

From Cognitive Overload to Individualized Learning: AI Tutoring in Electrical Engineering

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Abstract: First-year students in electrical engineering often encounter significant challenges in their undergraduate programs, particularly due to heterogeneous prior knowledge in mathematics and physics, as well as difficulties in managing their own learning processes. These issues frequently result in cognitive overload, poor exam performance, and high dropout rates. Traditional teaching methods, especially in large cohorts, struggle to address these challenges effectively, as excessive tutorial time is spent on basic calculation steps rather than fostering deeper, subject-specific understanding. To address this, a domain-specific AI tutor was piloted during the winter semester of 2025/2026 in the first-semester course "Fundamentals of Electrical Engineering". The AI, based on the Google Gemini 2.5 Pro language model, was enhanced with Retrieval-Augmented Generation (RAG) to integrate tailored teaching materials, such as annotated lecture transcripts and detailed solution manuals. Configured as a Socratic tutor, the AI provided individualized, asynchronous support by guiding students through tutorial preparation, verifying their calculation steps, and assisting with step-by-step troubleshooting. This tool was tested with a seminar group of 18 students who got access to the AI tutor via the platform you.com. The pilot project included continuous data collection throughout the semester. Weekly online reflection forms captured students' usage patterns, perceived task difficulty, and feedback on the AI's usefulness or limitations. These data were complemented by two comprehensive surveys conducted at midterm and end of semester. The study presents the technological configuration and didactic applications of the AI tutor, analyzing its impact across different student performance levels. The results indicate high acceptance of the AI tutor, particularly for verifying calculations and resolving short-term learning obstacles. However, the analysis also revealed limitations, especially in handling subject-specific visual and topological contexts. The findings underscore the importance of fostering critical AI literacy among students and highlight the need for future multimodal AI models to better support engineering education. In addition, the use of AI in undergraduate studies serves to build competencies within the context of a potential core curriculum.

Keywords: AI Tutor, Blended Learning, Fundamentals of Electrical Engineering, Artificial Intelligence, Learning Environment, E-Learning, Higher Education

1. Introduction

Reducing student dropout rates in engineering is a key challenge for higher education institutions. In Europe and North America, approximately 40 % to 50 % of students drop out of their engineering courses during the first year, highlighting that most problems arise in the critical initial phase of university education (Sultana, Khan and Abbas, 2017). University dropout is the result of multiple complex causes, including personal, family, sociocultural, and economic factors, which may interact with one another. The transition from secondary school to university studies is a sensitive phase in the academic career, characterized by cognitive, emotional, and socio-economic stress factors (Casanova *et al.*, 2021).

Several key factors have been identified as contributing to this development, including highly heterogeneous prior knowledge of mathematics and physics among incoming students, and general difficulties with independent learning organization and time management. However, the primary cause of early academic failure is being overwhelmed by complex subject-specific content, arising from a substantial discrepancy between the university's curricular requirements and high school graduates' actual initial prerequisites (Tayebi, Gómez and Delgado, 2021). This continuous academic overload leads to poor exam results at the end of the first semester, evokes frustration, and frequently ends in the final abandonment of the degree program. This situation is further intensified in modern education by concurrent financial cuts in the higher education sector. These budgetary restrictions create a significantly more challenging institutional starting position, as the available funds for sufficient teaching staff, student tutors, and modern technical equipment for students are increasingly reduced (Hartmann, 2025; John, 2026).

To effectively counter this structural deficit, novel technological approaches for supporting students during this critical phase are gaining importance (Fierro Saltos *et al.*, 2025). This paper presents and empirically evaluates a course-specific AI tutor designed to provide asynchronous, personalized learning support. Within the framework of this study, concrete research questions are addressed: The study investigates the specific ways in which students utilize the provided AI tutor throughout their first academic semester. Building upon this, the analysis focuses on the detailed description of specific usage scenarios over the entire semester and differentiating interaction behaviors within distinct student performance groups. Finally, the paper addresses the question of

what technical limitations and systemic boundaries occur during the practical application of the AI tutor in the students' daily learning routines.

2. Related Work

The theoretical foundation of this work is based on the Cognitive Load Theory (CLT), which states that the human working memory has a strictly limited cognitive capacity (Sweller, 1988). In the field of electrical engineering, the subject's inherent complexity results in a very high intrinsic cognitive load. The primary educational objective is therefore to reduce extraneous cognitive load while maximizing germane cognitive load. However, particularly during the initial phases of university studies, students are confronted with high amounts of both intrinsic loads (inherent difficulty of the task or material itself) and extraneous loads (e.g. organization of study process) simultaneously. This continuous state of cognitive overload is one of the main reasons of university dropout (Naylor, Baik and Arkoudis, 2018; Tight, 2020).

A significant challenge for learners is the transition from procedural knowledge – involving the algorithmic execution of mathematical rules – to conceptual knowledge, which requires recognizing and applying abstract mathematical relationships. This transition becomes especially difficult when complex content is covered too quickly or is significantly beyond the students' prior knowledge level (Koudsia and Kirchner, 2024). Deficits in secondary school education and a lack of routine in performing basic mathematical calculations often mean that exercise sessions and seminars remain on a purely procedural level. Elementary calculation steps, such as solving equations, computing derivatives, or integrating functions, must be carried out in detail. As a compensation strategy, students often try to learn standard problems through pattern matching and overlearning, without truly comprehending the underlying theoretical principles. This ultimately leads to a severe lack of deep conceptual understanding (Kim and Pak, 2002). Furthermore, traditional teacher-centered instruction methods are not scalable due to the high heterogeneity of the student body. In such learning environments, low-performing students often fail at basic algebraic tasks, while high-performing students remain chronically unchallenged.

