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# Leveraging Generative Artificial Intelligence to make the literature search process easier for new researchers

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# Leveraging Generative AI to make the literature search process easier for new researchers

**Abstract**

This Tricks of the Trade paper explores how Generative AI (GenAI) can support early-career engineering education researchers in literature sourcing. Transitioning from engineering to engineering education research (EER) requires navigating unfamiliar literature in sociology, psychology, and education, a time-consuming process that poses barriers for newcomers.

Our approach distinguishes GenAI-assisted literature sourcing (finding, organizing, and retrieving) from literature review (reading, synthesizing, and critiquing), demonstrating how GenAI can assist in identifying relevant papers, theoretical frameworks, and methodological approaches while preserving the researcher's responsibility for verification, interpretation, and synthesis. The process is demonstrated through a case where a graduate student explores an unfamiliar research topic and an experienced researcher analyzes the process. We illustrate our strategy with prompts and reflections on the output. We also suggest verification measures (triangulation, citation chaining, and peer and mentor discussions) to address concerns about hallucinations, algorithmic bias, and cognitive offloading. While demonstrated in engineering education, this approach is applicable to other fields where the breadth of the literature creates barriers for newcomers.

**Background and Introduction**

Engineering Education Research (EER) is a relatively young field compared to programs like Mechanical or Civil Engineering [1]. While an increasing number of scholars are now formally trained in EER, the field historically, and still frequently, engages scholars transitioning from other engineering backgrounds [2]. This transition, in addition to requiring learning new vocabulary and experimental methods, also demands a fundamental epistemological shift from positivist framings of problems with well-defined constraints to post-positivist, interpretivist, or constructivist paradigms, in which boundary definitions are subjective, context is essential, and multiple, conflicting truths can coexist [2], [3].

For researchers, the transition to EER is often motivated by a desire to address systemic issues witnessed or experienced during their own formation [4], [5]. They enter the field eager to solve problems relevant to their communities. However, this enthusiasm can quickly be dampened by the sheer breadth of the literature, which is fragmented across journals and disciplines [2], [6]. Consequently, researchers new to the field often struggle not only to find answers but also to understand how to frame their interests into research questions [6], [7]. For graduate students, this difficulty is compounded when their dissertation interest lies outside their advisor's immediate area of expertise, leaving them to navigate this complex landscape in isolation.

While traditional literature search practices, such as systematic literature reviews, are well documented as the gold standard for comprehensively understanding a field [6], they may be ill-suited to this initial exploration. Systematic reviews are time-consuming, requiring massive article screening processes that may lead to research fatigue before a new researcher has finalized their research area. Through the lens of Cognitive Load Theory (CLT) [8], this process creates an imbalance in mental effort where researchers expend their cognitive resources on extraneous cognitive load: the effort required by the chaotic process of locating relevant texts, rather than on germane cognitive load, which is the effort dedicated to processing, synthesizing, and creating schemas from the literature [8]. Generative Artificial Intelligence (GenAI) tools can serve as a bridge for the engineer entering EER. This approach seeks to reduce the extraneous cognitive load researchers face when searching for a new topic, thereby freeing space for germane cognitive load in engaging with the literature. It hinges on a crucial distinction: GenAI should be utilized to facilitate literature sourcing, not as a substitute for the literature review.

We view sourcing as the logistical task of finding, sorting, and mapping relevant scholarship, while reviewing is the intellectual task of reading, synthesizing, critiquing, and integrating that work. According to Grant and Booth [9], this aligns most closely with "mapping" or "scoping", identifying the boundaries and key concepts of a field, rather than a comprehensive synthesis. A common concern is that reliance on GenAI leads to a loss of critical thinking or introduces hallucinations [10]. However, when GenAI is used for sourcing to deliver targeted, relevant articles rather than interpreting them, these risks can be mitigated. The researcher must still read, critique, and integrate the work, but they no longer have to expend mental energy locating it.

The purpose of this *Tricks of the Trade* paper is to demonstrate how GenAI, specifically Large Language Models (LLMs) like ChatGPT, can streamline literature sourcing for early-career researchers. The workflow presented in this paper emerged from reflecting on a nonlinear learning process experienced by the first author while preparing for qualifying examinations in their PhD program. GenAI was not used in a planned or systematic manner initially. Instead, the first author asked broad questions, followed interesting lines of inquiry, requested targeted reading lists, and gradually refined searches as understanding increased. Although this approach felt messy in the moment, upon critical reflection, patterns emerged in how they used GenAI to locate relevant literature that proved helpful.

Based on that experience, the case presented in this paper was applied to a new research topic, situated within their doctoral advisor's (second author) area of expertise. By testing the workflow on a topic new to the student, the advisor could examine and verify the accuracy of the output, demonstrating the transferability of the described workflows for rigorously exploring a new domain.

**Overview of the GenAI-Assisted Literature Sourcing Workflow**

To operationalize the distinction between sourcing and reviewing, we articulate six strategies for GenAI-assisted literature sourcing, organized into three phases that reflect the progression of an early-career researcher's understanding.

