Chapter 10
Leveraging Agentic AI and LLMs to Enhance Conceptual Understanding of Structural Dynamics

Krishna Teja Josyula and Vijaya V. N. Sriram Malladi

Abstract This work introduces a novel educational framework that integrates large language models (LLMs) with agentic AI architectures to help students internalize complex structural dynamics concepts. The focus is on strengthening intuition for how system parameters influence dynamic response in lumped-parameter models. At the core is an interactive environment for single-degree-of-freedom (SDOF) systems, with planned extensions to multi-degree-of-freedom and continuous systems. Specialized AI agents collaboratively guide students through key vibration topics—natural frequency, damping ratio, resonance, transient response, and steady-state forced response—by combining conversational interaction with physics-based reasoning.

The framework employs a LangGraph backend with a NextJS conversational front-end, enabling natural language queries, adaptive explanations, and guided simulation. Integrated computational tools solve governing equations and generate visualizations, creating a seamless transition from conceptual discussion to mathematical solution to animated demonstration. This multimodal design consolidates resources that are traditionally fragmented across textbooks, software, and simulation platforms into a single, unified interface.

The system dynamically adapts to student inquiry, recommending related concepts, visualizations, or simulations aligned with ongoing exploration. For specific parameter configurations or behaviors, it generates contextually relevant video demonstrations that reinforce physical intuition. By unifying conversation, computation, and visualization, the framework supports personalized, adaptive learning and establishes a foundation for AI-driven pedagogical tools across the mechanical engineering curriculum. Potential applications extend beyond undergraduate education into professional training and continuing education.

Keywords Agentic AI · Large language models · Structural dynamics · Adaptive learning

Introduction

Structural dynamics education has long posed significant pedagogical challenges in undergraduate engineering curricula, particularly in conveying the relationships between system parameters and dynamic response behavior in lumped parameter systems. Traditional instruction often struggles to bridge the gap between theory and practice, leaving students grappling with abstract concepts such as resonance [1]. These challenges are compounded by the mathematical rigor required for system analysis, which can create barriers to engagement and limit deep conceptual understanding [2, 3]. Previous studies have shown that interactive and visual approaches are essential to foster conceptual intuition in vibration-related courses [4, 5, 6].

The emergence of Large Language Models (LLMs) represents a paradigm shift in educational technology, offering new opportunities to transform traditional pedagogical approaches [7] . Since the public release of ChatGPT in late 2022, their use in education has gained significant attention across a wide range of disciplines [8]. LLMs demonstrate strong capabilities in

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text generation, natural language understanding, and contextual reasoning, making them especially valuable for developing interactive learning environments.

In engineering education, preliminary studies have explored their potential for problem-solving assistance [9], code generation [10], and conceptual explanation [11]. More recent advances show that fine-tuned LLMs with retrieval-augmented generation can deliver course-specific content in mechanical engineering, with applications in finite element methods yielding measurable improvements in student alignment with course materials [12].

Despite these advances, comprehensive frameworks explicitly tailored to technically demanding topics such as structural dynamics remain scarce. Recent surveys emphasize that LLM agents for education are rapidly evolving, but their application has largely focused on general tutoring and domain-agnostic problem solving rather than specialized mechanical engineering contexts [13]. Promising work such as MechAgents demonstrates that multi-agent LLM systems can collaboratively solve mechanics problems by combining planning, coding, and physics reasoning [14], yet these systems remain primarily research prototypes with limited integration into structured curricula. Similarly, studies on agentic workflows argue that decomposing tasks among multiple AI agents can enhance adaptability and pedagogical coherence, but their educational implementation is still in its infancy [15]. In parallel, multimodal foundation models have been identified as having transformative potential in education, though challenges remain in aligning multimodal reasoning with discipline-specific conceptual learning [16]. Recent efforts to incorporate generative AI into engineering education highlight both the promise of enhanced engagement and the current lack of tailored frameworks for advanced topics such as vibrations and structural dynamics [17]. This paper addresses this gap by introducing an AI-driven, agentic framework designed specifically to integrate language, computation, and visualization for structural dynamics education.

The integration of agentic AI architectures with LLMs offers a novel opportunity to address persistent challenges in structural dynamics instruction [18]. Unlike conventional chatbot implementations, agentic systems coordinate specialized AI agents that provide domain-specific expertise, guide adaptive learning paths, and generate contextually relevant explanations. Such architectures enable the creation of sophisticated educational tools that dynamically respond to individual student queries while preserving coherence across multiple learning objectives and conceptual domains [10].

