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Personalized, Accessible, but Imperfect: Why Students Turn to GenAI for Academic Help

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Abstract

The rapid emergence of Generative Artificial Intelligence (GenAI) is reshaping how students seek academic help. While much research has focused on AI as a stand-alone support, its influence on students' choices among a broader range of support options remains less understood. This study investigates the factors influencing students' help sources selection in a learning environment where GenAI tools are readily available. Using a convergent mixed-methods approach, this research surveyed 52 postgraduate computing and information systems students and conducted interviews with seven students to capture both patterns and reasoning. The study is theoretically grounded in Giblin et al.'s Source Selection Model, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and Cognitive Load Theory (CLT). Findings show that while traditional factors like accessibility, availability, and quality remain important, their meanings are evolving in the context of GenAI. In addition, three new dimensions emerged: habitual use, concerns about dependency, and the desire to minimize cognitive effort. Together, these factors help explain students' preference for GenAI, which were valued for their immediacy, personalized responses, and streamlined cognitive demands. At the same time, students approached GenAI cautiously, reflecting its dual role as both an attractive and a potentially problematic support option. This research extends existing models of help source selection to account for the specific dynamics of GenAI, highlighting both its appeal and its risks as an academic support, and underscoring the need for institutions to equip students with AI-era information literacy to ensure critical and reflective use of academic support.

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

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1. INTRODUCTION

Academic help-seeking is a self-regulated learning strategy through which students seek support to understand content, overcome study difficulties, or enhance learning outcomes (Karabenick & Dembo, 2011). Effective help-seeking involves recognizing knowledge gaps, deciding to seek assistance, and selecting appropriate resources of support (Qayyum, 2018). This process is influenced by several factors, including the nature of the difficulty, learning goals, available sources of help, and students' assessment of those sources based on expertise, accessibility, and perceived helpfulness (Beisler & Medaille, 2016; Giblin et al., 2021). Therefore, students may avoid seeking help when competent support is lacking (Thomas & Tagler, 2019), or when the process feels too demanding or socially uncomfortable. The rapid emergence of generative artificial intelligence (GenAI) presents a significant shift in academic help-seeking by offering students new, accessible avenues for support. GenAI, known for producing human-quality text (Adiguzel et al., 2023), has quickly gained popularity among students, and has been reported recently to surpass Google Search as students' preferred academic tool (Zhang & Yang, 2025). As these GenAI tools continue to advance rapidly, they are poised to become a transformative and long-lasting presence in education, offering instant information, personalized feedback, and interactive, conversational support (Lim et al., 2023). As such, GenAI is likely to reshape how students engage with help-seeking in academic contexts.

GenAI tools, such as ChatGPT o3 and Claude Opus 4, exhibit expert-level knowledge across a wide range of undergraduate subjects—including STEM, the humanities, and the social sciences, achieving 88.8% on Massive Multitask Language Understanding (MMLU) test nearly matching the estimated human expert level of 89.9% (Anthropic, 2025; Hendrycks et al., 2021). With their high accessibility and ability to deliver quick, personalized responses and increasingly expert-level knowledge, GenAI tools have the potential to supplement or even surpass traditional help sources (Hou et al., 2025). However, further research is needed to validate this emerging trend and fully understand its implications and significance, especially in understanding how and why students continue to integrate GenAI tools into their source selection process during help-seeking (Chen et al., 2025).

Given this context, this study aims to explore how students select sources for academic help-seeking within today's increasingly AI-driven environment, focusing on the factors influencing their preferences, particularly regarding GenAI tools. For instructors, understanding these emerging help-seeking behaviors is essential for guiding students toward productive and ethical uses of GenAI in learning. Accordingly, the study aims to answer the following research question:

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 research question, the following sub-questions need to be examined:

- What key factors do students consider when selecting sources for academic help in an environment with readily available GenAI tools?
- 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?

To address these research questions, we adopted and expanded the theoretical framework proposed by Giblin et al. (2021), which outlines the academic help source selection process. This was complemented by the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) and Cognitive Load Theory (CLT) (Sweller et al., 2011), providing additional analytical lenses. Our investigation focused on emerging trends among postgraduate students in computing and information systems. This study provides empirical evidence to deepen understanding of students' source preferences, including their perceptions of GenAI tools and the criteria they use for selecting sources for academic help. The findings offer practical insights for academic institutions looking to integrate GenAI tools into their educational

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support systems.