Phase I: Orientation

1. Providing context and setting expectations
2. Mapping and scanning the research landscape

Phase II: Alignment

3. Theoretical and paradigmatic alignment (exploratory and confirmatory)
4. Operationalization and validity sourcing

Phase III: Consolidation

5. Rhetorical reading and synthesis support
6. Knowing when to close the loop and disengage from GenAI

**A Note on Voice and Perspective**

The paper follows a conversational format between the first author (a new EER graduate student) and the second author (the first author's dissertation advisor). For illustrative purposes, the first author demonstrates their approach to exploring a new topic within the second author's research area using GenAI. The given topic is co-curricular learning in engineering: student motivation in engineering clubs. The goal of the literature search was to review prior work before designing the study.

The first author writes in detail about their process and reflects on it. Complementarily, the second author comments on the output as an expert on the topic and as someone who learned to explore engineering education literature without GenAI.

**GenAI Models used**

Several specialized software platforms, such as Elicit, Consensus AI, and Undermind AI, have emerged to assist with synthesizing academic literature. These platforms distinguish themselves by grounding their responses in direct evidence from their internal repositories of scholarly literature [11]. Similarly, the landscape is shifting within established search engines; during the writing of this paper, Google Scholar launched *Scholar Labs*, an AI-powered system designed to retrieve publications without the need for complex Boolean operators [12]. These developments show the potential emergence of GenAI as a new standard for conducting literature searches.

For this case study, we utilized a general-purpose LLM, specifically OpenAI's ChatGPT (GPT-5.2 Instant, free tier, accessed December 2025). We selected this model to demonstrate workflows freely accessible to any graduate student. In practice, we recommend running the same prompts through multiple LLMs to identify where outputs converge and or diverge for deeper exploration. However, because this paper aims to demonstrate how to conduct GenAI-assisted literature sourcing rather than to compare model outputs, we present examples from a single model for clarity.

To minimize the potential influence of prior interactions, the workflow was conducted in a newly created chat session with no prior conversation history. At the time of data collection, the platform also indicated that account-level memory was full, limiting the addition of new personalized information. While it is not possible to fully determine how platform-level personalization may influence model responses, these steps helped reduce carryover effects from previous usage and support the transferability of the workflow to a typical user experience. The entire conversation with ChatGPT is shown in the appendix.

Furthermore, we adhere to established best practices for prompting GenAI, such as asking for reasoning, providing context, and specifications, as documented previously [13], [14]. This paper does not aim to reinvent or compare prompting architectures; instead, we focus on how these best practices can be leveraged within a literature search workflow. We describe the heuristic approach we used to navigate the search, detailing the rationale for our decisions to ensure transparency and reproducibility.

**Implementation**

In the following sections, the first author shifts to first-person narration to provide an authentic account of the workflow as it unfolded. While this paper is presented collaboratively, the search process and decision-making described were conducted by the first author.

**Phase I: Orientation**

1. **Providing context for the GenAI engine and setting expectations**

The first step in my workflow was to explicitly define the role the GenAI model should play in the conversation. Aligning with the 'Persona Pattern' documented in prompt engineering literature [14], I aimed to avoid the common pitfall of treating the model like a standard keyword search engine. Therefore, I provided comprehensive background information to ensure the model's output remained grounded and relevant to my inquiry, and constructed my prompt around six key elements shown below [13], [14]. Figure 1 demonstrates the prompts I used to orient ChatGPT.

- **Persona:** I asked that it assume the persona of an experienced researcher to guide my process as a research assistant or collaborator.
- **Context:** I explained my role as a newcomer to the field and my interest in understanding a particular area, which shapes how the model responds in subsequent exchanges within the same chat history.
- **Specification:** I explained that I wanted it to source for me, not synthesize. GenAI typically generates responses quickly, optimizing for readability over verifiability [15].

- **Constraint:** I added a strict requirement that the model's answers include an attached or linked paper (not names of articles or DOIs) and that it suggests relevant papers even if it could not access the full article. I used my institution's proxy to access those papers.
- **Details:** I varied the format requests based on how I thought the information would be best presented at a given stage. When I thought the information would be best presented in a table, I requested that the response be presented in a table.
- **Justification:** I asked the model to add an explanation or rationale for its choices, which makes it more transparent how the GenAI was processing my requests.

Author 1

*Awesome! Before we proceed, though, here are some things I want you to take note of and inform all your answers:*
*1. You'll assist me as an experienced member of the field of inquiry.*
*2. All your answers would be sourced from relevant information you would need to verify. In your answers, please include the appropriate sources and papers, with their links if available, so I can review them to cross-check. If you can't access it, then just direct me to the paper so that I can search it out myself. Finally, include rationales for all your answers.*
*Can you abide by this and all the questions in this session?*

ChatGPT

*Yes — I can abide by all of that for this session…*

**Figure 1. Step 1: Providing context for the GenAI engine and setting expectations for the conversation.**

### 2. Mapping and scanning the landscape

With clear expectations for my process in place, the next step was to get a broad overview of the topic of interest. Traditional database searches require familiarity with discipline-specific terminology, Boolean operators, and the syntax conventions of different search engines. For someone transitioning from engineering to EER, determining whether to search for "self-efficacy," "academic confidence," "competence beliefs," or "success expectations" can be a barrier, as one must know the terminology to locate relevant literature. GenAI enables researchers to describe their interests in natural language, without needing to master search syntax or know all the relevant terminology in advance.

