The Interdisciplinary Nature of Stochastic Systems: Challenges and Opportunities in STEM Education

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***Abstract*—**This paper examines the role of stochastic systems theory as an integrative framework for interdisciplinary STEM education. The cross-boundary nature of stochastic systems and control is illustrated through the human brain, one of the most complex stochastic systems known, serving as a platform that naturally unifies mathematics, neuroscience, engineering, and medicine. Drawing on sustained programs at the University of Kansas, iExplore Foundation for Sustainable Development, and collaborative work with biomedical researchers, we describe a pedagogical framework in which the classroom is treated as an uncertain dynamic system, teaching is an adaptive strategy, and student feedback provides data for continuous improvement. The dynamicity is further enhanced with the addition of individuality as a variable in the mentorship. The C5 principles (curiosity, creativity, connections, communication, and collaboration) are presented as practical design principles for interdisciplinary learning. We also report on a novel initiative in which students engaged with AI and machine learning tools as active participants in the peer review of conference submissions, extending the model of learning to collaborate and collaborating to learn.

Index Terms*—stochastic systems; control education; STEM education; adaptive control; neuroscience; adaptive mentorship; interdisciplinary learning; mentoring; artificial intelligence.*

I. INTRODUCTION

Stochastic systems and control provide a powerful language for modern interdisciplinary education. Randomness, uncertainty, feedback, adaptation, optimization, and data-driven decision-making are central to biomedical research, computational neuroscience, autonomous systems, finance, telecommunications, and robotics. CoDIT 2026, and in particular the special session on stochastic systems, control, optimization, and applications, offers a natural venue for examining how these concepts can be taught through examples that are mathematically rigorous, scientifically meaningful, and accessible to students at different stages of development.

The central thesis of this paper is that research, teaching, learning, mentoring, and outreach should be treated as connected parts of one adaptive educational system. The same ideas that make stochastic adaptive control useful for uncertain engineering systems can guide how educators design courses, mentor students, and build interdisciplinary programs [2], [3]. The instructor begins with incomplete knowledge of the students, observes feedback over time, updates teaching strategies, and seeks to optimize a criterion encompassing student learning, confidence, curiosity, and long-term engagement.

The human brain is used here as a motivating application. It is among the most complex stochastic systems encountered in science: high-dimensional, nonlinear, subject to noisy measurements, and individual variability, and connected to urgent biomedical questions including epilepsy and seizure prediction. As a teaching platform, the brain helps students see that probability, statistics, modeling, and computation are tools for understanding real systems that affect human life.

The contributions of this paper are threefold. First, we describe the pedagogical framework grounded in stochastic adaptive control theory. Second, we document specific evidence-based initiatives spanning K–12 outreach, undergraduate research, and graduate instruction [1], [4]. Third, we report on an emerging initiative integrating AI and machine learning into the educational pipeline, including student participation in peer review of technical papers.

II. STOCHASTIC SYSTEMS AS A CROSS-BOUNDARY EDUCATIONAL PLATFORM

Interdisciplinary research is attractive because it allows students to move beyond a single set of tools. Good understanding of randomness is an essential educational outcome. Noise in a system cannot simply be ignored: depending on the system and the feedback structure, noise may destabilize behavior, reveal hidden structure, or contribute to stabilization. These ideas give students a more mature framework for reasoning about uncertainty [2], [3].

The relevance of stochastic methods extends across a wide range of fields: finance, biomedicine, actuarial science, telecommunications, robotics, autonomous systems, and computational neuroscience. The rise of AI and machine learning has further elevated the practical importance of probability and statistical inference, as these methods underpin modern data-driven approaches to prediction, classification, and decision-making under uncertainty.

Control systems are present in cell phones, aircraft, vehicles, power grids, manufacturing, communication networks, biomedical devices, and autonomous systems, but they are often hidden from public view. This invisibility creates an educational challenge: students use controlled systems every day without seeing the theory that makes them possible. Outreach and classroom examples can make this hidden infrastructure visible and motivate deeper study [1], [4].

Biomedical examples are especially effective. Data analysis and modeling, combined with statistical methods, computational tools, and neuroimaging, can be used to study seizure prediction and other neurological problems. When students work with real biomedical data, they learn that statistical conclusions require careful sampling, critical interpretation, and humility about uncertainty, and that mathematical tools can connect directly to clinical and societal impact.

