

In this issue:

- 4. Revisiting Academic Source Selection: Habit, Dependency, and Cognitive Effort in the Age of GenAI**
Muqing Guo, The University of Melbourne
Winn Chow, The University of Melbourne
Hasti Samadi, The University of Melbourne
Arzoo Atiq, The University of Melbourne
Tanya Linden, The University of Melbourne
- 22. AI in IS Education: A Categorization of ISCAP Publications Using Zuboff's Automate-Informate-Transformate Framework**
Jason H. Sharp, Hardin-Simmons University
John E. Anderson, Utah Valley University
Guido Lang, Quinnipiac University
- 36. Toward Curriculum-Aligned Conversational NPCs for Cybersecurity Training Simulations: A Feasibility Framework and Prompt-Based Comparative Evaluation**
Chukwuemeka Ihekweazu, Sam Houston State University
Naomi Aghado, Viterbo University
Iheme H. S. Ihekweazu, Nasarawa State University
Elizabeth Adepeju Adelowo, St. Cloud State University
- 54. An Intersectional Approach to Exploring Computing Academic Success Self-Efficacy (CASS) for Black Undergraduate Students**
Sonal Dekhane, Georgia State University
Nannette P. Napier, Georgia State University
- 67. Teaching Case
Bridging the Gap via Community Engagement: Enhancing Systems Analysis & Design Education through Client-Based Projects**
Reda Haddouch, University of Montana
Clayton Looney, University of Montana
Eric Legvold, United Way of Missoula County
Shawn Clouse, University of Montana
Fang Chen, University of Montana
- 97. An Exploratory Analysis of Perceptions and Uses of Generative AI Tools for Higher Education**
Karen Poullet, Robert Morris University
Adnan Chawdhry, PennWest University
Jamie Pinchot, Robert Morris University

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ISEDJ is published online (<https://isedj.org>). Our sister publication, the Proceedings of the ISCAP Conference (<https://iscap.us/proceedings>) features all papers, abstracts, panels, workshops, and presentations from the conference.

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Revisiting Academic Source Selection: Habit, Dependency, and Cognitive Effort in the Age of GenAI

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Abstract

The rapid emergence of Generative Artificial Intelligence (GenAI) is fundamentally reshaping how students navigate academic help-seeking. While prior research has examined AI as a standalone support, its disruptive influence on students' choices among a broader ecosystem of support options remains underexplored. Our study investigates the factors driving students' help source selection in a GenAI accessible learning environment. Using a convergent mixed-methods approach, we surveyed 52 postgraduate computing and information systems students and conducted in-depth interviews with seven students to capture both their overall preferences and the reasoning behind them. Our study is primarily grounded in Giblin et al.'s Source Selection Model (SSM), with the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and Cognitive Load Theory (CLT) used as interpretive lenses, and extends SSM to account for AI-specific dynamics. Findings show that while traditional factors such as accuracy and institutional authority remain relevant for assessment tasks, GenAI has introduced three critical new dimensions to the selection process: habitual use, concerns about dependency, and the desire to minimize cognitive effort. The results indicate that students engage in a "pragmatic trade-off," often prioritizing GenAI's immediacy and low extraneous cognitive load to maintain progress, while strategically layering formal sources later for verification. This research offers an extended model of help-seeking that accounts for the tension between the convenience of GenAI and the necessity of academic rigor, providing institutions with a framework to guide students toward critical, rather than passive, engagement with GenAI tools.

Keywords: Generative AI, Academic help-seeking, source selection, habitual use, student dependency, cognitive effort.

Recommended Citation: Guo, M., Chow, W., Samadi, H., Atiq, A., Linden, T., (2026). Revisiting Academic Source Selection: Habit, Dependency, and Cognitive Effort in the Age of GenAI. *Information Systems Education Journal*, v24(n4) pp 4-21. DOI# <https://doi.org/10.62273/YZIG9056>

Revisiting Academic Source Selection: Habit, Dependency, and Cognitive Effort in the Age of GenAI

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1. INTRODUCTION

Academic help-seeking is a key self-regulated learning strategy through which students solicit support to increase understanding, overcome study difficulties, or enhance learning outcomes (Karabenick & Dembo, 2011). This process is not merely about finding an answer, but a complex decision-making process involving the recognition of knowledge gaps, the decision to seek assistance, and the selection of appropriate resources of support (Qayyum, 2018). It is influenced by several factors, including the nature of the difficulty, students' learning goals, the available sources of help, and students' assessment of potential sources based on expertise, accessibility, and helpfulness (Beisler & Medaille, 2016; Giblin et al., 2021). In the evaluation of sources, traditionally, students weigh these factors to minimize social discomfort or effort, often avoiding help when competent support feels inaccessible, demanding, or socially uncomfortable (Thomas & Tagler, 2019). The rapid emergence of generative artificial intelligence (GenAI) has fundamentally disrupted this evaluation by offering a source that is instantly accessible, highly personalized, and socially low-stakes.

GenAI tools, which can produce human-like responses through natural language interaction (Adiguzel et al., 2023), have quickly gained popularity among students and have recently been reported to surpass traditional search engines like Google as their preferred academic tools (Zhang & Yang, 2025). As GenAI continues to advance rapidly, it is expected to become a transformative and long-lasting presence in education, offering instant information, personalized feedback, and interactive, conversational support (Lim et al., 2023). Accordingly, GenAI is poised to fundamentally reshape how students engage in academic help-seeking.

This shift is closely tied to continuing advances in GenAI's capabilities. ChatGPT o3 and Claude Opus 4 demonstrate near expert-level performance across a wide range of undergraduate subjects, including STEM, the humanities, and the social sciences. For example,

they have achieved 88.8% on the Massive Multitask Language Understanding (MMLU) benchmark, closely approaching the estimated human expert score of 89.9% (Anthropic, 2025; Hendrycks et al., 2021). With capabilities that rival human experts, GenAI creates a new paradigm in educational support. These tools offer the immediacy of a search engine combined with more personalized, conversational forms of help typically associated with human instructors (Hou et al., 2025).

However, this shift raises critical questions about how students evaluate and select help sources in an AI-integrated environment. While GenAI brings benefits such as reducing barriers to access, it also introduces new complexities regarding reliability and dependency (Kasneci et al., 2023; Zhai et al., 2024). As a result, students' decisions to use GenAI tend to be shaped by multiple considerations rather than a single factor; involving trade-offs between the convenience of instant answers and the risk of "hallucinated" or imperfect information. Existing research has yet to fully unpack how students weigh these competing factors, specifically, how the allure of reduced cognitive effort and habitual use influences their preference for GenAI over established formal sources (Chen et al., 2025).

Given this context, our study aims to explore how students select sources for academic help-seeking in today's increasingly AI-integrated environment. Drawing on Giblin et al.'s (2021) Source Selection Model (SSM) as the theoretical framework, our study seeks to identify how established selection factors may be reinterpreted or reshaped in the presence of GenAI. Understanding these emerging help-seeking patterns is important for supporting students' more reflective and critical use of GenAI in learning. Accordingly, our study aims to answer the following research question:

RQ: *How do specific factors influencing academic help-seeking source selection shape students' preferences when choosing between GenAI tools and other established sources of help?*

To answer this overarching question, two sub-questions are examined:

1. *What key factors do students consider when selecting sources for academic help in an environment with readily available GenAI tools?*
2. *How does students' evaluation of these key factors influence their comparative preference for and use of GenAI tools over, or alongside, other help-seeking sources?*

Our investigation focuses on emerging trends among postgraduate students in computing and information systems. By integrating empirical evidence with the theoretical frameworks, our study highlights both the appeal and the risks of GenAI as a key source of academic support, offering insights for instructors seeking to equip students with the information literacy required for the AI era, guiding students toward productive and ethical uses of GenAI in learning.

2. LITERATURE REVIEW

Dynamics of Academic Help-seeking and Source Selection

Academic help-seeking occurs when students encounter problems they cannot solve independently and must turn to external sources for support (Li et al., 2023). As a fundamental self-regulated learning strategy, it enables students to overcome academic challenges and persist in their learning by effectively managing time and resources within the learning environment (Fong et al., 2021). Despite its importance, help-seeking is not an automatic response to difficulty. Students often avoid seeking help even when needed due to barriers such as fear of judgment, difficulty articulating their questions, or limited access to preferred sources (Hou et al., 2024; Karabenick & Dembo, 2011).