The goal of using GenAI as a search tool at this stage was to help the searcher identify multiple perspectives, preventing them from narrowing the topic scope too early, which is important when one does not yet know what perspectives exist. In my case, I requested an overview of the research on the topic I was exploring. I requested that the information be presented in a tabular form to compare different disciplinary approaches to that topic. Figure 2 shows the prompt:

Author 1

*Thanks so much for agreeing to help. The topic I want to explore is "Co-curricular learning in engineering: Student motivation in engineering clubs". Give me an overview of the research space, making sure to compare the different disciplinary approaches (e.g., psychology, sociology, etc) in a tabular form. Remember to keep to the instructions and guidelines provided initially.*

ChatGPT

*Below is a rigorous, sourced overview of the research space on co-curricular learning in engineering with a focus on student motivation in engineering clubs…*

**Figure 2. Step 2: Prompting ChatGPT to map the landscape I want to explore.**

ChatGPT gave me two responses to choose from. While both provided an overview, I selected the first response (Table 1) because it included clickable links, whereas the second listed only the paper titles and the journals in which they were published.

**Table 1: ChatGPT output based on the prompt.**

| Discipline / Approach | Core Focus | Typical Theoretical Frameworks | Research Methods | Example Findings & Sources |
|---|---|---|---|---|
| **Engineering Education Research** | How co-curricular activities support learning outcomes and professional competencies | Engineering identity, professional formation, high-impact practices | Mixed methods; surveys + interviews; quasi-experiments | Engineering students in co-curriculars show enhanced self-efficacy and professional skills (competition teams research) [16] |
| **Psychology (Motivation Theory)** | Internal processes governing why students engage in activities | Self-Determination Theory (SDT); Expectancy-Value Theory (EVT); goal orientation | Quantitative surveys; structural models; sometimes qualitative interviews | EVT explains student choices in co-curricular contexts by weighing value vs cost of participation [17, 18] |
| **Sociology of Education** | How social structures and identities shape participation | Social capital, communities of practice, identity formation | Ethnography; interviews; longitudinal) | Social connections and sense of community are motivators; norms around "valuable experience" shape engagement [17] |
| **Social & Developmental Psychology** | How motivation in one context (e.g., clubs) generalizes to other domains | Motivation generalization models; self-regulation | Longitudinal designs; mediation models | Motivation in extracurricular contexts can transfer to greater academic motivation in school contexts (though not engineering-specific) [19] |
| **Organizational Psychology / Education Policy** | Structural and systemic factors (time pressure, equity, policy) | Temporal and ecological models | Surveys; institutional data | Perceived high cost and structural barriers reduce participation and may reinforce inequities [17] |

The response provided an overview, key themes, disciplinary approaches, theoretical lenses, and representative sources for deeper dives, including references related to Foundational Motivation Theory [18, 19] and Engineering Co-curricular Studies [16, 17].

All the sources included in the results were open-access articles, which reduced the likelihood of hallucination, but may have limited the scope of the results. Among the recommended sources for deeper exploration, I chose to start with Olewnik et al.'s (2023) paper [17] because it appeared in multiple sections of the search results and had some keywords (co-curricular, engineering, motivation) in its title. Their research question was: *Which motivational factors might explain students' engagement in co-curricular activities?* The article was very detailed in its approach and aligned with the information I sought. As I read it, I was struck by one thing it raised: the perceived "high-cost" of co-curricular engagement. Essentially, "the rigors of the engineering curriculum could lead students to conclude that they do not have time to participate in co-curriculars" (p.11). Reading that sparked an interesting question: If engineering students do not have time due to the rigors of the curriculum, how might working engineering students approach co-curricular activities? This thought was reinforced by my interactions with friends who had to work while in school, and I decided to focus on that area for this case study.

**Phase II: Alignment**

**3. Theoretical Alignment and Examining Paradigms**

Once a general direction was chosen, the next hurdle in understanding the space was alignment. In EER, the same problem can be examined from multiple perspectives (e.g., post-positivist versus interpretivist). This area is where reading papers that address similar problems within specific paradigms can help the new researcher understand what each approach entails and how best to navigate it. GenAI can be used to address this problem in two ways.

**3a. Exploratory approach:** This approach is ideal when one has identified a research problem but has not yet committed to a theoretical framework. GenAI can help researchers rapidly and systematically map how different theoretical lenses have been applied to similar problems.

I asked the model to contrast how specific research paradigms shape the way scholars frame questions, collect data, and interpret findings (Figure 3). Importantly, I did not provide theoretical frameworks for it to choose from. Instead, I requested concrete examples that illustrate each framework in action, so that, by reading the papers, I could see the practical implications of each theoretical choice.