To address these challenges, the use of generative AI has been introduced in higher education. The overall goal is to promote sustainable and equitable education, as AI enables highly personalized learning environments and facilitates a shift from teacher-centered to student-centered instruction. Current AI systems in education generally fall into three main categories: intelligent tutoring systems, adaptive learning platforms, and AI-driven dialogue systems or chatbots (Asgar, 2025). Their implementation has shown potential for performance improvements, particularly within STEM disciplines (Kestin *et al.*, 2025) and they are most effective when used to supplement human teachers rather than replace them outright (Batsaikhan and Correia, 2024).

AI-driven dialogue systems based on large language models (LLMs) have been used to provide flexible, dialogue-based learning support. (Lin, Huang and Lu, 2023). This is achieved by combining standard language models, such as GPT, Claude, or Gemini, with a domain-specific knowledge base. Specifically, retrieval-augmented generation (RAG) is employed in educational contexts to prevent hallucinations and to seamlessly integrate subject-specific teaching materials (Lewis *et al.*, 2021; Reicher *et al.*, 2025). To prevent AI from merely providing unreflective explanations, it can be configured as a Socratic tutor. This didactic approach emphasizes helping students to help themselves rather than simply transmitting factual knowledge (Santos-Guevara *et al.*, 2026). This approach enables self-paced learning in a psychologically safe environment where students can ask questions without fearing embarrassment due to a lack of knowledge.

Although it has been shown that AI-based learning tools can improve the knowledge, motivation, and self-efficacy of higher education students, their practical impact on higher-order cognitive processes and professional skill acquisition varies considerably and inconsistently across different disciplines (Luo *et al.*, 2025). Furthermore, they often perform poorly as competent pedagogical tutors due to a lack of standardized, learning-science-based evaluation frameworks and specific mistake remediation skills (Maurya *et al.*, 2025). A significant risk associated with this technology is “cognitive offloading”, where a high dependence on AI leads to a decline in critical thinking and a reduced ability to solve problems independently (Qadir, 2023; Farrokhnia *et al.*, 2024; Krupp *et al.*, 2024).

Remaining technological limitations are particularly evident in the field of multimodality, where the integrated processing of voice, video, images and text is required. Moreover, AI systems still struggle with visual spatial “understanding” and the systematic analysis of complex scenarios. In the field of electrical engineering in particular, interpreting and understanding complex circuits remains an unsolved challenge (Skelic *et al.*, 2025).

3. Materials and Methods

The research design and methodology are based on a study conducted at the TUD, Dresden University of Technology, during the winter semester of 2025/26. During this period, an “AI tutor” was provided to 18 first-semester students enrolled in the course “Fundamentals of Electrical Engineering”. The didactic structure of the lecture follows an inverted classroom format: Students independently acquire the course content through self-study using interactive instructional videos, literature and digital tests. This is followed by an in-person session in the auditorium, to further develop conceptual understanding and discuss example problems. Each teaching unit concludes with the completion of four or five exercises, followed by a discussion of the solution approaches in a small-group seminar of approximately 20 students.

The course curriculum is structured to build foundational knowledge of electrical engineering progressively. Starting with basic electrical concepts and quantities (charge, current, voltage, power and energy), it then moves on to Kirchhoff's circuit laws and the characterization of resistive two-poles. Based on these principles, the syllabus then moves on to introduce elementary network analysis, covering topics such as voltage and current dividers, the superposition theorem and two-pole network theory. Subsequently, the course explores power dissipation and maximum power transfer. In the final phase, the curriculum advances to more complex circuit elements and systematic solving techniques, addressing dependent sources alongside nodal voltage analysis and mesh current analysis.

Google Gemini 2.5 Pro (Google LLC, 2026) was utilized and implemented as a RAG system via the you.com platform (SuSea Inc, 2026) for the technical realization of the interactive chat platform. A key feature of the system is the integration of subject-specific documents that are not regularly accessible to students. These include complete transcripts of the instructional videos as well as comprehensive model solutions for the exercises. The AI tutor was methodologically configured as a Socratic tutor, focusing on comprehension-enhancing questions rather than simply providing the complete solution. However, students could obtain the complete solution to a task by explicitly asking for it. To deepen the interaction, it was technically possible for students to upload copies of their own handwritten calculations in the form of photos or screenshots. Students were encouraged to use this feature to have their individual problem-solving approaches verified by the AI.

In line with the United Nations Sustainable Development Goals (SDGs) (United Nations, 2026) and the strategic objectives of both the TUD and the Faculty of Electrical Engineering and Information Technology, the specific foundational goals have been established for an AI tutor in electrical engineering. A key requirement is the utilization of a secure network host for the deployed AI models. Consequently, the approach incorporates the you.com pilot project at TUD, which ensures the privacy-compliant use of AI and LLM systems as a secure alternative to freely accessible models from commercial providers. Furthermore, the framework requires a secure, inclusive, and accessible design, coupled with the continuous evaluation and testing of the implemented AI systems. To guarantee reliable support, designated contact people possessing the necessary AI and technical expertise are continuously available to all users.