III. TEACHING AS A STOCHASTIC ADAPTIVE CONTROL PROBLEM

A classroom can be modeled as a stochastic system. At the start of a semester, the instructor does not know the state of the system: students arrive with different preparation, motivations, constraints, and expectations. The learning process evolves over time, influenced by lectures, examples, assessments, peer interactions, feedback, and guest speakers. From this perspective, teaching is not a static delivery of information but an adaptive process [2], [3].

The instructor collects information through short biographies, early assignments, classroom discussions, exam performance, surveys, and student reflections, and uses this information to update teaching strategies continuously. The objective is not only to maximize test performance but also to increase confidence, curiosity, critical thinking, and the ability to transfer knowledge across fields. The cost criterion for this optimization problem is the joint satisfaction of students and instructor from learning and teaching, together with evidence of durable skill development.

This analogy can be stated in the standard vocabulary of stochastic adaptive control (Fig. 1). The latent learning state of the class, comprising knowledge, confidence, curiosity, and engagement, plays the role of the plant state. It is never observed directly; the instructor receives only noisy, partial measurements through assessments, surveys, and discussion, which act as the output of a sensing channel. Teaching decisions, including pacing, choice of examples, guest speakers, and the balance between individual and collaborative work, are the control inputs. The mapping from the instructor's current belief about the class to the next teaching decision is a policy, and the parameters of that policy, such as how strongly feedback shifts the plan, are themselves updated as evidence accumulates. Because the underlying dynamics are uncertain and only partially observed, the problem is naturally one of adaptive control under uncertainty rather than open-loop planning: the instructor must simultaneously learn the system and act on it. This is the same coupling of estimation and control that characterizes stochastic adaptive control in engineering systems [2], [3], and framing teaching this way makes the feedback structure explicit and gives students a concrete instance of the theory they are studying.

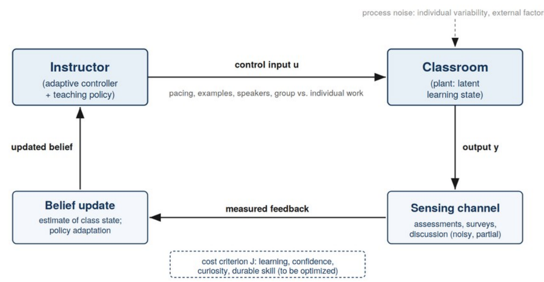

Fig. 1. Teaching modeled as a closed-loop stochastic adaptive control problem. The classroom is the plant, whose latent learning state is driven by teaching decisions (control input) and by process noise such as individual variability. The instructor observes only noisy, partial measurements through a sensing channel, updates a belief about the class state, and adapts the teaching policy to optimize a cost criterion defined over learning, confidence, curiosity, and durable skill.

This approach has been applied in courses including probability, mathematical statistics, stochastic processes, stochastic adaptive control (Math 750), and filtering, estimation, identification, and adaptive control (AE 713). In these settings, students are encouraged to build a case, test hypotheses, use data carefully, and challenge interpretations, an analogy to courtroom-style evidence evaluation that makes statistical thinking concrete and transferable.

IV. THE C5 FRAMEWORK

A practical framework developed through this work is C5: curiosity, creativity, connections, communication, and collaboration. Curiosity is the entry point: students learn more deeply when encouraged to ask why a system behaves as it does and what assumptions support a conclusion. Creativity follows when students generate their own examples, propose models, or seek alternative explanations. Connections emerge when mathematical ideas are linked explicitly to biology, medicine, finance, engineering, and everyday technology.

Communication is equally important. Students must be able to explain technical concepts to peers and to audiences outside their immediate discipline, a skill particularly important in interdisciplinary research, where collaborators often do not share the same vocabulary. Collaboration completes the framework. Group projects, peer tutoring, guest speakers, and outreach activities turn the classroom into a community of learners in which students who explain concepts to one another often develop deeper understanding than those who work individually.

The C5 framework also supports leadership development. Students who participate in peer tutoring, outreach, and interdisciplinary presentations learn to organize ideas, take responsibility for others, and communicate with confidence. Education in stochastic systems thereby becomes broader than technical training: it becomes preparation for research, professional service, and responsible participation in complex technological societies.

