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Large Language Model-driven Human–AI Collaboration: An Innovative Approach for Training and Knowledge Construction in Undergraduate Electronics Design Competitions

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In this study, we investigated the application of large language models (LLMs), a subset of AI systems specifically designed for natural language understanding and generation, in undergraduate electronics design competitions, with a focus on how these AI tools can facilitate human–AI collaboration. Using the National Undergraduate Electronics Design Contest as a case study, we examined how LLMs can enhance the design process, improve problem-solving skills, and facilitate the iterative optimization of engineering solutions. The design task centers on an ultrasonic audio jamming system (commonly referred to as a “recording shielding system”) that integrates key sensor-related technologies, including ultrasonic transducers, microphone-based audio monitoring, and frequency-domain signal analysis using the fast Fourier transform. These components form a functional sensor application scenario, where the system detects and discriminates audio signals to enable a dynamic response. In this study, we examined the application of LLM-driven tools to assist students during the design and development of the sensor-based system, demonstrating how these tools supported students in addressing complex technical challenges. We highlight the advantages of using AI for in-design proposal generation, system optimization, and troubleshooting, while also addressing the challenges of ensuring that AI-generated solutions are accurate and feasible within competition constraints. The findings suggest that LLMs make a significant contribution to students’ learning outcomes, fostering creativity, critical thinking, and technical proficiency in real-world engineering contexts. In this paper, we offer valuable insights into the evolving role of AI in enhancing educational practices in engineering design.

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1. Introduction

1.1 Overview and impact of the National Undergraduate Electronics Design Contest (NUEDC) in China

NUEDC, co-initiated by China's Ministry of Education and Ministry of Industry and Information Technology, is a nationwide academic competition designed to advance curriculum reform in electronic information disciplines and cultivate university students' innovation capabilities, teamwork, and engineering practice skills.(1) Established in 1994, the contest is typically held biennially in September of odd-numbered years since 1997, and the contest spans four days and three nights [Fig. 1(a)]. It operates under a "unified national problems, regional organization" structure with a "semi-open, relatively centralized" format. Participating student teams (usually three-member teams) independently complete the entire task—from design, fabrication, and debugging to report writing—within designated venues [Fig. 1(b)]. While consulting resources and internal team discussion are allowed, any form of guidance or intervention from teachers or external individuals and inter-team discussions are strictly prohibited. The problems cover a wide range of electronic information technology areas, including power supplies, signal sources, RF/wireless systems, amplifiers, instrumentation, data acquisition and processing, and control systems, emphasizing the integration of theory and practice, system integration, and innovation.(1)

As one of the largest and most influential undergraduate competitions in China's electronic information field, NUEDC plays a vital role in talent development and industry–academia integration. For instance, the 2023 contest attracted over 60000 students in 20939 teams from 1134 institutions nationwide.(2) NUEDC significantly promotes practical teaching reform in universities, markedly enhancing students' engineering practice abilities, innovative thinking, and teamwork skills. Furthermore, long-term sponsorship and support from renowned

(a) (b)

Fig. 1. (Color online) (a) NUEDC 2024 finals. (Source: https://www.nuedc-training.com.cn/) (b) Students from Shandong Polytechnic (the present research team) prepared for the competition.

companies such as Texas Instruments (TI) strengthen the ties between academia and industry, ensuring that the contest content reflects current industry trends and technological demands.[3] Furthermore, achievements in the NUEDC are widely recognized as a key indicator of students' practical innovation capabilities, positively impacting their prospects for postgraduate studies and employment.

1.2 Knowledge construction in university engineering science education driven by LLMs: Human–AI collaboration approach

In recent years, large language models (LLMs)—a specialized form of AI that focuses on processing and generating human-like text—have gradually entered higher education, particularly in engineering science, significantly transforming the way knowledge is constructed. With the development and application of these models, the human–AI collaboration teaching model has emerged as an innovative learning approach, combining the strengths of both human instructors and AI models to enhance students' learning outcomes and creative abilities significantly. In this paper, we explore how LLMs have driven knowledge construction in the engineering science domain in recent years. We analyze the practice and challenges of the human–AI collaboration model.

The human–AI collaboration model involves an active interaction between students and AI in the learning environment. In this model, AI is not just a tool but an active participant in the learning process, offering real-time feedback and adjusting to students' learning progress and needs. In this study, such collaboration is applied to the design of an ultrasonic recording shielding system—a representative sensor-based system that integrates audio sensing, analog signal conversion, and frequency analysis. These techniques are essential to many modern sensor systems, making this a meaningful case of LLM-driven knowledge construction in a sensing context. This model emphasizes AI as an active collaborator in learning, enhancing learning efficiency and helping students achieve better outcomes.[4] Such AI applications enhance students' learning experience and allow instructors to focus more on high-level guidance and academic research.[5]

LLMs can be applied in engineering science education not only to teach basic knowledge but also to foster higher-order skills and assist with professional research. For instance, Bernabei *et al*.[6] found that students using LLMs for engineering design and problem solving were able to increase the effectiveness of their learning and accelerate their understanding of complex concepts. These models provide precise calculations, visualizations, and explanations in areas such as mathematical derivations, physical simulations, and engineering design, even suggesting optimization strategies during the design process. Moreover, Filippi and Motyl[7] highlighted the widespread use of LLMs in engineering education for course assistance, problem solving, and academic research. These models also significantly enhance academic discussions and critical thinking, enabling students to approach problems from multiple perspectives and conduct a more profound analysis.