At present, educational resources for structural dynamics are highly fragmented: textbooks provide theoretical explanations, computational tools support equation solving, and visualization software illustrates system behavior. Students must navigate among these disparate platforms, often losing conceptual continuity and struggling to connect theory with application. This fragmentation imposes cognitive overhead, detracts from core learning goals, and limits the effectiveness of traditional instructional approaches.

In this paper, we present a novel educational framework that integrates Large Language Models (LLMs) with agentic AI architectures to create a unified, interactive learning environment for structural dynamics. Our initial focus is on single degree-of-freedom (SDOF) systems, providing a solid foundation in fundamental vibration principles before extending to multi-degree-of-freedom and continuous systems. The framework employs a LangGraph-based backend that coordinates specialized AI agents, each designed to guide students through core topics such as natural frequency, damping ratio, resonance, transient response, and steady-state forced response.

The system combines physics-based reasoning with conversational AI, enabling students to pose open-ended questions in natural language and receive explanations supported by guided simulation and visualization. By consolidating traditionally fragmented resources—textbooks for theory, computational tools for solutions, and separate software for visualization—into a single interface, the framework provides seamless transitions from conceptual discussion to mathematical computation to visual demonstration. The adaptive architecture further responds to individual student queries by recommending related concepts and generating visualizations that illustrate the corresponding physical phenomena.

Beyond tool development, this work establishes a foundation for broader applications of AI-driven pedagogy in the mechanical engineering curriculum [19, 20]. The framework's adaptive nature supports personalized learning paths, allowing students to progress at their own pace while maintaining engagement with increasingly complex material [21]. In doing so, it addresses a critical need for innovative educational technologies that enhance conceptual understanding and prepare students for the evolving landscape of engineering practice.

The figure 1 illustrates the system workflow of the Resonance framework, which adopts a dual-module architecture for structural dynamics education. Both damped and undamped SDOF modules follow identical processing workflows, ensuring consistency while addressing distinct vibration phenomena. The interaction begins with student input through a conversational UI, integrated with AI toolkit components to support natural language communication. Based on intent detection, the system transitions from conversational response to a back-end pipeline that coordinates context analysis, physics reasoning, parameter calculation, and code generation. This modular design allows students to explore either damped or undamped systems through a unified interface while receiving contextually appropriate explanations and dynamic visualizations. Embedded feedback loops further enable iterative refinement of responses, supporting the framework's adaptive learning objectives.

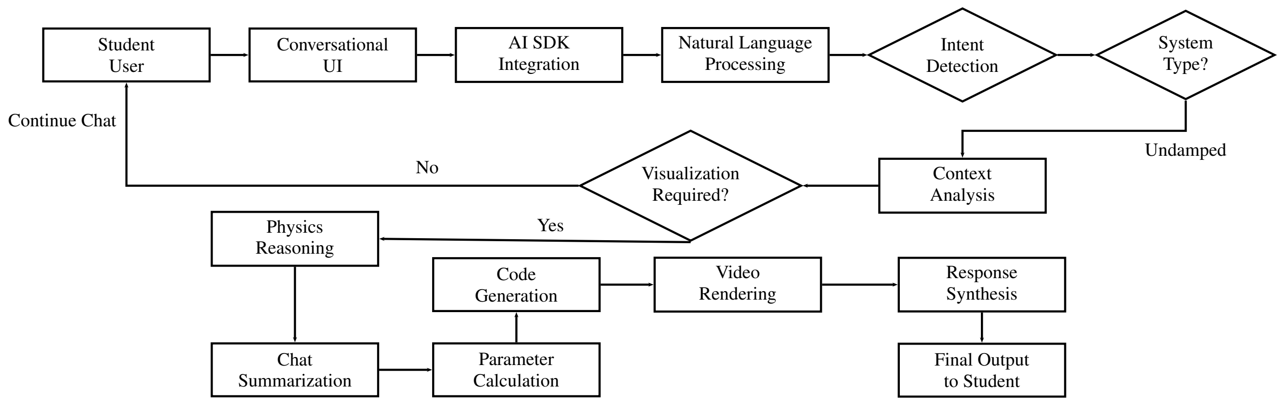

Fig. 1 System Overview: Agentic AI Framework for Structural Dynamics Education demonstrating the seamless integration of damped and undamped system modules within a unified pedagogical platform. The architecture shown represents the undamped SDOF workflow; the damped module follows an identical processing structure with homogeneous architecture.

