KI4ING: Integrating Generative AI Into Engineering Education – A Prototype LMS for Intelligent Tutoring in Technical Mechanics

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Abstract

Engineering programmes are widely regarded as demanding fields of study, with high dropout rates especially in early semesters. Foundational subjects such as Technical Mechanics pose particular challenges, requiring students to integrate conceptual understanding, mathematical reasoning, and structured problem-solving. Meanwhile, generative AI is increasingly used as an informal learning tool, often without sufficient guidance, raising concerns about surface-level learning strategies. The KI4ING project investigates how generative AI can be systematically embedded in digital learning environments to support students in Technical Mechanics. Following a Design-Based Research approach, the project combines iterative system development with empirical insights from expert interviews and accompanying student studies examining learning behaviour, problem-solving processes, and AI use in practice. Key findings reveal persistent difficulties in structuring solution strategies, applying conceptual knowledge, and critically engaging with AI-generated outputs. These insights directly informed the design of a custom AI-supported learning environment integrating a Moodle-based learning management system, a dialogue-based AI tutor, and structured learning pathways. The system's modular architecture enables domain-specific configuration, scaffolding-oriented interaction, and privacy-conscious deployment in higher education. This paper presents the conceptual design and technical implementation of the KI4ING system and discusses how empirically grounded design decisions can foster structured problem-solving and deeper conceptual understanding in engineering education.

Keywords: generative AI, engineering education, technical mechanics, intelligent tutoring systems, problem-solving approach

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Introduction

Engineering programmes are widely recognised as demanding fields of study, requiring students to develop both conceptual understanding and advanced analytical problem-solving skills. Despite their importance for technological and economic development, engineering programmes are characterised by comparatively high dropout rates, particularly during the early stages of study (Heublein et al., 2022; Klöpping et al., 2017). Foundational subjects such as Technical Mechanics play a central role in this context, as they often represent significant learning barriers that influence students' academic progression (Kautz et al., 2018).

Learning in Technical Mechanics is strongly problem-oriented and requires students to integrate conceptual knowledge with mathematical reasoning and structured solution strategies. However, empirical evidence suggests that many students struggle with these requirements. In particular, difficulties arise in structuring problem-solving processes, selecting appropriate solution strategies, and transferring theoretical knowledge to concrete tasks (Dammann & Lang, 2019). These challenges are further compounded by the fact that students often rely on surface-level learning strategies rather than developing deeper conceptual understanding (Biggs & Tang, 2011).

At the same time, the rapid development of generative artificial intelligence (AI) is increasingly influencing students' learning practices. Recent studies and reports indicate that generative AI tools are already widely used by students as informal learning aids (EY, 2024; Kasneci et al., 2023). These systems are often used to generate explanations, solve tasks, and receive immediate feedback. While such tools offer significant potential for supporting learning processes, they also pose risks, including unreflective use, overreliance on AI-generated solutions, and the reinforcement of superficial learning strategies. In addition, previous research has highlighted that AI systems in education often lack pedagogical structuring and domain-specific alignment, which limits their effectiveness in formal learning environments (Holmes et al., 2019).

Initial empirical findings from student research projects conducted within the KI4ING context further support these observations. Results from a survey-based study indicate that students perceive generative AI as a helpful learning tool, particularly for obtaining explanations and solving tasks, while at the same time highlighting uncertainties regarding appropriate use and potential risks (Golod, 2025). Complementary qualitative studies focusing on learning processes in Technical Mechanics reveal that students frequently experience uncertainty when approaching problem-solving tasks and often apply incomplete or incorrect solution strategies. Think-aloud protocols show that learners sometimes rely on overly simplified approaches or struggle to recall and apply relevant formulas and concepts, indicating gaps in both conceptual understanding and problem-solving competence.

However, existing AI tools are typically designed as general-purpose applications and are not well suited for integration into structured learning environments in higher education. In particular, they often lack domain-specific configurability, scaffolding-based interaction, and compliance with data protection requirements, which limits their applicability in formal educational settings.

The KI4ING project addresses this gap by investigating how generative AI can be systematically integrated into digital learning environments to support students in Technical Mechanics. The project follows a Design-Based Research approach and aims to develop an AI-supported learning environment that combines structured learning pathways with dialog-based tutoring and feedback mechanisms.