Central to this process is source selection, a dynamic and often covert internal deliberation where students weigh both external constraints and internal concerns to identify where they feel most comfortable seeking assistance (Giblin & Stefaniak, 2021; Hou et al., 2024). This choice is largely guided by students' expectations about the costs and benefits of seeking support, and is closely tied to the characteristics of the available help sources (Makara & Karabenick, 2013). Giblin et al. (2021) conceptualized source selection as a five-stage source selection model: (1) Narrowing of sources, (2) Evaluation of sources, (3) Solicitation, (4) Evaluation of presented help, and (5) Use of help. The critical decision-making occurs in the first two stages, where students

filter potential sources and assess their suitability.

Source selection is critical because it shapes the nature and quality of the support students receive, influencing its accuracy, timeliness, and relevance (Makara & Karabenick, 2013). Different choices involve different risks, including misinformation, confusion, or frustration. Moreover, when help is delivered in the form of direct answers without fostering deeper cognitive engagement, it may ultimately hinder rather than promote learning (Fong et al., 2021).

Source Options

When facing academic challenges, students are situated within a pool of potential options (Wirtz et al., 2018). These sources are commonly classified as formal or informal sources, a distinction proposed by Karabenick and Knapp (1988) and widely adopted in subsequent research (Fong et al., 2021; Ko et al., 2025; Li et al., 2023; Makara & Karabenick, 2013; Yang et al., 2024). Formal sources are typically provided by professionals, authority figures, or institutional resources, such as lecturers, tutors, textbooks, and institutional academic support services (Zusho et al., 2007). They are typically aligned with course expectations and provide detailed, academically relevant assistance (Fong et al., 2021). However, students are often reluctant to approach them due to response delays or the social discomfort associated with formal communication (Jiang & Simion, 2022; Yang et al., 2024).

In contrast, informal sources include peers, web searches, online communities, and, more recently, GenAI tools (Yang & Stefaniak, 2023; Zhang & Yang, 2025). They are frequently preferred for their perceived ease of use and low-pressure interactions (Hou et al., 2024; Yang et al., 2024; Zusho et al., 2007). This dichotomy highlights a persistent tension. While formal sources offer authority, students often prioritize the comfort and immediacy of informal options.

Factors Influencing Source Selection

Giblin et al.'s (2021) model offers a framework for understanding students' source selection decisions, visualizing the process as a funnel. Students begin with a broad pool of potential help sources and progressively narrow their choices based on a series of evaluative steps.

In the first stage (Step 1), students filter sources using foundational criteria: accessibility (how easily a source can be reached or used), availability (whether the source is ready to provide help), and quality (the perceived

reliability and accuracy of the information). In the second stage (Step 2), students evaluate the remaining candidates more closely by considering personal and relational factors, such as their comfort and familiarity with the source, the potential for reciprocity (i.e., mutual future support), the format of the help (e.g., face-to-face, written, or online), and other personal preferences. Only after these evaluations, students move into the stages of help solicitation and use. Empirical evidence supports this model. Wirtz et al. (2018), for example, found that perceived convenience was a significant predictor. Similarly, Ko et al. (2025) identified response speed and source availability as the two most influential factors when students decided which source to consult first. Together, these findings underscore the central role of accessibility and availability in source selection, a trend that persists across both the pre- and post-GenAI landscape.

While GIBLIN et al.'s (2021) model conceptualizes source selection as a structured, stepwise process, in practice the process is often recursive. HERRING and WALTHER (2016) emphasize the cyclical and adaptive nature of help-seeking through a "try again" loop, where students consult multiple sources until their problem is resolved. This recursive process incorporates students' self-evaluations and feedback from prior interactions into subsequent decisions. In addition, situational factors such as time pressure, required effort, and cost-benefit considerations further shape source choice (Ko et al., 2025; Makara & Karabenick, 2013). Together, these perspectives suggest that source selection is often more dynamic and iterative than a strictly linear model implies, pointing to the need to validate, extend, or refine existing frameworks.

GenAI and the Changing Landscape

GenAI tools complicate this established landscape by blurring the traditional boundaries between formal and informal help sources. They hybridize the benefits of traditional sources, offering the ease of access and low-pressure environment of informal sources, combined with the personalized, structured output typically associated with formal instruction (Adiguzel et al., 2023). This combination leads students to view GenAI as a tool that contributes to increased productivity (Zhou et al., 2024), as it enables the rapid generation of potentially usable outputs with minimal effort, aligning with their long-standing preference for efficiency. As a result, GenAI is increasingly being adopted (Adams et al., 2024), with recent evidence suggesting that students increasingly prefer tools such as

ChatGPT over traditional search engines for academic support (Zhang & Yang, 2025). However, this growing popularity introduces a new trade-off. While GenAI offers adaptive feedback and low-stakes assistance, it is prone to "hallucinations" and misinformation (Sun et al., 2024). Moreover, concerns about overreliance and potential skill erosion have sparked questions about its long-term impact on meaningful learning (Akgun & Toker, 2025; Zhai et al., 2024). When students fail to critically evaluate GenAI-generated content or struggle to uphold academic integrity, its use may ultimately undermine rather than support learning (Kasneci et al., 2023; Lo, 2023).

Echoing broader concerns, students themselves appear to be aware of these trade-offs (Zhou et al., 2024). Hou et al. (2024) found that while students perceived GenAI as efficient, they also viewed it as unreliable, leading to divided attitudes. Some students considered this trade-off acceptable, whereas others rejected GenAI in favor of more trusted sources. Beyond this core tension, students also valued GenAI for emotional comfort, creative assistance, and iterative support, which in some cases further enhanced its appeal relative to traditional help sources. Students are thus forced to navigate a tension: accepting the efficiency of GenAI while managing the risk of unreliable information, overreliance, and potential skill erosion. This suggests that foundational factors in GIBLIN et al.'s (2021) model warrant re-evaluation to inform a more AI-aware framework, as these factors may now be interpreted and prioritized differently or new factors may need to be introduced. For example, GenAI's 24/7 responsiveness and conversational interface reshape what "availability" means in practice. Its capacity to generate content across multiple formats (e.g. text, image, audio) and tailor responses to user prompts alters how "quality" is perceived. At the same time, GenAI's tendency to hallucinate or fabricate information complicates these perceived advantages, while habitual use raises concerns about overreliance and its impact on long-term skill development.

Theoretical Extensions: Habit and Cognitive Load

To fully understand these emerging dynamics, our study integrates two additional theoretical lenses: the Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012) and Cognitive Load Theory (CLT) (Sweller et al., 2011).

UTAUT2 suggests that technology use is often driven by habit rather than purely rational

evaluation. Recent studies identify habit as the strongest predictor of GenAI use in academia (Sergeeva et al., 2025), suggesting that repeated exposure and perceived benefits reinforce adoption, potentially overriding concerns about quality. CLT provides a framework for understanding the “effort” dimension of source selection. Traditional search engines often impose high extraneous cognitive load, requiring students to filter and synthesize information from fragmented sources. In contrast, GenAI reduces this load by providing instant, synthesized responses, making it an appealing help source that requires less effort, and is valued by students for supporting learning (Adams et al., 2024). However, this ease of use has educational implications. If students offload the cognitive work of synthesis to AI, they may fail to invest the germane cognitive effort required for deep or productive learning. This creates a critical tension in self-directed learning, where the desire to minimize effort must be balanced against the need for meaningful learning (Grund et al., 2024).

3. METHODOLOGY

Research Design

Our study employed a mixed-methods approach with a convergent design, underpinned by a pragmatic paradigm. Pragmatism was adopted to support the study’s aim of developing a holistic understanding of students’ academic help source selection, given the evolving nature of GenAI use in educational settings, where practices, norms, and implications are still taking shape (Clarke & Visser, 2019).

The design was guided by two research objectives: identifying key factors influencing students’ choice of help sources (Sub-question 1), and exploring their rationale, evaluations, and decision-making processes across different contexts (Sub-question 2), thereby addressing the overarching research question. Addressing these objectives required a mixed-methods approach, as students’ help-source selection exhibits recurring preference patterns, while also involving context-sensitive, evaluative considerations at individual level. A convergent design facilitated the simultaneous collection of both qualitative and quantitative data during a defined period (September to October 2024). This synchronized snapshot of student experiences was critical given the rapidly evolving context of GenAI use. At the time of data collection, GenAI usage was governed by subject-level rules, with individual coordinators determining permissions, and participation was entirely voluntary, with no

extra credit or other incentives provided.