This human–AI collaborative approach is especially valuable in competition-oriented education environments. In many engineering competitions, students need to learn and apply complex theories and techniques rapidly, and AI can help them analyze problems, design solutions, and perform simulation tests. For example, the ChatGPT-powered intelligent car racing competition training model proposed by Chen *et al.*[8] uses AI to assist students in problem exploration and solution optimization, significantly enhancing their performance in competitions.

Although LLMs have brought significant learning benefits to engineering education, there are challenges in practice. First, AI-generated responses may not always be accurate, especially when handling highly specialized problems, leading to potential errors or biases.[9] This necessitates instructors' additional guidance and corrections. Moreover, the reasoning capabilities of current AI models are still not at the level of human experts, limiting their use in more advanced academic problems.[10]

In this study, instructors act as domain experts and design reviewers. Although direct intervention during the competition is prohibited, instructors provide guidance in pre-competition training and simulation, helping students assess the feasibility of AI-generated proposals, identify flaws, and refine designs on the basis of engineering best practices. Their role is critical in bridging the gap between AI suggestions and real-world implementation constraints.

1.3 Study objective

In this study, we explore how LLMs can foster human–AI collaboration in undergraduate electronics design competitions. Specifically, we aim to investigate the integration of LLM-driven AI tools into knowledge construction and design processes, enhancing students' learning experiences and competitive performance. NUEDC serves as the primary case study, highlighting its role in promoting innovation, teamwork, and practical engineering skills among students. We examine how LLMs can assist students in generating innovative design proposals, optimizing technical solutions, and addressing real-world challenges encountered during these competitions. We identify the benefits and limitations of incorporating LLMs into such high-pressure, performance-oriented environments and assess their potential for improving the overall educational experience in engineering design. Additionally, we seek to provide insights into the practical application of human–AI collaboration models in fostering creativity, problem solving, and iterative learning, which are essential skills in modern engineering education.

The paper is organized as follows. In Sect. 1, we outline the context of the NUEDC and introduce human–LLM collaboration in engineering education. In Sect. 2, we describe the LLM-assisted design workflow of a simple recording shielding system, detailing the iterative interactions among students, LLMs, and instructors. In Sect. 3, we present the system implementation, focusing on design integration, optimization, and feasibility under competition constraints. In Sect. 4, we discuss the collaborative model, compare it with related work, and identify key implications and limitations. In Sect. 5, we conclude the study and outline directions for future research on LLM-supported design and learning systems.

2. Optimal Design of Simple Recording Shielding System by LLMs

2.1 Simple recording shielding system design: Tasks and requirements

In this section, we introduce one of the tasks for the 2024 NUEDC Regional Competition and the Preliminary Competition of the Simulation Electronic System Design Topic—designing an ultrasonic audio jamming system, officially titled in the competition as a "Simple Recording Shielding System".[11] This system aims to emit targeted ultrasonic interference to prevent audio recording by nearby devices while allowing normal human conversation to proceed unaffected. Unlike physical shielding, this design relies on inaudible sound waves to disrupt microphone input, a method grounded in acoustic interference rather than mechanical isolation (see Fig. 2). The system consists of two main components: the signal generator and the audio monitoring/recognition module. The sound source device is required to emit audio signals with an intensity of approximately 50 dB/1 m (equivalent to everyday human speech), a duration of at least 10 s, and the ability to replay. The recording/playback device must receive and record audio signals within a frequency range of 100 Hz to 20 kHz and include storage capable of recording for at least 10 s. The sound source and recording/playback devices can be implemented using smartphones.

In terms of specific requirements, the signal generator must emit effective shielding signals with a shielding distance ≥1 m and a shielding angle ≥60° (see Fig. 3). The audio monitoring and recognition module must detect the presence or absence of audio signals and, when no audio is present, the signal generator must be automatically controlled to stop and turn off the LED indicator. The signal generator's input power must be ≤6 W, with an output power adjustable between 1 and 4 W in 1 W steps. The system must also identify different types of audio signal and selectively shield voice or music signals on the basis of the recognized type. Finally, a detailed design report covering the design process and related testing must be submitted.

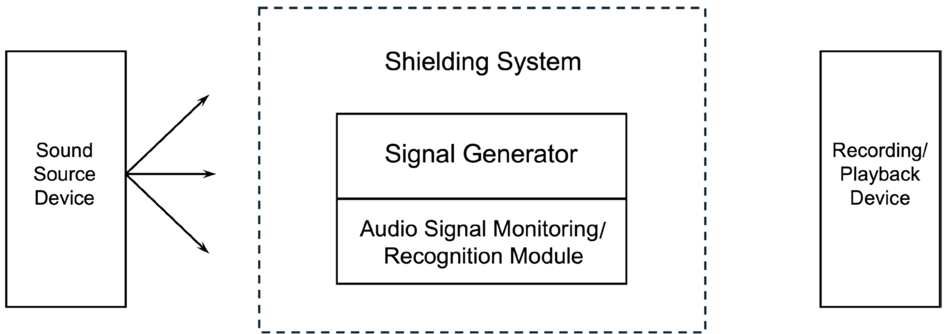

Fig. 2. Schematic of working principle of ultrasonic audio jamming system, which emits directional sound waves to interfere with microphone recordings.