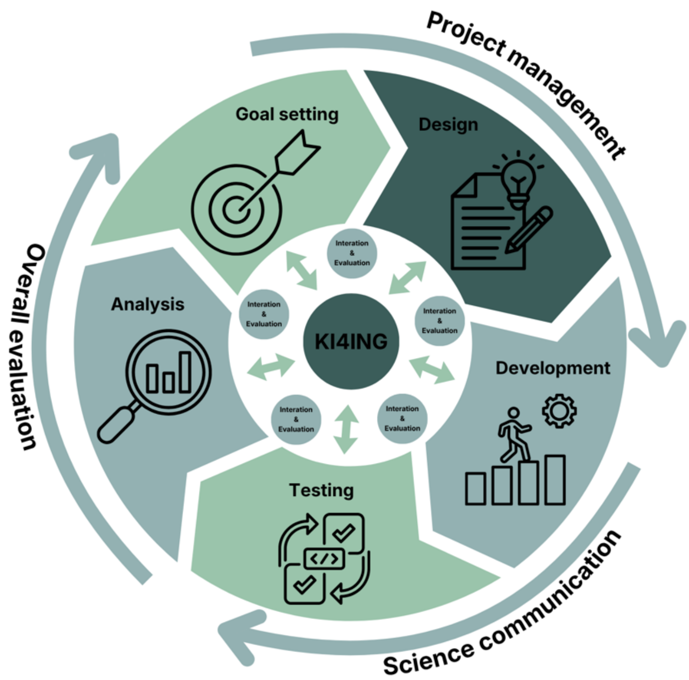
The aim of this paper is to present the conceptual design and prototype implementation of the KI4ING system and to discuss its potential contribution to AI-supported learning in engineering education.

Methodology

The KI4ING project follows a Design-Based Research (DBR) approach to guide the development and investigation of an AI-supported learning environment for Technical Mechanics. DBR is particularly suitable for research that aims to design, implement, and iteratively refine educational interventions in authentic learning contexts while simultaneously generating transferable design knowledge (Euler & Collenberg, 2018; Reinmann, 2020).

The methodological approach combines the systematic development of a technological solution with the continuous integration of empirical insights from multiple data sources. The development process is structured as an iterative cycle consisting of problem analysis, design, implementation, testing, and refinement. These phases are revisited throughout the project in order to improve both the technical system and the underlying instructional design.

Figure 1
Design Based Research Based on Reinmann, 2020; Euler & Collenberg, 2018



In addition to these general DBR principles, the KI4ING development process explicitly incorporates a structured analysis of existing AI-based tools. This analysis aimed to identify technological, pedagogical, and legal limitations of current systems, particularly with regard to domain-specific applicability, scaffolding-based interaction, integration into learning management systems, and compliance with data protection requirements. The findings of this analysis revealed that existing tools are typically designed as general-purpose applications and are not well suited for structured use in higher education contexts. These insights directly informed the design decisions underlying the KI4ING system.

As part of the initial context analysis, semi-structured expert interviews were conducted with lecturers in Technical Mechanics from several German universities and universities of applied sciences. The interviews aimed to explore typical learning challenges, existing support structures, and the role of digital tools and generative AI in current teaching and learning practices. The findings indicate that Technical Mechanics courses are characterised by large student cohorts, high failure rates in early semesters, and considerable variation in students' learning strategies.

In addition to the expert perspective, the KI4ING project is informed by accompanying student research projects conducted within the project context. These include a bachelor's thesis (Golod, 2025), a completed master's thesis (Merke, 2025), and an ongoing study that builds on previous findings. The studies investigate students' learning behaviour, problem-solving processes, and their use of generative AI in the context of Technical Mechanics.

Methodologically, these studies employ a combination of quantitative and qualitative approaches. Survey-based data provide insights into students' perceptions and usage patterns of generative AI as a learning tool (Golod, 2025). Complementary qualitative approaches, including semi-structured interviews and think-aloud protocols, allow for an in-depth analysis of students' problem-solving processes (Merke, 2025). The think-aloud method enables the reconstruction of cognitive processes during task completion by capturing students' verbalised reasoning while solving engineering problems (Ericsson & Simon, 1993).

The analysis of these data reveals recurring patterns in students' learning processes. Students frequently experience difficulties in structuring solution strategies, selecting appropriate methods, and transferring theoretical knowledge to concrete problem contexts. Furthermore, the findings indicate that generative AI is already widely used as an informal support tool, although often without critical reflection on the correctness of the generated outputs.

Taken together, the methodological approach of KI4ING can be understood as a form of triangulation across different perspectives and data sources. While the expert interviews provide insight into structural challenges in teaching Technical Mechanics, the accompanying student studies contribute a more fine-grained understanding of how learners actually approach tasks, where they experience uncertainty, and how they already make use of generative AI in their learning processes. This combination is particularly valuable for the development of the KI4ING platform, as it allows design decisions to be informed not only by lecturers' assumptions about typical learning barriers but also by empirical observations of students' reasoning and behaviour.

