2026 ASEE ANNUAL CONFERENCE June 21–24, 2026 | Charlotte Convention Center, NC
Host Sponsor UNC Charlotte
Paper ID #52657

# Motivation, Context, and Consequence: Using Learning Theory to Guide Engagement with AI in Engineering Education

**Dr. Benjamin David Lutz, California Polytechnic State University, San Luis Obispo**

Ben Lutz is an Associate Professor of Mechanical Engineering at Cal Poly San Luis Obispo. He is the leader of the Critical Research in Engineering and Technology Education (CREATE) group, which supports undergraduate and graduate research across a wide range of mechanical engineering education settings and methodologies. His research interests include sociotechnical thinking in engineering education and practice as well as engineering design theory and pedagogy. His current work is focused on how engineers develop sociotechnical thinking and reasoning skills over time, and how this might be leveraged to inform educational and professional development experiences for engineers.

**Prof. Josh Brake, Harvey Mudd College**

## Abstract

The ways that generative AI (e.g., tools built on and around Large Language Models) have been thrust upon both engineering students and educators has many of us confused and apprehensive about how the tools might impact central issues like teaching, learning, and assessment. And while there are some ways AI might make positive contributions to engineering, there are also looming questions about academic integrity, the impact on traditional forms of assessment, and the role of higher education in society. This paper offers a framework grounded in diverse educational theories that can help engineering educators engage with AI in ways that discourage the use of AI tools in ways that subvert authentic, generative learning process. We focus on three areas: the individual, the relational, and the contextual. By attending to individual student motivations, educators can leverage student autonomy and control over learning to encourage productive AI practices that avoid extrinsic reward seeking and the disingenuous behaviors that result from it. In each area of focus, we offer both theoretical overviews and practical examples. By focusing on the relational aspects of learning, educators can create social, embodied learning experiences that discourage the use of AI to “farm out” important interactions, reflections, and the learning that accompanies authentic experiences. Third, when students can see how their learning has consequences and exists within a larger disciplinary context, the inherent value perceived in learning can encourage productive AI use through engagement with disciplinary norms and methods of communication. Taken together, these three aspects can offer educators a way to design learning environments that avoid the ratcheting up of surveillance, an uncritical application of things like blue books, or any other aspects of what we see as an increasingly untenable game of cat-and-mouse when it comes to AI use in engineering courses.

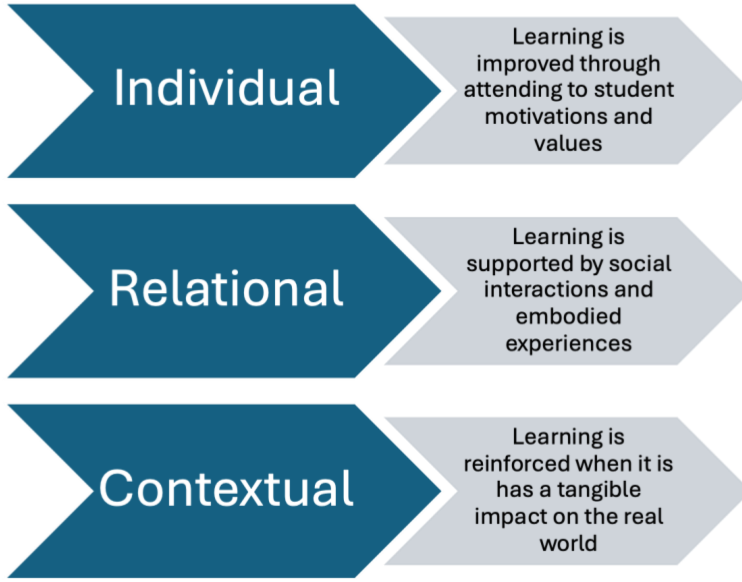
## Introduction, Motivation, and Purpose

The manner and speed with which generative AI has been injected into higher education has left many educators and students confused and apprehensive about its role in learning, teaching, assessment, and other core areas of engineering education. By generative AI, we mean existing tools like the chatbots or multimedia generators of January 2026 (e.g., ChatGPT, Claude), but also the potential suite of thus far undeveloped educational technologies that might flow from the aggregation of all human knowledge. On the one hand, AI has the potential to offer more students access to more information about more topics than has ever been possible. On the other hand, it has introduced new questions about teaching and learning, academic integrity, and indeed the role of higher education in society more broadly.