The data collection was designed as a longitudinal analysis, using weekly online reflection questionnaires to continuously monitor usage patterns and perceived task difficulty. These weekly instruments served for self-assessment and contained specific quantitative and qualitative items. Subjective difficulty was evaluated using the question “How easy was it for you to complete the tasks without the support of an AI tutor?” measured on a five-point scale ranging from “very easy” (1) to “very difficult” (5). Concrete usage behavior was documented via the prompt “Please select how you utilized the AI tutor for the task.” Multiple-choice options included: non-usage, asking for an initial approach, asking for hints on the next steps, verifying one's own calculation, checking the final result, searching specifically for errors in one's own calculation, and requesting an explanation of the entire calculation path. This was supplemented by a free-text field in which students were asked to briefly describe what they found helpful or unhelpful during their usage.

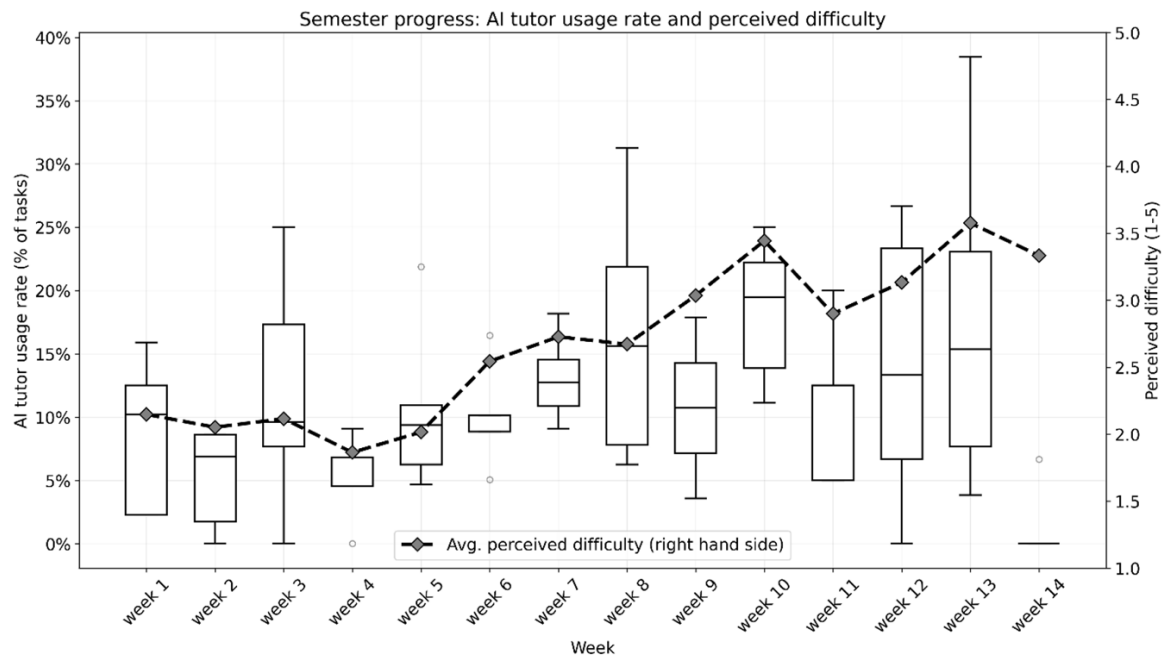


Figure 1: The usage rate of the AI tutor (the percentage of exercise tasks for which the AI tutor has been requested by all students) and the perceived average task difficulty over the 14-week semester.

In addition to the weekly data collection, the evaluation design included two cross-sectional surveys. A mid-term evaluation focusing on the general usefulness of the AI tutor and identifying immediate technical limitations was conducted in the middle of the semester. The study concluded with a final survey at the end of the semester, before the examinations. This served to evaluate the tool's effectiveness and prompted critical self-reflection from the students regarding their current and future use of AI in the context of their university studies.

4. Results and Discussion

Data on the students' interactions with the AI tutor has been collected over the 14-week winter semester. Initially, participation in the weekly feedback forms was high, with all 18 students responding in the first week. However, this number gradually decreased, with only five students responding by week 14. During the semester, the average perceived difficulty of the exercises increased steadily, rising from 2.15 in week 1 to 3.33 in week 14, on a 5-point scale (see Figure 1). Concurrently, the median usage rate of the AI tutor increased slightly, and the variance in AI tutor usage among the students also widened as the semester progressed, indicating diverging interaction strategies over time.

An analysis of the types of AI support requested and categorized by perceived task difficulty reveals distinct usage patterns (see **Error! Reference source not found.**). For tasks perceived as very easy (difficulty level 1), the AI tutor was largely ignored, with students opting not to use the system in 97 % of these cases. Across all difficulty levels, students rarely requested only the final result of an exercise. As the perceived difficulty increased to moderate and high levels, however, students predominantly used the AI tutor to verify their own calculations, search for errors or request hints and approaches for the next steps. Requests for a complete explanation of the calculation path were exclusively reserved for the most difficult tasks, specifically those rated as difficulty levels 4 or 5.

At the end of the course, the students' final exam scores were compared against their average perceived difficulty ratings for the exercises completed throughout the semester. As shown in Figure 3, the data indicates a weak negative correlation between these two. Students who rated the weekly tasks as more difficult on average tended to achieve lower scores in the final examination.