Quantitative and qualitative data were analyzed independently and subsequently integrated to address the research questions. The target population was postgraduate students studying information technology (IT) and information systems (IS) at a leading Australian university. Ethical approval was obtained prior to data collection (Approval ID: 20833).

Instruments

The data collection instrument was informed by the multidimensional framework of helping sources proposed by Makara and Karabenick (2013) as a foundation and further shaped by the expanded set of technology-based sources identified by Hou et al. (2024). This integration resulted in a coherent list of commonly used eight academic help sources (Table 1) which functioned as a shared baseline to facilitate focused discussion and to ensure that participants considered a consistent range of key resource types in both the survey and interviews.

Quantitative Strand (Survey)

Administered via Qualtrics, the survey asked participants to rank their preferences across the eight sources and indicate reasons for preferring formal or informal options. Response options were informed by factors from Giblin et al.’s (2021) source selection framework. Additional questions explored the impact of prior experience and source reuse. Survey data were analyzed descriptively using frequencies and percentages to summarize source preferences and the prevalence of specific selection factors.

Participants were recruited through convenience sampling. Researchers requested subject coordinators of selected IT and IS subjects to distribute the invitations via announcements, supplemented by direct contact with students. Of the estimated 600 students reached, 52 provided complete and valid responses.

Qualitative Strand (Interviews)

Semi-structured interviews, lasting 45 minutes approximately, explored the decision-making process behind source selection and the reasons behind their preferences or avoidance of specific sources. Key questions included: “Do you have a preferred source for getting help?” and “What factors influence your decision to use it?” All interviews were audio-recorded and then transcribed for analysis. Interview transcripts were analyzed inductively using Reflexive Thematic Analysis (RTA), with a focus on identifying semantic themes aligned with

Source Name	Type	Medium	Description
Online class materials	Formal	Digital	Class materials in the Learning Management System (e.g., textbook, readings, lecture slides, and tutorial worksheets)
Instructors	Formal	Interpersonal	Sending emails or posting a question online to the instructors
University online library	Formal	Digital	Online library (e.g., online databases of the university)
Peers	Informal	Interpersonal	Contacting peers/friends/classmates
Search engines	Informal	Digital	Searching through online search engines (e.g., Google, Wikipedia)
Online educational content	Informal	Digital	Searching for educational content on online platforms (e.g., YouTube, Coursera, Khan Academy)
GenAI tools	Informal	Digital	Using Generative AI Tools (e.g., ChatGPT)
Non-university online forums	Informal	Digital	Discussion in the online non-university communities (e.g., Reddit, Quora)

Table 1: Eight Common Academic Help Sources

participants' experience (Braun & Clarke, 2012).

A group of five researchers collaboratively engaged in the theme construction process to support the reflective examination of how interpretations were shaped and to make analytical decisions transparent, thereby ensuring analytic responsibility. The subjectivities of researchers were drawn upon as resources for meaning construction, enabling the generation of additional insights and the identification of interpretive gaps or tensions in understanding. To deepen interpretation, themes were reviewed through the complementary theoretical lenses of Giblin et al.'s (2021) source selection model, UTAUT2 (Venkatesh et al., 2012) and CLT (Sweller et al., 2011). This process was iterative, involving reflexive dialogue, supporting the refinement of themes.

Interview participants were recruited using purposive sampling in stages. Initially, five postgraduate students pursuing master's degrees were recruited. Subsequently, to explore potential variations of themes across different academic disciplines, two postgraduate students pursuing master's degrees in business management were recruited. Analysis revealed a convergence in help-seeking strategies between these groups, suggesting the identified themes were not strictly discipline-specific. Consequently, recruitment concluded at seven participants (N = 7), as the dataset was deemed sufficiently rich to support coherent thematic development. All seven interviewees had prior experience using AI tools for academic purposes.

4. FINDINGS

This section presents the integrated findings from both the survey (N = 52) and interviews (N = 7). As no substantive disciplinary differences were identified between IT/IS and business management participants in the qualitative findings, the interview results are presented collectively.

Theme 1: Evaluative Source Selection — Balancing Accuracy, Speed, and Effort

While the survey captured participants' general preferences across the eight academic help sources, interview data revealed that these preferences were not static. Instead, students' choices reflected dynamic evaluative judgments shaped by task demands and situational constraints.

Theme 1.1 "I Want to Make Sure It Is Accurate": Quality and Assessment Safety

Online class materials were the most consistently preferred help source among survey respondents. Fifty percent of respondents (n = 26) ranked them as their number one choice, and 90% (n = 47) placed them in their top three (see Figure 1). Interviews revealed that this preference was driven by both perceived quality and assessment safety. When addressing assessment-related tasks, participants emphasized the importance of obtaining reliable, high-quality information aligned with course expectations. As explained by one participant: "Because I'm doing university [assignments], so I think [class materials] are the most official, authorized and trustworthy" [P3, human-computer interaction major].

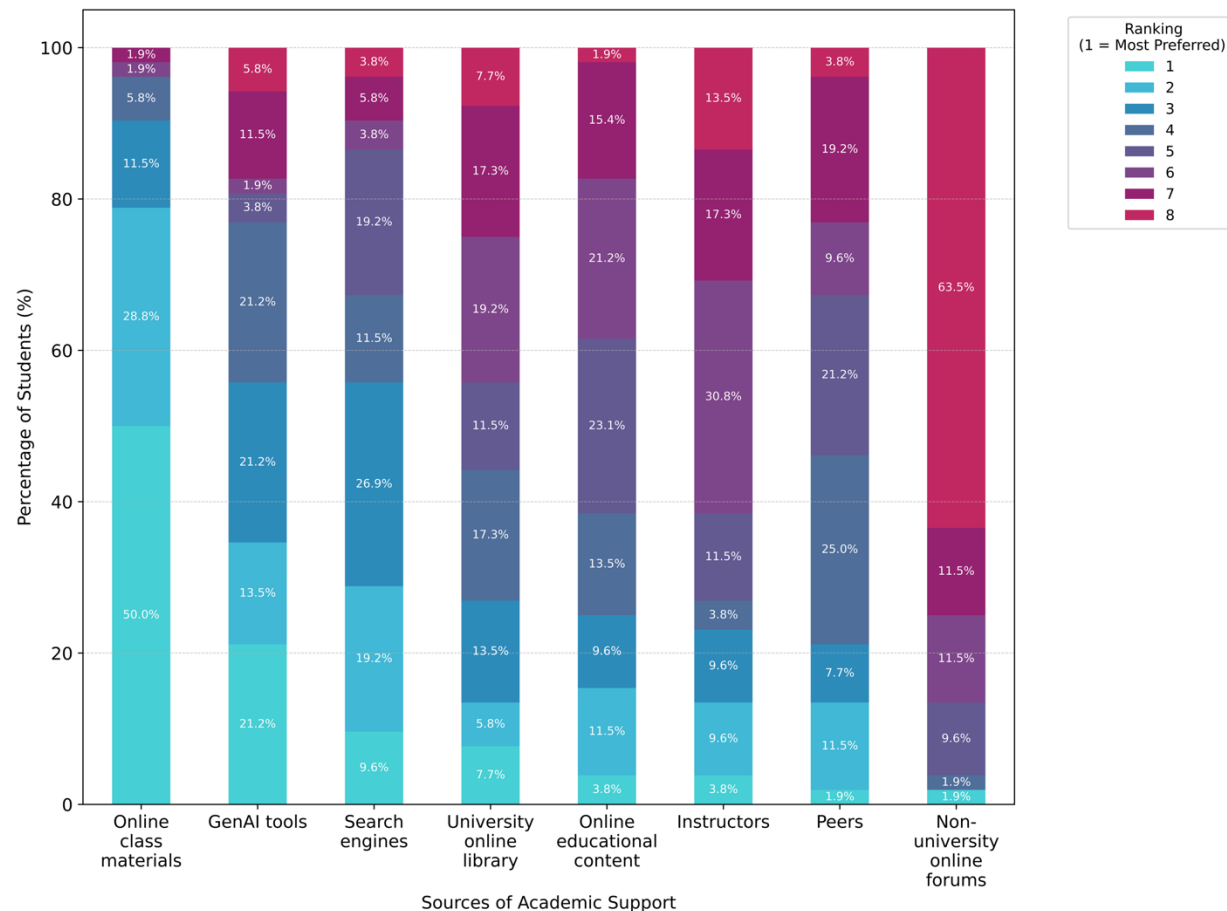


Figure 1: Students' Ranking of Preferred Help-seeking Sources

Similarly, participants from non-IT/IS backgrounds described class materials as the preferred option for academic work: "We want to make sure that we follow materials given by the lecturer, it helps us to do better in assignments" [P6, management major].