One important aspect of the AI in higher education question concerns the role of assessment. While some educators have made convincing calls for a return to more traditional forms of assessment such as blue books or oral exams, we also recognize that these methods are not suitable for all contexts (e.g., large lectures, design courses) and can be limited in what they are ultimately able to assess from our students (e.g., complex, higher order thinking). Further, the return to these forms of assessment can signal to students that they cannot be trusted to be honest with us or themselves when it comes to being accountable for their own learning. We want to chart a way through this new technology landscape that helps educators avoid the untenable cat-and-mouse game created by the increases in capability and ubiquity of AI tools.

The purpose of this paper is to provide an organizing framework for engineering educators as they consider how to (or if they should) engage with AI in their classrooms and assess student learning. We argue that thinking about AI in these terms can help educators work with the technology in ways that discourage student AI use in ways that subvert authentic, generative learning opportunities. In this paper, we use *authentic, generative learning experiences* to refer to learning processes that (1) are grounded in real contexts or practices, (2) require active participation and judgment by students, (3) involve interaction with others, and (4) produce durable changes in how students understand problems, practices, or their own roles as engineers. In short, we seek to preserve the kinds of learning experiences that change how students see and engage with the world. We aim to preserve these experiences through several different approaches that both appeal to students' values and motivations as well as introduce productive friction into the learning process when AI is used. We are not arguing for a ban on AI in higher education. We believe this to be a futile effort with little chance of success. Instead, we call for more critical engagement with generative AI tools, a deeper consideration of the nature of higher education, and a deeper consideration of what we ask of our students and ourselves.

To anchor our ideas, we organize the following sections in terms of three different areas of focus: 1) The individual, 2) the relational, and 3) the contextual. The first area of focus, the individual, is concerned with the motivations and values of our students. Attending to the motivational aspects of students has demonstrated numerous benefits and can be used to help students avoid dishonest, counterproductive use of AI tools. The second area of focus, the relational aspects, recognizes that learning is embodied and takes place via social exchanges. Providing embodied learning experiences in which students engage in authentic social interactions (e.g., with peers, experts, stakeholders) promotes productive learning practices and discourages the use of AI in ways that subvert learning. Finally, a focus on the context or impact of learning attends to the ways in which engineering solutions can have consequences in the real world. When students' learning artifacts have an impact on the world, disingenuous use of AI is mitigated through the need for accountability for one's learning. We address each of these topics in more depth in the following sections, anchoring each aspect to a relevant educational theory and providing brief examples from the authors' own pedagogical practices. This paper does not present a systematic empirical analysis of student generative AI use. Rather, it offers a theoretically grounded framework for designing learning environments in which the role of AI is shaped by instructional conditions, expectations, and norms.




### Individual Aspect: Attending to Student Motivations and Values

By helping students see the value of the activity for their own learning and find that activity interesting, useful, or advancing some kind of intrinsic goals, they are more likely to engage in that learning in productive ways. In other words, when students are motivated to learn something, they are less likely to use generative AI in ways that subvert authentic, generative learning processes. Although the existence and ubiquity of generative AI tools introduce a more convenient and accessible means for cheating compared to pre-existing platforms like Chegg, paper mills, or the internet (Austin & Brown, 1999; Etter et al., 2006), generative AI is not the first time educators have grappled with issues of cheating or plagiarism. Historically, one way educators have worked to address this issue is through focusing on student motivation (Lang, 2013), and we argue that these ideas can also apply to situations where students might be tempted to use AI to complete work for them in ways that subvert formative learning processes.

### Theory: Self-Determination Theory

One useful way to think about motivation is through the concept of Self-determination Theory (Deci & Ryan, 2004, 2010). SDT emphasizes three primary factors that impact individuals' intrinsic motivation: autonomy, relatedness, and competence. Autonomy refers to an individual's sense of control over their actions. In learning environments, this often refers to offering students some kind of choice or control over the way they go about learning something. Relatedness refers to a feeling of connectedness or respect within a community (or classroom). In engineering education, this might look like encouraging interpersonal connections among student team members or developing rapport between students and instructors. Finally, competence refers to the degree to which students feel like they can succeed on a task or on a particular challenge. In educational settings, this can look like effective scaffolding, providing actionable feedback, and offering problems of appropriate challenge for students.