2. LITERATURE REVIEW

Academic Help-seeking and Source Selection

Help-seeking in academic contexts occurs when students encounter problems they cannot solve independently and must turn to external sources for support (Li et al., 2023). As a key self-regulated learning strategy, help-seeking enables students to overcome academic challenges and persist in their learning by effectively managing resources and time within the learning environment (Fong et al., 2021).

Despite its importance, students do not always seek help, even when in need. Barriers such as fear of judgment, difficulty articulating questions, or limited access to preferred sources can hinder this process (Hou et al., 2024; Karabenick & Dembo, 2011). Source selection is central to help-seeking and often unfolds as a covert and dynamic process shaped by internal deliberation (Giblin & Stefaniak, 2021; Hou et al., 2024). Students must navigate both external constraints and internal concerns to identify where they feel most comfortable and confident seeking assistance. Giblin et al. (2021) proposed a five-stage source selection model that outlines the student help-seeking process: (1) Narrowing of sources, (2) Evaluation of sources, (3) Solicitation, (4) Evaluation of presented help, and (5) Use of help. The source selection decision is concentrated in the first two stages, where students filter potential sources and assess their suitability.

Effective source selection is critical, as it influences whether students receive accurate, timely, and relevant support (Lee et al., 2012). Poor choices can lead to misinformation, confusion, and frustration. Moreover, when help is delivered as direct answers without encouraging deeper engagement, it may ultimately hinder rather than support learning (Fong et al., 2021).

Source Options

Students facing academic challenges can choose from a range of sources (Wirtz et al., 2018). Each help-seeking instance situates them within a pool of potential options, with source selection shaped by diverse influencing factors (Ko et al., 2025). This process requires students to identify accessible sources, evaluate their suitability in relation to academic goals and context, and decide whether and how to engage with them.

Sources are often classified as formal or informal. Formal sources include instructors, textbooks, and institutional support services, while informal sources encompass peers, web searches, digital communities, and GenAI tools (Yang & Stefaniak, 2023; Zhang & Yang, 2025). Although formal sources are typically better aligned with course expectations, students frequently prefer informal sources (Fong et al., 2021). This preference is largely attributed to their perceived ease of use and the comfort of informal interactions (Hou et al., 2024). In contrast, while formal sources are recognized for providing detailed and academically relevant assistance, students may be reluctant to approach them due to delays in response or the social discomfort associated with formal academic communications (Jiang & Simion, 2022; Yang et al., 2024).

Factors Influencing Source Selection

Giblin et al.'s (2021) model offers a comprehensive framework by accounting for a wide range of factors that influence students' source selection decisions. The process resembles a funnel, where students narrow a broad set of sources based on initial criteria (step 1), including accessibility (how easily a source can be reached or used), availability (whether the source is readily available to provide support), and quality (the reliability and accuracy of the information offered). Students then evaluate the remaining source candidates more closely, considering their personal relationship with the source (e.g. comfort, familiarity), reciprocity (the potential for mutual future help), format (whether the help is delivered face-to-face, in writing, or online), and other personal preferences (step 2), before moving into the solicitation and use stages. Aligning with the model, Wirtz et al. (2018) found that perceived convenience was a significant predictor of source use. Similarly, Ko et al. (2025) identified response speed and source availability as students' top two considerations when deciding which source to consult first. These findings reinforce the centrality of accessibility and availability, a trend that persists across both the pre- and post-GenAI landscape.

While Giblin et al.'s (2021) model outlines a structured, stepwise process, Herring & Walther (2016) highlight the cyclic and adaptive nature of help-seeking through a "try again" loop, where students consult multiple sources until they resolve their problem. This recursive process integrates students' self-judgment and feedback from prior interactions into future decisions (Makara & Karabenick, 2013). Additional factors such as time pressure, effort, and cost-benefit evaluations also influence source choice (Ko &

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Stephens-Martinez, 2023; Makara & Karabenick, 2013). These insights suggest that source selection is often more dynamic than a linear model suggests, indicating a need to validate or refine the existing framework.

