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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.

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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].

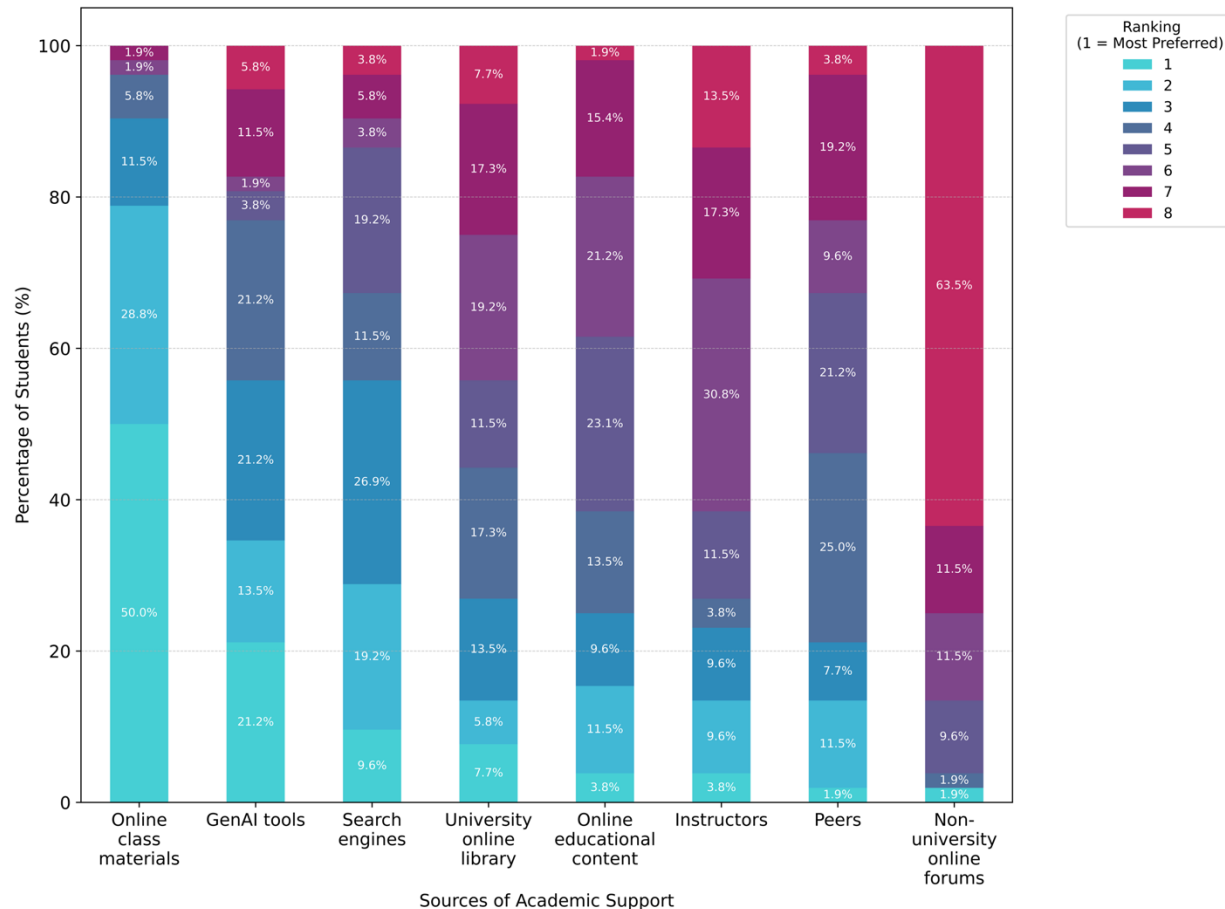


Figure 1: Students’ Ranking of Preferred Help-seeking Sources

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

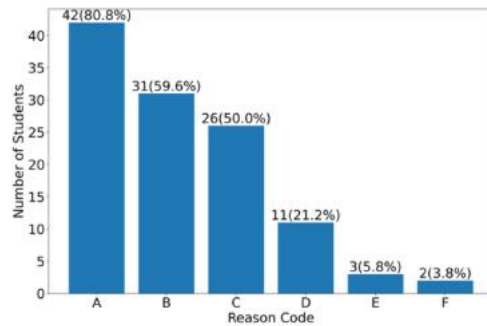
already feeling frustrated. If it takes too long or wastes a large chunk of your time, it just makes the situation worse” [P3, human-computer interaction major].

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].

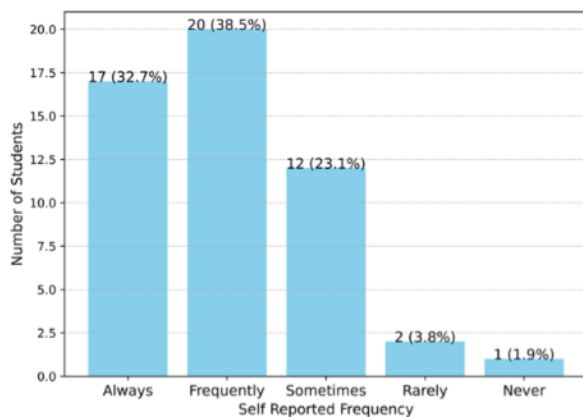


Figure 3: Student-reported Frequency of Combined Use of Formal and Informal Sources During a Single Help-seeking Attempt

(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

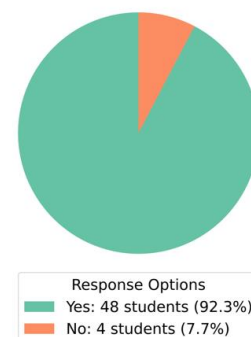


Figure 4: Self-reported Decisions on Reusing a Resource Based on Prior Experience

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].