Beyond perceived quality, participants noted that using sanctioned materials provided emotional reassurance, increasing confidence that their work met academic expectations [P2, AI major; P3, human-computer interaction major].

Conversely, interview participants who did not prioritize class materials cited concerns related to the level of elaboration and efficiency. Some found the lecture slides too brief or insufficiently detailed, making them less useful without a strong recollection of the original lecture discussion. Others noted that revisiting extensive assigned readings was too time-consuming: "[Class materials] provided by the university include a huge amount of content. It takes a lot of time to go through... But when you're seeking help, that's usually when you're

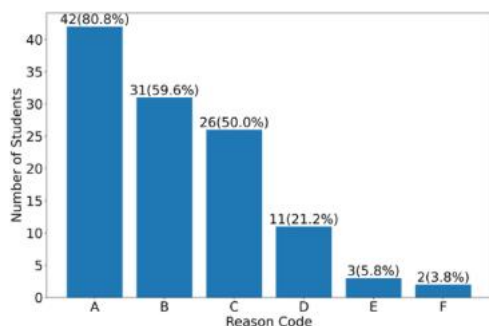
already feeling frustrated. If it takes too long or wastes a large chunk of your time, it just makes the situation worse" [P3, human-computer interaction major].

These findings suggest a trade-off: while online class materials are valued for their authority and relevance, students' assessments of their usefulness depend on practical and context-specific considerations such as content clarity, elaboration, and time demands.

Theme 1.2: "You Ask, It Answers Right Away": The Appeal of Immediacy

While class materials were preferred for accuracy, GenAI tools and search engines dominated when immediacy was the priority. Survey data indicated that 80.8% of respondents preferred informal sources specifically for "faster access and response" (Figure 2). GenAI was more frequently ranked as the top choice over search engines (Figure 1). However, when considering broader preference tiers, GenAI tools and search engines were equally represented among respondents' cumulative top three choices. Within

the top six, search engines slightly surpassed GenAI in preference.



A: They offer faster access and response.
B: They are easier to understand.
C: I can use my native language.
D: I feel embarrassed asking silly questions from people who know me.
E: I don't usually use informal help resources over formal ones.
F: Others

Figure 2: Reasons Students Prefer Informal Help Sources

Interview findings help clarify the survey patterns. When facing an academic challenge perceived as intrinsically difficult, lacking confidence, or working under time pressure, participants consistently preferred sources that were fast, readily available, and easy to understand. Immediate responses were particularly valued in high-pressure situations. As one participant observed: "Most of the students are doing their [assignments] just before the deadline," illustrating how time pressure shaped urgent, outcome-driven help-seeking [P4, computing major].

GenAI stood out in this context due to its immediacy and ability to consolidate information. Unlike search engines, which require navigating fragmented websites, GenAI provides direct, synthesized answers and was widely regarded as the "fastest" source. One participant explained: "[You] don't have to wait to get responses. You just need to tell ChatGPT that you have a problem, and you get the answer... It's direct and timely, efficient, so I don't need to jump from one website to another" [P5, human-computer interaction major].

Participants also compared GenAI favorably to formal sources, particularly in terms of responsiveness. As one participant noted: "If you compare AI to other sources, the library, for example... You need to find your answer in so many things...and for instructors, you have to wait till they respond, but if you talk to ChatGPT, you get the answer directly" [P2, AI major].

Theme 1.3: "Less Effort, More Progress":

Minimizing Cognitive Load

Closely linked to immediacy was the desire to minimize cognitive effort. Survey results showed that 59.6% of respondents preferred informal sources because they were "easier to understand" (Figure 2). Participants described traditional research methods as cognitively taxing, often requiring them to "filter a solution" from dense and extensive materials. As one participant noted: "Using class materials is quite time-consuming... You have to read them all and try to filter a solution yourself" [P5, human-computer interaction major].

In contrast, GenAI was widely perceived as a cognitive offloading tool. P5 reflected on how ChatGPT synthesizes fragmented knowledge: "Before ChatGPT, knowledge was from piece to piece, but ChatGPT is more inclusive [across] different areas. It can answer questions from different [domains]."

This was further reinforced by its capacity to summarize complex materials and reduce the need for extensive reading, substantially streamlining the mental demand of the task. Others echoed this view when discussing the GenAI tool Perplexity: "It does the filtering for you; you don't have to click the website one by one... it shows you all the information related to the contents you're looking for... You can give ChatGPT a link or upload a file and ask it to summarize... You don't have to read everything" [P1, AI major].

Theme 1.4: "I Want to Make Sure that I Did All I Could": The Social Cost of Human Help

Interpersonal help sources, instructors and peers, were rarely top-ranked, with only 23% of respondents placing instructors and 21% placing peers in their top three preferences (Figure 1). This reluctance was largely driven by perceived social costs.

Instructors were viewed as a "limited, public resource". Students felt a need to exhaust all other options before reaching out to avoid appearing incompetent. As one participant explained, "I want to make sure that I did all I could before I request a public resource" [P3, human-computer interaction major]. Additionally, the formality of academic communication, such as drafting carefully worded emails, and the often delayed responses were seen as barriers: "You have to wait until they reply... you have to format your language very politely and formally" [P4, computing major].

Comparatively, participants described peer

support as involving less social obligation, noting that seeking help from peers did not feel like “doing a huge favor”. At the same time, participants also expressed caution regarding peer help. Avoidance was primarily linked to academic integrity concerns, specifically the fear that discussing ideas might lead to unintentional overlap or plagiarism. As one participant remarked: “Maybe we will have some overlap in our ideas that may cause plagiarism” [P4, computing major].

These findings suggest that students’ low preference for interpersonal help sources is shaped by a combination of social and academic considerations.

Theme 2: The Cost of Convenience – Navigating Imperfection

While students valued GenAI’s efficiency, they were acutely aware of its limitations. The findings reveal a “pragmatic trade-off” where students accepted accuracy risks in exchange for momentum. Rather than treating convenience as an unquestioned advantage, participants actively weighed efficiency gains against potential drawbacks and adopted strategies to manage these risks.

Theme 2.1: “Not Perfect, But It Helps Me Move Forward”: The Pragmatic Trade-Off

Participants acknowledged that GenAI often “generates non-existent stuff” or inconsistent answers. As one participant noted, “Sometimes I’m confused about the [GenAI generated] answer... I’m not sure if it’s correct” [P4, computing major].

However, many viewed this as a calculated risk worth taking to overcome writer’s block or coding errors. One participant described this as a “betting game”: “Sometimes the accurate response is hidden in the [YouTube] video, but there is too much cost for me to test around, you may just need that one piece of code from that entire one hour tutorial video... so even ChatGPT generates weak responses sometimes, I would still bet five minutes on it to give me the accurate response...at least it helps me to make progress” [P3, human-computer interaction major].

Similarly, another participant reflected, “The answers from ChatGPT are not always consistent, but they’re comprehensive enough” [P5, human-computer interaction major].

These accounts suggest that imperfect help can still be perceived as acceptable and valuable when it demands minimal effort and enables

forward progress. Other participants reinforced this pragmatic stance: “if you can get access to more help [sources within the time you have], it may increase the quality of your help-seeking outcome” [P2, AI major].

Theme 2.2: “It Might Be Wrong, So I Double-Check”: Strategies for Verification

To mitigate the risks of this trade-off, participants engaged in active self-verification strategies:

- (1) Computational Testing: for programming tasks, students ran the generated code to verify functionality. As one participant noted, “For practical tasks, you can just run the [GenAI-generated] code to test and validate it” [P2, AI major].
- (2) Cross-Validation: Students compared GenAI outputs against other sources, such as textbooks or search engines, to check for consistency. As one participant explained, “If both Source A and Source B provide the same information on a topic, I believe it’s accurate” [P1, AI major].
- (3) Common Sense Filtering: Students applied their own domain knowledge and judgment to filter out “irrelevant” or dubious suggestions. As one participant put it, “I use common sense to filter irrelevant information” [P5, human-computer interaction major].

