Artificial Intelligence has considerable potential to support conceptual learning in calculus, particularly by helping students move between formal mathematical definitions, theorem-based reasoning, and applied engineering interpretation. At the same time, the reviewed evidence shows that the educational value of AI is highly dependent on how it is positioned within the learning process. AI appears most beneficial when it functions as a scaffold for explanation, representation, and guided reasoning, rather than as a substitute for mathematical thinking. A major finding of this review is that AI can support students who experience difficulty translating formal mathematical language into more accessible conceptual representations. This finding is consistent with Almarashdi et al. (2024), who reported that generative AI can provide adaptive explanations and immediate feedback in mathematics education. Baidoo-Anu and Owusu Ansah (2023) similarly emphasized that conversational AI can support personalized learning by allowing students to request clarification repeatedly and in different forms. Hassani and Silva (2023) further argued that ChatGPT has particular value in mathematics because it can reformulate abstract concepts using natural language and contextual examples.

The current findings extend these observations by showing that the explanatory role of AI is especially relevant when students need to move between formal definitions and theorem applications. In calculus, this distinction is important because procedural competence does not necessarily imply conceptual understanding. Dhakal (2025), for example, noted that students may successfully apply established calculus procedures while still demonstrating weak understanding of the underlying definitions. The present synthesis suggests that AI can partially reduce this disconnect by offering explanations that connect symbolic representations with intuitive or applied meanings. This role is particularly important in civil engineering education. Plevris et al.

(2023) showed that generative AI can solve many engineering mathematics problems and can provide useful explanatory support. However, their findings also revealed that mathematical correctness cannot be assumed across all problem types. The present review therefore supports a more cautious interpretation of generative AI in engineering education: AI should be understood primarily as an interactive explanatory environment, rather than as an authoritative mathematical solver.

This distinction becomes even more significant when calculus is used to interpret physical engineering phenomena. Civil engineering students are expected not only to manipulate mathematical expressions but also to understand what those expressions represent in structural mechanics, fluid mechanics, geotechnics, and transportation engineering. The reviewed evidence from Junaid et al. (2024) similarly indicates that AI chatbots can enrich civil engineering learning by providing rapid explanations and problem-solving support, but that their pedagogical usefulness depends on students' ability to evaluate and contextualize the generated responses.

The present findings also support the use of AI for constructing relationships between mathematical concepts. Yoo's (2024) concept of an Axiom-Based Atlas and proof vectors provides an important theoretical perspective for this result. Rather than treating theorems as isolated formulas, proof vectors represent the logical dependencies connecting axioms, definitions, and derived mathematical statements. This idea closely corresponds to the conceptual gap identified in the current review. Students who can perform a calculus procedure but cannot explain the underlying definition are effectively missing part of the logical chain between foundational concepts and applied theorems.

From this perspective, AI has the potential to make the “logical footprint” of calculus more explicit. For example, the relationship between shear force and bending moment can be taught not merely as an engineering formula, but as an application of differentiation and integration. Similarly, the interpretation of accumulated load or stress can be traced back to the conceptual meaning of definite integration. Such connections can potentially make calculus more meaningful for engineering students because mathematics becomes integrated with the physical systems they are learning to analyze.

The value of multiple representations is also supported by Gouia-Zarrad and Gunn (2024), who found that integrating ChatGPT and related digital tools into calculus learning can encourage students to explore mathematical ideas through different representations. This observation is compatible with the present finding that conversational explanations alone may not be sufficient. Conceptual understanding can be strengthened further when AI is combined with graphical, numerical, symbolic, and contextual representations. Similarly, Lee et al. (2025) demonstrated the potential of multimodal tutoring systems for collaborative and visual problem solving. Their findings suggest that the next generation of AI-supported calculus learning may extend beyond text-based conversation and incorporate diagrams, sketches, dynamic graphs, and interactive mathematical representations. This could be particularly beneficial in engineering education, where students frequently need to move between equations, diagrams, physical models, and numerical solutions.