In this regard, the completed student studies provide complementary evidence. Survey findings indicate that generative AI is already widely used by students as a learning tool, with one study reporting AI use for learning among a large majority of respondents. At the same time, the qualitative analyses show that many learners still struggle with basic conceptual understanding, the selection of appropriate strategies, and the structured execution of solution processes. Within the DBR framework, these combined insights are particularly relevant because they help identify both the technological opportunities and the pedagogical requirements that should shape the ongoing development of the KI4ING system.

At the current stage of the project, the KI4ING system is in the prototype development phase, and comprehensive evaluation with students has not yet been conducted. Instead, the focus of this paper lies on the design rationale, system implementation, and the integration of empirical insights into the development process. Future research will involve systematic evaluation phases, including expert-based testing and student-based studies, to further refine the system within subsequent DBR cycles.

KI4ING System Concept

The KI4ING system is designed as an AI-supported learning environment that aims to support students in learning Technical Mechanics, with an initial focus on Statics I. The pedagogical concept combines structured learning pathways with dialog-based AI support to assist students during problem-solving processes.

The conceptual design of the KI4ING system is based on both pedagogical considerations and identified limitations of existing AI tools. As outlined in the methodological analysis, current generative AI systems are typically designed as general-purpose applications and tend to provide complete solutions rather than supporting structured learning processes. In addition, they often lack domain-specific alignment and cannot be easily integrated into institutional learning environments. These limitations highlight the need for a system that combines pedagogical guidance with domain-specific control and technical integration.

Technical Mechanics is widely perceived as a challenging subject, particularly in the early stages of engineering education. Students often experience difficulties in understanding abstract concepts, structuring solution processes, and applying theoretical principles to complex problems (Dammann & Lang, 2019). These challenges are further reflected in empirical findings from accompanying student research within the KI4ING project. Qualitative analyses of students' problem-solving processes indicate that learners frequently struggle to structure their reasoning, select appropriate solution strategies, and transfer conceptual knowledge to specific tasks (Merke, 2025). In addition, survey-based findings show that students increasingly rely on generative AI tools as informal learning aids, often without critically reflecting on the correctness of the generated outputs (Golod, 2025).

In response to these challenges, the didactic design of the KI4ING system is grounded in the principle of scaffolding, which emphasises guided support to facilitate learning processes (Wood et al., 1976). Instead of providing direct solutions, the AI tutor is designed to support students through guided hints, targeted questions, and conceptual explanations. This approach directly addresses the observed tendency of both students and AI tools to focus on final answers rather than structured reasoning processes. By guiding learners through intermediate steps, the system aims to foster deeper conceptual understanding and improve problem-solving competence.

A further central design principle is the integration of learning-oriented feedback. The system is intended to provide feedback that supports reflection on solution processes rather than merely indicating correctness. This is particularly relevant in light of empirical findings showing that students often struggle to evaluate both their own solutions and AI-generated outputs. The emphasis on feedback is supported by research highlighting its importance for learning outcomes (Hattie, 2008).

Conceptually, the KI4ING system follows a layered architecture that integrates a learning management system with AI-supported tutoring functionality and structured domain knowledge. The Moodle learning management system serves as the central access point, providing course structure, learning materials, and access to exercises. Within this environment, a dialog-based AI tutor enables natural language interaction and supports students in analysing problem statements, identifying relevant physical principles, and reflecting on intermediate solution steps. This integration addresses the need for embedding AI functionality within structured learning environments rather than relying on external tools.

A central feature of the system is the provision of personalised learning pathways that take into account differences in students' prior knowledge, learning strategies, and individual needs. Upon entering the platform, students provide contextual information about their study programme and complete a self-assessment of their current level of understanding. In addition, an optional diagnostic test enables a more detailed assessment of foundational competencies in Statics I. Based on these inputs, the system assigns students to an appropriate learning pathway. In the current implementation, this assignment follows a rule-based and semi-adaptive approach, enabling differentiated learning sequences without relying on fully automated adaptive learning algorithms.

The design of these learning pathways is directly informed by empirical insights into students' learning processes. Findings from qualitative studies indicate that many students tend to apply surface-level strategies and experience difficulties in linking conceptual understanding with procedural steps. These observations highlight the importance of structuring learning content in a way that gradually increases complexity while providing continuous guidance. Accordingly, the task pool underlying the learning pathways is organised according to conceptual focus and level of difficulty, allowing students to progressively develop their understanding from basic principles to more complex problem-solving scenarios.

In addition to task-level support, the system provides learning-oriented feedback based on students' interactions. This feedback highlights recurring difficulties, identifies areas for improvement, and suggests subsequent learning steps. By combining structured learning pathways with dialog-based AI support and feedback mechanisms, the KI4ING system aims to create a coherent learning environment that supports both conceptual understanding and the development of problem-solving competence in Technical Mechanics.