Author 1

*I was intrigued by the idea of students considering the high cost of cocurricular activities, especially given that the engineering curriculum already places challenging demands on their time. This led me to wonder about those students who, in addition to schooling, also have to work to support themselves. Are they excluded? Would they have time for it? What kinds of co-curricular activities do they engage in, and what would motivate them to participate? Thus, I will explore engineering students' motivation for cocurricular activities, focusing on those who must work to support themselves. I am unsure of the best theoretical framework for exploring this. So I want you to present a comparison of how this or similar problems have been studied using a variety of theoretical lenses. For each, provide 3 specific papers that exemplify this approach. Describe the rationale for presenting each of the theories included.*

ChatGPT

*Excellent — this is a sharp, well-scoped research question. Below I present a clear, usable comparison of theoretical lenses that researchers have used (or could use) to study engineering students' motivation for co-curricular activities….*

**Figure 3. Step 3a: Prompting ChatGPT to explore my chosen topic.**

The model provided a comprehensive, hierarchically organized response. It began with a brief overview explaining its approach and the rationale for selecting each theoretical lens. Next, it provided a snapshot section presenting six theoretical frameworks with concise explanations and initial references, functioning as a quick overview to help me assess which frameworks might be most interesting. The core of the response was a detailed, framework-by-framework breakdown, providing at least three exemplar papers per theory (20 sources in total), along with guidance on how each framework could be operationalized for my specific research question.

While the citation formatting was inconsistent: some entries lacked years, used descriptive rather than exact titles, or omitted authors, all 20 links in the detailed section directed me to legitimate, relevant papers. All linked materials except two were open access. The paywalled articles provided sufficient metadata (title, abstract, and section snippets) in the link preview, and I accessed the full text through my institution's library. After verifying each source, I compiled the corrected citations in Table 2 below.

**Table 2: Theoretical Frameworks for Co-Curricular Motivation Among Working Engineering Students**

| Theory | Rationale for Working Students | Papers | Key Constructs to Measure |
|---|---|---|---|
| Expectancy-Value Theory (EVT) | Directly models how perceived value (career utility, enjoyment, identity) and perceived costs (time, money, effort) predict engagement. For working students, perceived cost is a core variable—EVT helps quantify whether paid work reduces participation via higher costs or lower perceived benefits. | [20-22] | Expectancy (can I succeed?), value (career, social, intrinsic), costs (hours, wages lost, stress); model participation as outcome |
| Self-Determination Theory (SDT) | Parses why students persist (autonomy, competence, relatedness). Working students may join clubs for instrumental reasons (extrinsic) or because clubs satisfy psychological needs (intrinsic). Distinguishing these helps predict sustained engagement vs. one-off attendance. | [23-25] | Basic Need Satisfaction scale for club environments; test whether autonomy/relatedness/competence moderate effect of working status |
| Social Capital / Cultural Capital (Bourdieu) | Explains who benefits and how participation converts into career capital (recommendations, internships). Working students may lack time to accrue social capital or may depend on clubs to build it. Addresses equity and access. | [26-28] | Network size/quality, mentor ties from clubs; compare gains for working vs. non-working students |
| Role Strain / Role Conflict | Explicitly examines friction between paid employment and student roles (time scarcity, fatigue, scheduling conflicts)—directly addresses exclusion risk. Useful for modeling participation as constrained by role conflict | [29-32] | Hours worked, perceived role conflict, schedule inflexibility; test effects on club participation and outcomes (burnout, belonging) |
| Conservation of Resources (COR) & Study Demands–Resources (SD-R) | Treats time/energy/finances as resources. Paid work depletes resources or competes for them; clubs require resource investment. Models stress, burnout, and when supports can buffer negative effects | [33-36] | Treat paid work as demand; model how resource buffers (financial aid, flexible scheduling) enable participation; test mediation of burnout/engagement |

As Table 2 demonstrates, the model successfully identified diverse theoretical approaches spanning psychology (EVT, SDT), sociology (Social Capital), organizational theory (Role Strain, COR), and career development (SCCT). Importantly, while ChatGPT also provided study design recommendations and measurement suggestions, I treated these as background information, consistent with using GenAI to source literature rather than to replace the researcher's analytical work.

After briefly reviewing the literature from the exploratory search, I began to see a clearer focus for this case study. I was further interested in two interconnected questions: First, how do working students weigh the competing demands of paid work versus academic and co-curricular activities, especially when these demands conflict? Second, what factors drive their decision to work in the first place, and how do those factors (economic necessity, family obligations, living arrangements) shape their ability or willingness to participate in engineering clubs?

These questions pointed me toward two complementary frameworks: EVT, which explains how students assess the costs and benefits of participation, and Role Conflict Theory, which addresses the friction between competing roles (student, worker, family member). Rather than choosing one framework over the other, I wanted to see whether and how researchers have combined these approaches, particularly in engineering education contexts.

**3b. Confirmatory and Contrastive Approach:** This approach is well-suited when one has already identified a specific theoretical framework but needs to validate it against the existing literature and understand its limitations. Unlike the exploratory approach, this approach examines if a chosen framework is appropriate and assesses where it may fall short.

In my case, I decided to combine EVT and Role Conflict Theory. Still, I needed to verify whether this combination had precedent in the literature and understand any critiques or limitations of this combined approach. I used GenAI to find papers that successfully integrate both frameworks to see whether my combined approach aligns with how the scholarly community has addressed similar problems. Equally important, I asked for work that uses only one framework and explains why combining them might be problematic or unnecessary. Seeing both supporting and opposing perspectives helped me make an active decision in the process, as I gained the tools to position my work thoughtfully within the body of literature and to address potential methodological concerns before they arise (Figure 4).