Methods

This work examines the integration of agentic AI systems in engineering education, particularly in technical domains such as structural dynamics, where traditional pedagogical approaches are limited. To assess the effectiveness of the proposed framework, we pose the following research questions (RQs):

- **RQ1.** Can agentic AI architectures improve undergraduate students' conceptual understanding of structural dynamics compared to traditional instructional methods?
- **RQ2.** How does the integration of conversational AI with in-context reasoning affect student engagement and learning outcomes in mechanical system analysis?
- **RQ3.** What are the pedagogical benefits and limitations of consolidating fragmented educational resources into a unified AI-driven environment?
- **RQ4.** To what extent does the adaptive nature of the framework support personalized learning paths while maintaining rigor in structural dynamics concepts?
- **RQ5.** How does contextual text–video generation enhance conceptual learning when dynamic visualizations are synchronized with conversational explanations?

Each stage of the framework was designed to address specific RQs:

- **Step 1: Conversational Infrastructure.** AI SDK capabilities were embedded directly into the frontend to unify access to resources, addressing RQ3 on the benefits and limitations of consolidating traditionally fragmented tools. Eliminating backend text-generation dependencies ensures a seamless user interface as the foundation for resource integration.

- **Step 2: Pedagogical Intelligence Layer.** Module-specific prompt engineering and a suggestive card interface provide scaffolded learning paths. This phase targets RQ2 (conversational AI's impact on engagement) and RQ4 (supporting adaptive, personalized learning while maintaining rigor). Contextual prompt injection aligns generated explanations with course objectives.

- **Step 3: Specialized Backend Pipeline.** LangGraph orchestration implements sequential nodes for chat summarization, physics reasoning, parameter calculation, and code generation. These enable synchronized text–video responses, directly addressing RQ5 on the role of multimodal visualization in conceptual learning.

- **Step 4: System Integration and Evaluation.** The complete system was deployed and evaluated against traditional instructional methods. This phase confronts RQ1 by testing the overall effectiveness of the agentic AI framework, while also validating RQ5 through real-time multimodal demonstrations of vibration phenomena. Step 4 integrates the complete system architecture and evaluates its effectiveness against traditional methods, directly confronting RQ1's central question of agentic AI effectiveness while simultaneously validating RQ5's text-video synchronization hypothesis through the delivery of synchronized multimodal responses that demonstrate physical phenomena in real-time.

Case Study

This section demonstrates the functional capabilities of the Resonance framework as a proof of concept for agentic AI–driven structural dynamics education. Although the system has not yet been deployed in classroom settings, the case study validates the feasibility of the proposed architecture through systematic testing of its core functionalities: conversational AI interaction, visualization generation, and multimodal response delivery. The demonstration traces the complete workflow—from student query processing through the LangGraph pipeline to synchronized text–video output—providing concrete evidence of the framework's ability to address the research questions outlined above. Representative single degree-of-freedom (SDOF) scenarios are used to evaluate system responses, technical performance metrics, and pedagogical content alignment. Results confirm three key capabilities: (1) consolidation of fragmented educational resources into a unified interface, (2) effective integration of conversational AI for adaptive explanations, and (3) successful implementation of contextual text–video synchronization. Together, these findings establish the foundation for future empirical evaluation with student populations and prepare the framework for expanded educational assessment in subsequent journal studies.

System Architecture Validation

This subsection demonstrates the end-to-end functionality of the Resonance framework. Validation focused on the dual-module design for damped and undamped SDOF systems, confirming that the LangGraph-based backend successfully coordinates with the NextJS frontend via AI SDK integration. Representative test scenarios were implemented to verify correct query routing through the appropriate processing pathways, including context analysis, physics reasoning, parameter calculation, and visualization generation. Figure 2 illustrates the consolidation of damped and undamped system architectures into a cohesive educational platform, empowering students to pursue adaptive learning pathways that integrate theoretical comprehension with visual representation.

Results confirm that both modules exhibit consistent architectural behavior, with identical processing workflows maintained across damped and undamped cases. This validation establishes that the framework's modular design reliably supports multiple system types without requiring architectural modifications, providing a scalable foundation for extension to multi-degree-of-freedom and continuous systems.