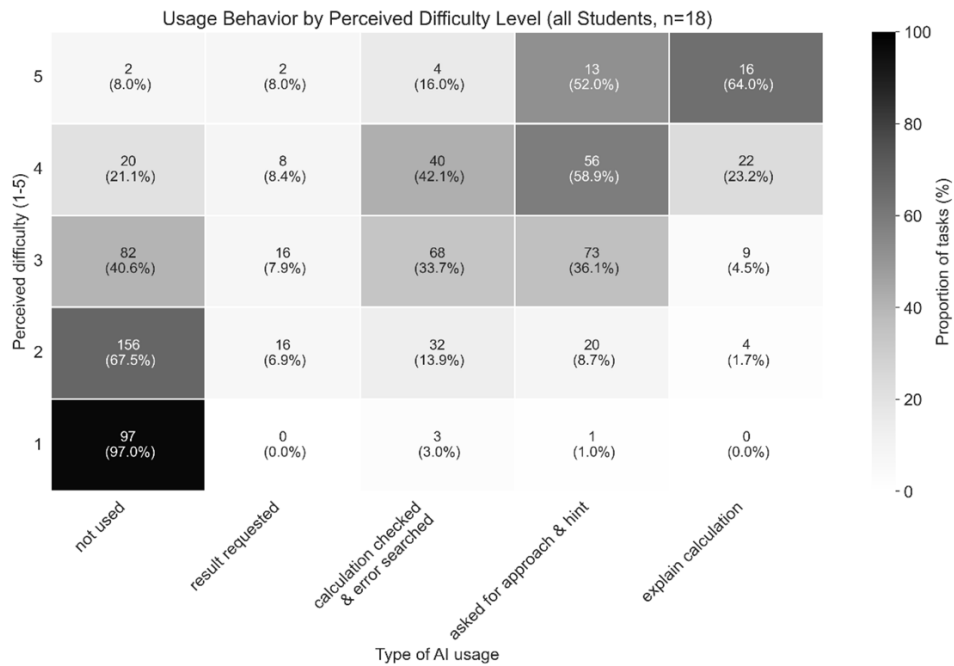


Figure 2: Usage of AI tutor by perceived difficulty of exercise tasks. Each entry gives the absolute number of responses and the percentage of tasks for which the respective type of AI usage was used. Because multiple choices were allowed, the total percentage in a row may exceed 100 %.

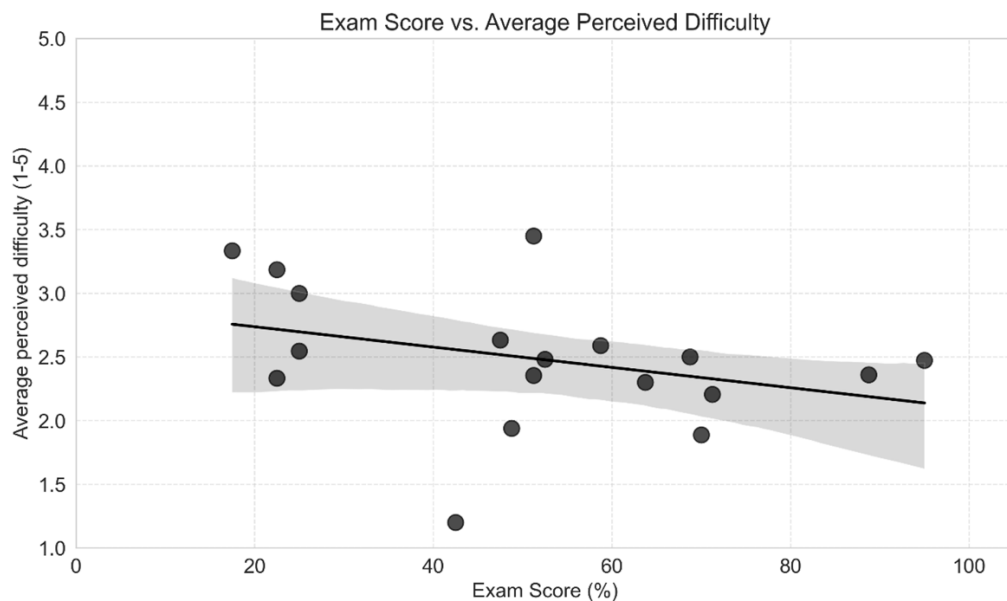


Figure 3: Average perceived difficulty of exercise tasks versus the score in the final exam, where each dot represents one student. The black line shows a linear regression, and the gray area indicates the 95 % confidence interval.