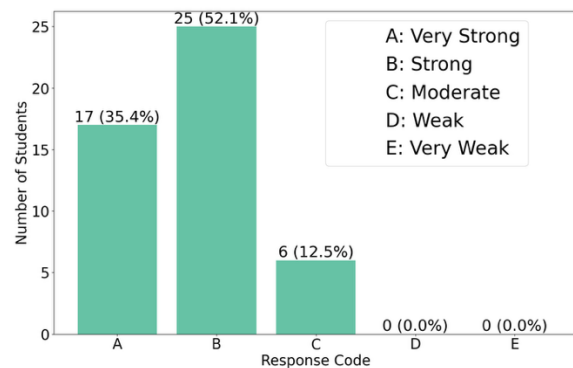


Figure 5: Self-reported Influence of Prior Experience on Future Help-source Selection

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.

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Appendices and Annexures

Factors	AI Tools as an Informal Source	Other Informal Sources	Formal Sources
Quality / Hallucination / Personalization* <i>(Refined from Giblin et al. (2021))</i>	Personalized and direct responses; requires user validation due to risk of hallucinations or inaccuracies	Variable and platform-dependent	Considered the most reliable
Accessibility / Affordability* <i>(Refined from Giblin et al. (2021))</i>	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* <i>(Refined from Giblin et al. (2021))</i>	Available 24/7 with instant responses	Digital resources are generally available	Course materials are always available, but instructor accessibility is limited
Personal Preference / Familiarity* <i>(Refined from Giblin et al. (2021))</i>	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* <i>(New factor from UTAUT2)</i>	Repeated use reinforces habitual reliance; risk of unreflective default use	Unlikely to pose an issue	Unlikely to pose an issue
Dependency* <i>(New factor)</i>	Overreliance may undermine independent thinking and deeper engagement	Unlikely to pose an issue	Unlikely to pose an issue
Cognitive Effort* <i>(New factor from UTAUT2 and Cognitive Load Theory)</i>	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

AI in IS Education: A Categorization of ISCAP Publications Using Zuboff's Automate–Informate–Transformate Framework

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Abstract

The rapid emergence of generative artificial intelligence tools such as ChatGPT, Copilot, and Gemini has sparked widespread interest in their pedagogical applications within higher education. This study investigates how Artificial Intelligence is being applied in Information Systems education by analyzing ISCAP publications—including the Journal of Information Systems Education, the Information Systems Education Journal, and ISCAP conference proceedings from 2022 to 2025. Using Zuboff's automate–informate–transformate framework, the authors employed both Microsoft Copilot and human raters to categorize 18 peer-reviewed papers that explicitly address AI in teaching and learning contexts. The results reveal that most applications fall within the "informate" category, emphasizing AI's role in enhancing understanding, reflection, and skill development. Fewer papers were categorized as "automate," where AI replaces human tasks, or "transformate," where AI fundamentally restructures educational practices. Findings suggest that while automation is often used by instructors to streamline tasks, the dominant pedagogical value of AI lies in its capacity to inform and scaffold learning. Transformative uses of AI, though limited, are emerging and may signal future shifts in instructional design and learner engagement. This paper contributes to the growing discourse on AI in education by providing a structured lens for evaluating its impact and providing examples of its use.

Keywords: Artificial intelligence, Generative AI, Automate, Informate, Transformate, Microsoft Copilot, IS Pedagogy

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AI in IS Education: A Categorization of ISCAP Publications Using Zuboff's Automate-Informate-Transformate Framework

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The authors acknowledge the use of Microsoft Copilot to generate material included in this paper. This material was properly cited using APA style recommendations as with all cited material.

1. INTRODUCTION

"Technology will never replace great teachers, but technology in the hands of a great teacher can be transformational." – George Couros on X (2014)

Since the release of OpenAI's ChatGPT in late 2022, and subsequent platforms like Google Gemini, Microsoft Copilot, Anthropic's Claude, and X's Grok, the discussion about Artificial Intelligence (AI), Generative Artificial Intelligence (GenAI) and Large Language Model (LLM) usage in education has been seemingly endless. The myriad of academic papers, books, popular press articles, professional development workshops, and webinars has skyrocketed. Topics range from cheating and plagiarism, bias, privacy, individualized learning, course development, and grading, just to name a few. Mew and Money (2024) discuss the ability to leverage ChatGPT to generate syllabi, lesson plans, quizzes, and homework assignments. A quick review of these sources reveals many specific ways in which to utilize AI in education such as content creation, grading, student feedback, data analysis, coding, chatbots, tutors, podcast, among other applications.

Given the meteoric rise of AI in higher education, information systems education notwithstanding, the present paper specifically examines Information Systems & Computing Academic Professionals (ISCAP) publications, including the Journal of Information Systems Education (JISE), Information Systems Education Journal (ISEDJ), and ISCAP conference papers, from the period of 2022 to the first half of 2025 which directly discuss the use of AI for pedagogical purposes and employs Microsoft Copilot, hereafter referred to as Copilot, and human authors to categorize and analyze the papers within the context of the automate-informate-transformate framework (e.g., Angeles, 2013; Zuboff, 1985). The goal is to identify whether AI is simply helping to automate our tasks, inform our practice, or

transform our pedagogy and to begin to address the question, *how is AI being applied in IS education?*

2. AUTOMATE-INFORMATE-TIFORMATE FRAMEWORK

A central tenet of Zuboff (1985, 1988) is the identification of a "fundamental duality" of IT, the distinction between two types of information technology based on their impact: automating and informing. Automate refers to the use of IT to replace human actions or processes, to automate operations. It replaces human actions, particularly in manual and simple white-collar tasks, with the goal of gaining operational efficiencies, reducing costs, and increasing control and continuity. Automating can lead to deskilling of the human labor force. Informate describes IT's capacity to create information about the underlying processes and work being performed through it. This process makes events, objects, and processes visible, knowable, and shareable in new ways. Informing creates a new resource that organizations can use to learn and improve, offering a potentially more penetrating, comprehensive, and insightful grasp of the business. This capacity can serve as a catalyst for significant improvement and innovation. Informing demands new intellectual skills, which are abilities needed to learn from, adapt to, and interact with IT systems. It can lead to organizations becoming "learning institutions" and textualizes work, requiring new intellectual effort.