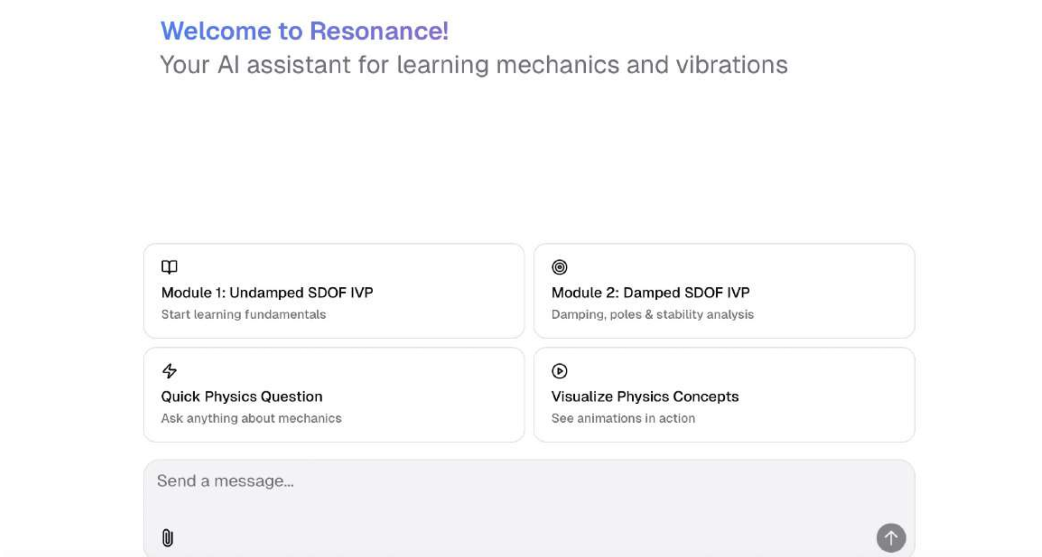

Fig. 2 Dual-module interface showing damped and undamped system selection

Figure 3 illustrates the request–response lifecycle initiated from the front-end as the student interacts with the conversational user-interface. The diagram highlights how user inputs are processed, routed through the AI integration layer, and returned as adaptive responses, demonstrating the seamless flow between the interface and back-end components.

As the student navigates the interface, the LangGraph backend is activated to process each request and generate the corresponding visual explanation of the system under study. Node activations are traced in real time using the LangSmith IDE, a monitoring tool within the LangChain ecosystem, providing transparent tracking of the framework's internal workflows. Figure 4 demonstrates the sequential activation pattern of processing nodes during a typical visualization request, showing the