Together, these strategies highlight GenAI’s mixed impact on cognitive load. While students valued GenAI for reducing perceived mental effort (Theme 1.2), the need to verify and evaluate its outputs often reintroduced additional cognitive demands.

Theme 2.3: “One Source is Never Enough”: Layered Help-Seeking

Reflecting these verification strategies, survey data show that 71% of respondents reported using both formal and informal sources to solve a single issue (Figure 3). This suggests a deliberate, multi-source, layered approach. As one participant explained, “Explore multiple sources is a good way to validate answers” [P2, AI major].

- (1) GenAI First, then Formal Verification: Students often began with GenAI to generate initial ideas or clarify confusion, using it as a starting point before turning to formal sources for verification and refinement. This layered strategy was particularly evident when students faced complex or ill-defined tasks, or when they felt overwhelmed at the outset. In these situations, GenAI helped

them make initial progress, even if the output was not fully reliable.

As one participant explained: "Because I am exploring from [nothing to something that is workable], it is very confusing, but AI saves me a lot of time. [The AI-generated solution] is sometimes not accurate, but it at least tells you how to do it" [P3, human-computer interaction major].

This approach illustrates how students used GenAI not as a final authority, but as a cognitive scaffold to reduce initial uncertainty before engaging in more rigorous verification processes. Another participant described the process further: "ChatGPT is good at generating initial ideas, but it's not that reliable ... I sometimes have very vague and broad ideas, so I ask ChatGPT to suggest narrower topics I could focus on... Once I have a clear hypothesis, I consult formal resources to validate it" [P5, human-computer interaction major].

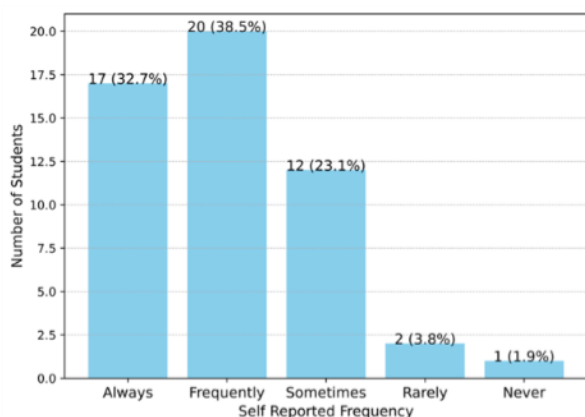


Figure 3: Student-reported Frequency of Combined Use of Formal and Informal Sources During a Single Help-seeking Attempt

- (2) Formal First, then GenAI Elaboration: Conversely, for tasks requiring credible guidance, particularly assessment-related work, students consulted formal rubrics first for structure, and class materials for credible direction, then used GenAI to explain or elaborate on specific concepts that were unclear. As one participant explained this initial preference for formal guidance: "I will first look at the rubric and the requirements of this assignment. And if I need to study more, I will go through the lecture slides myself" [P4, computing major].

Others also noted that class materials provide "a big structure, a big outline of what is expected," reinforcing their value as authoritative sources [P5, human-computer interaction major; P6, management major]. However, participants acknowledged that these formal resources primarily offer a general overview. When deeper understanding or elaboration was required, students turned to informal sources, particularly GenAI tools, for further explanation. As reported by one participant, "Class materials cannot support us with help like that" [P7, AI major].

These findings highlight that students strategically combine formal and informal sources, using GenAI to boost efficiency and reduce uncertainty while relying on authoritative resources to ensure accuracy and credibility, reflecting a layered approach to academic help-seeking.

Theme 3: Evolving Patterns — Habit, Dependency, and Access

Beyond immediate task completion, the data reveal long-term behavioral shifts in students' engagement with academic help, encompassing aspects of habit formation, equity and access, and potential dependency on GenAI tools.

Theme 3.1: "If It Works, I'll Stick with It": The Power of Habit

Prior experience showed a strong influence on source selection. Survey data indicate that 92.3% of respondents reported that past success affected their decision to reuse a help source (Figure 4). Specifically, 35.4% (17 of 48) indicated a "very strong impact," agreeing that they would "always choose sources that have worked well in the past and completely avoid those with negative outcomes," while 52.1% (25 of 48) reported a "strong impact," noting that

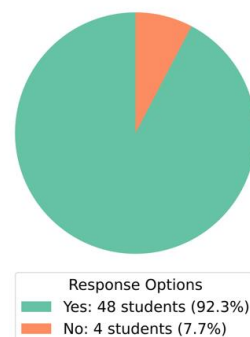


Figure 4: Self-reported Decisions on Reusing a Resource Based on Prior Experience

they would “usually rely on past experiences to guide choices but may occasionally reconsider a source” (Figure 5).

Interviews confirmed that repeated positive interactions with GenAI reinforced its use, turning it into a “default” behavior. As one participant explained, “I personally use AI now when I used to go to Google or YouTube” [P4, computing major]. Another participant added, “I am more and more relying on ChatGPT to solve my problems first-hand... if you have a good experience with it, you are going to be addicted to it” [P5, human-computer interaction major].

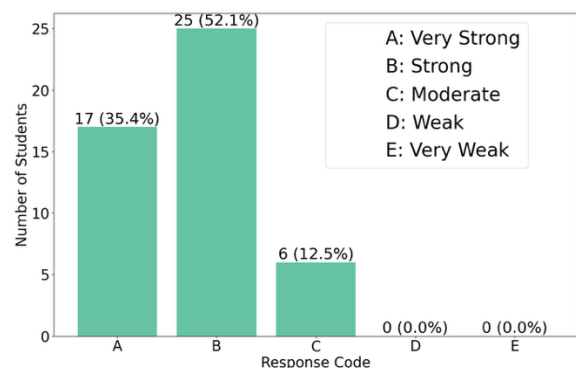


Figure 5: Self-reported Influence of Prior Experience on Future Help-source Selection

Even early negative experiences were often overcome by the rapid improvement of the tools. As one participant noted: “In the very early stage of ChatGPT... it could not give you the right answer... but after its development ... I use it more frequently now” [P2, AI major].

These findings highlight the influence of habitual use, where repeated positive experiences can reinforce students’ reliance on GenAI as a default academic help source.

Theme 3.2: “I Use It, But I Don’t Want to Rely on It”: The Dependency Tension

A critical emergent theme was the fear of dependency. Participants expressed concern that habitual GenAI use could erode their learning and reduce engagement with challenging material. As one participant reflected, this dependency creates a conflict between the convenience of the answer and the satisfaction of genuine study:

“I was supposed to learn more... but I actually use ChatGPT, so I kind of have a dependency on it. It’s like a continuing behavior... so I tell myself that maybe I don’t need to learn it very hard because ChatGPT will give me the answer... but I’m not fully satisfied with it because you feel

more satisfied if you are fully engaged in your study” [P4, computing major].

To counter this, some students actively regulated their use, intentionally attempting to solve problems via formal materials first and reserving GenAI as a last resort to preserve their critical thinking skills. As one participant explained regarding this deliberate sequencing:

“I don’t really want myself to rely on ChatGPT that much. So, when I find something hard to understand, I will not directly copy-paste and ask it for an explanation. I’ll try my best—read the question line by line, look at [class] materials, or see what the professor has provided. Only if I still don’t get it, then I’ll ask ChatGPT” [P5, human-computer interaction major].

This behavior highlights that students recognized the risk of overreliance. It suggests a tension between immediate support and long-term skill development, an ambivalence likely to grow as GenAI tools evolve.

Theme 3.3: “It’s Worth It, If You Can Afford It”: Equity and Access

Finally, accessibility was complicated by financial models. While some viewed paid subscriptions (e.g., ChatGPT Plus) as a worthwhile investment for superior answers, others cited the recurring cost (AUD\$20-\$30/month) as a barrier. This highlights a disparity in the quality of help available to students based on financial means. As one participant explained: “I only have to pay AUD\$30 per month for [ChatGPT], and I get answers to all my questions” [P3, human-computer interaction major].

In contrast, others noted: “I would consider the cost of using GenAI tools; many now have a membership fee of about \$20 a month, and it might increase in the future” [P1, AI major]. These perspectives underscore how financial access can influence the quality and range of help available to students, raising broader questions of equity in engagement with emerging technologies.