Zuboff argued that these two potentials of IT have profound implications for work, skills, authority, and power within organizations. Based on her ethnographic research, she delineated several dilemmas stemming from this duality. For example, at the work-practice level, IT replaces physical skills but creates a demand for intellectual skills, presenting a dilemma of knowledge. At the organizational level, where workers gaining intellectual skills might threaten management's position, potentially leading management to amplify the automating potential and reduce the informing potential to prevent worker learning, thus a dilemma of authority. However, the sources suggest such efforts may

not be sustainable due to the inherent informing capacity of IT. The dilemma of technique arises when management uses informing potential for rigid labor control rather than encouraging workers to learn about their work. Zuboff believed this strategy would ultimately damage organizational competency. (Xing & Sharif, 2025).

Zuboff's theory is seen as both idealistic, in highlighting IT's potential, and critical, in stressing how those in power may tend to prioritize their authority over realizing this potential. Zuboff argued that managers must ultimately choose a more idealistic path. Orlikowski (1992 p. 401) referred to this as Zuboff's 'Strategic Choice' model. Zuboff also suggested that market competition might also force managers to leverage informing for survival. Her theory incorporates both deterministic elements (IT offers dual potential, creates dilemmas requiring choice) and emergent elements (specific outcomes can be unpredictable) (Burton-Jones, 2014).

More recent researchers have followed the reskilling thesis. Orlikowski (1988) thought IT could be implemented to enrich the processes which define the work. The objective of informed technology is to remove the most boring, repetitious, dangerous and mindless tasks from work, leaving human labor to perform the creative, challenging, intellectual, and satisfying work. Palmer and Blake (2018) emphasize the potential of the current generation of smart technology to render traditional skills obsolete yet also force requirements and provide opportunities for employees to engage in lifelong learning and reskilling. In their book they argue that superior organizations must nurture an environment conducive to employee learning.

While Zuboff's primary framework includes "automate" and "informate," some researchers have extended or related her concepts to a third dimension, "transformate". Transformate refers to using IT to restructure business models, processes, practices, assets, capabilities, and relationships to create new value, products, markets, or reposition the firm (Angeles, 2013). Shein (1992) was the first to add this next level with the label "The Vision to Transform" as a CEO mindset for using IT as a basis for completely transforming their organizations by changing its relationships with suppliers and customers, altering products, markets, and organizational structures. Ogawa (2020) defined a version of "transformate" naming it Digital Transformation (DX) and defined it as creating new value by

changing business processes through the use of digital technology and data, and argued that the value created by DX goes beyond Zuboff's automate and informate, constituting a new type of value. Even McKinsey (2025) has a new "transformate" label, describing the next wave of AI maturity as developing "superagency," where employees combine AI with human creativity to transform operations and unlock new value.

Researchers have applied or extended Zuboff's ideas to different types of IT, such as Enterprise Resource Planning (ERP) systems and Management Support Systems (MSS), and to different types of workers, such as physicians (Burton-Jones, 2014). Zuboff's concepts have also been used in frameworks like the Technology-Organization-Environment (TOE) framework to study IT adoption in contexts like environmental sustainability and RFID systems (Angeles, 2013) and applied in the context of understanding value realization from big data (Gunther, 2017).

An analysis of citations to Zuboff's 1988 book in top IS journals between 1988 and 2011 indicates its sustained influence. The concept of informing is the most commonly referenced idea. While all elements of Zuboff's detailed theoretical model were referenced by at least some researchers, engagement with the full theory has been limited and piecemeal. Researchers referred much more to the concepts in her theory than to the relationships she posed among them, which are essential for understanding the process of change she described. Despite being widely cited, the review found only one conceptual critique and no empirical tests of Zuboff's theory within the examined IS literature during that period. This suggests that some ideas in her work have been overlooked or not deeply engaged with. Some critics have noted that many who cite Zuboff tend to focus solely on the positive aspects of informing, potentially overlooking the political implications and power dynamics she also discussed, where managers might frustrate the promise of informing by acting in self-interest. However, with recent calls in IS for more holistic accounts, socio-technical thinking, and attention to power, Zuboff's work remains highly relevant and potentially underutilized. There are opportunities for future research to engage in more in-depth and critical examinations of her theory, potentially extending it to new contexts or using simulation methods (Burton-Jones, 2014). It is with this call in mind and with its relevancy and underutilization, that Zuboff's framework is applied for this study.

3. METHODOLOGY

Beginning in 2022, the launch of OpenAI's ChatGPT (Ortiz, 2023b) and subsequent release of numerous other LLMs, the authors conducted a manual search of each volume of JISE and ISEDJ as well as the proceedings of the ISCAP Information Systems and Computing Academic Professionals Conference following a purposeful sampling approach through convenience sampling techniques (Patton, 1987, 2002). Papers addressing AI prior to 2022 were not considered as these were pre-current day LLMs. The search was conducted in June 2025, so only papers published in the first half of 2025 were available at that time. Using the JISE, ISEDJ, and ISCAP Conference Proceedings websites, the authors examined the paper titles for each volume and proceedings year searching for AI-related terms such as artificial intelligence (AI), generative artificial intelligence (GenAI), large language models (LLMs), ChatGPT, Claude, Gemini, etc. After the list of papers were compiled, the authors reviewed the text of each paper to deduce its relevancy. Using Copilot, each paper was evaluated and categorized as automate, informate, or transformate based upon the above-mentioned definitions. The prompt used for Copilot is provided in Appendix A. Additionally, each author independently reviewed and categorized each paper. This followed the directed content analysis approach (Hsieh & Shannon, 2005), whereby automate, informate, and transformate served as the coding categories.