Overall, the KI4ING system concept reflects an attempt to integrate generative AI into a pedagogically structured and domain-specific learning environment that addresses both the opportunities and limitations of current AI technologies in higher education.

KI4ING Prototype Development

The development of the KI4ING platform began with a structured benchmarking of existing AI-powered tools and platforms, including WolframAlpha, Perplexity AI, ChatGPT, Fobizz, DeepSeek, Google Gemini, NotebookLM, and Claude, among others. Each tool was assessed across multiple dimensions relevant to the KI4ING use case: domain-specific competence in Technical Mechanics, pedagogical quality of feedback, LMS integration capability, file format support, and data protection compliance. While several tools, notably ChatGPT and Perplexity AI, demonstrated strong capabilities for processing engineering problems and generating step-by-step solutions, two fundamental limitations emerged consistently across the evaluated options. First, all tested tools tended to deliver complete solutions upon request rather than guiding students through the problem-solving process in a scaffolded manner, which is pedagogically counterproductive in the context of engineering education. Second, the vast majority of tools were assessed as critically non-compliant or legally uncertain with respect to GDPR requirements applicable to German higher education: most collect and transfer user data to third countries without sufficient legal safeguards, and the only tool offering full GDPR compliance (Fobizz) does not support external LMS integration. These findings established that no off-the-shelf solution simultaneously satisfied the requirements of domain-specific configurability, scaffolding-based instructional design, Moodle integration, and adequate data protection. This provided the primary rationale for constructing a custom, modular architecture, with Moodle as the LMS, OpenAI GPT-4.1 as the language model, FlowiseAI as the low-code RAG pipeline builder, and Langfuse as the observability and evaluation layer.

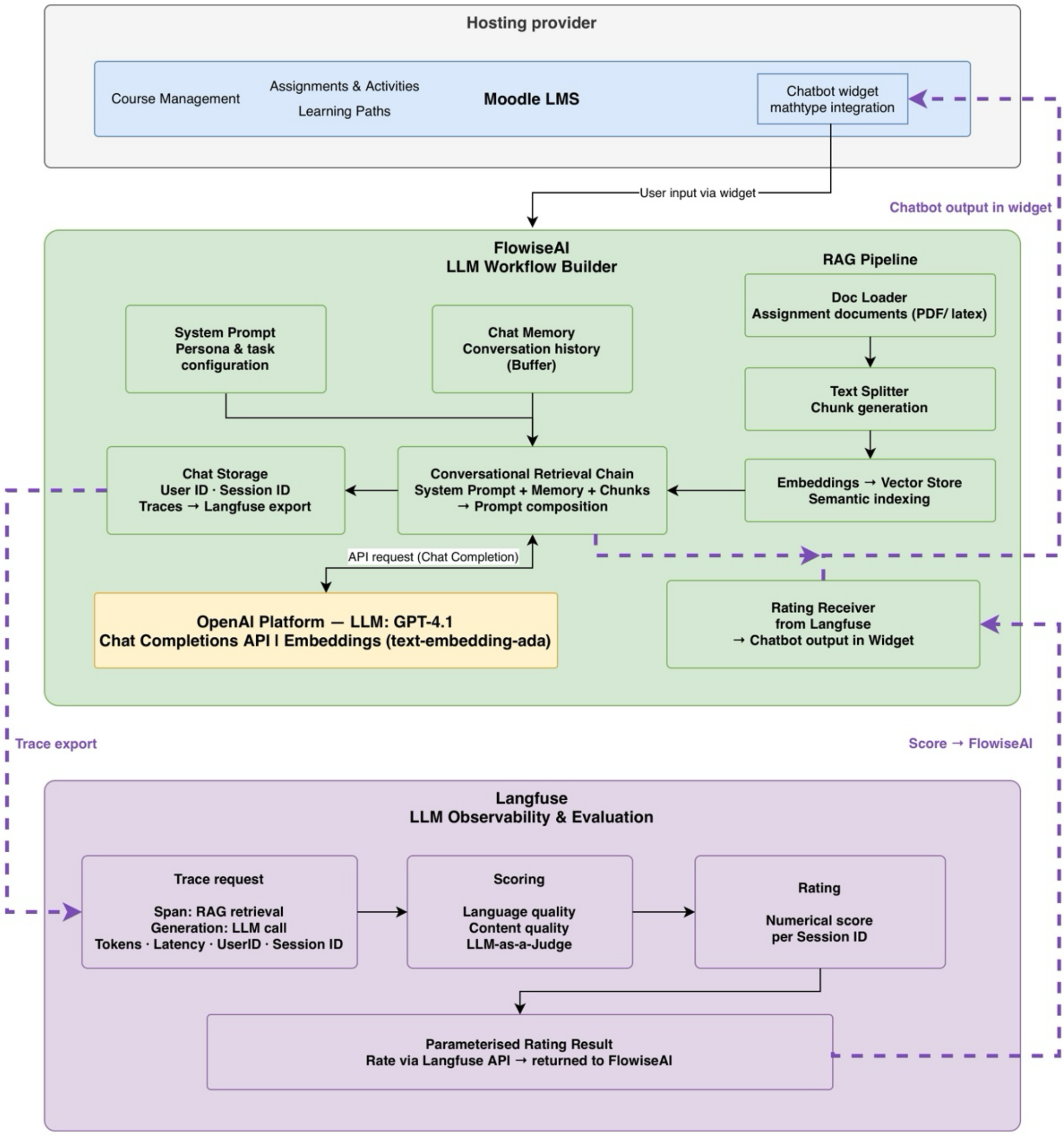
Following the technology selection, Moodle was deployed via an external hosting provider and configured as the central student-facing environment, providing course structure, learning pathway management, and access to assignments. The AI chatbot, built on FlowiseAI, was embedded directly into the Moodle interface via an iFrame, ensuring that students can interact with the AI tutor without leaving the course environment. This integration is pedagogically intentional: presenting the tutoring system as a natural extension of the course rather than a separate tool lowers the threshold for student engagement. To address the multimodal nature of engineering tasks, which typically combine textual problem descriptions, geometric sketches, and mathematical notation, the system supports assignment documents in both PDF and LaTeX format, and integrates a MathType formula editor directly within the chat interface. This allows students to input mathematical expressions graphically rather than manually, removing a significant usability barrier for early-semester students without prior experience in formal mathematical notation.