GenAI tools have added another layer of complexity to source selection. These tools retain the strengths of traditional informal sources, such as ease of access, instant availability, and low-pressure interaction, with added benefits like personalized responses and structured output (Adiguzel et al., 2023). These features mirror students' long-standing preference for accessible and efficient help. Research shows students are rapidly adopting GenAI and view it as a valuable academic help (Adams et al., 2024). Zhang and Yang (2025) found a growing preference for GenAI, particularly ChatGPT, over traditional search engines. GenAI's rising popularity has also raised significant concerns due to some drawbacks associated with its use. While its capacity to provide adaptive feedback, personalized learning pathways, and low-stakes assistance presents promising educational opportunities (Chan & Hu, 2023), issues regarding misinformation, overdependence, and potential skill erosion have sparked questions about its long-term impact on meaningful learning (Zhai et al., 2024). If students fail to critically evaluate GenAI-generated content or struggle to uphold academic integrity, its use may ultimately hinder, rather than support learning (Kasneci et al., 2023; Lo, 2023).

Echoing broader concerns, students themselves are aware of these trade-offs. Hou et al. (2024) found that while students perceived GenAI as efficient, they also considered it unreliable, leading to divided attitudes. Some students accepted this trade-off as manageable, 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, enhances its appeal over traditional help sources.

Given these shifts, the applicability of Giblin et al.'s (2021) model warrants re-evaluation to inform a more AI-aware framework. With the rise of GenAI tools, foundational factors within the model may be interpreted or prioritised differently. GenAI's 24/7 responsiveness and conversational design reshape notions of "availability." Its ability to generate content across formats (text, image, audio) and tailor responses to user prompts alters how "quality" is perceived. However, GenAI's tendency to hallucinate or fabricate information complicates this perceived benefit.

GenAI may also introduce new considerations in the student source selection process. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) and Cognitive Load Theory (CLT) (Sweller et al., 2011) provide valuable theoretical extensions to explore these emerging dynamics. UTAUT2 explains technology adoption through constructs like performance expectancy, effort expectancy, and habit, dimensions particularly relevant to GenAI, given that its use in academic contexts is typically voluntary. Recent studies have found that habit is the strongest predictor of GenAI use for academic purposes, followed by performance expectancy (Sergeeva et al., 2025), suggesting that repeated exposure combined with perceived benefits reinforces students' adoption. However, UTAUT2 was developed primarily for consumer technologies and does not address dimensions that are important to the educational context. CLT partially addresses UTAUT2 deficiencies for the educational domain by offering a cognitive perspective. Recent research shows that students often value GenAI for simplifying complex tasks and providing personalized responses that aid understanding (Adams et al., 2024). However, it remains less clear how students perceive these cognitive loads, that is, the demands on their working memory, when making source selection choices. On the one hand, GenAI can reduce extraneous cognitive load (effort required for processing irrelevant information), thereby allowing learners to devote their cognitive effort to processing the germane load that results in productive learning. This makes it appealing as a low-effort, high-reward source. On the other hand, its increasingly sophisticated, tailored responses raise concerns about whether these advantages discourage students from investing cognitive effort in help-seeking, thereby shaping their choices between GenAI and other help sources. This tension is especially significant in self-directed learning, where sustained, self-initiated effort is critical for deeper learning (Grund et al., 2024).

Although there have been a multitude of studies addressing the use of GenAI as a help source for students, there is still a need for deeper investigation of how GenAI compares with traditional help sources on a range of parameters.

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3. METHODOLOGY

This study used a mixed-methods approach with a convergent design, underpinned by a pragmatic paradigm. Pragmatism supported the integration of qualitative and quantitative methods to explore the context-specific factors shaping students' academic help-seeking and source selection behaviours in an AI-influenced learning environment (Clarke & Visser, 2019). The study design was guided by two research goals: identifying key factors influencing students' choice of help sources (Sub-question 1), and exploring their rationale, evaluations, and decision-making across varying contexts (Sub-question 2), thereby addressing the overarching research question.