Several meta-analyses and research studies highlight the positive impact of SDT-focused interventions in student intrinsic motivation (Wang et al., 2024), persistence (Bureau, Howard, et al., 2022; Howard et al., 2021), and ethical behavior (Bureau, Gareau, et al., 2022). In contrast, when these needs are not met for students, they are more likely to engage in surface-level learning, where shortcuts such as generative AI tools become more appealing. SDT therefore offers a useful theory from which to develop practices for engineering education that can help students engage in more meaningful learning process and avoid the deleterious effects of generative AI on academic integrity.

### Practice 1: Offer students choices

Lutz: One thing I like to do is offer students choices about the substance of a project or assignment. In my Design and Social Justice class, students work in groups to identify a concept or topic from the class and dig deeper into it. Then they must present their findings to the rest of the class through a video they create. In this assignment, students spend time with their teams deciding which topic they would like address or learn more about. When they pick they topic, they are more personally invested in the ideas and see the things they are learning as more useful or valuable. When students can see the value of what they are learning they are more likely to engage in positive behaviors that are supportive of effective learning (Niemiec & Ryan, 2009). In this case, effective learning processes are framed such that AI may be used as a collaborator rather than a substitute for engagement. For example, instructors can invite students to use AI to help teams converge on an idea or identify relevant resources, while retaining responsibility for interpretation, judgment, and final decisions. In these cases, the generative AI tool is used in ways that positively augment the learning process (e.g., offering clarity to group assignments, providing broad literature searches in shorter amounts of time).

### Practice 2: Scaffolding interest and encouraging ownership

Brake: I likewise attempt to offer students opportunities to choose the topic for their projects whenever possible. At Harvey Mudd College, many of our classes culminate with a final project completed in small teams. When I teach our embedded systems technical elective course, the only requirements for the final project are that it does something fun or useful and meaningfully uses both the microcontroller and field programmable gate array that they learn to use in the labs leading up to the final project. The open-ended design of the project topic and the small teams directly contribute to the autonomy and relatedness emphasized by SDT.

Furthermore, the fact that the final project follows a set of structured lab exercises that make up the first half of the course sets students up with sufficient competence to successfully propose and complete the project. This model of first preparing students with structured learning opportunities to build the core competencies in a discipline and then giving them more freedom as the course progresses is well suited for the integration of generative AI tools into the learning process. During the first part of the course, I specifically design the assignments to be completed without AI, so that students can build their skills independent of it. But in the final project phase, I allow more permissive use of AI tools, with the only requirement being that they share how they are using the tools and reflect on how their use shaped their learning.

## Relational Aspect: Encouraging Embodied, Situated Learning

Authentic, meaningful learning takes place in relation to others through engagement and interaction. When students engage with other people (in classrooms, in communities) and produce artifacts that account for and reflect on that engagement, AI becomes a less useful means to threaten authentic, generative learning experiences. By designing learning environments, assignments, and assessments based on the production of real-world, embodied experiences, we argue that instructors can create scenarios that encourage more productive and appropriate use of AI tools. At the same time, we argue that if students were to use AI to help them produce an artifact that does correspond to some real-world activity (e.g., synthesize interview/survey data, develop action items from meeting minutes), that the work done in these cases would resemble the learning experiences instructors were trying to create.

### Theory: Situated Cognition and Communities of Practice

Learning and cognition are situated (Brown et al., 1989; Johri & Olds, 2011; Lave & Wenger, 1991). That is, ideas and concepts always exist in some context, and our engagement with them is always impacted by that context. By context, we mean the physical setting, but also the institutional/organizational setting, social setting, and other factors that shape our understanding and engagement with ideas. Learning also involves participation in Communities of Practice (CoP). The concept of CoP helps illuminate the ways that authentic learning takes place via social interactions and in pursuit shared goals. Relatedly, social constructivism posits that social interactions form the basis for meaningful learning and that interactions and conversations with others are a primary way we acquire important concepts (Vygotsky & Cole, 2018). Across these theories, one critical insight is the focus on learning not as the rote acquisition of knowledge, but as a process of *becoming* a member of a larger community. By taking on the behaviors, discursive practices, and other relevant modes of interaction, learners acquire the knowledge and skills relevant to their discipline. Individuals become members of a community through diverse social interactions and increased legitimate participation in activities central to both the discipline broadly (e.g., mechanical engineering) and specific organization (e.g., student robotics club). Seen this way, learning is a process of increasing legitimate participation in activities relevant to a practice, and that process is mediated through social interactions and communication with others.