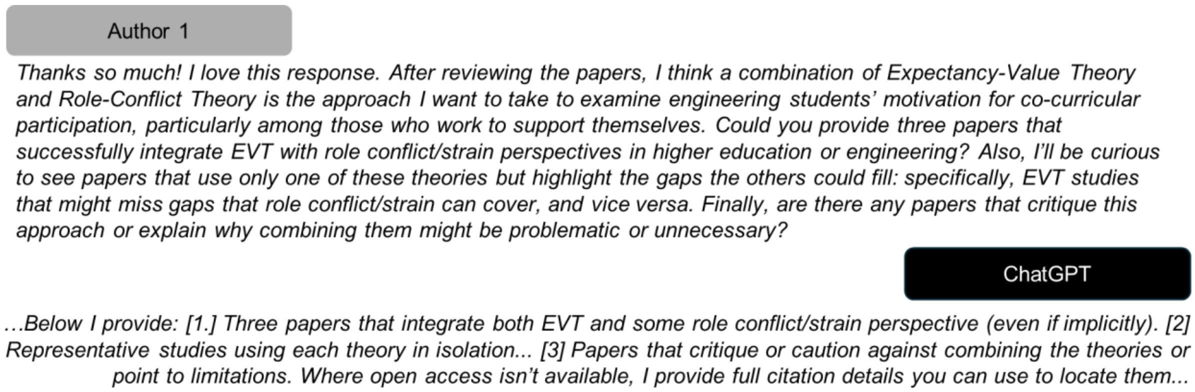


**Figure 4. Step 3b: Using ChatGPT to confirm the feasibility of a chosen approach.**

Because of the specifications in my instructions, the response included an important caveat at the beginning: *"Because explicitly integrated EVT + role conflict papers are rare, I include studies that combine motivational choice frameworks with inter-role conflict dynamics (work-study or similar)—the closest empirical analogs to integrating EVT and role conflict for your research."* This context was helpful as it made clear up front that my planned combination might be novel rather than established. The response was organized into four sections, each with papers, totaling over a dozen sources with working links. The three "closest analog" papers were [29, 37, 38].

For each paper, the response also included brief descriptions of its approach, relevance, and apparent gaps. As this interaction was meant to illustrate the workflow (not my actual dissertation research), I did not read all these papers in full. Instead, I skimmed abstracts to confirm relevance and noted which papers I would prioritize if I were actually pursuing this research question further.

It is important to note that the model's annotations regarding what each paper contributes or omits should be treated as provisional until the original sources are consulted. From personal experience, engagement with the original texts often reveals nuances, emphases, and methodological details that are not captured in model-generated summaries. Thus, the primary value of the tool lies in accelerating the identification and organization of potentially relevant literature. In this example, that value was reflected in quickly identifying an underexplored theoretical combination and generating a roadmap for subsequent, deeper engagement with the literature.

## 4. Operationalization and Validity

By this point in the search and reading process, researchers likely have a fair idea of the constructs they want to study based on how papers they have read operationalize and measure key concepts. However, GenAI can help identify other papers that focus on specific measurement approaches, which can be easy to miss when reading primarily for theory.

This step is important because knowing what one wants to study is different from learning how to measure it. A significant challenge is understanding how to measure abstract concepts such as motivation, value, or cost. At this stage, my research planning shifted from abstract theory to concrete measurement tools, focusing on methods papers that establish how to operationalize constructs with evidence of validity and reliability (Figure 5).

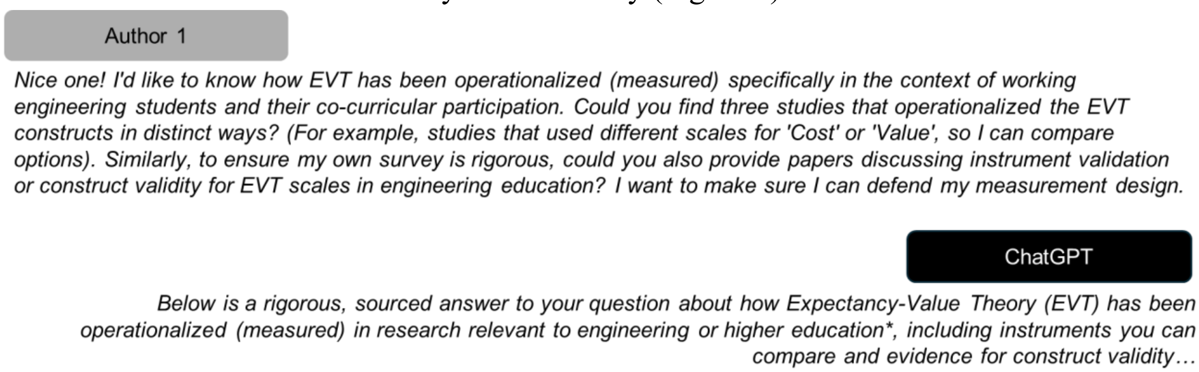


**Figure 5. Step 5: Prompting ChatGPT for operationalization and validity focus.**

The model provided three papers demonstrating distinct EVT operationalization approaches [17, 39, 40] with details about the studies referenced, plus four papers on instrument validation and construct validity [40-43]. ChatGPT's complete response, including detailed descriptions of how each paper operationalized EVT constructs, is included in the Appendix. The value of this step lies in its efficiency in locating method-focused papers, which are often harder to find through typical keyword searches. However, the actual work of evaluating which measurement approach is most appropriate, considering factors such as population match, psychometric quality, and research design fit, required engaging directly with these papers.