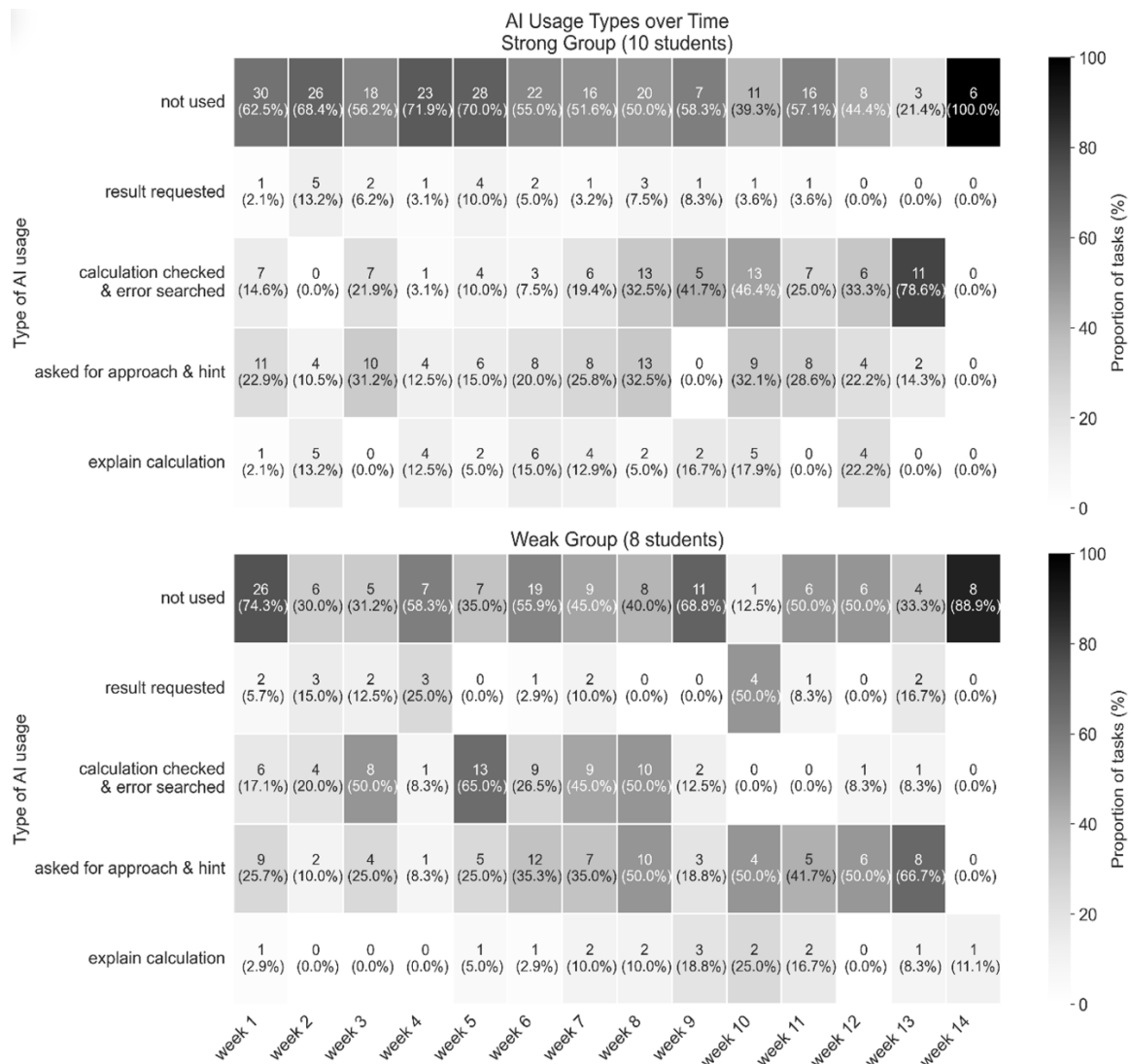


Figure 4: Usage of AI tutor over the semester for the cohort of high-performing students (top) and low-performing students (bottom). Each entry gives the absolute number of responses for all tasks of the respective week (up to 5 responses for each student possible) and the percentage of tasks for which the respective type of AI usage was used. Because multiple choices are allowed, the total percentage in a column may exceed 100 %. Example: In the lower diagram (weak group) at week 5 over all exercise tasks a total of 13 responses to the categories “own calculation checked” and “error in own calculation searched” were registered and the students of this cohort used the AI in 65 % of all tasks to “check own calculation” or to “find errors in own calculations”.

To gain a better understanding of usage behaviour, the cohort was divided retrospectively into two groups based on final exam performance: higher-performing students (10 students), who scored at least 50 %, and lower-performing students (8 students), who scored below 50 %. Figure 4 shows the longitudinal data highlighting differences in how these two groups interacted with the AI tutor in terms of intensity and regularity. The stronger group demonstrated a more consistent usage pattern throughout the semester, frequently using the AI to check their calculation steps, particularly as the semester progressed. In contrast, the weaker group exhibited slightly different behavior: Their engagement in checking their own calculations dropped significantly in the later weeks. Towards the end of the semester, the proportion of tasks for which the AI was not used at all was often noticeably higher for the lower-performing group than for their higher-performing peers.

The didactic focus of the AI interactions also varied considerably between the two performance cohorts. The higher-performing students primarily utilized the AI tutor as a validation tool. Their requests to check calculations and search for errors increased substantially towards the end of the semester. For this group, the AI functioned as an efficiency tool to secure their own academic performance. In contrast, the lower-performing students utilized AI more frequently to overcome cognitive blockages. They regularly asked for general

approaches and hints to find an entry point into the tasks. Furthermore, during the first half of the semester (weeks 2 to 4), the weak group tended slightly more to request the final result outright (up to 25 % of tasks), whereas the strong group rarely exhibited this behavior. This suggests a stronger tendency among the weaker cohort to consume ready-made solutions.

As the inherent complexity and the perceived difficulty of the course material increased throughout the semester, the two groups reacted differently. The strong group responded by using the AI tutor more frequently to verify complex calculation steps. In contrast, the weaker group showed a growing tendency to fall behind. By week 14, 88.9 % of the weak group had not used the AI tutor. This high rate of non-usage, combined with the overall decline in questionnaire response rates, suggests potential resignation or abandonment of the exercise tasks altogether.

Qualitative data gathered from the open-text fields of the weekly questionnaires provides deeper insights into these usage patterns. Students appreciated the Socratic guidance, with one stating that "the approach helped me solve the task without the AI giving the answer directly, allowing me to complete it independently". The AI also served as a safety net, providing a "sense of security" by enabling students to "have the entire solution path explained and ask specific follow-up questions". One student specifically highlighted its value in error detection: "I make many careless mistakes, and the AI sometimes helps me with them."