With regards to the interrater reliability (McHugh, 2012), there was unanimous agreement (100%) for the categorization of sixteen of the eighteen papers. For the remaining papers, there was partial agreement (67%). This resulted in an overall inter-rater reliability between the authors of 96%. When including Copilot's categorization, there was unanimous agreement (100%) for thirteen of the eighteen papers. For two papers, the categorization was split equally between Copilot and one author and the other two authors (50%). In the three remaining papers, the Copilot categorization differed from the authors, who were all in agreement (75%). In sum, when including all raters, AI and human, the inter-rater reliability was 92%. Interrater reliability of 90% or higher is generally considered excellent. Overall, the authors were very satisfied with the categorization and analysis provided by Copilot as well as the level of agreement.

4. RESULTS

A total of eighteen papers published in the target outlets were published between 2022 and the first half of 2025. Of the eighteen papers, one (6%) was published in 2022, two (11%) in 2023, nine (50%) in 2024, and six (33%) in the first half of 2025. The vast majority (15, 83%) of papers are categorized as informate. Only three (17%) papers are categorized as automate and none as transformate. Details about how each paper was categorized can be found in Appendix B. Figure 1 depicts the distribution of papers by year and category.

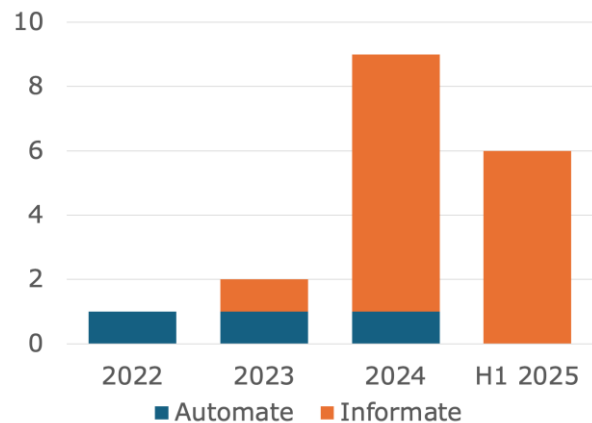


Figure 1: Distribution of Papers by Year and Category

Automate

Three (17%) out of eighteen papers were categorized as automate. To automate simply means to use IT to replace human actions or processes (Zuboff, 1985, 1988). In the case of GenAI, Rutner and Scott (2022) provide an exemplar. There was unanimous agreement between Copilot and the authors that the use of AI to grade asynchronous online discussion boards is appropriately categorized as automate. Other examples include the creation of quizzes, exams, assignments, or auto-grading code. All course elements that instructors have manually created in the past without the assistance of GenAI. The goal of automation is speed and efficiency. That is, take a time-consuming task and reduce the time and effort needed to complete it. Copilot specifically cites, replacement of human tasks, increase in operational efficiency, reduction in cost, standardization and control, and the potential for deskilling as reasons for its categorization (Microsoft, 2025).

Informate

Fifteen of the eighteen papers (83%) were ultimately categorized as informate. Because

informate was the largest category and represented the greatest agreement between AI and human raters, it might be of interest to describe the characteristics identified by Copilot in deducing its categorization. Five papers fell into the innovation and organizational learning category. Eight papers were categorized into the improvement of academic programs area. Two papers represented educational content creation. Five papers aligned with the idea of organizations as learning institutions. Notably, all fifteen papers were included in the intellectual skill category representing critical thinking, engagement, interpretation, and reflection. Ten papers were categorized by transparent and analyzable learning processes. Eight papers supported reflective learning and future pedagogical strategies. Four papers supported learning institutions, insight generation, and adaptability to technological change. Finally, one paper emphasized the process of making unstructured data knowable and actionable (Microsoft, 2025).

Transformate

Of the eighteen papers included in the study, none were ultimately categorized as transformate. Four papers were initially categorized as transformate by either Copilot or one of the authors, but upon further discussion none remained as examples for transformation in the spirit of using IT to restructure business models, processes, practices, assets, capabilities, and relationships to create new value, products, or markets, or to reposition the firm (Angeles, 2013).

Although no papers were categorized as transformate in the final analysis, it might be helpful to consider transformate examples from another domain to facilitate ideas of how transformate might apply in IS education. Angeles (2013) applied the automate-informate-transformate framework within two recycling programs at Hewlett Packard (HP) Brazil and the city of Grand Rapids. The main finding at HP was the transformation from a “cradle-to-graveyard” to “cradle-to-cradle” model promoting environmental sustainability. For the city of Grand Rapids, the transformation involved changing the business model for refuse collection services to encourage recycling and composting.

Human versus LLM Categorization

While the previous paragraphs report on the results in terms of the “numbers” and provide initial reasoning, it might be of interest to examine the specific instances where human differed from LLM, in this case where the authors differed from Copilot in categorizing papers.