The convergent design enabled the simultaneous collection of broad and in-depth data during a defined period (September to October 2024). This approach ensured a synchronized snapshot of student experiences, which was important given the rapidly evolving context of GenAI use. At the time of data collection, the use of GenAI tools was governed by subject-level rules, with coordinators determining whether their use was permitted. Quantitative and qualitative data were analyzed independently and then integrated. The target population was postgraduate students studying information technology (IT) and information systems (IS) at a leading Australian university. A total of 52 postgraduate CIS students completed the survey, and 7 postgraduate students participated in interviews. Ethical approval was obtained (Approval ID: 20833).

Quantitative Strand (Survey)
Administered using Qualtrics, the survey was designed to capture students' general reasons for selecting formal and informal sources. Participants were initially asked to rank their preferences across eight common help sources, then indicate reasons for preferring formal or informal options, with response options informed by factors identified in Giblin et al.'s (2021) academic source selection framework. Additional questions explored other factors identified from the literature, such as the impact of prior experience on source reuse. Survey data were analyzed descriptively, using frequencies and percentages to summarize responses.

Participants were recruited through convenience sampling. Researchers contacted the coordinators of selected IT and IS subjects and requested the distribution of the survey invitation via subject announcements. Additionally, some invitations were shared through direct contact with students known to the research team. Approximately 600 students were estimated to have received the survey invitation. A total of 52 students responded, and all responses were deemed complete and valid for inclusion in the analysis.

Qualitative Strand (Interviews)
Semi-structured interviews were used to explore students' help-seeking processes, source choices for various academic tasks, and reasons behind their preferences or avoidance of specific sources. Key interview 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 data were analyzed inductively using Reflexive Thematic Analysis (RTA) (Braun & Clarke, 2012). The analysis focused on identifying semantic themes closely aligned with participants' expressed experiences and perceptions of source selection. To deepen the interpretation of the inductively derived themes, Giblin et al.'s (2021) source selection model, UTAUT2 (Venkatesh et al., 2012) and CLT (Sweller et al., 2011) were used as complementary lenses. This phase of analysis was iterative, with intervening time gaps, to enable critical researcher reflection on assumptions and analytical decisions.

Interview participants were recruited using purposive sampling in stages. Initially, five IT postgraduate students were recruited. Subsequently, to explore the potential variation of themes across different academic disciplines, two postgraduate students pursuing master's degrees in business management were purposefully recruited. Although the study primarily focused on the students studying in the IT and IS domains, these additional interviews were conducted to provide a limited comparative perspective. This approach helped assess whether themes identified among the participants from IT and IS domains were discipline-specific or indicative of broader trends across the university student population. Our analysis of the interview data from these two business students revealed a notable convergence in their help-seeking strategies described and the primary themes that emerged from their experiences. This resulted in a total of seven interview participants. All seven participants had prior experience using AI tools for academic purposes. Each interview lasted approximately 45 minutes. Recruitment was concluded at seven participants as thematic saturation was found to have been reached.

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4. FINDINGS

The findings presented below reflect the patterns observed across all participants, as our analysis did not identify substantive disciplinary differences between the computing and business management students.

Theme 1: Immediate, Effortless, Always There — The Triple Appeal of GenAI Support

Participants consistently preferred sources that were fast, always available, and easy to understand. GenAI stood out for its immediacy and for reducing the cognitive effort typically required by traditional help sources.

Theme 1.1: "You Ask, It Answers Right Away" — Why Immediacy Matters

Participants frequently highlighted the importance of immediate responses. As P4 (Computing major) observed, "Most of the students are doing their [assignments] just before the deadline," emphasizing how time pressure shaped urgent, outcome-driven help-seeking. Survey data reinforced this preference, as shown in Figure 1, which summarizes students' reasons for preferring informal help sources, 80.8% of respondents selected "faster access and response" as a key factor (participants were able to select multiple reasons).

Among informal options, GenAI tools were widely regarded by participants as the "fastest". P5 (Human computer interaction major) 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." This comparison illustrates a key advantage of GenAI over traditional web searches, which often require users to navigate multiple fragmented sources to find an answer. In contrast, GenAI enhances immediacy by delivering consolidated answers instantly.