However, the review also reveals a fundamental tension between cognitive support and cognitive substitution. AI can reduce unnecessary difficulty, but excessive assistance can also reduce the mental effort required to develop independent reasoning. Farrokhnia et al. (2024) described this issue in relation to cognitive load, emphasizing that educational technology should reduce extraneous cognitive burden without removing the productive cognitive effort necessary for learning. This concern is strongly reinforced by Wang et al. (2024), who describe the phenomenon of epistemic offloading in AI-supported undergraduate mathematics. When students rely on AI to generate explanations, reasoning steps, or complete solutions, the immediate task may become easier, but the learner may not fully internalize the underlying knowledge. The current review found similar concerns across several studies, particularly when generative AI was used to solve calculus problems without requiring students to verify or reconstruct the reasoning.

Qawqzeh (2024) similarly argues that excessive AI dependency may negatively influence critical thinking. This finding is highly relevant to engineering education because engineering mathematics is not only concerned with obtaining numerically correct answers. Students must be able to evaluate assumptions, identify inappropriate models, verify whether an answer is physically plausible, and determine whether the chosen mathematical approach is suitable for the engineering problem. The results therefore support the concept of productive friction proposed by Yu et al. (2024). Productive friction refers to maintaining a level of cognitive difficulty that encourages learners to think rather than providing immediate solutions to every problem. In AI-supported calculus learning, this could involve prompting students to attempt a solution first, asking AI for hints instead of complete answers, requiring them to critique an AI-generated proof, or comparing alternative AI-generated solution pathways.

This approach changes the role of AI from an answer provider to a cognitive partner. Students are still required to perform intellectual work, while AI provides targeted assistance when conceptual barriers arise. The current findings suggest that this model is more educationally sustainable than unrestricted use of generative AI. The review also identified important differences between generative AI and more structured Intelligent Tutoring Systems. Pögelt et al. (2024) demonstrate that personalized mathematical task recommendations can be generated using intended learning outcomes and reinforcement-learning methods. Unlike general-purpose language models, intelligent tutoring systems typically operate within a defined pedagogical structure. This provides greater control over learning sequences, difficulty progression, and feedback.

However, generative AI offers greater conversational flexibility. Students can formulate questions freely and request explanations tailored to their own difficulties. The implication is that these technologies should not necessarily be viewed as competitors. A potentially stronger instructional model would combine the structured progression of an Intelligent Tutoring System with the conversational flexibility of generative AI. The findings can also be interpreted using the TPACK framework discussed by Javaid et al. (2023) and Sánchez-Ruiz et al. (2023). Effective integration of AI requires lecturers to combine technological knowledge with pedagogical knowledge and calculus content knowledge. Simply introducing ChatGPT into a calculus class does not constitute meaningful technological integration. Lecturers must understand what mathematical concepts students find difficult, which AI-supported activities can address those difficulties, and how those activities can be incorporated into assessment and instruction.

The same conclusion can be examined through the SAMR perspective. Much current AI use remains at the substitution or augmentation level, where AI mainly replaces conventional search engines, calculators, or tutoring assistance. More transformative use would involve the modification or redefinition of learning tasks. For instance, students could be asked to compare several AI-generated proofs, identify inconsistencies, reconstruct the correct argument, and then relate the theorem to an engineering problem. Such an activity would be difficult to reproduce using conventional instructional tools alone.

The findings of this study are also consistent with Nguyen et al. (2025), who emphasized the potential of generative AI to support first-year civil engineering students in mathematical problem solving. Students entering engineering programs often experience a transition from secondary-school procedural mathematics to university-level mathematical modeling and abstraction. AI can potentially provide additional scaffolding during this transition, particularly for students who need repeated explanations or contextual examples. Ngo (2025) similarly highlighted the use of generative AI for supporting first-year civil engineering students during this transition. Nevertheless, the current review suggests that the success of such interventions should not be measured solely by whether students produce correct solutions. Longer-term conceptual retention, independent reasoning, and the ability to solve unfamiliar problems without AI assistance are equally important outcomes.