In contrast, critical feedback highlighted significant technical and pedagogical limitations. Some users reported that "the AI makes gross errors" and noted that certain tasks were "too complex for the AI in its current state". The lack of multimodal capabilities was particularly criticized, with one student remarking that "the AI tutor is somehow not suitable for more graphical explanations" as certain concepts can only be understood "if someone explains them using the circuit diagram". Finally, some students found the AI's responses "too general," which "did not help move the calculation forward". These reported limitations can be attributed to two main factors. Firstly, the errors may originate directly from the system's inherent technical constraints. Alternatively, the issues may stem from how the AI model is operated by the users. A lack of AI literacy among students can result in inputs that are inadequate or poorly structured. Consequently, suboptimal prompting can exacerbate the model's tendency to hallucinate, leading directly to an increase in erroneous or overly general outputs.

The end-of-semester evaluation revealed that the participating students generally had a positive perception of the AI tutor. As shown in Figure 5, the students particularly valued the system's ability to verify their individual calculation methods. The tool was recognized for its effectiveness in helping students to overcome short-term learning blockades, thereby successfully promoting independent and asynchronous learning outside of the traditional classroom environment and schedule.

The evaluation of the AI tutor revealed a clear correlation between the increasing perceived task difficulty and course content progression. Students perceived topics introduced later in the semester, such as network analysis, dependent sources and nodal voltage analysis, as significantly more complex than basic calculations involving elementary electrical quantities. Despite this increasing complexity, students reported very few technical issues when interacting with the AI tutor (see Figure 5). The final evaluation indicates that students generally found the AI's answers comprehensible. In some cases, however, they felt the tutor gave away the solution paths unprompted. Overall, the AI was perceived as a highly beneficial tool for finding an entry point into complex tasks. Students emphasized that the system enabled them to start assignments that they would otherwise not have been able to work on and prevented them from getting stuck without making progress. Consequently, using the AI tutor can significantly reduce cognitive overload by supporting the problem-solving process. Furthermore, the system proved highly effective in helping students identify computational errors that they would otherwise have overlooked.

The AI's ability to identify basic calculation errors could reduce the need for in-person teaching. By delegating routine error correction to the AI, valuable time during exercise sessions can be freed up for deeper, more conceptual discussions. However, it is important to emphasize that the AI tutor is not a standalone replacement for human instructors. Students strongly disagreed with the notion that a technically mature AI tutor eliminates the need for a weekly exercise session with a human teacher. Additionally, the results critically show that the AI tutor only marginally increased the students' intrinsic motivation to solve the tasks.