A critical element of the implementation was the design and iterative refinement of the system prompt, which governs the persona, instructional approach, and behavioural constraints of the AI tutor. Configured centrally within FlowiseAI and transmitted with every API request, the system prompt is the primary mechanism through which the chatbot's behaviour is shaped. The central design challenge was steering the language model away from its default tendency to provide immediate, complete answers and towards a scaffolding-oriented interaction style in which students are guided through guiding questions, partial hints, and conceptual explanations rather than receiving ready-made solutions. This required substantial iterative refinement: successive prompt versions were tested against a range of task types and student query patterns, and progressively adjusted to achieve more consistent scaffolding behaviour. These observations from the development process indicate that effective prompt engineering in domain-specific educational contexts demands a close interplay of technical iteration, subject-matter expertise, and pedagogical judgement, and remains an ongoing design challenge to be investigated further in the upcoming evaluation phases.

Alongside the functional components described above, a privacy-preserving data architecture was implemented as a foundational design principle. Rather than linking chatbot interactions to identifiable student accounts, the system assigns each user a pseudonymised UserID and each session a unique SessionID, both generated automatically and captured by Langfuse during each interaction. No student names, email addresses, or institutional identifiers are transmitted to or stored within the tracing infrastructure. This pseudonymisation approach serves a dual purpose: it enables session-level analysis and evaluation (including the automated quality scoring planned for later development stages) without requiring access to personal data, and it limits the scope of personal data processing to what is strictly necessary for the system's educational function.

The KI4ING system is built on a modular, API-based architecture that integrates four main components: the Moodle Learning Management System as the student-facing interface (blue), FlowiseAI as the central workflow and RAG pipeline engine (green), the OpenAI platform as the underlying language model provider (yellow), and Langfuse as the observability and evaluation layer (purple). Together, these components form a closed-loop system in which student interactions are processed, grounded in domain-specific content, evaluated, and (in future development stages) fed back into adaptive learning path recommendations. Figure 2 provides a schematic overview of the data flows described below.

Figure 2
KI4ING Architecture Diagram



The core processing layer (green) is implemented in FlowiseAI, which manages the full lifecycle of each chatbot interaction through a Retrieval-Augmented Generation (RAG) pipeline. When a student submits a query, the system performs a semantic similarity search against an in-memory vector store to retrieve the most relevant chunks of domain-specific assignment content. These documents, loaded as PDF and LaTeX files and indexed via OpenAI's text-embedding-ada-002 model, serve as the factual grounding for the chatbot's responses. The retrieved chunks are then combined with the session's conversation history buffer and the centrally configured system prompt into a single composed prompt by the Conversational Retrieval Chain, which is subsequently dispatched to the language model. The conversation buffer is session-scoped, preserving contextual coherence across dialogue turns within a session while avoiding the accumulation of persistent personal interaction histories. This RAG architecture is a critical design choice for the KI4ING use case: general-purpose language models, when queried without domain-specific retrieval, tend to generate responses that are either overly generic or factually inconsistent with the specific tasks and conventions used in the course. By anchoring every response in the actual assignment content, the system substantially reduces this risk and ensures that AI-generated guidance remains aligned with the pedagogical material students are working with.