### Practice 1: Design projects with authentic stakeholders

Lutz: One practice that aligns with the ideas of situated learning comes from assignments that Author Lutz gives in his classes *Philosophy of Design.* The course addresses concepts related to stakeholder engagement and discovery, and one way students engage with stakeholders is through semi-structured interviews. Students must identify the range of direct and indirect stakeholders using a rainbow diagram (Leydens & Lucena, 2017) and interview people from at least three different stakeholder groups. Students must then work together in their design teams to share their interview findings and synthesize them into a final high-level summary. The work is *situated* in an authentic context through the engagement with real stakeholders in the problem. In this assignment, AI use becomes something that might aid in the synthesis of the findings but cannot produce the findings themselves. Students must talk with real people, record their findings, share them with their team, and combine them into a single coherent narrative. And while it is not possible to fully prevent students from fabricating interview data, we do require that students create field notes and interview reflections based on their individual work; these are important aspects of humanistic data collection and analysis. This individual component, combined with the need to share findings with others, can help mitigate the potential for students to be lured into fabricating interviews.

In this assignment, AI was discussed with students as a potential tool for synthesizing collective interview notes, with the expectation that any AI-generated output would be evaluated against students' firsthand impressions from conducting the interviews. As of this writing, AI is unable to conduct the semi-structured interviews like those required in this course, and so the text students produce must correspond to embodied actions that they undertook in the world. While generative AI tools could be used to fabricate interview data, the assignment is structured around shared discussion of interview experiences, comparison across stakeholder accounts, and reflective justification of design decisions, making such fabrication difficult to sustain without detection and pedagogically unproductive even when it occurs. Used this way, the AI-assisted synthesis does not replace students' interpretive responsibility but rather becomes another tool to be leveraged for the collective sensemaking of the group. By requiring legitimate engagement with real stakeholders, using AI to outsource thinking or subvert learning becomes unhelpful and unproductive from a design process standpoint. (Important to note here are issues of privacy and human subjects data. Instructors should address issues regarding participant protection, anonymity, and/or confidentiality when working with generative AI tools.)

Designing learning environments and assessments informed by Situated learning thus becomes a way to help students more effectively use AI. Requiring learning to flow from embodied, local, contextual experiences (e.g., interviews, observations) encourages students to make connections between theory and their lived experiences and introduces friction into the process of using AI to subvert meaningful learning.

**Practice 2: Necessarily collaborative experiments**

Brake: A second practice that aligns with these ideas is from the design of Author Brake's sophomore-level experimental engineering course. The course is structured as a series of seven lab assignments followed by a final project. While there are a few course elements that are completed individually by each student (e.g., weekly quizzes and writing assignments), most of the course deliverables are completed by the students in teams of four or five students. This heavy reliance on learning in teams connects with the ideas of situated learning and communities of practice by creating pathways in which students must learn together. The course is designed such that the work cannot be completed by an individual and requires the engagement of all team members.

Designing courses that require engagement not just as an individual but on teams creates an environment where AI can be explored constructively. Within teams, there is an opportunity for students to use generative AI in small groups and then together interrogate whether the response they get is trustworthy or helpful.

## Contextual Level: Emphasizing Impact and Consequence of Learning

When the results of a learning process have the potential to create a meaningful or consequential impact on the world, students are more likely to engage with AI in ways that are productive. If what students do to learn a subject is produce solutions to problems that they already know the teacher has the right answer to, then it is not unreasonable for them to see what they do as of little consequence. Right or wrong, the answer was already known. On the other hand, if learning artifacts are produced in response to authentic questions within a discipline and subject to scrutiny and revision, then students might therefore see their work as having some consequence in the world. When students see how the outputs of their learning processes (e.g., assignments, problems, reports) can have a tangible impact on the world beyond the classroom, the use of AI again becomes likely more to enhance learning than detract from it. That is, introducing real-world consequences into student work can help avoid unproductive use of AI and encourage more effective modes of engagement with the tools.