Peer Tutoring

A peer tutoring program has been implemented across multiple courses. Students who have demonstrated mastery serve as volunteer tutors, with formal recognition through instructor letters of recommendation. This program builds a community of learners, reinforces content knowledge for tutors through the act of teaching, and has measurably reduced course withdrawal and failure rates.

Guest Speakers

The integration of domain experts from outside mathematics and engineering, including neurologists, biostatisticians, and industry researchers, provides students with concrete evidence of the real-world relevance of stochastic methods. Speakers addressing epilepsy, COVID-19 epidemiological modeling, and algorithmic decision-making have consistently been identified by students as among the most motivating elements of the course, grounding abstract mathematical content in empirically important problems.

V. OUTREACH, VERTICAL MENTORING, AND LONG-TERM IMPACT

A major component of this work has been vertical mentoring spanning K–12 students through undergraduate, graduate, and faculty levels. Since 1994, an ongoing mathematics outreach partnership with Lawrence, Kansas elementary schools has engaged hundreds of students annually in topics spanning algebra, probability, and mathematical reasoning. Annual workshops at KU attract between 40 and 200 elementary-age participants. A mathematics competition affiliated with the KU Mathematics and Statistics Awareness Month (MSAM) has reached more than 2,000 students from over 90 Kansas schools and has received recognition from state and municipal government [4].

The NSF-supported workshop series, originally titled Ideas and Technology Control Systems and later renamed to emphasize the power, beauty, and excitement of the cross-boundary nature of control, has been associated with the American Control Conference (ACC), the IEEE Conference on Decision and Control (CDC), and IFAC World Congresses since 2000. The program has convened in more than 20 U.S. cities and in the Czech Republic, Cyprus, South Korea, Poland, Spain, and South Africa. Over its 26-year history it has engaged more than 25,000 students and teachers, with contributions from over 235 presenters and 200 volunteers [4].

REU students supported through NSF and NIH funding have participated in research bridging stochastic control, biomedical data analysis, and neuroscience. Undergraduate participants have received Goldwater Scholarships, NSF Graduate Research Fellowships, and awards at international mathematics conferences. Many have subsequently completed doctoral degrees at leading research universities and pursued careers in academia and industry [1], [4].

The long-term impact of early encouragement is illustrated by individual outcomes. A former sixth-grade participant in a KU mathematics contest later wrote that the prize money was long gone, but the encouragement had remained, and that he had returned to school to complete a degree in electrical engineering. Such examples support the evidence that early exposure and sustained mentorship can durably shape educational and professional trajectories.

The KU student chapter of the Association for Women in Mathematics (AWM), established 25 years ago, remains an active forum for undergraduate and graduate students. The co-founding of Women in Control, a professional network for women working in control theory and its applications, reflects a sustained commitment to broadening participation in the field. Students engaged through these initiatives have assumed leadership roles in IEEE, IFAC, and other professional organizations.

VI. BIOMEDICAL COLLABORATION AND THE BRAIN AS A LEARNING LABORATORY

Collaboration between mathematics, control, and biomedical research has created significant opportunities for students to engage with large-scale neuroimaging data. Through collaboration with the University of Southern California medical research environment, students from the University of Kansas were exposed to rigorously organized MRI datasets and to the challenges of data quality, variability, and biomedical interpretation [14]. Guided by neuroscience and clinical collaborators, students learned that data analysis requires domain knowledge, careful modeling, and respect for the limits of statistical inference.

This experience motivated the development of new teaching practices in probability and mathematical statistics, in which real-world problems from biomedicine, insurance, and finance make statistical reasoning relevant and concrete. Students applied probabilistic and statistical methods to the problem of seizure prediction in epilepsy, seeing directly how mathematical tools connect to clinical questions affecting human health [13]. Several students subsequently pursued graduate work in neuroscience and biomedical engineering.

The brain remains an especially rich platform for STEM education. It allows educators to discuss randomness, feedback, adaptation, optimization, and the ethical implications of AI-assisted clinical decision support, creating a bridge between technical fields and human health that motivates students who might otherwise view mathematics or control theory as distant from real-world concerns.