Summary of Findings

Our findings affirm the relevance of Giblin et al.’s (2021) SSM while extending it to reflect the specific dynamics of help-seeking in an AI-integrated context. Traditional factors have evolved: availability is now defined by GenAI’s immediate, 24/7 responsiveness, while quality increasingly requires active user evaluation due to the risk of hallucinations. Accessibility has expanded to include financial constraints linked to

paid AI models. Furthermore, student expectations regarding format have shifted, showing a marked preference for GenAI's low-effort, conversational outputs over more cognitively demanding sources.

Crucially, our study identified three new dimensions not fully accounted for in prior models: habitual use, dependency, and the desire to minimize cognitive effort. These factors suggest that students are navigating a complex tension between convenience and learning quality, engaging in a pragmatic trade-off to balance immediate progress with long-term skill development. A detailed breakdown of how these findings extend Giblin et al.'s (2021) SSM is provided in

Appendix A: Extended Giblin et al.'s (2021) SSM in the AI Era

5. DISCUSSION

Our findings indicate that students' help-seeking decisions are a layered and context-sensitive process, shaped by continuous negotiation between effort, efficiency, and perceived quality. Within this dynamic, GenAI has emerged not merely as a tool, but as a central actor that fundamentally alters the cost-benefit analysis of seeking academic support.

The Enduring Authority of Formal Sources

Despite the ubiquity of AI, online class materials remained the preferred initial point of reference for resolving difficulties. Students viewed these resources as the "source of truth," providing a direct pathway to meeting assessment expectations, consistent with prior findings (Wirtz et al., 2018). This suggests that while GenAI offers convenience, it has not displaced the perceived authority of institutionally sanctioned sources. Students continue to prioritize alignment with instructor expectations, particularly when grades are at stake.

The Appeal of Efficiency: Cognitive Load and Immediacy

Conversely, when the priority shifted to overcoming immediate hurdles or managing high workloads, the appeal of GenAI became dominant. This preference towards efficiency aligns with previous research identifying responsiveness and accessibility as key drivers of source selection (Holland & Ciachir, 2025; Ko et al., 2025; Limna et al., 2023). GenAI's interactive, conversational interface further enhanced its usability (Chan & Hu, 2023), reducing the cognitive burden of interpreting fragmented resources. From a theoretical

perspective, this aligns with UTAUT2's construct of effort expectancy, with technologies requiring less effort being more readily adopted (Venkatesh et al., 2012; Sergeeva et al., 2025).

Through the lens of CLT, GenAI's conversational interface significantly reduces extraneous cognitive load. Unlike search engines, which force students to synthesize fragmented information, GenAI provides consolidated, low-friction responses. This allows students to bypass the cognitive burden of information retrieval, positioning GenAI as a "low-effort, high-reward" option that rivals or surpasses traditional search engines. This aligns with Zhang and Yang (2025), reporting a marginal preference for ChatGPT (51.7%) over Google (48.3%). This marks a shift from earlier studies that showed a strong preference for search engines (Hou et al., 2024; Skripchuk et al., 2024).

The Pragmatic Trade-Off: Performance vs. Learning

Despite its efficiency, GenAI introduces a critical tension. While GenAI fulfills the performance expectancy of UTAUT2 (Venkatesh et al., 2012; Sergeeva et al., 2025), by providing quick answers, students expressed significant ambivalence regarding its reliability (Adiguzel et al., 2023).

To navigate this, students engaged in a "pragmatic trade-off," accepting the risk of imperfections in exchange for progress. This necessitated self-initiated verification, such as testing code or cross-referencing textbooks. GenAI's lack of source transparency makes verification difficult (Choi et al., 2025). When students critically evaluate AI outputs, while cognitively demanding, it can foster germane cognitive load and deeper learning. However, uncritical acceptance, often driven by time pressure, bypasses this processing, potentially hindering skill acquisition and independent thinking (Lodge & Loble, 2026; Macnamara et al., 2024).

The Erosion of Reciprocity

Our findings also point to a shift in the social dynamics of help-seeking. The role of reciprocity, a key factor in Giblin et al.'s (2021) model, was notably diminished. Students avoided instructors due to perceived social "debts" (e.g., the need to show prior effort) and peers due to plagiarism anxieties. GenAI appears to fill this gap by offering a non-reciprocal, non-judgmental alternative, but this shift may erode collaborative dialogue with instructors and peers, reducing essential social dimensions of learning (Hou et al.,

2025).

New Dimensions: Habit and Dependency

Finally, our study validates the inclusion of habit and dependency as critical factors in modern source selection. Consistent with UTAUT2, repeated positive experiences with GenAI reinforced habitual use, potentially creating a dependency that entrenches passive learning behaviors. Students recognized unreflective habit formation and dependency on AI as a long-term risk, particularly problematic in academic contexts that prioritize independent thinking and self-regulated learning (Strzelecki, 2024; Zhai et al., 2024). Such concerns resonate with Kasneci et al.'s (2023) findings on AI-induced laziness, which may undermine students' motivation for independent inquiry and deep learning. Furthermore, the tiered access models of AI tools (e.g., paid vs. free versions) introduce new accessibility barriers, raising equity concerns where financial means dictate the quality of academic help.

Theoretical and Practical Implications

Theoretically, our study contributes to understanding students' academic help-seeking in AI-integrated learning environments. While reaffirming the relevance of Giblin et al.'s (2021) source selection model, it highlights a need to reinterpret several existing factors in the context of GenAI technologies. Additionally, our findings empirically validate habitual use and cognitive effort, constructs from UTAUT2 and CLT, as decisive factors in the AI era, while also identifying dependency as an emergent concern voiced by students. In

Appendix A: Extended Giblin et al.'s (2021) SSM in the AI Era we propose an extended model that integrates these new AI-specific dimensions, offering a conceptual framework to guide future research.

Practically, our findings point to the need for institutions to move beyond simply restricting or permitting AI. In a context where there is a lack of reliable technology to distinguish between human- and AI-generated content, discursive changes that focus on policy implementation may become unenforceable in practice, resulting in what Corbin et al. (2025) describe as an enforcement illusion. There is a need for pedagogical interventions that support students in navigating key trade-offs as active decision-makers (Bearman et al., 2024). In particular, as GenAI is capable of generating plausible outputs with minimal effort (Nikolic et al., 2023), students' ability to use GenAI critically becomes increasingly important. Students who are unable

to actively engage in evaluative processes and maintain agency may become over-reliant on AI-generated outputs. This tendency is reflected in recent research showing that students may engage in copying without thinking (Ma et al., 2025). In addition, this raises the question that within any predominantly product-oriented assessment systems, students may be motivated to rely on GenAI for help-seeking, as outcome-oriented evaluation can incentivize efficient task completion over deeper engagement.

As these tools become embedded across a wide range of academic activities (Choi et al., 2025), their influence may extend beyond help support to shaping students' broader conceptions of learning. As suggested by recent research, engaging in task completion with GenAI shifts the production of intellectual outcomes from internal integration and evaluation of information to the verification and integration of co-generated responses (Lee et al., 2025). If GenAI-supported help-seeking leads to the bypassing of desirable difficulties, such that learning opportunities traditionally embedded within tasks are offloaded to AI, students may complete tasks without engaging in the underlying processes of reasoning, evaluation, and knowledge construction. This risks creating an illusion of competence (Lodge & Loble, 2026).

6. CONCLUSIONS

Our study investigated the transformation of academic help-seeking in an era where GenAI serves as an omnipresent, albeit imperfect, support system. By integrating Giblin et al.'s (2021) source selection framework with insights from UTAUT2 and Cognitive Load Theory, we demonstrated that source selection is no longer a simple choice between formal and informal options. Instead, it is a complex negotiation where students engage in a "pragmatic trade-off," prioritizing the immediacy and reduced cognitive load of GenAI while managing the inherent risks of inaccuracy through strategic verification.

The findings highlight that while GenAI facilitates rapid progress, it introduces critical challenges regarding habitual dependence and the potential erosion of independent problem-solving skills. The emergence of these factors suggests that traditional models of help-seeking must expand to account for the cognitive and behavioral loops reinforced by AI interaction.

Practically, this underscores that access to tools does not equate to effective learning. Institutions

must move beyond simple regulation to foster AI information literacy. The goal of such support should be to equip students to act as critical evaluators, capable of leveraging AI for efficiency without surrendering the cognitive struggle necessary for deep learning.