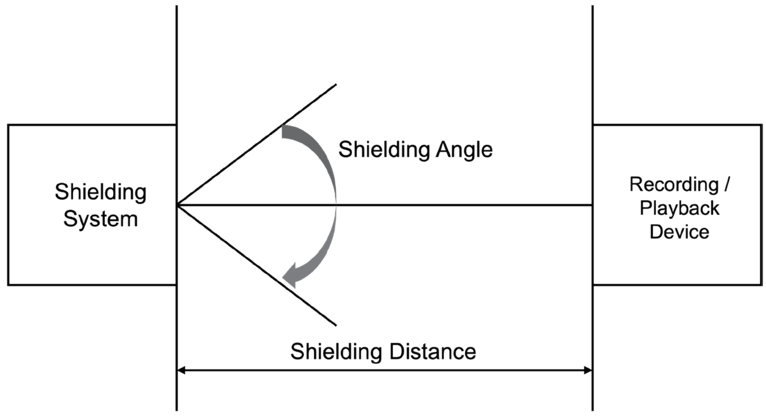

Fig. 3. Effective jamming distance and angle for ultrasonic signal emitted by audio jamming system.

The instructions specify that the signal generator should use a low-frequency ultrasonic transducer to generate the shielding signal. This ultrasonic signal is inaudible to humans but effective at blocking recording devices. Care must be taken to avoid excessive power output and direct exposure to humans to prevent harm when using ultrasonic transducers. Additionally, shielding distance refers to the maximum straight-line distance at which the shielding signal can block recordings, and shielding angle refers to the angular coverage of the signal. During the design process, test ports should be reserved to facilitate the testing of parameters such as the power input of the signal generator. Throughout this process, using commercially available recording shielding products for modification is prohibited; all designs must be self-developed and constructed.

2.2 LLM-generated design proposal and optimization

We employed the Gemini 2.0 Flash Thinking Experimental to generate the design proposal. Table 1 provides a brief introduction, followed by a table that summarizes the key points of the process. The table presents the evolution of the design for the ultrasonic recording jamming system, a device that actively interferes with microphones using sound waves by summarizing student queries (P01–P06), Gemini's deep thought process (T01–T06), and the corresponding responses (R01–R06). It reflects the progression from initial requirement definition and problem breakdown to detailed module design and overall system integration, incorporating instructor feedback on feasibility, implementation challenges, and optimization directions. The detailed process is presented as follows.

(1) Initial Inquiry: The entire workflow of generating and optimizing the design proposal involves a multi-stage, iterative process that fully reflects the comprehensive balance between theoretical analysis, solution conception, expert feedback, and practical feasibility considerations. Initially, the participating students raised questions (P01) on the basis of the competition problem, clarifying the required basic functions and technical specifications the

Table 1
LLM-generated processes of design proposal and optimization.

Phase ID	User Prompts (P)	LLM Deep Thoughts (T)	LLM Deep Response (R)
P01/T01/R01	Initial competition requirements: design a recording shielding system with a signal generator and an audio monitoring module, with specified performance metrics.	Analyze the problem, decompose core functions (shielding effect, audio detection, power control, and signal recognition), and outline initial implementation ideas.	Provide a detailed plan with system modules, basic working principles, and initial implementation methods.
P02/T02/R02	Request annotations mapping each part to specific requirements, checking for conflicts, and generating a design report outline.	Analyze design requirements, verify internal consistency, and formulate detailed annotations and a report outline with translation considerations.	Revise the plan with clear requirement mappings and present the design report outline with expert feedback.
P03/T03/R03	Request a more complete design for the audio monitoring/identification module, including hardware, circuit design, software implementation, and testing optimization.	Detail the design of the audio module, discussing the selection of components (microphone, op-amp, filter, ADC, and MCU), circuit structure, software algorithms, and testing strategies.	Present a comprehensive design for the audio module with specific component choices, typical circuits, AI-generated code, and testing strategies.
P04/T04/R04	Request a detailed design plan for the signal generator module, covering hardware composition, circuit design, software control, and testing optimization.	Discuss the selection of ultrasonic transducers, driver circuit design, power adjustment methods (manual or programmable), and testing approaches.	Provide a detailed plan for the signal generator, including an ultrasonic array, driver chip, programmable power adjustment, code examples, and optimization methods.
P05/T05/R05	Request a complete design plan for the power supply section, covering input protection, voltage regulation, filtering, and power monitoring.	Analyze power supply requirements, plan for USB or DC input, ESD and overvoltage protection, voltage regulation (LDO/DC–DC), filtering, and monitoring solutions.	Offer a detailed power supply plan, including input protection, regulator selection, filtering design, monitoring circuitry, and testing optimization methods.
P06/T06/R06	Request a comprehensive software design plan (microcontroller program) detailing architecture, audio detection, signal recognition, state control, etc.	Develop the software architecture (superloop or interrupt-driven), detailing algorithms for audio detection (thresholding, filtering, and debouncing), signal recognition (FFT or time-domain features), and state machine control.	Provide a complete software design with algorithm flows, state machine logic, AI-generated code examples, debugging, and tuning strategies.

system needs to meet, such as shielding distance, shielding angle, power control, and audio signal monitoring and recognition requirements.