VII. RELATED WORK

The development of 21st-century skills, including critical thinking, creativity, collaboration, and communication, is widely regarded as essential preparation for a complex and globalized world. Collaborative learning has been studied extensively for its impact on STEM education. Xinh et al. developed a Student Teams-Achievement Divisions collaborative learning model that produced a significant increase in these skills by structuring the classroom so that learning is achieved through organized group work [8].

Johnson examined collaborative technologies for the skill development of adult learners in community-based learning centres, applying Salmon's five-stage model. The study assessed higher-order thinking and self-directed learning through online discussion forums and wikis, and proposed an arrow-model framework for online collaboration [9].

Salmons emphasizes the value of technology-supported online collaboration and offers guidance for designing collaborative learning activities together with appropriate assessment methodologies [10].

A personalized collaborative e-learning model developed by Kurnaedi et al. for vocational high school students proved effective in improving learning quality, outcomes, and engagement in developing practical skills, combining interactive support with context-based collaboration in a practical learning environment [11].

Rusman et al. describe the transformation required of educators in the Society 5.0 era, in which artificial intelligence and the Internet of Things support not only learning but also students' lifelong career skills. They argue that complex thinking competencies, including critical, logical, analytical, and systematic thinking, are needed for teachers to cultivate higher-order thinking in their students [12].

Taken together, these models confirm the value of collaborative learning for educational effectiveness, but each addresses only one or two aspects of the teaching and learning process. The proposed C5 framework is intended as a more holistic model: it begins by instilling curiosity as the entry point into STEM and then sustains an effective learning process through multiple influences and resources.

VIII. MENTORSHIP BASED ON INDIVIDUALITY

While working on the C5 framework, it is important to include one of the core variables that can change the outcome of the application of the framework on a student- the individuality of the student. Individuality is the set of behavioural characteristics that vary between the similar specimens of a species, and which persist during their lifetime. The individuality of a person is determined by several factors and one of the most important factors is the stochastic processes that occur in the brain of the person [5]. Variation in axons or the brain wiring which targets choices and dynamics is responsible for this individuality [6].

Every learner differs in the prior knowledge and technical background and so can be expected to differ in their pace of learning too. In addition, the depth of curiosity, motivation, and the cognitive style are the individual traits of the person, which also will play an important role in the application of the framework. A standardized mentorship approach such as the C5 framework assumes uniformity and often expected to result in underchallenging the high potential learners and overwhelming the learners who need continuous support.

It is important for the framework to recognise individuality to enable adaptive guidance and personalised learning trajectories, especially in interdisciplinary fields. For instance, how much a student depends on AI for learning, depends on the ethical decision-making ability of the student making it as a judgement-based approach. This changes the approach of the mentorship during the collaboration phase. Without individuality as a variable in the framework, defining the over or under dependency of the student on AI will be difficult.

Mentorship becomes impactful when the common ground for the mentorship is established before the mentorship begins. Understanding the student's goals, interests, and their sense of purpose is an important goal of the mentorship program. This was found when the framework was applied to a set of school students in secondary schools in India. iExplore Foundation for Sustainable Development, India performed a program called Women in AeroSTEM Experiential Program with 50 students which combined experiential learning, mentoring, and exposure to real world innovation. The students were in 12- 17 age category and selected from a rural school to ensure similar educational background. The program had 5 teachers trained as STEM facilitators and 30 IEEE volunteers were engaged in mentoring and outreach, ensuring individual support.

It was found that while all the students displayed healthy curiosity about aerospace technology at the outset, the degree of learning, confidence, and originality of ideas varied considerably across students. Based on facilitator ratings recorded during the workshop, roughly a quarter of the students showed consistently proactive learning, and about a third connected their environment to the material to generate original ideas at various stages of the eleven-day workshop. These figures are observational rather than the result of a controlled instrument and are reported here to characterize the range of responses rather than to establish precise effect sizes.

It was also found that individuality plays an important role in the level of analytical thinking, comfort with hands on training and tendency to iterate vs finalizing quickly. The mentors had to reorient themselves when dealing with the different students regarding the time given to grasp the concept, reorientation, and encouragement. We could see the various students responding differently to failures such as when the circuit was not working despite assembling it diligently. There were some emotional responses, some intellectual responses, and some neutral responses which made the mentors also rethink their strategies. The mentors who could do this also displayed adapting to the individuality of the students.