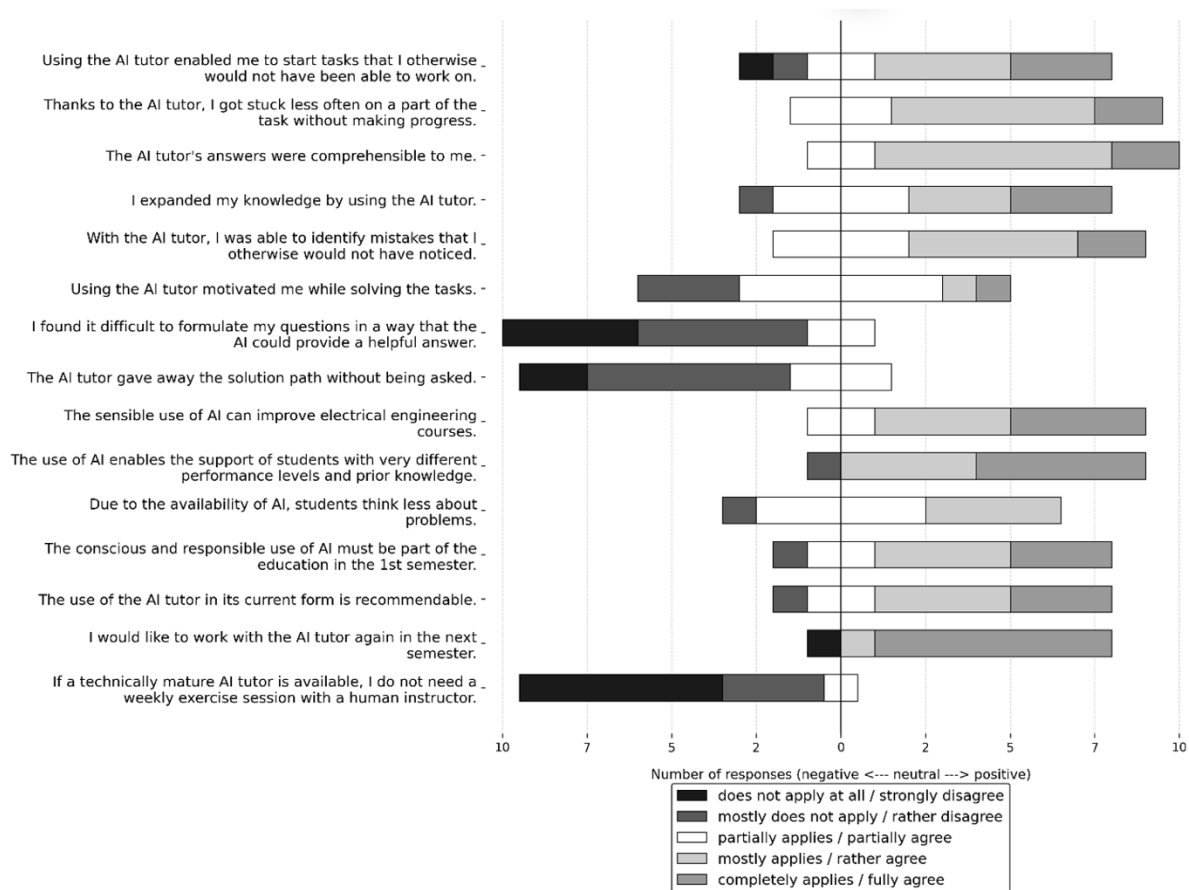


Figure 5: Final evaluation of the AI tutor. (excerpt; questions with redundant content have been omitted)

A highly critical finding of the final evaluation is the students' self-reflection regarding their own cognitive engagement: a large majority (9 out of 10 students) partially or rather agreed that the availability of AI leads to students thinking less about the problems (see Figure 5). This alarming trend highlights the urgent need to integrate "AI literacy" into the university curriculum. Students strongly agreed that learning the conscious and responsible use of AI must be a mandatory part of first-semester education. The ability to critically question and evaluate AI-generated results is an essential skill that must be actively taught to prevent over-reliance and superficial learning. Despite these concerns, there remains a strong consensus among the cohort that the sensible use of AI can generally improve electrical engineering courses.

Finally, the methodological limitations of the current study must be reflected critically: The overall validity of the findings is constrained by the small group size and a noticeably declining response rate in the feedback questionnaires over the semester. This drop in participation threatens the representativeness of the late-semester data. However, this is also consistent with the frequently observed decline in commitment to class attendance and the preparation of homework assignments over the semester. Furthermore, the technical implementation focused entirely on one specific language model. To meet the specific and complex demands of engineering education in the future, true multimodality will be required. Future systems must be capable of processing, interpreting, and *generating* circuit diagrams, technical charts, and visual schematics to provide adequate and comprehensive support.

5. Outlook and Conclusion

From the authors' perspective, future developments should focus on an integrated, AI-driven learning environment capable of continuously assessing individual learning progress to provide targeted and personalized recommendations on established and purpose-built teaching methods. To complement this student-centered approach, it is highly desirable to establish a data pipeline that provides instructors with aggregated, anonymized insights into exercise performance, usage patterns, student–AI communication, and emerging hallucinations. This would enable lecturers to adapt content dynamically, implement demand-oriented interventions and review or restructure complex topics based on empirical learning analytics.

In the current semester, the pilot project has been scaled up to include a larger cohort of around 200 second-semester students. This includes a comparative evaluation of different LLMs regarding their practical usability. However, expanding the use of these tools highlights the importance of fostering AI literacy among students and educators to ensure accurate and productive interactions. Although enabling users to customize and optimize AI tutors according to their specific needs offers significant potential for sustainable personalization, this fundamentally requires highly responsible and ethical engagement with generative AI. Ultimately, the core findings confirm that, while the AI tutor is an effective instrument for personalizing undergraduate education, it remains supplementary to, rather than a replacement for, human mentorship and supervision.

Ethics Declaration

Participation in this study was strictly voluntary. All collected data was analyzed anonymously, and prior informed consent was obtained from all participating students.

AI Declaration

During the preparation of this work, the authors used Google Gemini 3.1 Pro to generate Python program code for the creation of diagrams in Figures 1-5. Specifically, the generated code was used to process the database containing the feedback forms collected during the semester and the results from the mid-term and final evaluations, and to visualize the respective data series. Additionally, AI assistance was employed to refine the orthography, grammar, and language throughout the manuscript.

Sustainable Development Goals

Below are all the key United Nations Sustainable Development Goals (United Nations, 2026) that are relevant to this paper: Goal 4: Ensure inclusive and equitable quality education and promote lifelong learning opportunities; Goal 5: Achieve gender equality and empower all women and girls; Goal 8: Promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all; Goal 9: Build resilient infrastructure, promote inclusive and sustainable industrialization and foster innovation; Goal 10: Reduce inequality within and among countries; Goal 16: Promote peaceful and inclusive societies for sustainable development, provide access to justice for all and build effective, accountable and inclusive institutions at all levels.