### Theory: Productive Disciplinary Engagement

One theory that seems useful in helping emphasize consequence in learning is *Productive Disciplinary Engagement* (Engle & Conant, 2002). In PDE, Engle et al describe learning in ways that encourage social interactions and discourses consistent with real disciplinary (e.g., professional) contexts. PDE is useful because it helps students take ownership of their learning and see how it fits into the larger constellation of disciplinary knowledge and discourse—critical aspects of professional formation for engineers. To create learning environments that encourage PDE, Engle et al. emphasize four key principles that emphasize both the social and cognitive dimensions of effective learning:

1. Problematizing content. Educators should encourage students to address legitimate issues within a discipline, and to do so in ways that are appropriate for novices. Students can define problems in ways that spark curiosity within a subject area.
2. Giving Students Authority. Encouraging students to play an active role in defining and addressing problems; Helping students take ownership of their learning processes.
3. Holding Students Accountable to Disciplinary Norms: Providing space for students to understand relevant issues and contexts surrounding the problems they are addressing; student work is informed by disciplinary norms for good practice.
4. Providing relevant resources: Ensuring students have access to the materials needed to engage in the learning as well as the pedagogical support needed to engage in the three principles above.

Importantly, students do not necessarily need to be engaged with cutting edge theories or advanced unanswered questions within the field. Engle et al. demonstrate how these techniques can be leveraged to help students address fundamental concepts such as counting and addition (Engle & Conant, 2002). In theory, these principles might apply to a wide range of courses from engineering sciences to those focused on design.

**Practice 1: Product archaeology**

Lutz: One practice I engage in that touches on some of these ideas has been the implementation of a technique call “Product Archaeology” (Devendorf et al., 2011; Lewis et al., 2011). Essentially, PA entails exploring an engineering product or artifact from an archaeological perspective, going through phases such as preparation (background research, broader context of problem space), excavation (product dissection, component analysis), evaluation (experimenting, benchmarking), and explanation (examine global, societal, environmental factors). These four phases are analogous to the process an archaeologist might go through when examining artifacts from an ancient civilization but based on modern engineering artifacts and supported by the engineering design process. The content is problematized by having students ask questions about products that they might have otherwise taken for granted (e.g., what is the environmental impact of single-use cameras?). Students are given authority and ownership in terms of how to draw conclusions from the different phases of the process. Students are held accountable to disciplinary practices using proper scholarly attribution as well as peer review/feedback sessions. (However, providing the resources to students to accomplish all this work is certainly time-consuming and demanding on instructors’ time, so examining the existing literature for examples might be a good place to start for resources.)

Some prior examples of PA implementation have included disposable cameras (Lamancusa et al., 1996), electric drills (Lewis et al., 2011), and rice cookers (Kang et al., 2012). In all of these cases, the artifacts are leveraged as ways to explore the broader contextual factors surrounding and artifacts’ development, use, disposal, etc. I have personally conducted a PA project that examined razors (disposable and electric). Students examined the cultural context for the development of these tools and ultimately developed a stronger understanding of how engineering work impacts society, culture, beliefs about hygiene, and the ways engineers are involved in these different aspects of a product.

Within this structure, AI can be positioned as a tool for preliminary background exploration or comparison of perspectives, while interpretation, critique, and explanation remain grounded in students’ direct engagement with the artifact and its broader context. By engaging in the PA process, students are making connections between their own knowledge and the rest of the world. They are situating what they learn within a larger global, societal, environmental, etc. context, and they are doing so in ways that involve sequential phases consistent with real-world projects. In these cases, AI can be leveraged to advance particular goals (background research), but its role in synthesizing information would be in service of learning and action that takes place in relation to others and that is subject to critique by professors and classmates. And while uncritical acceptance of generative AI output is a potential outcome, students’ ability to validate information and explore multiple viewpoints can still be assessed in this context In this sense, Product Archaeology creates sufficient friction to limit unhelpful reliance on AI while preserving opportunities for productive use. Because knowledge is developed through situated investigation, accountable interpretation, and iterative critique, any AI-generated input must be taken up, evaluated, and reworked by students in ways that align with the learning goals of the practice itself.

**Practice 2: Meeting real-world specs**

Brake: I engage PDE by designing my embedded systems course around industry standard microcontroller and field-programmable gate array boards and designing labs that mimic real-world design challenges. These labs are more like open-ended mini design projects that students must complete without clear step-by-step guidance. Instead, they are presented with a list of specifications that their project must meet and then must design a system that satisfies those specifications. These labs particularly emphasize the third dimension of PDE that Engle *et al.* highlight, using the list of specifications to directly communicate disciplinary norms. For example, even in the early stages of their work in the course, students are required to provide comprehensive documentation such as schematics, block diagrams, and well-commented code. Requirements like these help students learn their skills within the context of the expectations of the profession.