There were also instances in which students who grasped concepts more slowly began to lose interest in the learning environment. In these cases the creativity of the mentors came to the forefront: some recognized leadership as an individual trait among certain students and used peer mentorship to encourage collaborative problem solving.

IX. ARTIFICIAL INTELLIGENCE AND NEW EDUCATIONAL PRACTICES

The rapid adoption of AI and machine learning tools by students creates both challenges and opportunities. Students can use AI superficially, but they can also learn to critique AI outputs, identify assumptions, evaluate evidence, and improve drafts. In recent KU courses, experts in AI and machine learning have served as guest speakers, and, for the first time, students were engaged as reviewers of a manuscript in active preparation for submission to CODIT 2026.

The experiment proved highly effective. Student reviews identified substantive issues of exposition and contributed to meaningful revisions of the submitted papers. The experience gave students direct exposure to the standards of technical communication expected at international conferences and to the reality that papers are iteratively revised, arguments are clarified, and claims are sharpened through structured critique.

AI also strengthens the case for rigorous probability and statistics education. Large-scale models, data-driven prediction, clinical decision support, and autonomous systems all require students who can reason probabilistically, assess uncertainty, and question spurious precision. The rise of AI is therefore not a reason to reduce mathematical training; it is a reason to make that training more connected, applied, and critical.

Here too, individuality plays an important role in how the AI is used by each student during their learning and how much of "thinking" is delegated to the tool. As mentioned before, the effectiveness and the ethical development of the student in using AI for complex problems depends on the individuality of the student. The students may use AI for exploring a topic deeply and use it for augmentative learning. In some cases, they may use it for short cut thinking or for quickly finding a solution for a problem. The depth of curiosity also depends on the time available for exploration, the knowledge of the student on the topic, and personal values of the student. The knowledge and personal values of the student, here are individuality indicators.

X. ASSESSMENT AND EVIDENCE OF EFFECTIVENESS

Assessment in this approach is continuous rather than limited to final examinations. Students share goals and expectations at the beginning of a course. Feedback is collected after each examination. Reflections are collected near the end of the semester. Self-evaluation forms ask students to organize evidence from the entire term and to evaluate their own performance logically and critically reinforcing the idea that learning itself can be analyzed with data.

Student reflections indicate that probability and statistics courses taught under this framework can change how students reason beyond the classroom. Students report greater confidence in evaluating data-based claims, stronger appreciation for scientific institutions when evidence is understood on its merits, and improved ability to articulate logical reasoning. These outcomes are particularly important for engineers, scientists, and citizens who must make consequential decisions in uncertain environments. A recurring theme in these reflections concerns collaborative work: in courses including probability, mathematical statistics, stochastic processes, and stochastic adaptive control, students complete final collaborative papers, and end-of-term self-evaluations consistently identify this learning-to-collaborate and collaborating-to-learn experience as valuable, an approach informed by sustained faculty engagement with the collaborative learning literature [10].

In the case of AeroSTEM students, the assessment was based on the originality of the ideas, the complexity of the proposed ideas, degree of completion of the hands-on model, level of the grasp of the concepts, and the innovation displayed during the course. The assessment was used to identify the contributors, innovators, and leaders.

The proposed model treats assessment as feedback for adaptation. Just as a controller uses measurements to update its action, the instructor uses student evidence to update teaching strategy. The goal is not a rigid method but a disciplined adaptive posture: observe, interpret, adjust, and reassess.

XI. CONCLUSION

Stochastic systems and stochastic adaptive control offer a powerful and intellectually honest framework for integrating research, teaching, mentoring, and outreach across STEM disciplines. The human brain, biomedical data, and AI-enabled learning environments provide compelling platforms for demonstrating how randomness, feedback, adaptation, and optimization shape real systems that matter.

Evidence from more than three decades of sustained teaching, outreach, and mentoring demonstrates that this approach is both effective and scalable. The C5 framework provides a practical implementation of the adaptive teaching philosophy. Emerging integration of AI into the educational pipeline, including student participation in peer review, points toward productive directions for future development.

The longevity and vitality of the stochastic systems and control field depend on sustained investment in education and outreach that communicates the power and beauty of the discipline to the broadest possible audience. This work represents one evidence-based contribution to that collective effort [1], [7].