**Phase III: Consolidation**

**5. Rhetorical reading and synthesis support**

A literature search is not only about identifying relevant studies; it is also about learning how arguments are constructed. To build a coherent study, one must understand how other authors frame their claims, where they position their contributions, and how they justify their conclusions. Beyond the features already articulated, GenAI can help new researchers see how authors link results to discussions and implications, providing a foundation for thinking about a proposed study.

For targeted connections or arguments researchers want to understand, they can seek targeted information about how claims are constructed across multiple papers. For this case, I was interested in how authors connect student club participation to retention. I requested papers that explicitly establish that link, so I could see where and how they make that argument (Figure 6).

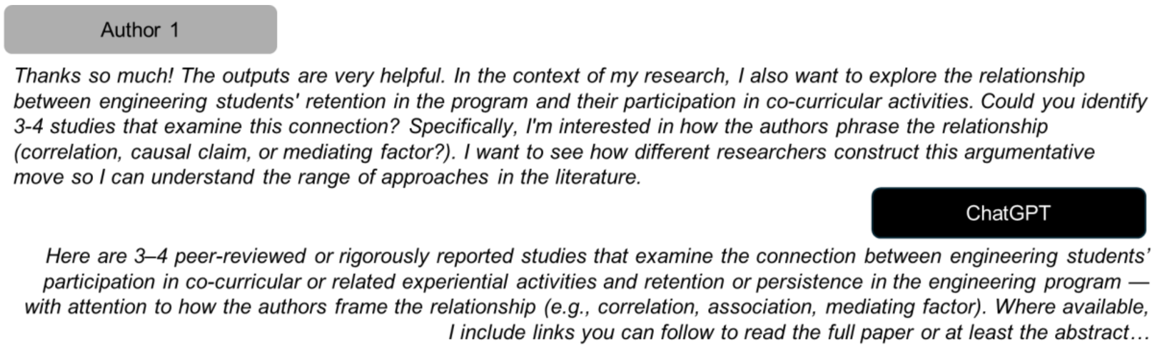


**Figure 6. Step 5: Prompting ChatGPT for rhetorical reading.**

The model provided four studies examining the retention-participation connection [17, 44-46]. The response also included a comparative table showing the type of relationship claimed, evidence basis, and notes on the argument construction for each study. Importantly, the model successfully identified papers that explicitly discuss the link between retention and participation. This output made it easier to create a targeted reading plan: I would read these papers, focusing on their discussion sections and specifically looking for how they constructed the retention argument, rather than reading entire papers in the hope of encountering that connection. Used in this way, GenAI points to where arguments are made; the researcher must read those sections and determine for themselves whether the arguments are convincing, how they compare across studies, and what that means for their own work.

**6. Knowing when to close the loops**

After working through Strategies 1-5, I had a growing collection of papers, notes, and emerging ideas. However, one of the more subtle challenges of AI-assisted literature searching is knowing when to stop. Researchers new to the field can either stop too early, without gaining sufficient understanding, or become too reliant on AI outputs rather than engaging directly with the primary texts. As such, it was helpful to continually remind myself that the goal is to become familiar with the new topic. Once that sense of direction is attained, one can close the GenAI-sourcing loop and proceed to fully human-driven synthesis. Here are some points that I use to support that conclusion for my own process.

- **Saturation:** When multiple GenAI models begin recommending papers that I have already encountered through previous prompts.
- **Framework clarity:** If I can articulate my theoretical framing and paradigmatic position to my advisor or others with sufficient basis on the literature, and without referring back to AI outputs.
- **Source confidence**: Once I can build my literature review table with highly relevant sources that I have read in full, and whose notes have filled the gaps in my research plan.

Knowing when to close the loop can mean different things to different people, but it is always helpful to keep in mind that the goal is to preserve cognitive autonomy and to use it as a tool to reduce extraneous cognitive load. Once that is achieved, the researcher becomes more comfortable in that new space.

**Implementation Comparison and Critique from an Experienced Researcher**
This section presents the second author's reaction to the literature search process, providing context on how it aligned with or diverged from their experience as a novice in EER, and a discussion of the cited sources based on their familiarity with the field. As with the first author's description of the search process, this section is presented in the first person for clarity.

The search processes I used when starting in EER would have started in Step 2. I concur that in many of the initial searches I performed, determining search terms was a key challenge. The language used to describe the contexts I was interested in varied by field, even when discussing similar topics. For example, some scholars differentiate between co-curricular and extra-curricular activities based on the activity's ability to contribute to specific, major outcomes, whereas others use a much broader definition [46]. In terms of initial search outputs, I noticed that the two key papers selected were very new (i.e., published in 2023). This omitted some foundational literature, which was likely captured in the reference lists of the cited papers (e.g., [47-51]). I thought the theories identified in Step 2 were reasonable, and theories I had seen in engineering co-curricular research in the past (e.g., EVT [52]). I think there was an opportunity to request more papers in Step 2 to avoid narrowing the topic's scope too early in the process.