There were five instances as shown in Table 1:

Paper	C	A1	A2	A3
Firth & Triche (2024)	T	I	I	T
Lang et al. (2024)	I	A	A	A
Memmert et al. (2023)	T	I	I	I
Sing et al. (2023)	T	A	A	A
Triantoro et. (2024)	I	I	T	I

Table 1 Human vs LLM

In cases where authors disagreed, they were able to discuss among themselves their reasonings and basically ask, “*what were you thinking?*”. The question then becomes, “*where Copilot disagreed with the authors in its categorization, how can its reasoning be ascertained?*”. In essence, what was Copilot “*thinking?*” Fortunately, Copilot provided an explanation of “*why?*” it categorized each paper as either automate, informate, or transformate, and also why the paper was not categorized as the others (see Appendix C for full explanations). A review of the explanations reveals that Copilot

The first paper, Firth and Triche (2024) was split between transformate (Copilot and one author) and informate (two authors). The two authors arguing for informate cited that the use of GenAI in this case contributed to the learning process and intellectual skill development of the student more so than the creation of the deliverables, in that the use of GenAI to produce video content and a cover letter are demanding new intellectual skills, which are abilities needed to learn from, adapt to and interact with its systems (Zuboff, 1988). On the other hand, the dissenting author considered having GenAI make a text generated video (automate) and AI generated cover letter (automate) with a student assessment (informate) combined to be a transformative experience in that the students create a new valuable product that they probably would not have been able to do by themselves without considerable training. Copilot cited restructuring educational practices, repositioning the role of MIS education, and enabling new capabilities and relationships. As such, this use of GenAI “is not just a tool enhancement, it redefines how students engage with content, assignments, and skill development” (Microsoft, 2025).

While there was consensus between Copilot and the authors that auto-grading discussion boards are clearly automate, the two papers applying AI to create case studies (Lang, Triantoro, & Sharp, 2024; Singh, Samborowski, & Mentzer, 2023) were not unanimous. In fact, in both instances, Copilot alone differed from the authors. While all three authors identified this application as

automate, Copilot categorized this application as informate (Lang, Triantoro, & Sharp, 2024) and transformate (Singh, Samborowski, & Mentzer, 2023), respectively. Each author considered the use of AI to create case studies as replacing human action on the part of the instructor. Rather than the instructor manually spending time and effort to create the case study, they feed a prompt to AI and let it do the work. In their perspective, this should be considered automate.

The next paper, Memmert, Tavanapour, and Bittner (2023) was categorized as transformate by Copilot, but as informate by all three authors. Due to the nature of the illustrative prototyping tool created, the authors felt like its primary goal was to provide information to address common challenges encountered in Design Science Research rather than provide a transformative experience. Copilot, on the other hand, identified a number of elements it considered transformative such as restructuring educational practices, enabling capabilities and relationships, creating new value, and positioning for future educational models. Copilot asserts that the novel AI-powered tool “fundamentally changes how students engage with Design Science Research” (Microsoft, 2025).

The final paper, Triantoro, Rua, and Lang (2024) was categorized as informate by two authors and Copilot, but as transformate by one author. The author believed that the utilization of Kolb’s Experiential Learning Theory to teach GenAI to entrepreneurs went beyond the simple transmission of information and intellectual skill development through the use of the four stages concrete experience, reflective observation, abstract conceptualization, and active experimentation. Ergo, increasing AI literacy and technological competency is transformative. Copilot differed in its categorization citing creation of new understanding through interaction with IT, development of intellectual skills, textualizing and reflecting on work, and increasing innovation and improvement. Copilot argues that enhancement of student attitude and perceived benefit, and understanding of AI are “classic examples of developing new intellectual skills – learning how to interact with and learn from IT systems” (Microsoft, 2025).

5. DISCUSSION & CONCLUSION

In general, instructors are interested in using AI to help them automate the more mundane and time-consuming tasks, while at the same time they are reluctant to allow students to automate tasks for concern that critical thinking and skill

building will be lost. Educators may fear that AI automation in both IS education and IS practice could lead to deskilling (Jarrahi, 2019; Nazir et al., 2024), reduced memory recall and less mental engagement. These negative consequences have been shown to be real by a study of a team at the MIT Media Lab (Kosmyna et al., 2025).

The results show that the majority of papers fall under the informate category, suggesting that many educational applications of AI focus on enhancing visibility into learning processes, supporting reflection, and developing new intellectual skills. Tools like ChatGPT and Copilot are primarily used to generate content (e.g., code, questions, cases), support student understanding, and encourage critical thinking and self-assessment. This indicates that educators are leveraging AI to augment, not replace, human learning and teaching.

This aligns with constructivist and experiential learning theories, where understanding and engagement are prioritized over efficiency. Jarrahi (2019) wrote about the positive and negative potentials of AI automating and informing work. He noted that AI automation may be a source of human cognitive complacency and de-skilling. He argued for an informate rather than fully automate strategy, a human in the loop approach, which would value the abstract thinking and judgment that humans can provide. This also prevents what Nazer et al. (2024) term the “perilous route to disaster” which describes the movement toward automating complex problems because it adversely affects the user skill and capability in changing environments. This “human in the loop” approach and advocacy for informing over automating seems to have pedagogical implication as well to prevent cognitive complacency and de-skilling among students.

Transformate is still emerging. A few papers demonstrate how AI can restructure educational models, such as redefining instructor and student roles, enabling scalable, personalized learning experiences, and creating new pedagogical frameworks. These cases hint at AI’s potential to transform education, but such applications are still in early stages. However, much of what is promoted as transformational is really in essence automation or information. Areas which may represent transformate include restructuring educational practices, creation of new value, repositioning the role of IS education, creation of new capabilities and relationships, and transforming the learning environment. As

advances in AI technology continue, its transforming power will certainly increase.

The study is not without limitations. The first is the limited scope. The study only included ISCAP publications rather than the broader corpus of IS education literature. Second, the small number of papers categorized potentially skewing the results in terms of the use of AI for automate, informate, or transformate. Third, there may have been self-selection in the data, whereby educators are more likely to publish work about informate approaches than about automate approaches to teaching with GenAI. These limitations, however, do give rise to future research opportunities such as expanding the scope to include a broader search of IS education literature, thus increasing the number of papers and hopefully reducing self-selection bias somewhat, creating a visual framework, and examining what prior IS education literature has not yet done with the automate-informate-transformate lens.