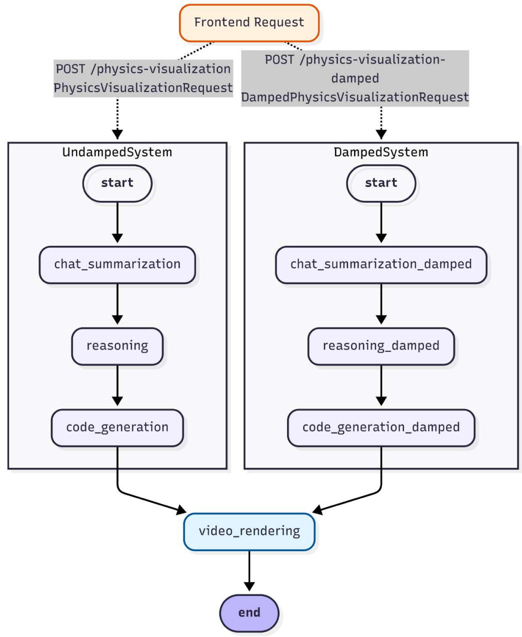

Fig. 3 Request response lifecycle from UI

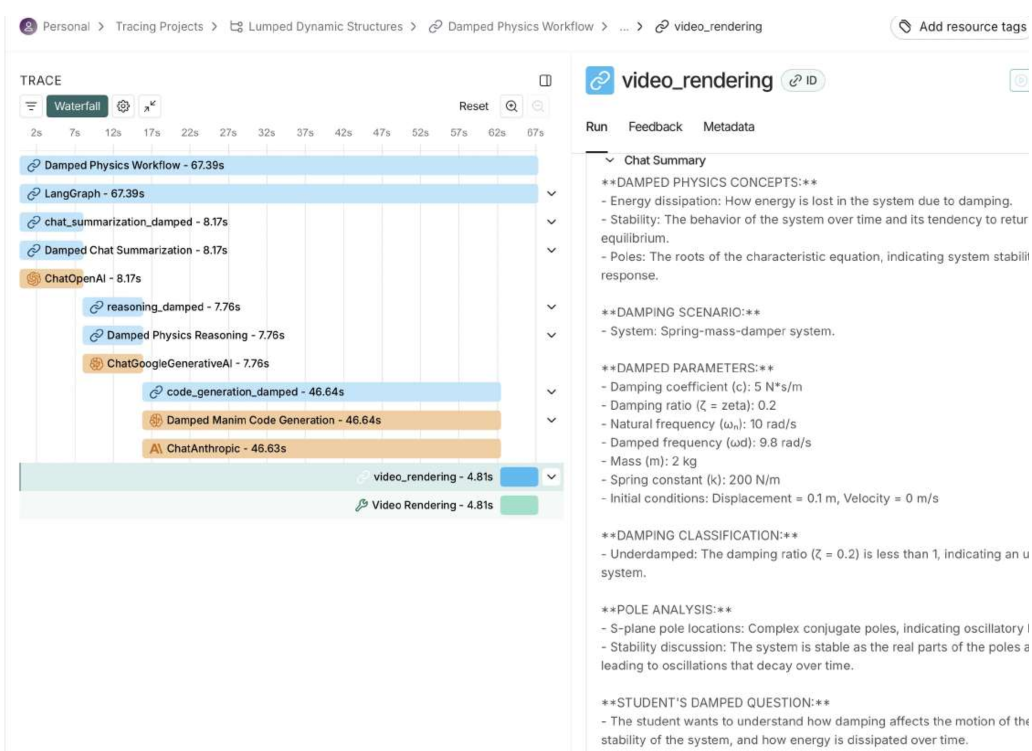

Fig. 4 Real-time tracing of LangGraph node activations during query processing, demonstrating sequential coordination of specialized agents through the backend pipeline

coordination between chat summarization, physics reasoning, parameter calculation, code generation, and video rendering components.

Functional Prototype Demonstration

This subsection presents representative interaction scenarios that highlight the prototype's ability to transition seamlessly from conversational explanations to visualization generation. Example student queries progress from conceptual questions to parameter exploration and ultimately to explicit visualization requests, demonstrating the system's capacity to preserve educational context while adapting to different learning modalities.

Snapshots included below illustrate the complete learning pathway: a student begins with theoretical inquiry, advances through parameter-based analysis, and concludes with synchronized visual explanations. These demonstrations validate the framework's core objective of unifying fragmented resources—conversation, computation, and visualization—into a single adaptive platform.

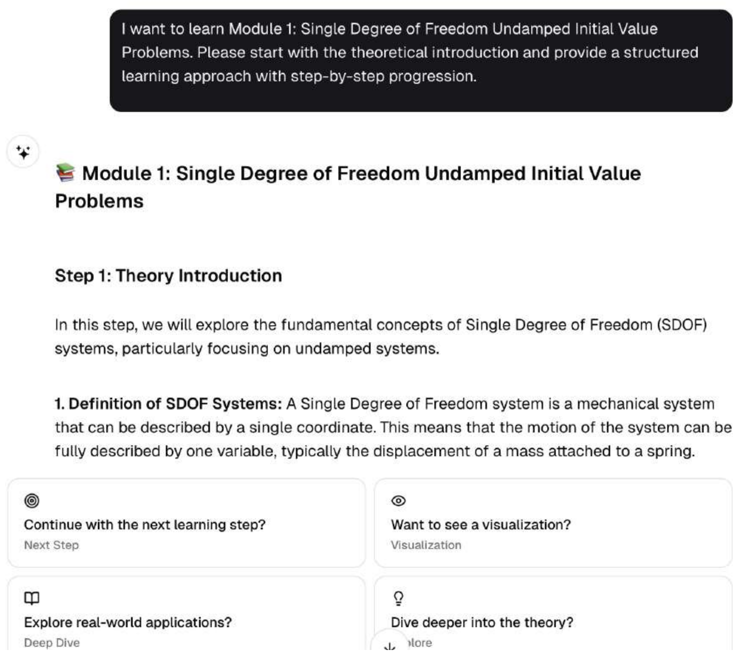

Fig. 5 Initial conversational interaction demonstrating the system's ability to provide conceptual explanations of SDOF fundamentals in response to student inquiry

Conclusion and Future Work

This work addresses a critical gap in structural dynamics education through the development and validation of Resonance, an agentic AI framework that unifies conversational interaction, computational analysis, and dynamic visualization within a single adaptive platform. The framework demonstrates technical feasibility in consolidating resources that have traditionally been fragmented across textbooks, computational tools, and simulation software—addressing persistent challenges in conveying abstract concepts such as resonance, parameter sensitivity, and dynamic response behavior.