## Discussion and Conclusion

The widespread availability of generative AI amplifies existing tensions around assessment, authenticity, and student engagement, making the underlying values of instructional design more visible and consequential. Our framework of individual, relational, and contextual dimensions of learning offers a way to think about engineering education and the design of learning environments that can help to encourage productive student engagement with generative AI as well as mitigate student use of AI that strictly subverts authentic, generative learning processes. The first aspect considers the **individual** student in terms of their motivations, goals, and values. Designing learning environments and experiences that align with diverse students is vital to encouraging more productive engagement with AI. The second aspect considers **relational** dimensions of learning and the role of social interactions in facilitating that learning. By anchoring learning outcomes in embodied experiences, we can design learning experiences that encourage student collaboration and collective voices. Finally, the third aspect emphasizes the importance of the **contextual** impact of learning outputs. By providing space for authentic engagement with relevant disciplinary questions, students can more readily see the importance of the kinds of skills and expertise needed to more appropriately engage with AI systems.

One noteworthy aspect of this framework is that the theories of learning, cognition, and motivation leveraged in this paper were developed before the mass adoption of educational technologies, and certainly before AI as we have come to know it in 2026. These theories are neither new nor specific to generative AI technologies. This continuity highlights how longstanding theories of learning, motivation, and participation provide a stable foundation for instructional design even during moments of rapid technological change and uncertainty. Sound theories of learning and motivation can transcend contexts and inform educational practices across a wide range of settings and technological eras.

The practical implications of SDT, situated cognition, and PDE all leverage central aspects of teaching and learning that can operate alongside changes in technology and education contexts. Therefore, we are not primarily arguing for new ways of teaching that respond directly to unique challenges posed by generative AI. Rather, when the design of educational experiences is grounded in sound theories of learning, motivation, collaborative engagement, etc., learning environments can be designed in ways that are resilient to the challenges that any new technology may pose for learning. While generative AI is the current technology of focus in our current moment, it is one technology in a long line of technologies that have been and will be thrust upon educators. What we hope to offer is a way for educators to critically examine the role of AI and other educational technologies and the choices they make when designing learning environments and assessing learning artifacts or outcomes.

At a deeper level, this framework rests on a view of engineering as a fundamentally human endeavor. Engineering is a practice that involves judgment, interpretation, responsibility, and care for others. Engineers work with and for people, within social, cultural, environmental, and institutional constraints, and these dimensions of engineering practice are learned through participation, reflection, and engagement with others. When generative AI is used to bypass different elements of learning, it risks narrowing students' understanding of what engineering is and what it demands of them as professionals. By contrast, learning environments that emphasize motivation, relationships, and impact make visible the human work of engineering and position AI as a tool to be integrated thoughtfully into that work.

Approaching learning environment design through a more humanistic lens also helps clarify the value of a college education in an era of ubiquitous access to information and automated assistance. The value of higher education lies in the opportunity to engage in sustained, guided participation in a community of inquiry and practice—to wrestle with ideas, to fail and recover, to negotiate meaning with others, and to develop a sense of responsibility for one's work and its impacts. When educational experiences foreground these dimensions, they make clear why learning cannot be reduced to output alone and why tools like generative AI, while powerful, cannot replace the developmental work that higher education is meant to support. In this way, designing learning environments that center the human dimensions of engineering does not merely respond to the challenges posed by AI; it articulates and reinforces the legitimate purpose of engineering education itself.

## References

Austin, M. J., & Brown, L. D. (1999). *Internet Plagiarism: Developing Strategies to Curb Student Academic Dishonesty*. http://www.cheathou-

Brown, J. S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, *18*(1), 32–42.

Bureau, J. S., Gareau, A., Guay, F., & Mageau, G. A. (2022). Investigating how autonomy-supportive teaching moderates the relation between student honesty and premeditated cheating. *Wiley Online LibraryJS Bureau, A Gareau, F Guay, GA MageauBritish Journal of Educational Psychology, 2022•Wiley Online Library*, *92*(1), 175–193. https://doi.org/10.1111/BJEP.12444

Bureau, J. S., Howard, J. L., Chong, J. X. Y., & Guay, F. (2022). Pathways to student motivation: A meta-analysis of antecedents of autonomous and controlled motivations. *Journals.Sagepub.ComJS Bureau, JL Howard, JXY Chong, F GuayReview of Educational Research, 2022•journals.Sagepub.Com*, *92*(1), 46–72. https://doi.org/10.3102/00346543211042426

Deci, E. L., & Ryan, R. M. (2004). *Handbook of self-determination research*. University Rochester Press.