The language model powering the system is GPT-4.1, accessed via the OpenAI Chat Completions API. It processes the composed prompt and returns a response displayed in the student-facing widget within Moodle. The same OpenAI platform also provides the embedding model (text-embedding-ada-002) used to index assignment content in the vector store. All interactions are simultaneously traced in Langfuse, which records each session as a structured hierarchy of events: a RAG span capturing the retrieval step, a generation event logging the full prompt and model response, and associated metadata including token counts, response latency, and the pseudonymised UserID and SessionID. No personally identifiable information is transmitted to or stored within Langfuse. Student interactions are linked exclusively to anonymised identifiers, consistent with the privacy-preserving architecture described above.

The three remaining development steps represent the planned trajectory from the current prototype towards a more analytically capable and adaptive system. In a first extension, an automated end-to-end session evaluation pipeline will be implemented using an LLM-as-a-Judge approach, in which a secondary language model assesses each recorded session along two quality dimensions, language quality and content quality, and assigns a numerical score per SessionID, returned to FlowiseAI via the Langfuse API. Building on this infrastructure, the system will aggregate scores across all sessions of a given user and deliver 9ealization9ed, privacy-preserving formative feedback directly within the chat interface, supporting students in reflecting on their progress without exposing personal session content. In the final planned stage, longitudinal scoring patterns will be used to identify recurring conceptual difficulties and dynamically adjust individual learning paths, directing students towards exercises and content that target their specific areas of weakness. The 9ealization of these components is contingent on the availability of sufficient interaction data from upcoming student testing phases and on the formal validation of the automated evaluation mechanisms and is planned as a medium-term development goal within the DBR framework.

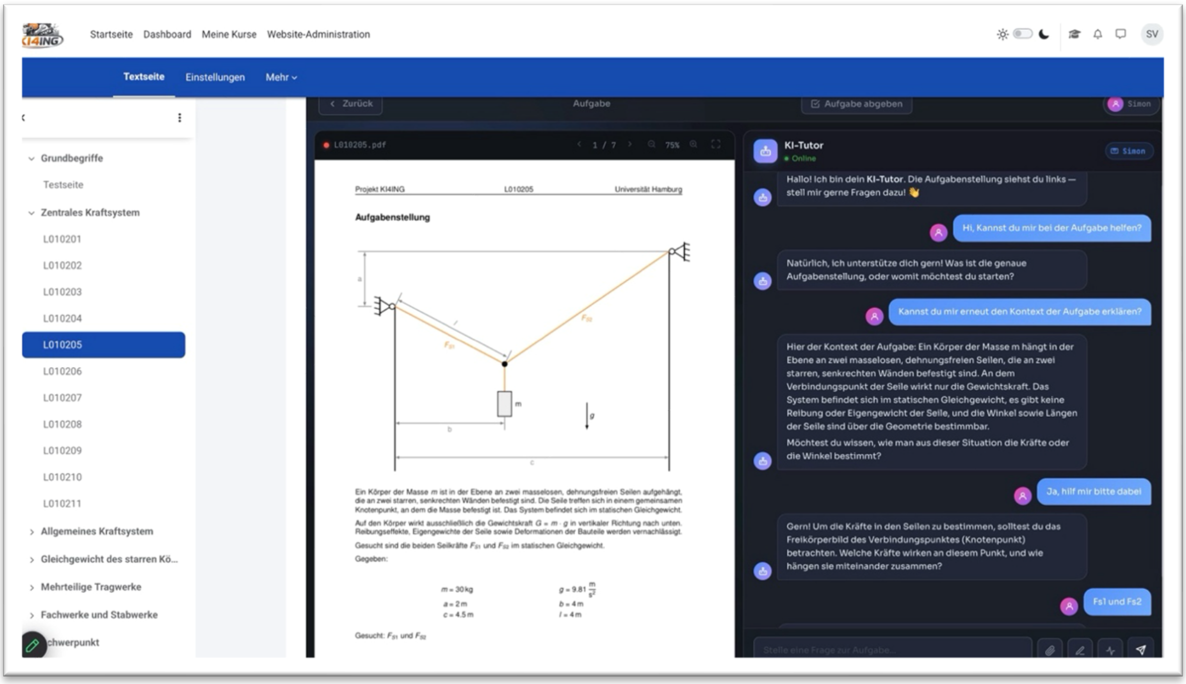
Discussion and Future Work

The KI4ING project is currently in the prototype development phase and provides initial insights into the design and implementation of AI-supported learning environments for Technical Mechanics (cf. figure 3). While comprehensive empirical evaluation with students has not yet been conducted, the development process is informed by a combination of expert perspectives and empirical insights from accompanying student studies.