References

- Asgar, D. (2025) "Analysing the Effectiveness of Different AI-Based Tutoring Systems and their Impact on Education across Global Contexts: A Literature Review," *The National High School Journal of Science* [Preprint]. Available at: <https://nhsjs.com/2025/analysing-the-effectiveness-of-different-ai-based-tutoring-systems-and-their-impact-on-education-across-global-contexts-a-literature-review/>.
- Batsaikhan, B. (Zack) and Correia, A.-P. (2024) "The effects of Generative Artificial Intelligence on Intelligent Tutoring Systems in higher education: A systematic review," *Studies in Technology Enhanced Learning*, 4(1). Available at: <https://doi.org/10.21428/8c225f6e.33570bb1>.
- Casanova, J. et al. (2021) "University Dropout in Engineering: Motives and Student Trajectories," *Psicothema*, 4(33), pp. 595–601. Available at: <https://doi.org/10.7334/psicothema2020.363>.
- Farrokhnia, M. et al. (2024) "A SWOT analysis of ChatGPT: Implications for educational practice and research," *Innovations in Education and Teaching International*, 61(3), pp. 460–474. Available at: <https://doi.org/10.1080/14703297.2023.2195846>.
- Fierro Saltos, W.R. et al. (2025) "Leveraging Artificial Intelligence for Sustainable Tutoring and Dropout Prevention in Higher Education: A Scoping Review on Digital Transformation," *Information*, 16(9), p. 819. Available at: <https://doi.org/10.3390/info16090819>.
- Google LLC (2026) *Gemini 2.5 Pro Documentation*, online. Available at: <https://docs.cloud.google.com/gemini-enterprise-agent-platform/models/gemini/2-5-pro?hl=de> (Accessed: May 21, 2026).
- Hartmann, R. (2025) "Finanzielle Sorgen an Sachsens Hochschulen – Kürzungen treffen auch Gleichstellung und Lehre." Available at: <https://www.mdr.de/nachrichten/sachsen/politik/uni-hochschulen-finanzierung-sparen-kuerzungen-100.html>.
- John, C. (2026) "Another Wave of Faculty and Program Cuts Is Hitting American Universities. Here's Who's Cutting What — and Why It Won't Stop." Available at: <https://www.universityherald.com/articles/80226/20260316/another-wave-faculty-program-cuts-hitting-american-universities-heres-whos-cutting-what.htm>.
- Kestin, G. et al. (2025) "AI tutoring outperforms in-class active learning: an RCT introducing a novel research-based design in an authentic educational setting," *Scientific Reports*, 15(1), p. 17458. Available at: <https://doi.org/10.1038/s41598-025-97652-6>.

- Kim, E. and Pak, S.-J. (2002) "Students do not overcome conceptual difficulties after solving 1000 traditional problems," *American Journal of Physics*, 70(7), pp. 759–765. Available at: <https://doi.org/10.1119/1.1484151>.
- Koudsia, S. and Kirchner, M. (2024) "Reducing cognitive overload for students in higher education: A course design case study," *Journal of Higher Education Theory and Practice*, 24(10), pp. 97–124.
- Krupp, L. et al. (2024) "Unreflected Acceptance – Investigating the Negative Consequences of ChatGPT-Assisted Problem Solving in Physics Education." Available at: <https://doi.org/10.3233/FAIA240195>.
- Lewis, P. et al. (2021) "Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks." Available at: <http://arxiv.org/abs/2005.11401>.
- Lin, C.-C., Huang, A.Y.Q. and Lu, O.H.T. (2023) "Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review," *Smart learning environments*, 10(1), p. 41.
- Luo, J. et al. (2025) "Design and assessment of AI-based learning tools in higher education: a systematic review," *International Journal of Educational Technology in Higher Education*, 22(1), p. 42. Available at: <https://doi.org/10.1186/s41239-025-00540-2>.
- Maurya, K.K. et al. (2025) "Unifying AI Tutor Evaluation: An Evaluation Taxonomy for Pedagogical Ability Assessment of LLM-Powered AI Tutors," *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*. Stroudsburg, PA, USA: Association for Computational Linguistics, pp. 1234–1251. Available at: <https://doi.org/10.18653/v1/2025.naacl-long.57>.
- Naylor, R., Baik, C. and Arkoudis, S. (2018) "Identifying attrition risk based on the first year experience," *Higher Education Research & Development*, 37(2), pp. 328–342. Available at: <https://doi.org/10.1080/07294360.2017.1370438>.
- Qadir, J. (2023) "Engineering Education in the Era of ChatGPT: Promise and Pitfalls of Generative AI for Education," *2023 IEEE Global Engineering Education Conference (EDUCON)*. IEEE, pp. 1–9. Available at: <https://doi.org/10.1109/EDUCON54358.2023.10125121>.
- Reicher, H. et al. (2025) "A Generative AI-Empowered Digital Tutor for Higher Education Courses," *Information*, 16(4), p. 264. Available at: <https://doi.org/10.3390/info16040264>.
- Santos-Guevara, A. et al. (2026) "Fostering Student Engagement and Learning Perception Through Socratic Dialogue with ChatGPT: A Case Study in Physics Education," *Education Sciences*, 16(2), p. 184. Available at: <https://doi.org/10.3390/educsci16020184>.
- Skelic, L. et al. (2025) "CIRCUIT: A Benchmark for Circuit Interpretation and Reasoning Capabilities of LLMs." Available at: <http://arxiv.org/abs/2502.07980>.
- Sultana, S., Khan, S. and Abbas, M.A. (2017) "Predicting performance of electrical engineering students using cognitive and non-cognitive features for identification of potential dropouts," *International Journal of Electrical Engineering Education*, 54(2), pp. 105–118.
- SuSea Inc (2026) *you.com chat, online*. Available at: <https://you.com/chat> (Accessed: May 21, 2026).
- Sweller, J. (1988) "Cognitive load during problem solving: Effects on learning," *Cognitive science*, 12(2), pp. 257–285.
- Tayebi, A., Gómez, J. and Delgado, C. (2021) "Analysis on the Lack of Motivation and Dropout in Engineering Students in Spain," *IEEE Access*, 9, pp. 66253–66265. Available at: <https://doi.org/10.1109/ACCESS.2021.3076751>.
- Tight, M. (2020) "Student retention and engagement in higher education," *Journal of Further and Higher Education*, 44(5), pp. 689–704. Available at: <https://doi.org/10.1080/0309877X.2019.1576860>.
- United Nations (2026) *THE 17 GOALS*. Available at: <https://sdgs.un.org/goals> (Accessed: May 21, 2026).