(2) Model Planning: On the basis of this preliminary inquiry, Gemini initiated its deep-thinking process (T01), breaking down the complex problem into several core modules. It then provided preliminary plans for each module's technology paths, component selection, and implementation methods, eventually presenting an overall design solution (R01).

(3) Instructor-guided Refinement: Building on the initial solution, instructors prompted students to critically review AI's responses, pointing out potential shortcomings in implementation difficulty, real-world application, and time constraints. These guided revisions prompted the

model to revise and optimize the solution in subsequent answers to ensure that the design met theoretical requirements while being practically feasible. Subsequent queries (e.g., P02), informed by instructor feedback, asked for detailed annotations of each part of the solution, reviewing the design descriptions and their alignment with the requirements while generating an outline for the design report to provide structural guidance for writing the full report. Gemini in T02 and R02 elaborated on annotating design requirements, resolving conflicts between solutions, and integrating illustrations and a report outline.

(4) Module Design: The workflow then delved into the specific design of each module. P03 focused on the audio signal monitoring and recognition module, requiring a detailed process for the hardware circuits, including the microphone, preamplifier, filter circuits, and analog-to-digital converter (ADC), among others. P03 also pays attention to software signal processing, including threshold detection, fast Fourier transform (FFT) analysis, feature extraction, and classification, as well as parameter testing and optimization. In T03 and R03, Gemini provided a detailed design plan, including specific component choices, typical circuit design schemes, AI-generated code (pseudocode) examples, and testing strategies, while also offering expert suggestions on practical feasibility and debugging difficulty.

(5) Component Selection and Detailing: Next, P04 requested a complete design plan for the signal generator module, requiring a detailed description of how to achieve the specified shielding distance and angle through an ultrasonic transducer array, drive circuits (e.g., using dedicated chips or discrete components), and power adjustment methods (manual or programmable), along with corresponding code examples and testing optimization plans. Gemini expanded on this in T04 and R04, detailing everything from component selection and driver circuit construction to programmable adjustment schemes and testing calibration methods while incorporating instructor feedback on simplifying hardware and prioritizing software solutions. In P05, the student focused further on the power section of the design, requiring detailed plans for input protection, voltage regulation, filtering, and power monitoring. The LLM (Gemini) in T05 and R05 discussed USB or DC power input options, electrostatic discharge (ESD) and overvoltage protection, the choice between low dropout regulator (LDO) or DC to DC converters, and how to implement power monitoring using voltage dividers and sampling resistors. It also provided an AI-generated code (pseudocode) to demonstrate how the microcontroller unit (MCU) could sample and compute these parameters. Instructor feedback in this section emphasized considering high current demands and heat management in practical applications.

(6) Software Design and Testing Strategy: Finally, P06 proposed more comprehensive software design plans, requiring the coverage of the microcontroller program architecture, audio signal detection, signal type recognition, state machine control logic, LED indication, and optional low-power management and debugging communication functions. In T06 and R06, the LLMs presented detailed flowcharts, specific algorithm steps (such as sliding-window-based filtering, threshold detection, simplified FFT analysis, and state machine implementation), sample codes, and instructor-guided feedback, illustrating how to build a control program that is both efficient and meets competition requirements.

(7) Proposal Integration: Overall, the workflow for generating and optimizing this design proposal was an iterative process involving student queries, model deep thinking, model

responses, and instructor feedback. From the initial concept to the gradual refinement of each module and the integration of all parts into a complete report outline, this process fully reflects a design philosophy that emphasizes both theory and practice, as well as systematization and operability, providing a detailed reference and direction for the students to finalize their solutions.

The LLM-generated multi-stage iterative design proposal workflow is presented in Fig. 4.