GenAI was also seen as more responsive than formal sources. P2 (AI major) 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."

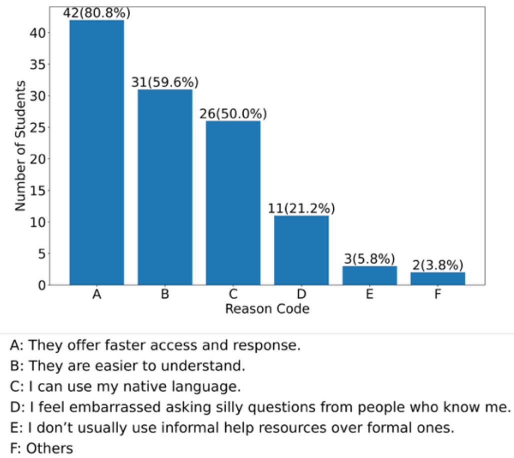

Figure 1: Reasons students prefer informal help sources

Theme 1.2: "Less Effort, More Progress" — Cognitive Ease as a Key Driver

Another appeal of GenAI tools was their ability to minimize cognitive effort. P5 reflected on how ChatGPT streamlined 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 reflection illustrates how the integration and consolidation of information within a single GenAI tool reduces the mental effort needed to navigate multiple resources. P1 (AI major) 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."

This preference extended to tasks involving dense materials, where traditional study methods were perceived as cognitively demanding. As P5 noted, "Using class materials is quite time-consuming… You have to read them all and try to filter a solution yourself." In contrast, when using GenAI tools, P1 shared, "You can give ChatGPT a link or upload a file and ask it to summarize… You don't have to read everything." This shift illustrates how GenAI enables the offloading of cognitive effort, contributing to students' preference for sources that streamline and accelerate the comprehension of complex content.

Supporting this pattern, survey results (Figure 1) show that 59.6% of respondents selected "easier to understand" as the reason for preferring informal sources. Together, these insights highlight GenAI's appeal as a tool that reduces perceived cognitive effort.

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Theme 2: The Cost of Convenience — Navigating Between Accuracy and Efficiency
Despite valuing speed and ease, students were mindful of GenAI's limitations. They weighed its convenience against concerns about credibility and accuracy.

Theme 2.1: "Not Perfect, But It Helps Me Move Forward" — A Pragmatic Trade-Off
Participants acknowledged GenAI's limitations. P1 noted, "It can generate non-existent stuff." P4 added, "Sometimes I'm confused about the [GenAI generated] answer… I'm not sure if it's correct."

Still, many accepted this risk in exchange for progress. As P5 reflected: "The answers from ChatGPT are not always consistent, but they're comprehensive enough." P3 (Human computer interaction major) described help-seeking 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." This calculated trade-off suggests that imperfect help can be considered acceptable if it facilitates academic progress. P2 reinforced this view: "if you can get access to more help [sources within the time you have], it may increase the quality of your help-seeking outcome."

Theme 2.2: "It Might Be Wrong, So I Double-Check" — Verification Adds to Cognitive Effort
Aware of potential risks, participants who wished to benefit from GenAI tools engaged proactively in self-verification:

(1) Testing — for programming tasks, participants ran GenAI-generated code to confirm its functionality. P2 noted: "For practical tasks, you can just run the [GenAI-generated] code to test and validate it."

(2) Cross-validation — responses were compared with other non-human sources, such as search engines or textbooks: "If both Source A and Source B provide the same information on a topic, I believe it's accurate."

(3) Common sense filtering — some participants applied their own judgement to filter irrelevant or dubious information: "I use common sense to filter irrelevant information."

These approaches reflect GenAI's mixed effect on cognitive load: while students valued it for lowering perceived mental demands (Theme 1.2), the need for verification introduced additional cognitive demands.

Theme 3: Familiar, Affordability, and Risky — Evolving Patterns of GenAI Use
Beyond immediate use cases, students also reflected on long-term patterns shaping their engagement with GenAI, including financial cost, habit, and growing concerns about dependence.