Beyond initial paper identification, I found Step 3 to be the most transformative part of a student's literature search and initial synthesis. When I began reading papers in my first year of doctoral study, I did not systematically attend to the theories or epistemological stance presented in each paper. Those connections became evident to me only after taking a course on theoretical frameworks. While there are likely other strategies to support a focus on the role of theory or epistemology in study design (e.g., literature review tables, structured notes, etc.), I think Step 3 has a strong potential to bring these considerations into a student's literature review process early on, strengthening their understanding of the field. I do think it is important to note that some of the sources outputted for each theory were either 1) outside of engineering education or 2) focused on describing constructs rather than an application of a theory. As in Step 2, there were references I am familiar with, and that would likely have been relevant, that did not appear in the output (e.g., [53] for SCCT or [52] for EVT). These results highlight the continued importance of scholarly synthesis and discussion with others in interpreting the outputs of the GenAI search process. Mentors might consider sitting down with new EER scholars to talk through the citations identified by this process to discuss what they notice as missing or inaccurate to further support their mentee's literature review process.

In Step 4, I noticed a strong emphasis on quantitative outputs in the prompt. While I think the outputs of the prompt were reasonable for a quantitative approach, I wondered what those results might look like for a qualitative approach, where it is less common to publish data collection instruments. Because the prompt did not ask ChatGPT to compare qualitative and quantitative approaches to construct measurement, I think this step highlights another important area for a mentor to support a student's literature search and synthesis. Without recognizing the importance of aligning the epistemological underpinnings of their approach, theory, and methods, this step could lead to a decision to move forward with a research trajectory that is poorly aligned.

In thinking about Steps 5 and 6, it was evident that GenAI can be a powerful tool to help a novice EER scholar scope a research topic, but that the final step, that is, knowing when they have read enough, is likely also supported by a research community, which further highlights the importance of critical thinking about GenAI as a tool to supplement literature searches.

**Discussion: Verification Measures and Best Practices**

Upon reflection on this process, we recommend three essential considerations that complement the six steps outlined above. These might be a natural part of people's approach to studying the literature, but explicitly including them helps your work become more robust.

1. **GenAI Triangulation**

Because LLMs are probabilistic, relying on a single tool introduces unnecessary risk. Just as searching for information in a single database or search engine is not ideal, neither is using a single LLM. We therefore recommend what we call *GenAI triangulation*, in which key prompts are used across multiple models, and their outputs are compared. By using the same prompt across models, you can easily compare outputs and assess divergence or convergence relative to key literature. We recommend using 2-3 LLMs for exploration to avoid inadvertently accumulating extraneous cognitive load.

2. **Citation Chaining**

The second practice, known as citation chaining or "snowballing" in traditional literature review methodology [54], has long been a cornerstone of literature reviews. When GenAI identifies a paper as influential, we recommend manually examining its reference list to identify other works it cites, tracing citations backward to find foundational texts, and using tools such as Google Scholar to identify who has cited it since publication. Citation chaining enables researchers to locate 1) foundational texts that may be overlooked due to training data limitations or cutoffs, 2) recent publications that postdate the model's training data, and 3) marginalized voices that are under-cited or less visible in open databases. Triangulation and citation chaining address the mechanical aspects of maintaining rigor.

3. **Peer and Mentor Discussions**

While the above recommendations address mechanical verification, human consultation remains essential. As highlighted in our process, discussing the search with others is critical. In doing so, the searcher can refine their prompts to move in the desired direction or identify potential missing literature from experts. For example, in this case study, the second author immediately recognized that work on out-of-class activities for engineering students [46] was overlooked in ChatGPT's response. Such conversations can provide targeted information helpful to the new researcher. Beyond sourcing, peer and mentor discussions support literature synthesis in unique ways. The first author has found such conversations increasingly helpful for developing nuanced critiques of literature. While GenAI can summarize individual papers, dialogue with knowledgeable others helps researchers learn to critically evaluate papers and situate them within broader scholarly conversations.

**Discussion: Addressing Key Concerns**

While the six steps and verification measures provide a practical framework, several legitimate concerns about the use of GenAI in literature searching warrant direct attention.

1. **Cognitive Offloading vs. Cognitive Replacement**

A primary concern is that over-reliance on GenAI may erode students' critical thinking skills [55-57]. We therefore emphasize that this protocol is designed for extraneous cognitive offloading, not cognitive replacement. In CLT [8], extraneous cognitive load refers to mental effort imposed by poor instructional design or logistical barriers—effort that doesn't contribute to learning. In contrast, germane cognitive load is the productive mental effort of building schemas and integrating knowledge. By delegating lower-order search tasks to AI, researchers preserve cognitive resources for higher-order synthesis and interpretation.

As a safeguard, we recommend that the researcher read the full text of any paper they include in their reviews. Although asking the model to present its rationale for its answers improves accuracy, it can also yield AI-generated summaries that are never sufficient substitutes for engagement with primary sources. Maintaining a reading log (e.g., a spreadsheet) that documents how each source contributes to an emerging argument reinforces this practice. Throughout this paper, we have been explicit about maintaining this boundary: GenAI identifies sources; the researcher reads, evaluates, and synthesizes them. This distinction fundamentally emphasizes that human judgment is non-negotiable.