3. Human–AI Collaboration for Designing a Simple Recording Shielding System

3.1 Task analysis and design solution optimization

In modern engineering design, particularly in competition-based projects, integrating human expertise with AI technology has become a crucial factor in enhancing competition-based projects, and integrating human knowledge with AI technology has become a crucial factor in improving design efficiency and quality. [7] This synergy is exemplified in the design of the simple recording shielding system. The core objective, derived from the competition requirements, was to create a device capable of jamming nearby microphones using ultrasonic signals, a concept explored in various studies on ultrasonic jammer effectiveness and evaluation.[12,13] The close collaboration between students, teachers, and AI led to the development of a solution that met the competition requirements while being efficient and feasible.[7] This solution met the competition requirements and aligned with goals of similar implementations, such as the STM32-based system described by Wang and Sa.[14] However, while previous works have reported the use of LLMs in course-based design tasks or problem-solving tutorials,[6,7] our study advances the field by embedding LLMs directly into a real-world,

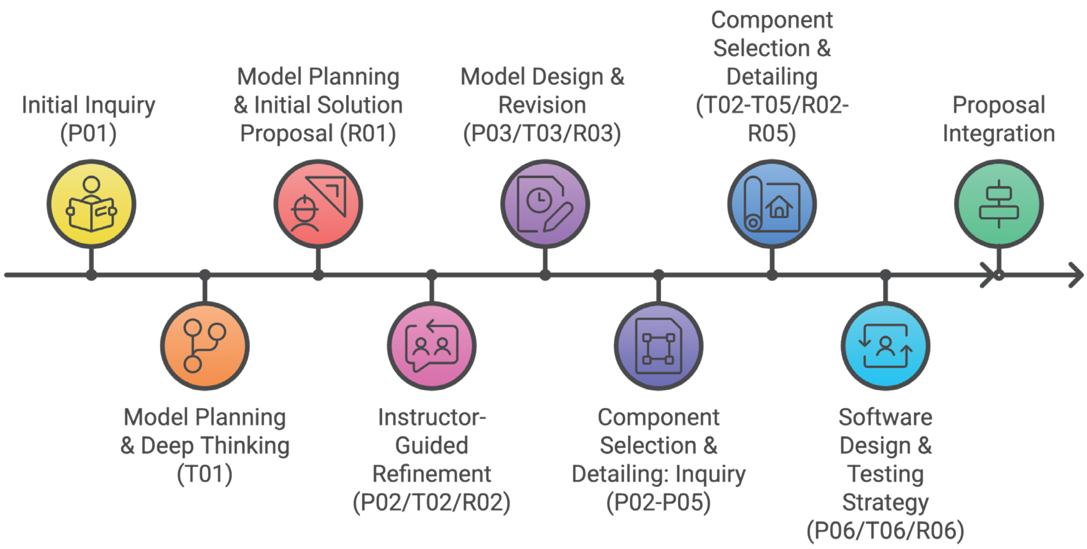

Fig. 4. (Color online) LLM-generated multi-stage iterative design proposal workflow.

high-stake competition workflow. Unlike previous models that focus solely on student–AI dialogue, our approach introduces a structured triadic interaction among students, AI (LLMs), and instructors. This results in a more reliable design cycle that balances model suggestions with human feasibility checks. In this section, we reflect on the entire design process, showcasing how human–AI collaboration shaped task analysis, solution generation, module design, optimization, and decision making, ultimately leading to a rational system design.

Figure 5 shows an optimal design solution for the simple recording shielding system. During the design, the process began with an in-depth task analysis by the students, who clarified the system's core functions and requirements. AI-generated initial solutions (described in Sect. 2) provided a theoretical framework for further discussion. Through continuous dialogue and optimization between students and teachers, the AI's proposed solutions became a key technical reference, with adjustments made to ensure the solution's practicality and cost-efficiency, reflecting the iterative nature of engineering design supported by interaction with AI tools.[7]

Each design decision, particularly in signal generation, audio monitoring, power control, and power management, was iteratively refined with expert advice and AI support, ensuring that the final solution not only met the technical requirements of the competition but also had high feasibility and cost-effectiveness.

Table 2 shows the simple recording shielding system's task analysis and solution determination process, emphasizing the human–AI collaboration perspective among the AI-generated solution, the teacher's guidance, and the students' knowledge construction through discussions.