A central finding across these data sources is the importance of structured support for problem-solving processes. In Technical Mechanics, learning is not limited to understanding individual concepts but requires the ability to organise and structure complex solution procedures. Qualitative analyses of students' problem-solving processes indicate that learners frequently struggle with structuring their reasoning and selecting appropriate solution strategies (Merke, 2025). In many cases, students rely on incomplete or incorrect approaches or express uncertainty regarding relevant formulas and methods. These observations highlight the need for guided support mechanisms that go beyond providing final answers.

Figure 3

Example Task Shown in Chatbot Widget Implemented in KI4ING Learning Platform Prototype



More specifically, the accompanying student studies suggest that the challenges addressed by KI4ING are not limited to advanced or highly specialised topics, but can already be observed in fundamental areas of Technical Mechanics. Think-aloud protocols indicate that students sometimes apply oversimplified strategies even in introductory tasks and show uncertainty when recalling appropriate formulas or deciding how to proceed. In one case, a learner directly added orthogonal force components instead of treating them as vector quantities, while in other cases students explicitly stated that they knew there "had to be a formula" but were unsure how to apply it. Such observations point to difficulties not only in content knowledge, but also in the monitoring and regulation of one's own problem-solving process.

At the same time, the available findings should not be interpreted as evidence of a general lack of motivation. On the contrary, the analyses reported in the accompanying master's thesis indicate that students also show metacognitive potential, for example by openly articulating uncertainty, critically checking intermediate results, or deliberately requesting support. These observations are highly relevant for KI4ING, because they suggest that students do not simply need answers, but rather structured and responsive support that helps them stabilise and refine their reasoning processes.

These findings are consistent with the limitations identified in existing AI tools, which tend to prioritise answer generation over guided learning processes and are not designed for structured integration into formal educational settings. The benchmarking conducted during the development of the KI4ING prototype further confirmed that current systems typically lack scaffolding-oriented interaction, domain-specific configurability, and integration into institutional learning environments.

The KI4ING system addresses these challenges by implementing a dialog-based AI tutor that supports students through scaffolding-based interaction. Instead of delivering complete solutions, the system guides learners through problem-solving steps and encourages reflection on intermediate results. This design aligns with established instructional approaches that emphasise guided learning and structured support as key mechanisms for fostering conceptual understanding (Wood et al., 1976).

Another important aspect concerns the role of feedback in AI-supported learning environments. The KI4ING system places strong emphasis on learning-oriented feedback that helps students reflect on their reasoning processes and identify areas for improvement. Empirical findings from student studies suggest that while learners value AI-generated feedback, they often do not critically evaluate its correctness. This highlights the importance of designing feedback mechanisms that actively support reflection and critical engagement. These considerations are consistent with educational research demonstrating the significant impact of feedback on learning outcomes (Hattie, 2008).

In addition, the findings underline the growing role of generative AI as an informal learning tool. Survey-based results indicate that students already use AI systems extensively for solving tasks and obtaining explanations (Golod, 2025). However, this use is often characterised by a lack of structured guidance, which may reinforce surface-level learning strategies. The KI4ING approach addresses this issue by embedding AI functionality within a structured learning environment that combines domain-specific knowledge with pedagogically guided interaction.

From a technical perspective, the prototype implementation demonstrates that the integration of generative AI into higher education contexts requires custom system architectures rather than relying on existing off-the-shelf solutions. In particular, the combination of a learning management system, a retrieval-augmented AI pipeline, and a privacy-preserving data infrastructure proved essential for meeting both pedagogical and institutional requirements. These findings highlight the importance of aligning technological design decisions with didactic and regulatory constraints.

Future work will focus on the systematic evaluation and iterative refinement of the KI4ING system. In line with the Design-Based Research approach, the next phase involves expert-based evaluation with “critical friends” to assess the usability, technical reliability, and pedagogical coherence of the system. This will be followed by student-based testing in authentic learning contexts, where user interactions, learning processes, and the effectiveness of AI-supported feedback will be analysed in more detail.

The insights gained from these evaluation phases will inform subsequent development cycles and contribute to a deeper understanding of how generative AI can be effectively integrated into engineering education. In particular, future research will examine how structured AI support influences students’ problem-solving strategies, conceptual understanding, and learning behaviour over time.