Theme 3.1: "It's Worth It, If You Can Afford It" — Unequal Access
While some students considered paid GenAI subscriptions a worthwhile academic investment, others raised concerns about affordability. This tension reflected broader questions of accessibility and equity in students' ability to engage with emerging technologies. As P3 shared: "I only have to pay $30 per month for [ChatGPT], and I get answers to all my questions." In contrast, P1 raised concerns about the rising cost of these services, noting, "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". These differing perspectives highlight how financial access can shape the range of source options available to students.

Theme 3.2: "If It Works, I'll Stick with It" — Familiarity and Source Reuse
Students' preferences were influenced by prior experience, which strongly determined whether a source was reused.

Survey data supports this clearly: 92.3% of respondents reported that prior experience affects their decision to reuse a help source (Figure 2). Specifically, 35.4% (17 out 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." And 52.1% (25 out of 48) reported a "strong impact," noting that they would "usually rely on past experiences to guide choices but may occasionally reconsider a source" (Figure 3).

Interview data echoed this pattern. P4 said, "I personally use AI now when I used to go to Google or YouTube." P5 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." Even negative early experiences could improve with tool development. As P2 noted: "In the very early

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stage of ChatGPT… it could not give you the right answer… but after its development … I use it more frequently now." This pattern underscores the influence of habitual use, where repeated positive experiences can potentially reinforce students' reliance on GenAI as a default help source.

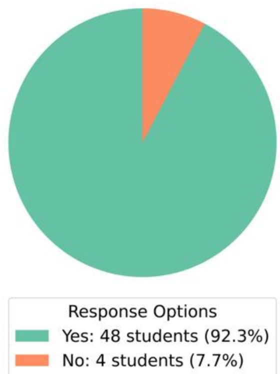

Figure 2: Self-reported decisions on reusing a resource based on prior experience

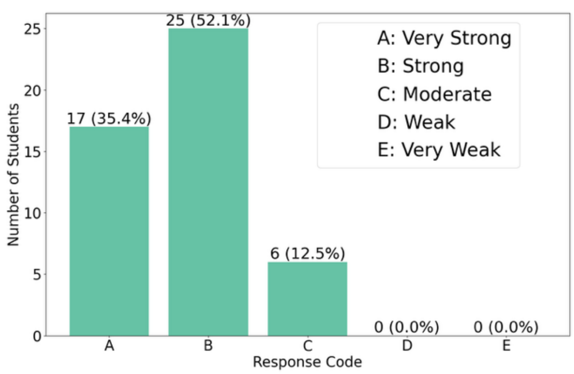

Figure 3: Self-reported influence of prior experience on future help-resource selection

Theme 3.3: "I Use It, But I Don't Want to Rely on It" - Resisting Dependency

Participants voiced concerns about developing a dependency on tools like ChatGPT, recognizing that habitual use could undermine their learning and reduce engagement with challenging material. As P4 reflected, "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".

With this concern, participants described intentional strategies to avoid overuse. P5 explained, "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." This deliberate sequencing reflects an effort to balance support and self-directed learning, and it highlights dependency as an emerging dimension of source selection, where students recognized the risk of overreliance. It suggests a tension between immediate support and long-term skill development, an ambivalence likely to grow as these tools evolve.

Summary of Findings

Our findings affirm the relevance of Giblin et al.'s (2021) source selection model while extending it to reflect help-seeking in an AI-integrated context. Availability is redefined through GenAI's immediacy, while quality now requires active user evaluation. Accessibility includes financial constraints linked to paid AI tools. Expectations around help format have shifted, with students preferring GenAI's low-effort, conversational responses over more demanding sources. Familiarity, shaped by repeated positive experiences, also strongly influenced source preference, while reciprocity was largely absent in participants' accounts.

Additionally, we identified three new dimensions: habitual use, dependency, and cognitive effort. These reflect students' evolving behaviors in using AI support tools. Together, our findings suggest that students are navigating a complex landscape of convenience, learning quality, and long-term skill development. A detailed breakdown is provided in Appendix A.