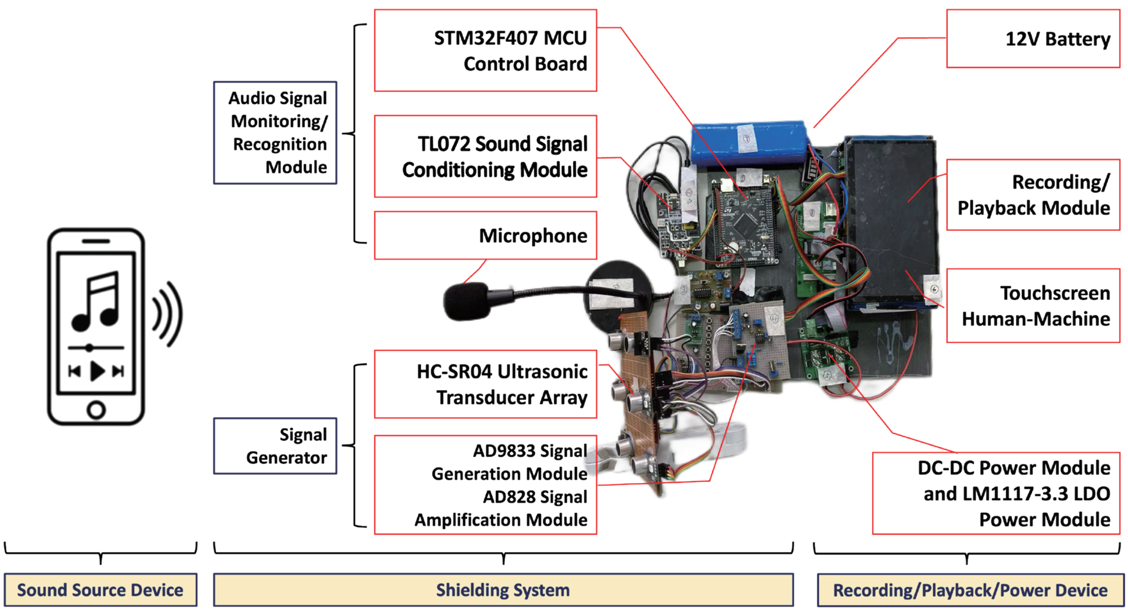

Fig. 5. (Color online) AI-enhanced optimal design implementation for a simple recording shielding system.

Table 2
Detailed processes of human–AI collaboration for designing the simple recording shielding system.

Phase	Analysis and discussion results	AI-generated solutions and decision making	Final design solution formation
Task analysis and requirement confirmation	The students clarified the competition objectives, dividing the system into the signal generator and audio monitoring modules and outlining the functional requirements.	AI provided an initial design proposal, outlining the use of ultrasonic transducers and the audio monitoring module framework.	On the basis of AI's proposal, the teacher–student team adjusted the functional requirements and feasibility to ensure that the solution was simplified and highly practical.
Signal generation module design	The students and teacher discussed the signal generator design, focusing on power control and ultrasonic signal generation methods.	AI suggested using the TI DRV2667 chip and PWM modulation for power control, but owing to cost and implementation difficulty, this solution was not adopted.	The team decided to use the AD9833 DDS chip to generate the signal, coupled with a power amplifier for power control. The solution was simplified and met the competition's requirements.
Audio monitoring and recognition module design	The detection method for audio signals was discussed, and the team initially planned to use hardware circuits, later deciding on software processing.	AI recommended using RMS conversion or envelope detection circuits to condition the signal and use FFT analysis for signal type recognition.	The team adopted FFT for frequency spectrum analysis to identify signal types, simplifying hardware and increasing recognition accuracy.
Power control and system integration	The team discussed methods for power control and ultimately chose the digital potentiometer to control the power amplifier's gain, simplifying the design.	AI recommended using DACs and operational amplifiers for precise power control, but the team decided that the digital potentiometer offered a simpler and more feasible solution.	The decision was made to use a digital potentiometer to adjust power by controlling the resistance, simplifying the design and ensuring precise power control that met the competition's requirements.
Power management solution	The team discussed battery power and DC–DC conversion options, ultimately choosing the battery power solution to ensure system stability.	AI recommended using USB Type-C with LDO voltage regulation, but considering convenience, the team chose the battery-powered solution.	The team opted for battery power with a DC–DC converter and a LDO regulation for voltage conversion, ensuring efficiency and ease of demonstration.
Final solution integration and optimization	The team integrated all modules, optimizing system performance and feasibility.	AI provided modular design solutions and debugging frameworks, optimizing technical details for each module.	Through teacher–student discussions and AI optimizations, the final design solution was determined, ensuring that it was feasible, and cost-effective, and met the competition's requirements.

3.2 Task analysis and requirement confirmation

In the initial phase, the students analyzed the competition problem and clearly identified the design goal: to effectively shield recording devices without interfering with normal audio communication (see Ref. 12 for evaluation frameworks of such systems). The system was divided into two core modules: the signal generator and the audio monitoring/recognition module. This analysis laid the foundation for the subsequent design. On the basis of this analysis, the initial AI-generated solutions (Sect. 2) were reviewed.

On the basis of the task analysis, Gemini was introduced to generate initial solutions. AI proposed a comprehensive design, including the ultrasonic transducer for generating shielding signals—a common technique in microphone jamming research[13,15]—and the concept for the audio monitoring module. While AI's solution was technically sound, the students and teachers recognized the need for further adjustments in practical feasibility, a crucial step in applying theoretical AI suggestions to real-world constraints.[7] Therefore, the team decided to adjust the AI-generated solution to ensure feasibility and economic viability.

3.3 Signal generation module design

The design of the signal generation module is one of the core components of the entire system, responsible for producing the ultrasonic interference. Research has explored various methods for ultrasonic jamming, including those leveraging microphone circuit nonlinearity,[15] selective jamming techniques,[16] and even wearable form factors,[17] providing context for the design space. An alternative privacy approach involves actively canceling speech signal[18] ultrasonic jamming, as specified in the competition guidelines. During this phase, students and teachers had in-depth discussions on various design options for the signal generator, including PWM signal modulation, the use of DDS chips, and the selection of ultrasonic transducers. The discussion focused on achieving the precise generation of ultrasonic signals, the feasibility of power control, and the implementation difficulty of the proposed solutions.