In STEM project-based mentorship, individuality plays a critical role in shaping the student's output from the beginning stage: problem formulation, methodological choices, ethical reasoning, and learning depth. Standardizing the mentorship approaches will lead to loss of innovation, resilience, and responsible research. This shows that the mentorship should encourage the students arriving at meaningful, valid, and well-reasoned solutions rather than a stereotypic approach to arrive at a common or same solution by all students killing the innovative streak.

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REFERENCES

[1] J. Velasquez de Bedout, B. Pasik-Duncan, and M. Verleger, "Education and Qualification for Control and Automation," in S. Y. Nof, Ed., Springer Handbook of Automation, 2nd ed. Cham, Switzerland: Springer, 2023, pp. 717–728.

[2] B. Pasik-Duncan, "Plain talk on stochastic adaptive control and its broader impact: Some reflections from the IFAC Technical Board Liaison to Education," IFAC-PapersOnLine, vol. 52, no. 9, pp. 184–189, 2019.

[3] B. Pasik-Duncan and T. E. Duncan, "Stochastic adaptive control: Integrating research and teaching," in Proc. 11th IFAC Symp. Advances in Control Education, Bratislava, Slovakia, 2016, pp. 105–109.

[4] B. Pasik-Duncan and D. Duncan, "Undergraduates' partnership with K-12," in Proc. American Control Conference, Anchorage, AK, USA, 2002, pp. 1085–1088.

[5] Kyle Honegger, Benjamin de Bivort, "Stochasticity, individuality and behavior," in Current Biology, Volume 28, Issue 1, 2018, pp. R8-R12.

[6] Andriatsilavo M, Barata C, Reifenstein E, Dumoulin A, Tao Griffin T, Dutta SB, Stoeckli ET, von Kleist M, Hiesinger PR, Hassan BA, "Sequential and independent probabilistic events regulate differential axon targeting during development in Drosophila melanogaster", Nat Neurosci. 2025 May;28(5):998-1011. doi: 10.1038/s41593-025-01937-y. Epub 2025 May 7. PMID: 40335773.

[7] National Science Foundation, NSF's 10 Big Ideas: Investing in Bold Ideas for U.S. Science and Engineering. Alexandria, VA, USA: National Science Foundation, 2017. [Online]. Available: https://www.nsf.gov/news/special_reports/big_ideas/

[8] L. T. Xinh, D. N. Trung, B. V. Hong, N. T. Luong, and L. T. M. Nga, "Organizing Collaborative Learning in STEM Education to Develop Students' 21st-Century Skills," 2025 10th International STEM Education Conference (iSTEM-Ed), Pattaya, Thailand, 2025, pp. 1-6, doi: 10.1109/iSTEM-Ed65612.2025.11129362.

[9] C. Johnson, "Collaborative technologies, higher order thinking and self-sufficient learning: A case study of adult learners," Res. Learn. Technol., vol. 25, 2017, doi: 10.25304/rlt.v25.1981.

[10] J. Salmons, Learning to Collaborate, Collaborating to Learn: Engaging Students in the Classroom and Online, 1st ed. New York, NY, USA: Routledge, 2019, doi: https://doi.org/10.4324/9781003445708

[11] D. Kurnaedi and S. Widyarto, "Collaborative e-learning model development for increased quality learning in vocational school," bit-Tech, vol. 7, no. 2, pp. 463-473, 2024, doi: 10.32877/bt.v7i2.1846.

[12] Rafsanjani H. Education transformation in 5.0 society development era. In AIP Conference Proceedings 2023 (Vol. 2727, p. 020050).

[13] D. Duncan, P. Vespa, and A. W. Toga, "Detecting features of epileptogenesis in EEG after TBI using unsupervised diffusion component analysis," Discrete Contin. Dyn. Syst. Ser. B, vol. 23, no. 1, pp. 161–172, Jan. 2018, doi: 10.3934/dcdsb.2018010.

[14] A. A. Bruckhaus, A. Bennett, M. Brawer-Cohen, M. Sinclair, G. Ramirez-De La Cruz, G. Ragusa, and D. Duncan, "Evaluation of students' digital literacy through an immersive university-high school collaboration," Front. Educ., vol. 9, art. 1429893, 2024, doi: 10.3389/feduc.2024.1429893.