The structural engineering findings reported by Ross et al. (2025) further reinforce this caution. Students may perceive generative AI as useful for basic explanations and routine tasks, while

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advanced structural analysis remains more challenging for current AI systems. This suggests that the educational value of AI may vary considerably according to the complexity of the mathematical and engineering problem. These limitations are particularly important because generative AI can present incorrect solutions in confident and fluent language. A novice learner may therefore interpret fluency as correctness. Consequently, AI-supported calculus education should explicitly teach verification strategies. Students should be encouraged to compare generated solutions with established mathematical rules, perform dimensional checks, test boundary conditions, use graphical representations, and evaluate whether numerical outcomes are physically realistic.

Another important contribution of the review concerns the Indonesian context. Febriana and Khaerani (2025) indicate that AI integration in mathematics education must account for pedagogical readiness and technological capacity, not merely technological availability. This finding aligns strongly with the current review, which identified lecturer readiness, infrastructure, digital literacy, and institutional guidance as major implementation factors. Mudjib et al. (2025) similarly emphasize technological challenges associated with advanced mathematical learning approaches in Indonesia. These challenges suggest that AI integration strategies developed in well-resourced universities cannot automatically be transferred to every Indonesian higher education institution.

Susilawati et al. (2024) further identify barriers associated with digital infrastructure and institutional readiness. These findings imply that national or institutional AI strategies should account for differences between universities in terms of internet connectivity, technological resources, lecturer competencies, and student access to digital platforms. In this respect, the Indonesian context may require a phased implementation model. Institutions could initially introduce AI in low-risk learning activities, such as conceptual explanation, formative feedback, or visualization, before expanding its use into more complex problem-solving activities. Lecturer training should occur simultaneously so that instructors understand both the capabilities and limitations of generative AI.

The review also supports a reconsideration of assessment practices. If students can use AI to generate mathematically correct homework solutions, traditional take-home assignments may become less reliable indicators of individual understanding. Assessment should therefore increasingly measure reasoning processes rather than only final answers. This may include oral explanation, supervised problem solving, reflective justification, error analysis, or tasks requiring students to critique AI-generated solutions. In this context, the most appropriate role of AI is not to reduce academic rigor, but to shift the focus of assessment from routine calculation toward conceptual explanation, verification, and engineering interpretation. Such a shift may ultimately strengthen the relationship between calculus education and professional engineering reasoning.

Overall, the findings of this review show substantial agreement with previous research regarding the benefits of AI-supported explanation and personalized learning (Baidoo-Anu & Owusu Ansah, 2023; Hassani & Silva, 2023; Almarashdi et al., 2024), while also confirming concerns regarding reliability, dependency, and cognitive offloading (Farrokhnia et al., 2024; Qawqzeh, 2024; Wang et al., 2024). At the same time, the current review extends these discussions by specifically framing AI as a mediator between formal definitions, theorem comprehension, and civil engineering applications. This mediating perspective represents an important distinction. The primary educational question is not whether AI can solve calculus problems, because current systems clearly can solve many routine problems. The more important question is whether AI can help students understand why mathematical procedures work, how theorems arise from formal definitions, and how those relationships can be transferred to engineering contexts.

Based on the synthesis, the answer appears cautiously positive. AI can support these processes when it is combined with structured pedagogy, independent problem solving, verification requirements, and lecturer supervision. Conversely, when AI is used primarily as an automated solution generator, the same technology may widen rather than reduce the conceptual understanding gap. Therefore, effective AI integration in civil engineering calculus should be guided by three principles: AI should explain rather than merely answer, scaffold rather than replace reasoning, and promote verification rather than passive acceptance. These principles provide a more sustainable foundation for integrating generative AI into engineering mathematics education.

V. CONCLUSION AND RECOMMENDATION

This study has synthesized 29 articles on the role of AI in calculus learning for civil engineering. The main conclusions are as follows. First, AI has significant potential to bridge the conceptual understanding gap between theorems and definitions through three main mechanisms: conceptual explanation, logical relationship visualization, and proof scaffolding. Second, the effectiveness of AI heavily depends on a blended approach with clear instructional guidance. Third, the risk of epistemic offloading is a serious challenge that must be anticipated; the academic integrity gap between proctored and unproctored tasks indicates that AI-assisted assignments may not reflect genuine student comprehension. Fourth, the Indonesian context requires adaptive and gradual integration strategies.

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