These conclusions should be interpreted within the context of the study's exploratory nature. The small sample consisted primarily of postgraduate students in computing and information systems, a demographic likely to possess higher digital affinity than the broader student population. Consequently, these findings represent an initial snapshot of emerging trends. Future research is needed to validate these factors across diverse disciplines and undergraduate cohorts to fully understand the transferability of these new help-seeking behaviors.

7. REFERENCES

- Adams, D., Chuah, K.-M., Devadason, E., & Azzis, M. S. A. (2024). From novice to navigator: Students' academic help-seeking behaviour, readiness, and perceived usefulness of ChatGPT in learning. *Education and Information Technologies*, 29(11), 13617–13634. <https://doi.org/10.1007/s10639-023-12427-8>
- Adiguzel, T., Kaya, M. H., & Cansu, F. K. (2023). Revolutionizing education with AI: Exploring the transformative potential of ChatGPT. *Contemporary Educational Technology*, 15(3), ep429. <https://doi.org/10.30935/cedtech/13152>
- Akgun, M., & Toker, S. (2025). Short-Term Gains, Long-Term Gaps: The Impact of GenAI and Search Technologies on Retention. In A. I. Cristea, E. Walker, Y. Lu, O. C. Santos, & S. Isotani (Eds.), *Artificial Intelligence in Education. Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners, Doctoral Consortium, Blue Sky, and WideAIED* (pp. 44–52). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-99264-3_6
- Anthropic. (2025, May 23). Introducing Claude 4. <https://www.anthropic.com/news/claude-4>
- Bearman, M., Tai, J., Dawson, P., Boud, D., & Ajjawi, R. (2024). Developing evaluative judgement for a time of generative artificial intelligence. *Assessment & Evaluation in Higher Education*, 49(6), 893–905. <https://doi.org/10.1080/02602938.2024.2335321>
- Beisler, M., & Medaille, A. (2016). How Do Students Get Help with Research Assignments? Using Drawings to Understand Students' Help Seeking Behavior. *The Journal of Academic Librarianship*, 42(4), 390–400. <https://doi.org/10.1016/j.acalib.2016.04.010>
- Braun, V., & Clarke, V. (2012). Thematic analysis. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Eds.), *APA handbook of research methods in psychology, Vol 2: Research designs: Quantitative, qualitative, neuropsychological, and biological*. (pp. 57–71). American Psychological Association. <https://doi.org/10.1037/13620-004>
- Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education*, 20(1), 43. <https://doi.org/10.1186/s41239-023-00411-8>
- Chen, A., Xiang, M., Zhou, J., Jia, J., Shang, J., Li, X., Gašević, D., & Fan, Y. (2025). Unpacking help-seeking process through multimodal learning analytics: A comparative study of ChatGPT vs Human expert. *Computers & Education*, 226, 105198. <https://doi.org/10.1016/j.compedu.2024.105198>
- Choi, W., Bak, H., An, J., Zhang, Y., & Stvilia, B. (2025). College students' credibility assessments of GenAI-generated information for academic tasks: An interview study. *Journal of the Association for Information Science and Technology*, 76(6), 867–883. <https://doi.org/10.1002/asi.24978>
- Clarke, E., & Visser, J. (2019). Pragmatic research methodology in education: Possibilities and pitfalls. *International Journal of Research & Method in Education*, 42(5), 455–469. <https://doi.org/10.1080/1743727X.2018.1524866>
- Corbin, T., Dawson, P., & Liu, D. (2025). Talk is cheap: Why structural assessment changes are needed for a time of GenAI. *Assessment*

- & Evaluation in Higher Education, 50(7), 1087–1097.
<https://doi.org/10.1080/02602938.2025.2503964>
- Fong, C. J., Gonzales, C., Hill-Troglin Cox, C., & Shinn, H. B. (2021). Academic help-seeking and achievement of postsecondary students: A meta-analytic investigation. *Journal of Educational Psychology*.
<https://doi.org/10.1037/edu0000725>
- Giblin, J., & Stefaniak, J. (2021). Examining Decision-Making Processes and Heuristics in Academic Help-Seeking and Instructional Environments. *TechTrends: Linking Research and Practice to Improve Learning*, 65(1), 101–110.
<https://doi.org/https://doi.org/10.1007/s11528-020-00556-7>
- Giblin, J., Stefaniak, J., Eckhoff, A., & Luo, T. (2021). An exploration of factors influencing the decision-making process and selection of academic help sources. *Journal of Computing in Higher Education*, 33(1), 1–18.
<https://doi.org/10.1007/s12528-020-09252-0>
- Grund, A., Fries, S., Nückles, M., Renkl, A., & Roelle, J. (2024). When is Learning “Effortful”? Scrutinizing the Concept of Mental Effort in Cognitively Oriented Research from a Motivational Perspective. *Educational Psychology Review*, 36(1), 11.
<https://doi.org/10.1007/s10648-024-09852-7>
- Hendrycks, D., Burns, C., Basart, S., Zou, A., Mazeika, M., Song, D., & Steinhardt, J. (2021). Measuring Massive Multitask Language Understanding (arXiv:2009.03300). *arXiv*.
<https://doi.org/10.48550/arXiv.2009.03300>
- Herring, C., & Walther, J. (2016). Academic Help-seeking as a Stand-alone, Metacognitive Action: An Empirical Study of Experiences and Behaviors in Undergraduate Engineering Students. 2016 ASEE Annual Conference & Exposition Proceedings, 26490.
<https://doi.org/10.18260/p.26490>
- Holland, A., & Ciachir, C. (2025). A qualitative study of students’ lived experience and perceptions of using ChatGPT: Immediacy, equity and integrity. *Interactive Learning Environments*, 33(1), 483–494.
<https://doi.org/10.1080/10494820.2024.2350655>
- Hou, I., Man, O., Hamilton, K., Muthusekaran, S., Johnnykutty, J., Zadeh, L., & MacNeil, S. (2025). “All Roads Lead to ChatGPT”: How Generative AI is Eroding Social Interactions and Student Learning Communities. *Proceedings of the 30th ACM Conference on Innovation and Technology in Computer Science Education V. 1*, 79–85.
<https://doi.org/10.1145/3724363.3729024>
- Hou, I., Mettelle, S., Man, O., Li, Z., Zastudil, C., & MacNeil, S. (2024). The Effects of Generative AI on Computing Students’ Help-Seeking Preferences. *Proceedings of the 26th Australasian Computing Education Conference, ACE ’24*, 39–48.
<https://doi.org/10.1145/3636243.3636248>
- Hou, I., Nguyen, H. V., Man, O., & MacNeil, S. (2025). The Evolving Usage of GenAI by Computing Students. *Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 2, SIGCSETS 2025*, 1481–1482.
<https://doi.org/10.1145/3641555.3705266>
- Jiang, A., & Simion, B. (2022). Help Supports during Online Delivery: Student Perception and Lessons Learnt from an Online CS2. *Proceedings of the 53rd ACM Technical Symposium on Computer Science Education - Volume 1, SIGCSE 2022*, 1, 105–111.
<https://doi.org/10.1145/3478431.3499369>
- Karabenick, S. A., & Dembo, M. H. (2011). Understanding and facilitating self-regulated help seeking. *New Directions for Teaching and Learning*, 2011(126), 33–43.
<https://doi.org/10.1002/tl.442>
- Karabenick, S. A., & Knapp, J. R. (1988). Help Seeking and the Need for Academic Assistance. *Journal of Educational Psychology*, 80(3), 406–408.
<https://doi.org/https://doi.org/10.1037/0022-0663.80.3.406>
- Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for