5. DISCUSSION

Our findings show that students' help-seeking decisions emerged as a layered and context-sensitive process, shaped by trade-offs between effort, efficiency, and expected benefits, within which GenAI tools play a central yet ambivalent role.

Immediacy, ease of use, and reduced cognitive effort are factors consistently prioritized, making GenAI especially attractive in high-workload situations. This 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).

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GenAI's interactive, conversational interface further enhanced its usability (Chan & Hu, 2023), allowing students to bypass the cognitive burden of interpreting fragmented resources. This simplicity aligns with CLT's extraneous load and UTAUT2's effort expectancy, where technologies requiring less effort are more readily adopted (Sergeeva et al., 2025; Venkatesh et al., 2012). The ability to obtain fast, direct answers, with minimal procedural friction, reinforced GenAI's status as a cognitively efficient and user-preferred tool.

However, the convenience of GenAI was recognized as a trade-off. While GenAI helped students meet immediate academic goals, reflecting performance expectancy in UTAUT2 (Sergeeva et al., 2025; Venkatesh et al., 2012), concerns about accuracy and reliability were common (Adiguzel et al., 2023). GenAI's polished outputs often masked factual errors, and its lack of source transparency made verification difficult (Choi et al., 2025). Hence, verification demands highlighted a nuanced relationship with germane load: when students critically evaluated GenAI outputs, through strategies such as testing, cross-referencing, or applying prior knowledge, they engaged in cognitively productive strategies that supported deeper learning. However, uncritical acceptance of GenAI responses, especially under time pressure, risked reducing engagement with germane load, hindering the development of deeper understanding and independent academic skills.

Finally, as our findings revealed the potential diminished relevance of others (e.g., reciprocity), three significant long-term risks emerged. The diminished role of reciprocity may reflect the more independent nature of postgraduate study or the fact that interactions with GenAI are inherently non-reciprocal. One key risk relates to unreflective habit formation and dependency on AI. Repeated use of AI risks creating a dependency that entrenches passive learning behaviors, 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. Secondly, the tiered access models of AI services, where advanced features are locked behind paywalls, raise critical equity concerns. Lastly, aligning with Hou et al. (2025), the shift toward non-reciprocal, AI-mediated support may erode the social dimensions of learning, reducing vital peer collaboration and dialogue with instructors that are essential for a robust educational experience.

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 the importance of habitual use and cognitive effort, constructs from UTAUT2 and CLT, in this new context, while also identifying dependency as an emergent concern voiced by students. We propose that this extended model, integrating traditional factors with these new AI-specific dimensions, can serve as a preliminary framework to guide future research in this area.

Practically, our findings suggest that educational institutions have an important role in guiding students to develop reflective and critical approaches to GenAI use. 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. While GenAI tools can lower cognitive and logistical barriers, their potential to foster deep learning is not guaranteed. Without intentional pedagogical intervention, there is a risk that students conflate the convenience of information retrieval with genuine cognitive engagement, leading to surface-level understanding and overreliance on automated support. It is therefore crucial to equip students to act not as passive recipients of GenAI-generated content, but as active decision-makers capable of critically navigating the trade-offs between convenience, accuracy, and their own long-term learning.

6. CONCLUSIONS

This study examined students' help-seeking source selection amid the rise of GenAI. Building on Giblin et al.'s (2021) framework, we affirmed its relevance while refining dimensions to reflect how GenAI is reshaping academic support. Students balanced efficiency and quality, favoring low-effort, immediate responses while expressing ambivalence about GenAI's role in learning. Our findings indicate a shift toward cognitively efficient strategies and raise concerns about dependency, equity, and skill erosion. Practically, the study highlights the important role of institutional support, including AI literacy education and responsible GenAI integration to help students make informed, reflective choices.

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These findings should be considered in light of several limitations. The small sample was drawn primarily from postgraduate computing and information systems students at one Australian university, which may limit generalizability. This specific demographic may be more comfortable with AI than other student populations, such as students from different disciplines. As such, this study provides an exploratory snapshot of emerging trends, rather than a definitive account. Further research is needed to validate the identified factors across broader student populations and disciplines.

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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 synthesise 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: Students' Source Selection across AI, Informal, and Formal Sources