Overall, the KI4ING project highlights both the opportunities and challenges of integrating generative AI into domain-specific learning environments and contributes to the development of empirically informed design principles for AI-supported learning in Technical Mechanics.

Conclusion

This paper presented the conceptual design and prototype development of the KI4ING system, an AI-supported learning environment for Technical Mechanics. Building on a Design-Based Research approach, the project aims to explore how generative AI can be adapted to provide technically reliable and pedagogically meaningful support for students in engineering education.

The integration of empirical insights from both expert interviews and accompanying student research highlights the relevance of addressing persistent challenges in students' learning processes. In particular, the findings underline the importance of supporting structured problem-solving, fostering conceptual understanding, and promoting reflective engagement with AI-generated outputs. The results further indicate that students already make extensive use of generative AI tools, but often without sufficient guidance, which can reinforce superficial learning strategies.

The KI4ING system responds to these challenges by combining structured learning pathways with dialog-based AI tutoring and learning-oriented feedback. In doing so, it demonstrates how generative AI can be embedded within pedagogically designed learning environments that not only provide answers but actively support learning processes and the development of problem-solving competence. At the same time, the project illustrates that the effective use of generative AI in higher education requires custom system architectures that integrate domain-specific knowledge, pedagogical control, and institutional requirements such as data protection.

An important strength of the KI4ING project lies in the integration of accompanying student research into the development process. By combining survey-based findings, qualitative process analyses, and think-aloud protocols, the project gains a more detailed understanding of students' learning behaviour, their use of generative AI, and their typical difficulties in problem-solving. These insights make it possible to align the system more closely with the needs of the target group and to translate empirical findings into concrete design decisions.

While the current work focuses on the design and implementation of the prototype, future research will investigate its effectiveness in authentic learning contexts. Planned evaluation phases, including expert-based testing and student-based studies, are expected to provide valuable insights into user interaction patterns, the usability of the system, and the impact of AI-supported feedback on learning processes.

Through iterative testing and refinement, the KI4ING project aims to contribute to a deeper understanding of how generative AI can be effectively integrated into higher education. In this regard, the project not only provides a concrete technological solution but also contributes to the development of empirically grounded design principles for AI-supported learning in engineering education.

References

Biggs, J., & Tang, C. (2011). *Teaching for quality learning at university* (4th ed.). Open University Press.

Dammann, E., & Lang, M. (2019). Unterschiede des mathematischen Wissens bei Studierenden des Bauingenieurwesens zu Studienbeginn [Differences in Mathematical Knowledge among Civil Engineering Students at the Beginning of Their Studies]. *Journal of Technical Education (JOTED), 7*(1), 53–55.

Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal reports as data* (Rev. ed.). MIT Press.

Euler, D., & Collenberg, B. (2018). Design-based research. In R. Tippelt & B. Schmidt-Hertha (Eds.), *Handbuch Bildungsforschung* (pp. 101–120). Springer.

EY. (2024). *Generative AI in education: Opportunities and challenges*. Ernst & Young.

Golod, L. (2025). *Generative AI as a learning support tool in higher education: Student perspectives and usage patterns.* [Bachelor's thesis, University of Hamburg].

Hattie, J. (2008). *Visible learning: A synthesis of over 800 meta-analyses relating to achievement*. Routledge.

Heublein, U., Richter, J., Schmelzer, R., & Sommer, D. (2022). *Ursachen des Studienabbruchs in Deutschland. Deutsches Zentrum für Hochschul- und Wissenschaftsforschung (DZHW)* [Causes of University Dropout in Germany. German Centre for Higher Education Research and Science Studies (DZHW)].

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274.

Kautz, C., Brose, A., & Hoffmann, N. (2018). *Tutorien zur Technischen Mechanik* [Tutorials in Engineering Mechanics]. Springer Vieweg.

Klöpping, S., Ressel, W., Bruder, R., Krieg, A., Scherfer, M., Umbach, E., & Dachsberger, S. (2017). *Studienabbruch in den Ingenieurwissenschaften. Empirische Analyse und Best Practices zum Studienerfolg* [University Dropout in Engineering Sciences: Empirical Analysis and Best Practices for Academic Success]. Herbert Utz Verlag.

Merke, J. (2025). *Künstliche Intelligenz und studentisches Lernen in der Technischen Mechanik: Eine qualitative Studie zur studentischen Arbeitsweise und Unterstützungsangeboten* [Artificial Intelligence and Student Learning in Engineering Mechanics: A Qualitative Study on Students' Working Methods and Support Services]. [Master's thesis, University of Hamburg].

Reinmann, G. (2020). Design-based research. In *Handbuch Hochschullehre*. Springer.

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry, 17*(2), 89–100.

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