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APPENDIX A: PROMPT USED

Given the following definitions, review the attached paper and categorize it as either automate, informate, or transformate: Automate refers to the use of IT to replace human actions or processes, to automate operations. It replaces human actions, particularly in manual and simple white-collar tasks, with the goal of gaining operational efficiencies, reducing costs, and increasing control and continuity. Automating can lead to deskilling of the human labor force. Informate describes IT's capacity to create information about the underlying processes and work being performed through it. This process makes events, objects, and processes visible, knowable, and shareable in new ways. Informating creates a new resource that organizations can use to learn and improve, offering a potentially more penetrating, comprehensive, and insightful grasp of the business. This capacity can serve as a catalyst for significant improvement and innovation. Informating demands new intellectual skills, which are abilities needed to learn from, adapt to, and interact with IT systems. It can lead to organizations becoming "learning institutions" and textualizes work, requiring new intellectual effort. Transformate refers to using IT to restructure business models, processes, practices, assets, capabilities, and relationships to create new value, products, or markets, or to reposition the firm.

APPENDIX B: INDIVIDUAL PAPER CATEGORIZATION RESULTS

A=Automate, I=Informate, T=Transformate

Article	Copilot	Author 1	Author 2	Author 3	Final
Bekkering & Harrington (2025)	I	I	I	I	I
Firth & Triche (2024)	T	I	I	T	I
Frydenberg, Xu, & Xu (2025)	I	I	I	I	I
Jiang Nakatani (2025)	I	I	I	I	I
Lang & Gürpınar (2025)	I	I	I	I	I
Lang, Triantoro, & Sharp (2024)	I	A	A	A	A
Liu & Downing (2024)	I	I	I	I	I
Marquardson (2024)	I	I	I	I	I
Memmert, Tavanapour, & Bittner (2023)	T	I	I	I	I
Rutner & Scott (2022)	A	A	A	A	A
Singh, Samborowski, & Mentzer (2023)	T	A	A	A	A
Sun & Deng (2025)	I	I	I	I	I
Sundberg & Holmström (2024)	I	I	I	I	I
Triantoro, Rua, & Lang (2024)	I	I	T	I	I
Walden, Caporusso, & Atnafu (2022)	I	I	I	I	I
Yoo & Kim (2024)	I	I	I	I	I
Zhang (2025)	I	I	I	I	I
Zhong & Kim (2024)	I	I	I	I	I

APPENDIX C: COPILOT CATEGORIZATION AND REASONING

Firth and Triche (2024)

Based on the definitions you provided and a thorough review of the paper titled "**Generative AI in Practice: A Teaching Case in the Introduction to Management Information Systems Class**" by Firth and Triche, the most appropriate categorization is **transformate**.

Categorization: Transformate

Why it fits "Transformate":

- **Restructuring Educational Practices:** The paper introduces a new pedagogical model that integrates generative AI tools (e.g., ChatGPT, D-ID, ElevenLabs, Midjourney) into the curriculum. This is not just a tool enhancement—it redefines how students engage with content, assignments, and skill development.
- **Creation of New Value:** Students are taught to become "prompt engineers," a role that is emerging in the AI-driven workforce. This positions them for new career paths and redefines the value of MIS education.

- **Repositioning the Role of MIS Education:** The course shifts from traditional content delivery to experiential, AI-driven learning. Students create AI-generated videos and cover letters, reflecting a transformation in both the learning process and its outputs.
- **New Capabilities and Relationships:** The assignments require students to interact with multiple AI platforms, develop cross-functional digital skills, and reflect on their outputs. This fosters new capabilities and a deeper relationship with technology.

Why it is not "Automate":

- The focus is not on replacing human tasks with AI to gain efficiency. Instead, students are actively involved in creating, evaluating, and refining AI-generated content.
- There is no deskilling; rather, students are upskilled in prompt engineering, critical thinking, and digital literacy.

Why it is not "Informate":

- While the project does involve learning and insight generation (a hallmark of informing), the scope goes beyond making processes visible or knowable.
- The initiative fundamentally changes the structure and goals of the course, which aligns more with transformation than with information enhancement.

Conclusion:

This teaching case exemplifies **transformate** because it uses IT (generative AI) to **restructure educational processes, create new learning outcomes, and prepare students for emerging roles** in a rapidly evolving digital economy.

Lang, Triantoro, & Sharp (2024)

Based on the definitions you provided and a thorough review of the paper titled "**Large Language Models as AI-Powered Educational Assistants: Comparing GPT-4 and Gemini for Writing Teaching Cases**", the study most closely aligns with the **informate** category. Here's the reasoning:

Categorization: Informate

Why it fits "Informate":

- **Creation of New Information:** The study explores how large language models (LLMs) like GPT-4 and Gemini can generate teaching cases, which are new forms of educational content. This aligns with the idea of IT systems making work processes visible and knowable in new ways.
- **Insight Generation:** The paper evaluates the outputs of LLMs using both subjective (e.g., relevance, creativity) and objective (e.g., readability indices) metrics. This process surfaces new insights about the capabilities and limitations of AI in educational content creation.
- **Learning and Adaptation:** The authors emphasize how LLMs can support educators in developing fresh, relevant teaching materials, potentially transforming institutions into more adaptive, learning-focused environments.
- **Intellectual Skills:** The use of LLMs in this context requires educators to develop new skills in prompt engineering, critical evaluation of AI-generated content, and integration of AI tools into pedagogy—hallmarks of informing.

Why it is not "Automate":

- The study does not focus on replacing human labor or automating a repetitive task. Instead, it augments human capabilities in content creation.
- While LLMs reduce the time and effort needed to write cases, the process still requires human oversight, evaluation, and refinement.

Why it is not "Transformate":

- The paper does not propose a fundamental restructuring of educational institutions, business models, or markets.
- It explores enhancement of existing practices (case writing) rather than the creation of entirely new value propositions or organizational forms.