AI recommended using an ultrasonic driver chip (such as TI DRV2667) combined with a DAC chip for power control. Although this solution was technically sound, it was not adopted owing to the long procurement cycle and high costs—practical constraints often encountered when moving from simulation/proposal to implementation.[14] After careful consideration, the student team, guided by the instructor, decided to use the AD9833 DDS chip, which provided a cost-effective and reliable solution for generating the necessary ultrasonic shielding signals, aligning with the goals described in studies such as those by Gao *et al.*[18] on speech signal cancellation and privacy protection systems, although using a different mechanism (jamming vs cancellation). Their findings reinforce the importance of effectively choosing the right components for achieving system goals. This choice ensured stable signal generation and better adjustability, meeting the power control requirements of the competition while being cost-effective.

3.4 Audio monitoring and recognition module design

The design of the audio monitoring and recognition module is another key part, enabling the system to activate only when needed and potentially distinguish between different sound types (although the final implementation focused on presence detection). Students and teachers explored how to accurately detect audio signals and distinguish speech from music.[19] Detecting the presence of audio [voice activity detection (VAD)], a related task, is often optimized for low power.[20] Initially, students planned hardware circuits for audio energy detection. However, complexity led them to a simplified digital processing solution.

AI recommended using RMS conversion or envelope detection circuits to convert the audio signal into a DC signal for MCU processing. While theoretically reliable, hardware complexity and debugging difficulties made it less practical. Instead, the team adopted frequency-domain analysis using FFT, which efficiently converts time-domain signals into their spectral components. In this context, FFT provides real-time spectral analysis, enabling the system to identify dominant frequency bands and determine whether acoustic signals such as speech or music are present. The algorithm's computational efficiency and compatibility with embedded systems (such as STM32) make it a widely used tool in digital signal processing applications.(21)

Consequently, the teacher–student team decided to handle signal processing entirely through software, using FFT analysis for frequency domain processing. For possible future enhancements involving signal type classification on the microcontroller, techniques for model compression on edge devices would be relevant.(22) This software-centric approach simplified hardware design and significantly reduced debugging complexity, focusing efforts on the software implementation for the STM32 platform.(14)

3.5 Power control and system integration

In the power control design phase, students and teachers discussed adjusting the power within the range of 1 to 4 W. AI proposed a solution using a DAC and operational amplifier for power adjustment. While this would ensure high-precision power control and a relatively simple circuit design, the teacher–student team decided, after thorough consideration, to use a digital potentiometer to control the gain of the power amplifier. This solution allows for precise power adjustment, reduces costs, and simplifies implementation.

During the system integration phase, students and teachers made final optimization decisions on the basis of each module's complexity, cost, and feasibility. All modules were integrated, followed by system testing and debugging to ensure stability and reliability, culminating in a functional prototype.(14) The collaborative process was central, guided by both AI suggestions and practical experience.(7)

3.6 Power management solution

Power management is an essential component for system design. During discussions, AI recommended USB Type C and DC power inputs. However, for convenience during on-site demonstrations and stable operation, the team ultimately chose battery power with a DC–DC converter for voltage regulation. This practical decision prioritized ease of use and demonstration reliability within the context of competition over the potentially more flexible AI-suggested options.

3.7 Final solution integration and optimization

Through multiple iterations involving AI feedback,(7) expert (teacher) guidance, and practical testing, the final design implementation for the simple recording shielding system(14) was optimized across signal generation,[15] audio monitoring,[20] power control, logic, and power management. The team leveraged the AI's professional recommendations, adjusting based on actual requirements, resource constraints, and the known effectiveness and limitations of ultrasonic jamming techniques.[13,17] The resulting design met competition requirements and demonstrated high feasibility for implementation.

4. Discussion

In this study, we presented an innovative approach to the integration of LLMs in the context of undergraduate electronics design competitions[1] with a specific focus on the NUEDC in China.[1–3] We explored the dynamic interaction between students, instructors, and AI,[4,7,9] emphasizing how this collaboration enhances design efficiency, problem-solving ability, and technical learning outcomes.[5,6] By investigating the iterative design process of the simple recording shielding system,[11] we demonstrated the critical role of LLMs in supporting students through complex engineering challenges,[9,10] providing expert-level feedback,[6,7] and facilitating optimized solutions in real time.[8]

4.1 Summary of findings

The study's core findings center on implementing LLM-driven tools in an educational setting,[7] specifically for designing systems that involve sensing and signal analysis. The recording shielding system designed in this study exemplifies a sensor-based application, utilizing microphone input for sound detection, ADCs for data acquisition, and FFT for audio classification. LLMs, as a subset of AI tools, acting as interactive AI collaborators,[7,9] provide invaluable support in generating initial design proposals, refining sensor system architectures, and optimizing implementation strategies.[6]

Unlike previous implementations in theoretical or course-based settings,[6,7] LLMs in this study acted as real-time design partners, assisting in system conceptualization, module implementation, and error analysis. This human–AI collaborative model resulted in measurable improvements in creativity, system completeness, and troubleshooting efficiency. The iterative nature of the collaboration, with students posing questions, AI models analyzing responses, and experts offering guidance, mirrors the iterative engineering design process seen in professional environments.[9] This workflow allows students to engage with AI in a way that promotes self-directed learning while benefiting from human expertise.[5,7]