The case study validates three foundational capabilities that establish the framework's readiness for empirical evaluation: (1) successful integration of conversational AI with physics-based reasoning to provide contextually appropriate explanations, (2) reliable implementation of dual-module architecture supporting both damped and undamped SDOF systems with homogeneous processing workflows, and (3) effective synchronization of text-based explanations with dynamically generated video demonstrations. The LangGraph-based backend coordinates specialized agents through sequential nodes—context analysis, physics reasoning, parameter calculation, code generation, and video rendering—while the NextJS frontend with AI SDK integration enables natural language interaction and seamless response delivery.

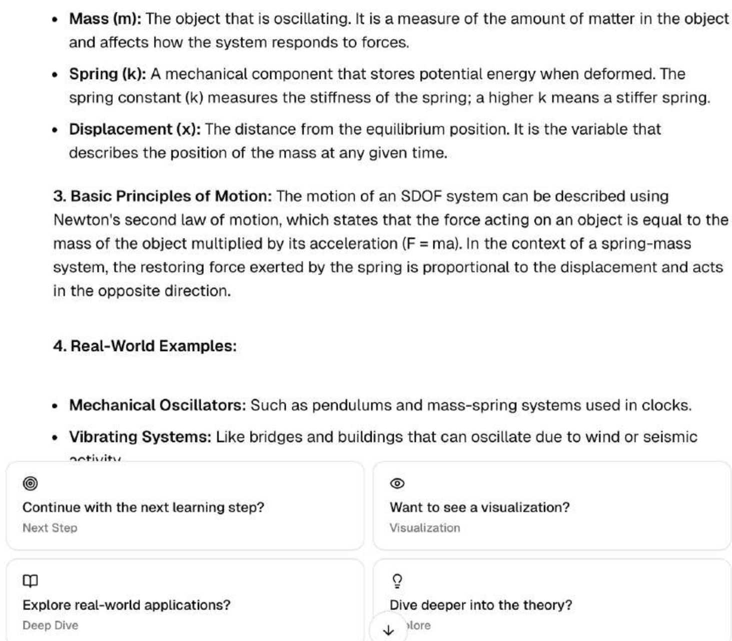

Fig. 6 Integrated learning interface showing the seamless transition from conversational AI guidance to parameter-based exploration