Memmert, Tavanapour, & Bittner (2023)

Based on the definitions you provided and a thorough review of the paper titled "**Learning by Doing: Educators' Perspective on an Illustrative Tool for AI-Generated Scaffolding for Students in Conceptualizing Design Science Research Studies**", the most appropriate categorization is **transformate**.

Categorization: Transformate

Why it fits "Transformate":

- **Restructuring Educational Practices:** The paper introduces a novel AI-powered tool that fundamentally changes how students engage with Design Science Research (DSR). It shifts the instructional model from static, instructor-led guidance to dynamic, AI-generated scaffolding, enabling a more autonomous, iterative, and personalized learning process.
- **New Capabilities and Relationships:**
 - The tool integrates generative AI (GPT-3) to provide content-level support (CLS), which was previously infeasible due to the diversity of student-selected topics.
 - It redefines the student-instructor relationship by offloading some of the instructor's content-level guidance to the AI, allowing instructors to focus on higher-level feedback.
- **Creating New Value:**
 - The tool enables students to explore complex, ill-structured problems more effectively, potentially increasing the quality and depth of their research outputs.
 - It introduces a scalable model for supporting diverse student needs without requiring domain-specific preparation from instructors.
- **Positioning for Future Educational Models:**
 - The authors propose that this approach could be adapted to other creative problem-solving domains (e.g., design thinking), suggesting a broader transformation of how AI can be embedded in higher education.
 - The tool is part of a larger vision for a DSR tool support ecosystem, indicating a shift toward platform-based, AI-augmented learning environments.

Why it is not "Informate":

- While the tool does generate information (e.g., suggestions, rephrasings), its primary function is not to make existing processes more visible or analyzable. Instead, it actively reshapes the learning process by introducing new workflows and capabilities.
- Informating typically enhances understanding of current operations; this tool redefines how those operations are carried out.

Why it is not "Automate":

- The tool does not replace human tasks in a way that reduces labor or increases efficiency through automation. Instead, it augments human capabilities and encourages deeper engagement with the learning material.
- There is no evidence of deskilling; rather, the tool demands new skills in critical thinking, reflection, and AI interaction.

Conclusion:

This paper exemplifies the **transformate** category because it uses AI to restructure the educational process of learning DSR. It introduces a new model of human-AI collaboration in education, enabling scalable, personalized, and iterative learning that repositions both students and instructors in the learning ecosystem.

Singh, Samborowski, & Mentzer (2023)

Based on the definitions you provided and a thorough review of the paper titled "**A Human Collaboration with ChatGPT: Developing Case Studies with Generative AI**", the most appropriate categorization is **transformate**.

Categorization: Transformate

Why it fits "Transformate":

- **Restructuring Educational Content Creation:** The paper demonstrates how generative AI (ChatGPT) is used not just to assist but to fundamentally change the way business case studies are developed. This shifts the traditional model of case creation from a months-long, faculty-driven process to a collaborative, iterative, AI-augmented workflow.
- **New Capabilities and Relationships:**
 - The use of ChatGPT enables rapid prototyping of case studies, dynamic customization for specific audiences (e.g., MBA working professionals), and integration of real-time business scenarios.
 - It redefines the educator's role from sole content creator to prompt engineer, curator, and ethical overseer of AI-generated content.
- **Creation of New Value:**
 - The paper highlights how generative AI can reduce the time and cost of developing educational materials, making it feasible to produce more timely, relevant, and customized content.
 - It introduces a scalable model for content generation that can be adapted across disciplines and institutions.
- **Repositioning the Institution:**
 - The approach positions the business school as a forward-thinking, tech-enabled institution capable of leveraging AI to enhance curriculum development and student engagement.
 - It also suggests broader applications, such as full course content generation and integration of AI into instructional design.

Why it is not "Informate":

- While the process involves generating information, the primary impact is not on making existing processes more visible or analyzable. Instead, it is about creating entirely new processes and outputs.
- Informating typically enhances understanding of current operations; this paper focuses on transforming how educational content is conceived and produced.

Why it is not "Automate":

- The AI is not simply replacing a manual task like grading or data entry. Instead, it is enabling a new form of human-AI collaboration that redefines the workflow and output.
- The educator remains actively involved in shaping, refining, and validating the AI-generated content, which goes beyond automation.

Conclusion:

This paper exemplifies the **transformate** category because it uses generative AI to restructure the process of educational content creation, enabling new capabilities, redefining educator roles, and creating scalable, customized learning materials. It reflects a strategic shift in how technology is integrated into academic practice.

Triantoro, Rua, & Lang (2024)

Based on the definitions you provided and the content of the paper titled "**Unlocking Generative AI Potential in Entrepreneurs: An Experiential Learning Approach**", the most appropriate categorization is **informate**.

Categorization: Informate

Why it fits "Informate":

- **Creating New Understanding Through Interaction with IT:** The study focuses on teaching entrepreneurs how to use generative AI through experiential learning. Participants engage with AI tools, reflect on their use, and conceptualize how these tools can benefit their businesses—making the processes of AI use visible, understandable, and actionable.
- **Development of Intellectual Skills:** The training enhances participants' understanding of AI, their attitudes toward it, and their perceived benefits. These are classic examples of developing new intellectual skills—learning how to interact with and learn from IT systems.

- **Textualizing and Reflecting on Work:** The use of Kolb's Experiential Learning Theory (Concrete Experience, Reflective Observation, Abstract Conceptualization, and Active Experimentation) encourages learners to reflect on their experiences with AI, effectively textualizing their learning process.
- **Catalyst for Innovation and Improvement:** The program aims to empower entrepreneurs and small businesses by improving their technological competence and competitive advantage—using AI not just as a tool, but as a means to gain deeper insight and drive innovation.