Deci, E. L., & Ryan, R. M. (2010). *Self-Determination*. Wiley Online Library.

Devendorf, E., Cormier, P., Moore-Russo, D., & Lewis, K. (2011). Using Product Archaeology to integrate Global, Economic, Environmental, and Societal factors in introductory design education. *ASME 2011 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 729–739.

Engle, R. A., & Conant, F. R. (2002). Guiding principles for fostering productive disciplinary engagement: Explaining an emergent argument in a community of learners classroom. *Taylor & Francis*, *20*(4), 399–483. https://doi.org/10.1207/S1532690XCI2004_1

Etter, S., Cramer, J. J., & Finn, S. (2006). Origins of academic dishonesty: Ethical orientations and personality factors associated with attitudes about cheating with information technology. *Taylor & FrancisS Etter, JJ Cramer, S FinnJournal of Research on Technology in Education, 2006•Taylor & Francis*, *39*(2), 133–155. https://doi.org/10.1080/15391523.2006.10782477

Howard, J. L., Bureau, J., Guay, F., Chong, J. X. Y., & Ryan, R. M. (2021). Student motivation and associated outcomes: A meta-analysis from self-determination theory. *Journals.Sagepub.ComJL Howard, J Bureau, F Guay, JXY Chong, RM RyanPerspectives on Psychological Science, 2021•journals.Sagepub.Com*, *16*(6), 1300–1323. https://doi.org/10.1177/1745691620966789

Johri, A., & Olds, B. M. (2011). Situated engineering learning: Bridging engineering education research and the learning sciences. *Journal of Engineering Education*, *100*(1), 151–185.

Kang, K., Simpson, T. W., & Okudan Kremer, G. E. (2012). Exposing Students to Culturual Issues in Rice Cooker Design Through Product Archaeology. *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (ASME)*, 285–296. https://asmedigitalcollection.asme.org/IDETC-CIE/proceedings-abstract/IDETC-CIE2012/285/253594

Lamancusa, J., Torres, M., Kumar, V., & Jorgensen, J. (1996). Learning engineering by product dissection. *American Society for Engineering Education Annual Conference*. https://peer.asee.org/learning-engineering-by-product-dissection

Lang, J. M. (2013). *Cheating Lessons: Learning from Academic Dishonesty*. Harvard University Press.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge university press.

Lewis, K., Moore-Russo, D. A., Ashour, O. M., Simpson, T. W., Kremer, G. E. O., Neumeyer, X., McKenna, A. F., & Chen, W. (2011). Teaching the Global, Economic, Environmental, and Societal Foundations of Engineering Design through Product Archaeology. *118th ASEE Annual Conference and Exposition*.

Leydens, J. A., & Lucena, J. C. (2017). *Engineering justice: Transforming engineering education and practice*. John Wiley & Sons.

Niemiec, C. P., & Ryan, R. M. (2009). Autonomy, competence, and relatedness in the classroom: Applying self-determination theory to educational practice. *Journals.Sagepub.ComCP Niemiec, RM RyanTheory and Research in Education, 2009•journals.Sagepub.Com*, *7*(2), 133–144. https://doi.org/10.1177/1477878509104318

Vygotsky, L., & Cole, M. (2018). Lev Vygotsky: Learning and social constructivism. *Learning Theories for Early Years Practice*, 69–79. https://www.torrossa.com/gs/resourceProxy?an=5282231&publisher=FZ7200&page=91#page=81

Wang, Y., Wang, H., Wang, S., & Wind, S. (2024). A systematic review and meta-analysis of self-determination-theory-based interventions in the education context. *Elsevier*. https://www.sciencedirect.com/science/article/pii/S0023969024000572?casa_token=EoEL0HQ0crsAAAAA:ubLtI38EoMiyrQ2Nm_skqdA9RDBlOvaMCbopZmc9Y8a9gtQb3GSLaAdfgQvy3Oza7ebzbsWNCWU