Throughout the design of the simple recording shielding system,[11] AI played a pivotal role in problem exploration and solution optimization.[6,8] The AI-generated proposals provided a solid theoretical foundation for the students' designs, addressing challenges inherent in ultrasonic jamming,[12,13,15] while expert feedback ensured practical feasibility and cost-effectiveness.[10] Key design decisions such as signal generation,[15] audio monitoring,[20] power control, and power management were refined through this collaborative process, resulting in a final solution that met competition requirements[1,11] while being both technically and economically viable,[14] considering the known complexities of selective or adaptive jamming techniques[16,17] and alternative approaches such as signal cancellation.[18]

4.2 Comparison with related work and human–AI collaboration model

Integrating expert feedback into the iterative process is one of the major strengths of the human–AI collaborative approach.[7,9] Compared with previous studies, which either explore LLMs in isolated question-answering contexts or simulate design thinking processes through AI-driven prompts,[6,7,9] our work is distinct in its full integration of AI into hands-on hardware–software co-design under timed competition constraints. The innovation lies in embedding AI not just as a static tool, but as a dynamic team member, where its outputs are critiqued, modified, and integrated into a real circuit system in collaboration with human experts. This hybrid design-review cycle has not been explicitly demonstrated in previous studies.

In traditional education models, students often rely solely on instructors for guidance and feedback.[5] However, the collaboration with AI adds a layer of real-time responsiveness and flexibility,[6,9] allowing for continuous refinements based on both AI's suggestions (which may have limitations[10]) and expert insights. This dual feedback loop—where AI offers theoretical analysis[7] and experts guide practical application—creates an enriched learning environment that significantly boosts students' confidence and problem-solving ability.[4,6] Additionally, the combination of AI and expert input enhances the overall learning experience by addressing the complexities of real-world engineering problems,[9,10] which often require interdisciplinary knowledge and the balancing of theoretical knowledge with practical constraints, such as how measurement specifics can affect outcomes.[21]

The iterative nature of this process ensures that solutions evolve progressively, reflecting the realities of engineering design.[9] Each phase of the design, from initial inquiries to module design and final system integration,[14] involved multiple rounds of feedback, ensuring that the solutions developed were not only theoretically sound[6] but also feasible for real-world application.[10] This iterative model mirrors professional engineering practices, making learning more relevant and applicable to students' future careers.[5,7]

4.3 Implications and limitations

This study also highlights several opportunities for future research, particularly in refining the integration of AI into engineering education.[5,7] The findings suggest that LLMs can be further developed to create more comprehensive problem-solving agents[6,9,10] that can handle increasingly specialized and advanced engineering tasks, potentially addressing more profound technical challenges in areas such as advanced ultrasonic jamming[12,13,15–18] and sophisticated audio analysis.[19,20,22] LLMs, such as ChatGPT and Gemini, offer substantial support; however, their performance in highly specialized domains still requires close supervision and correction from human experts.[10] Future research can focus on improving AI's reasoning capabilities and reducing its limitations,[10] such as handling nuanced or specialized engineering queries with greater accuracy and less reliance on human oversight.

One promising direction involves developing AI agents capable of autonomously assisting throughout the engineering design process.[7,9] As AI evolves, these agents can shift from tools to indispensable collaborators.[4] Such agents might not only provide proposals and optimize solutions but also perform deep analysis, predict system failures addressing robustness concerns related to those highlighted in jamming research,[12,13] suggest alternative approaches (such as different jamming waveforms[15] or signal cancellation[18]), or even optimize algorithms for resource-constrained environments.[22] This level of collaboration can revolutionize engineering education[5,7] by offering students seamless, integrated engagement with AI.[9]

5. Conclusion

We demonstrated the transformative potential of LLMs in enhancing human–AI collaboration within undergraduate electronics design competitions. The iterative, feedback-driven approach, exemplified by the simple recording shielding system project, shows that LLMs are not merely passive tools but active participants in the learning process. By continuously interacting with AI, students can refine their ideas, optimize designs, and address specific technical goals, such as microphone jamming, by employing selective methods or understanding alternatives such as cancellation, and solve problems in novel ways. This collaboration fosters an environment that encourages creative problem solving and critical thinking, both of which are crucial for modern engineering.

We introduced a novel triadic interaction model that involves LLMs, students, and expert mentors in a live electronics design challenge. Unlike previous studies that demonstrate AI applications in simulated academic exercises or controlled environments, in our study, we documented how iterative feedback from both AI and instructors is operationalized into real-time hardware development. This not only strengthens the credibility of AI-generated proposals but also offers a new pedagogical model for competitive engineering education.

The results suggest that the synergy between human expertise and AI-driven tools is likely to increasingly shape the future of engineering education and design. As AI technology evolves, the potential to create more robust, automated, and intuitive design methodologies (addressing challenges such as audio detection and component selection, and their effects) becomes ever more achievable. Future research should focus on enhancing AI autonomy, expanding its application to specialized domains, and exploring its potential to revolutionize educational practices and real-world engineering design solutions. The ongoing development of AI tools holds the promise of transforming not only how students learn but also how engineers innovate, solve problems, and create the technologies of tomorrow.

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