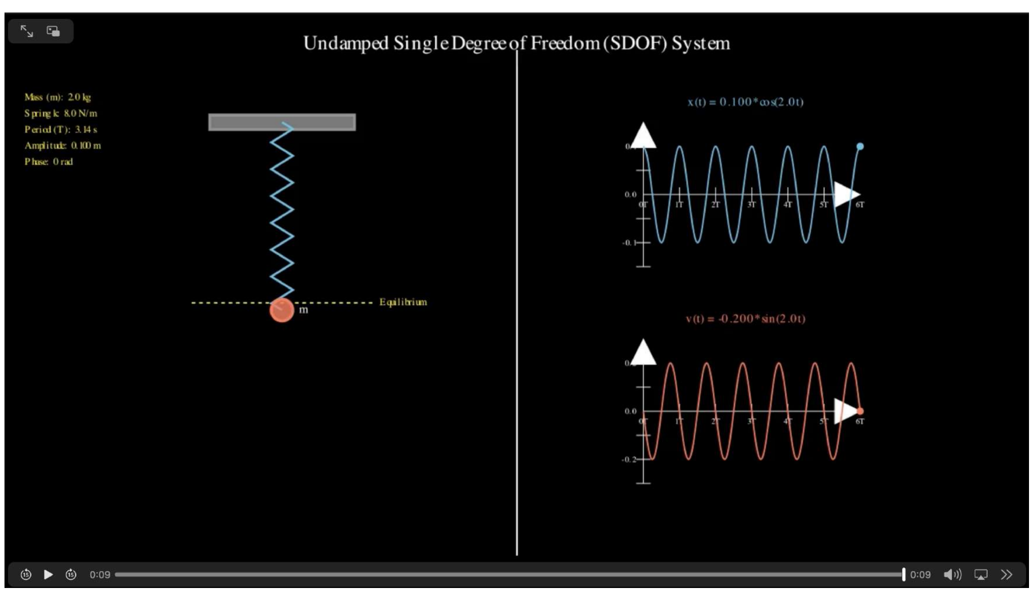

Fig. 7 Real-time undamped SDOF system demonstration with synchronized animation and analytical plots

While the architectural validation confirms the system's technical robustness, this work represents foundational infrastructure rather than conclusive evidence of pedagogical effectiveness. The framework has not yet been deployed in classroom settings, and empirical assessment of learning outcomes remains essential future work. Controlled studies comparing the

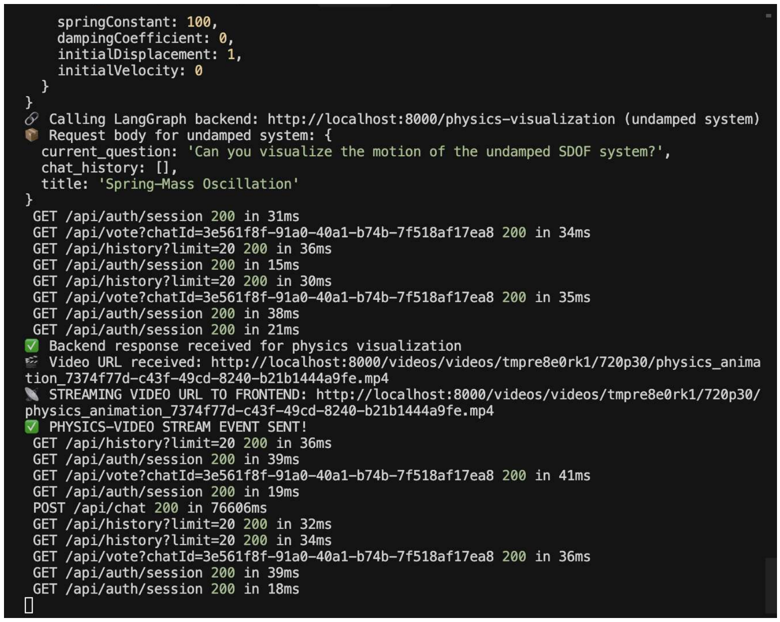

Fig. 8 Streaming transition moment capturing the real-time generation and delivery of multimodal educational content

framework against traditional instructional methods will be necessary to address the research questions posed under ”Methods”, particularly regarding conceptual understanding improvement (RQ1), student engagement (RQ2), and the pedagogical impact of multimodal text-video synchronization (RQ5).

The modular architecture positions the framework for systematic expansion beyond single degree-of-freedom systems. The consistent processing workflows demonstrated across damped and undamped modules suggest scalability to multi-degree-of-freedom systems and continuous structures without requiring architectural redesign. Furthermore, the agent-based approach enables domain extension—the same coordination patterns between specialized agents could be adapted to other technically demanding subjects in mechanical engineering, including finite element analysis, fluid dynamics, and thermodynamics.

Future work will proceed along three parallel trajectories. First, longitudinal classroom deployment with undergraduate engineering students will assess learning outcomes, engagement metrics, and conceptual retention compared to traditional instruction. Second, the framework will be extended to encompass forced vibration scenarios, multi-degree-of-freedom systems, and continuous systems, expanding coverage across the structural dynamics curriculum. Third, investigation of adaptive learning pathways will examine how the system's recommendation mechanisms influence student exploration patterns and conceptual development over time.

The integration of agentic AI architectures with domain-specific educational content represents a paradigm shift in engineering pedagogy. By demonstrating that conversational AI, computational reasoning, and dynamic visualization can be unified within a coherent framework, this work establishes a foundation for AI-driven educational tools that preserve rigor while adapting to individual student needs. As large language models continue to advance and agentic architectures mature, frameworks such as Resonance offer a pathway toward personalized, adaptive learning environments that bridge the persistent gap between theoretical instruction and conceptual intuition in technically demanding disciplines.