- education. Learning and Individual Differences, 103, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Ko, S.-H., Stephens-Martinez, K., Zahn, M., Velasco, Y., Battestilli, L., & Heckman, S. (2025). Student Perceptions of the Help Resource Landscape. Proceedings of the 56th ACM Technical Symposium on Computer Science Education V. 1, SIGSETS 2025, 596–602. <https://doi.org/10.1145/3641554.3701851>
- Lee, H.-P. (Hank), Sarkar, A., Tankelevitch, L., Drosos, I., Rintel, S., Banks, R., & Wilson, N. (2025). The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers. Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems, 1–22. <https://doi.org/10.1145/3706598.3713778>
- Li, R., Hassan, N. C., Saharuddin, N., Li, R., Hassan, N. C., & Saharuddin, N. (2023). College Student's Academic Help-Seeking Behavior: A Systematic Literature Review. Behavioral Sciences, 13(8). <https://doi.org/10.3390/bs13080637>
- Lim, W. M., Gunasekara, A., Pallant, J. L., Pallant, J. I., & Pechenkina, E. (2023). Generative AI and the future of education: Ragnarök or reformation? A paradoxical perspective from management educators. The International Journal of Management Education, 21(2), 100790. <https://doi.org/10.1016/j.ijme.2023.100790>
- Limna, P., Kraivanit, T., Jangjarat, K., Klayklung, P., & Chocksathaporn, P. (2023). The use of ChatGPT in the digital era: Perspectives on chatbot implementation. Journal of Applied Learning and Teaching, 6(1), Article 1. <https://doi.org/10.37074/jalt.2023.6.1.32>
- Lo, C. K. (2023). What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. Education Sciences, 13(4), Article 4. <https://doi.org/10.3390/educsci13040410>
- Lodge, J. M., & Loble, L. (2026). Artificial intelligence, cognitive offloading and implications for education (p. 1487662 Bytes). University of Technology Sydney. <https://doi.org/10.71741/4PYXMBNJAQ.31302475>
- Ma, B., Li, H., Li, G., Chen, L., Tang, C., Xie, Y., Gu, C., Shimada, A., & Konomi, S. (2025). Scaffolding Metacognition in Programming Education: Understanding Student-AI Interactions and Design Implications (arXiv:2511.04144). arXiv. <https://doi.org/10.48550/arXiv.2511.04144>
- Macnamara, B. N., Berber, I., Çavuşoğlu, M. C., Krupinski, E. A., Nallapareddy, N., Nelson, N. E., Smith, P. J., Wilson-Delfosse, A. L., & Ray, S. (2024). Does using artificial intelligence assistance accelerate skill decay and hinder skill development without performers' awareness? Cognitive Research: Principles and Implications, 9(1), 46. <https://doi.org/10.1186/s41235-024-00572-8>
- Makara, K. A., & Karabenick, S. A. (2013). Characterizing sources of academic help in the age of expanding educational technology: A new conceptual framework. In Advances in help-seeking research and applications: The role of emerging technologies (pp. 37–72). IAP Information Age Publishing.
- Nikolic, S., Daniel, S., Haque, R., Belkina, M., Hassan, G. M., Grundy, S., Lyden, S., Neal, P., & Sandison, C. (2023). ChatGPT versus engineering education assessment: A multidisciplinary and multi-institutional benchmarking and analysis of this generative artificial intelligence tool to investigate assessment integrity. European Journal of Engineering Education, 48(4), 559–614. <https://doi.org/10.1080/03043797.2023.2213169>
- Qayyum, A. (2018). Student help-seeking attitudes and behaviors in a digital era. International Journal of Educational Technology in Higher Education, 15(1), 17. <https://doi.org/10.1186/s41239-018-0100-7>
- Sergeeva, O. V., Zheltukhina, M. R., Shoustikova, T., Tikhvatullina, L. R., Dobrokhotov, D. A., & Kondrashev, S. V. (2025). Understanding higher education students' adoption of generative AI technologies: An empirical investigation using UTAUT2. Contemporary Educational Technology, 17(2), ep571. <https://doi.org/10.30935/cedtech/16039>
- Skipchuk, J., Bacher, J., & Price, T. (2024). An Investigation of the Drivers of Novice Programmers' Intentions to Use Web Search and GenAI. Proceedings of the 2024 ACM

- Conference on International Computing Education Research - Volume 1, ICER '24, 1, 487–501.
<https://doi.org/10.1145/3632620.3671112>
- Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, 32(9), 5142–5155.
<https://doi.org/10.1080/10494820.2023.2209881>
- Sun, Y., Sheng, D., Zhou, Z., & Wu, Y. (2024). AI hallucination: Towards a comprehensive classification of distorted information in artificial intelligence-generated content. *Humanities and Social Sciences Communications*, 11(1), 1278.
<https://doi.org/10.1057/s41599-024-03811-x>
- Sweller, J., Ayres, P., & Kalyuga, S. (2011). Intrinsic and Extraneous Cognitive Load. In J. Sweller, P. Ayres, & S. Kalyuga (Eds.), *Cognitive Load Theory* (pp. 57–69). Springer.
https://doi.org/10.1007/978-1-4419-8126-4_5
- Thomas, C. L., & Tagler, M. J. (2019). Predicting Academic Help-Seeking Intentions Using the Reasoned Action Model. *Frontiers in Education*, 4, 59.
<https://doi.org/10.3389/educ.2019.00059>
- Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178.
<https://doi.org/10.2307/41410412>
- Wirtz, E., Dunford, A., Berger, E., Briody, E., Guruprasad, G., & Senkpeil, R. (2018). Resource usage and usefulness: Academic help-seeking behaviours of undergraduate engineering students. *Australasian Journal of Engineering Education*, 23(2), 62–70.
<https://doi.org/10.1080/22054952.2018.1525889>
- Yang, F., & Stefaniak, J. (2023). A Systematic Review of Studies Exploring Help-Seeking Strategies in Online Learning Environments. *Online Learning*, 27(1).
<https://doi.org/10.24059/olj.v27i1.3400>
- Yang, F., Yang, X., Xu, M., & Stefaniak, J. (2024). An Exploration of How Students Prioritize Help-Seeking Sources in Online Learning Environments. *TechTrends*, 68(3), 456–468.
<https://doi.org/10.1007/s11528-024-00944-3>
- Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, 11(1), 28.
<https://doi.org/10.1186/s40561-024-00316-7>
- Zhang, M., & Yang, X. (2025). Google or ChatGPT: Who is the better helper for university students. *Education and Information Technologies*, 30(4), 5177–5198. <https://doi.org/10.1007/s10639-024-13002-5>
- Zhou, X., Zhang, J., & Chan, C. (2024). Unveiling Students' Experiences and Perceptions of Artificial Intelligence Usage in Higher Education. *Journal of University Teaching and Learning Practice*, 21(06).
<https://doi.org/10.53761/xzjprb23>
- Zusho, A., Karabenick, S. A., Bonney, C. R., & Sims, B. C. (2007). Contextual Determinants of Motivation and Help Seeking in the College Classroom. In R. P. Perry & J. C. Smart (Eds.), *The Scholarship of Teaching and Learning in Higher Education: An Evidence-Based Perspective* (pp. 611–659). Springer Netherlands. https://doi.org/10.1007/1-4020-5742-3_14

Appendices and Annexures

Factors	AI Tools as an Informal Source	Other Informal Sources	Formal Sources
Quality / Hallucination / Personalization* (Refined from Giblin et al. (2021))	Personalized and direct responses; requires user validation due to risk of hallucinations or inaccuracies	Variable and platform-dependent	Considered the most reliable
Accessibility / Affordability* (Refined from Giblin et al. (2021))	Financial constraints: premium features may require a subscription	Readily available but may require extensive searching and filtering	Long wait times for instructor responses
Availability / Immediacy* (Refined from Giblin et al. (2021))	Available 24/7 with instant responses	Digital resources are generally available	Course materials are always available, but instructor accessibility is limited
Personal Preference / Familiarity* (Refined from Giblin et al. (2021))	Strong influence from prior positive experiences; growing familiarity increases reuse likelihood	Varies depending on individual learning styles and habits	Varies depending on individual learning styles and habits
Format	Concise, tailored responses; conversational, interactive, and easy to follow	Content structure varies by platform and source	Class materials are comprehensive but lengthy; formal communication with instructors follows academic conventions
Relationship	No interpersonal stress or emotional negotiation involved	Typically informal and socially comfortable; emotional effort is minimal	Formal relationship with instructors; students may hesitate to reach out due to perceived social barriers
Reciprocity	Not observed	Not observed	Not observed
Habitual Use* (New factor from UTAUT2)	Repeated use reinforces habitual reliance; risk of unreflective default use	Unlikely to pose an issue	Unlikely to pose an issue
Dependency* (New factor)	Overreliance may undermine independent thinking and deeper engagement	Unlikely to pose an issue	Unlikely to pose an issue
Cognitive Effort* (New factor from UTAUT2 and Cognitive Load Theory)	Low extraneous load; reduces effort to find or synthesize information; but mixed impact on germane load (depends on verification and reflection)	Varies depending on the specific type of sources and students' needs	Requires effort to understand complex materials from textbooks; instructors offer guidance that requires self-effort

Appendix A: Extended Giblin et al.'s (2021) SSM in the AI Era