2. **Algorithmic Bias and Representational Gaps**

LLMs are trained on datasets that disproportionately favor highly cited, open-access, and Western-centric literature. As a result, work from the Global South, community colleges, Historically Black Colleges and Universities (HBCUs), and other marginalized contexts may be systematically underrepresented in AI-generated results [58-60].

For this reason, researchers could actively branch out beyond AI-generated lists and deliberately search databases that index underrepresented journals and venues. GenAI can serve as a powerful tool to help novice researchers develop an understanding of a topic, but it is critical to apply that new understanding alongside more traditional search methods to ensure marginalized research is included in ongoing scholarly conversations. This issue is not a limitation unique to GenAI, as traditional databases and search engines also exhibit similar biases toward highly cited, English-language, and Western-published work [61]. However, the ease and speed of AI-assisted searching may make it more tempting to stop searching prematurely. Researchers must remain vigilant about seeking out diverse voices and perspectives, particularly when studying issues related to equity, access, and underrepresented populations.

### 3. The Persistence of Hallucinations

While the proposed protocol reduces hallucination concerns, it does not eliminate them. Even when prompted to provide DOIs and links, models occasionally generate plausible but fabricated citations. This concern is why we were explicit throughout the strategies about requiring verifiable links and conducting verification checks. To address this risk, we enforce a simple rule: a source does not exist until the researcher opens the PDF or verifies it in a scholarly database. We recommend maintaining a verification log to document which AI-suggested citations were legitimate and which required correction. In our demonstration, all links were functional and directed to actual studies. However, some citations had shortened titles or used descriptions rather than exact titles, requiring manual correction. This experience underscores an important point: hallucinations are not just binary (real vs. fake). Sometimes the paper exists, but the citation details are imprecise; sometimes GenAI conflates two papers; sometimes it generates a plausible-sounding citation that doesn't exist. Verification is always required, regardless of how realistic the output appears. The recently released Scholar Labs could mitigate against this, since it sources all of its papers directly from Google Scholar.

## Limitations

We outline limitations of the simple demonstration in this paper, as well as more broadly, based on our current understanding of the field.

The examples presented in this paper were used solely for illustrative purposes to demonstrate the workflow, but several limitations exist. As explicitly stated throughout the case, the first author did not read all the recommended papers. In a full review, deep reading and synthesis are essential. This demonstration focused on the sourcing process rather than the complete review workflow. For simplicity, we presented single-prompt examples for each strategy. In practice, researchers should engage in multiple iterative exchanges with GenAI, refining prompts and progressively narrowing or expanding their search as their understanding develops. While we presented the strategies in sequence (1 through 6), researchers may search in various orders or cycle back to earlier strategies as their understanding evolves, as this framework is intended as a flexible guide. Also, while we recommend using multiple models to compare outputs, this case used a single model (ChatGPT) for clarity and simplicity. In practice, key prompts should be tested across multiple platforms.

Beyond this specific demonstration, there are inherent limitations to GenAI-assisted literature sourcing that researchers should be aware of. LLMs typically have training data cutoffs, meaning very recent publications may not be accessible. However, models that search the internet might be able to access those recent works. In those cases where LLMs cannot access recent work, traditional database searches and citation alerts remain necessary. The quality of prompts depends heavily on the researcher's growing knowledge and prompting skills. Early-career researchers may need guidance and practice to craft effective prompts. Our approach has been demonstrated in engineering education research, which draws on multiple disciplines and has a substantial body of published literature. Effectiveness may vary in smaller, more specialized fields or in emerging research areas with limited published work. Furthermore, although we emphasized the use of open-access sources, some papers may be behind paywalls. Since GenAI models can search the web when prompted, some of these papers, which have complete abstracts and publicly available section snippets, can be accessed by the models to recommend to users, without necessarily going through the full text. Researchers would then require institutional library access or alternative means to obtain full-text articles. Finally, GenAI tools are rapidly changing. The specific model capabilities, interfaces, and limitations described in this paper reflect the state of the technology in 2025. Future iterations may address some current limitations or introduce new considerations.

## Conclusion

The transition from traditional engineering research to engineering education research requires a substantial epistemological shift. For early-career researchers, the volume and interdisciplinarity of the literature can delay meaningful engagement with scholarship. This paper demonstrates that GenAI, when used as a sourcing tool and paired with explicit guardrails, can reduce this barrier without compromising rigor or researcher agency.

By reframing GenAI as a tool for logistical support rather than as an intellectual substitute, we provide a workflow that preserves critical thinking while improving efficiency. Our process offers a structured approach to navigating new literature, while the verification mechanisms ensure that GenAI's limitations do not compromise the quality or inclusiveness of the search.

Ultimately, the goal of this process is to make participation in EER more accessible, allowing emerging scholars to devote their cognitive resources to deep reading, critical thinking, and the generation of new knowledge. As GenAI tools continue to evolve, we hope this process provides a foundation that researchers can refine for their own disciplinary contexts and research needs.

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## Appendix

**Link to conversation: https://chatgpt.com/share/6945596d-5ff4-8013-901c-8a62e0415c84**