Declaration of generative AI and AI-assisted technologies in the writing process

While preparing this work, the author(s) used Claude to edit the language. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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References

1. L. D. Feisel, A. J. Rosa, The role of the laboratory in undergraduate engineering education, Journal of engineering Education 94 (1) (2005) 121–130.

2. T. A. Litzinger, P. V. Meter, C. M. Firetto, L. J. Passmore, C. B. Masters, S. R. Turns, G. L. Gray, F. Costanzo, S. E. Zappe, A cognitive study of problem solving in statics, Journal of Engineering Education 99 (4) (2010) 337–353.
3. M. J. Prince, R. M. Felder, Inductive teaching and learning methods: Definitions, comparisons, and research bases, Journal of engineering education 95 (2) (2006) 123–138.
4. Teaching engineering mechanics courses using active engagement methods.
5. S. Di Carlo, L. Benedetti, E. Di Gialleonardo, Teaching by active learning: A laboratory experience on fundamentals of vibrations, International Journal of Mechanical Engineering Education 50 (4) (2022) 869–882. doi:10.1177/03064190211017606.
6. N. Zhu, Embedding active learning and design-based projects in a noise and vibration course for the undergraduate mechanical engineering program, International Journal of Mechanical Engineering Education 50 (1) (2022) 78–88. doi:10.1177/0306419021996151.
7. A. Johri, A. S. Katz, J. Qadir, A. Hingle, Generative artificial intelligence and engineering education, Journal of Engineering Education.
8. S. Filippi, B. Motyl, Large language models (llms) in engineering education: A systematic review and suggestions for practical adoption, Information (2024).
9. M.-L. Tsai, C. W. Ong, C.-L. Chen, Exploring the use of large language models (llms) in chemical engineering education: Building core course problem models with chat-gpt, Education for Chemical Engineers (2023).
10. T. Wang, N. Zhou, Z. Chen, Enhancing computer programming education with llms: A study on effective prompt engineering for python code generation.
11. C. Zhang, Y. F. Zhao, R. El Haddad, Understanding the impact of applying large language model in engineering design education, Journal of Computing and Information Science in Engineering.
12. M. F. Shojaei, R. Gulati, B. A. Jasperson, S. Wang, S. Cimolato, D. Cao, W. Neiswanger, K. Garikipati, Ai-university: An llm-based platform for instructional alignment to scientific classrooms.
13. W. Xu, H. Li, Y. Zhao, et al., Llm agents for education: Advances and applications, arXiv preprint arXiv:2503.11733 (2025).
URL https://arxiv.org/abs/2503.11733
14. Y. Wu, Y. Sun, J. Zhang, et al., Mechagents: Large language model multi-agent collaborations can solve mechanics problems, arXiv preprint arXiv:2311.08166 (2023).
URL https://arxiv.org/abs/2311.08166
15. Q. Li, R. Chen, A. Gupta, Evolution of ai in education: Agentic workflows, arXiv preprint arXiv:2504.20082 (2025).
URL https://arxiv.org/abs/2504.20082
16. A. Gupta, J. Lee, S. Wang, On opportunities and challenges of large multimodal foundation models in education, npj Science of Learning 10 (1) (2025) 12. doi:10.1038/s41539-025-00301-w.
17. Z. Zhang, Y. Chang, Leveraging generative ai to enhance engineering education at both low-level and high-level study, in: 2024 Fall ASEE Mid-Atlantic Section Conference, ASEE, 2024.
18. R. Van Campenhout, D. Soto-Karlin, M. Selinger, B. Jerome, Learning engineering in practice: A case study on developing llm-based educational tools, in: International Conference on Human-Computer Interaction.
19. J. Pereira, J.-M. López, X. Garmendia, M. Azanza, Leveraging open source llms for software engineering education and training, in: 2024 36th International Conference on Software Engineering Education and Training (CSEE&T).
20. V. D. Kirova, C. S. Ku, J. R. Laracy, T. J. Marlowe, Software engineering education must adapt and evolve for an llm environment.
21. M. Bernabei, S. Colabianchi, A. Falegnami, F. Costantino, Students' use of large language models in engineering education: A case study on technology acceptance, perceptions, efficacy, and detection chances, Computers and Education: Artificial Intelligence.
22. M. Z. Li, Using prompt engineering to enhance stem education, in: 2024 IEEE Integrated STEM Education Conference (ISEC).