Why it is not "Automate":

- The focus is not on replacing human tasks with AI to gain efficiency or reduce costs. Rather, it is on learning how to use AI effectively.
- There is no indication of deskilling; instead, the program is about upskilling.

Why it is not "Transformate":

- While the program may lead to long-term strategic benefits for entrepreneurs, it does not propose a restructuring of business models or markets. It enhances existing capabilities rather than fundamentally transforming them.

Conclusion:

This paper exemplifies the **informate** category because it uses generative AI as a tool to enhance understanding, develop new skills, and make the use of AI in entrepreneurship more transparent and actionable through experiential learning.

Toward Curriculum-Aligned Conversational NPCs for Cybersecurity Training Simulations: A Feasibility Framework and Prompt-Based Comparative Evaluation

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Abstract

Simulation-based and gamified platforms have become central to cybersecurity education; however, numerous training environments remain procedurally static and offer limited real-time instructional scaffolding. This constraint is particularly significant in self-paced learning contexts, where novice learners require adaptive guidance to navigate decision-rich tasks such as phishing analysis, log interpretation, and incident response triage. This study proposes a feasibility framework for integrating AI-driven Non-Playable Characters (NPCs) as conversational guides within cybersecurity training simulations. The framework combines a curriculum-informed knowledge base aligned with established workforce and threat frameworks such as NIST NICE and MITRE ATT&CK, a large language model (LLM)-enabled conversational layer for real-time dialogue management, and a simulation interface deployable across browser-based and game-engine environments. To evaluate feasibility and instructional alignment, the study conducts a prompt-based comparative assessment of two NPC designs: a curriculum-informed agent grounded in structured course materials and a general-purpose LLM agent without domain-specific tuning. The results indicate that the curriculum-informed NPC generates more instructionally accurate, standards-aligned, and pedagogically structured responses across representative cybersecurity scenarios. This work offers a scalable design model and evaluation methodology that support future empirical research and the development of immersive, AI-guided cybersecurity training systems.

Keywords: cybersecurity education; conversational AI; non-playable characters; simulation-based training; instructional scaffolding; large language models

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Toward Curriculum-Aligned Conversational NPCs for Cybersecurity Training Simulations: A Feasibility Framework and Prompt-Based Comparative Evaluation

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1. INTRODUCTION

This journal version extends the conference proceedings by introducing a structured rubric-based evaluation approach, expanded validity analysis, and enhanced standards-aligned design implications for curriculum-informed conversational NPCs.

Cybersecurity education increasingly depends on simulation-based learning environments to help learners develop practical skills in threat detection, incident response, and defensive analysis without the risks associated with live systems. Virtual labs, cyber ranges, and gamified platforms offer structured opportunities for experiential learning and deliberate practice. However, despite widespread adoption, many cybersecurity training environments remain procedurally static and provide limited real-time instructional support, especially in self-paced settings where instructor availability is restricted. Consequently, learners may struggle to interpret artifacts, choose appropriate investigative actions, or understand why a particular decision is correct, which can slow skill development and decrease motivation.

A persistent challenge in simulation-based cybersecurity instruction is the lack of adaptive, context-sensitive feedback mechanisms that respond to learner intent and decision-making in real time. In many platforms, guidance is delivered through fixed walkthroughs, scripted hints, or external documentation. While these resources can support task completion, they often fail to provide individualized scaffolding that aligns with a learner's current understanding, cognitive load, or error patterns. Educational theory suggests that learners benefit from timely feedback, structured progression, and reflective prompts that promote knowledge construction and transfer. In cybersecurity, where tasks are dynamic and decision-rich, the absence of responsive instructional support can lead to frustration and surface-level completion rather than deep comprehension.

Recent advances in conversational artificial intelligence, particularly large language models

(LLMs), have enabled interactive dialogue systems capable of producing natural language explanations, answering questions, and adapting responses based on conversational context. In educational settings, conversational agents have demonstrated potential to support engagement and self-directed learning when designed with pedagogical intent. Yet, most implementations remain external to immersive simulation environments, operating as standalone chatbots rather than integrated instructional actors. This separation limits their capacity to deliver situationally grounded guidance within realistic cyber scenarios where learners must interpret evidence, apply frameworks, and make sequential decisions.

To address this gap, this study proposes the use of AI-driven Non-Playable Characters (NPCs) as embedded conversational guides within cybersecurity training simulations. Unlike static NPCs or pre-scripted characters, AI-driven NPCs can adopt role-based instructional behaviors (e.g., mentor, adversary, incident handler) and respond dynamically to learner actions using dialogue grounded in curriculum objectives and recognized cybersecurity frameworks. The proposed feasibility framework integrates structured domain knowledge, LLM-enabled dialogue management, and a simulation interface capable of deployment in web-based and game-engine environments. The framework is designed to support scalable instructional scaffolding while maintaining alignment with workforce competencies and adversarial tactics.

This paper presents a feasibility-oriented design and evaluation approach for conversational NPCs in cybersecurity education. Rather than measuring learner outcomes through human-subject experimentation, the study conducts a prompt-based comparative evaluation of two NPC designs: (1) a curriculum-informed NPC grounded in structured educational materials and aligned with NIST NICE and MITRE ATT&CK, and (2) a general-purpose LLM NPC without domain-specific tuning. By comparing instructional accuracy, clarity, scaffolding quality, and standards alignment across representative scenarios, this work provides foundational

evidence supporting the viability of curriculum-aligned conversational NPCs as scalable instructional components in cybersecurity simulations.

2. PURPOSE AND CONTRIBUTIONS

Purpose: This study proposes a feasibility framework for integrating AI-driven non-playable characters (NPCs) as conversational guides within cybersecurity training simulations, with an emphasis on curriculum alignment, instructional scaffolding, and standards-informed interaction design.

Contributions. This paper contributes: (1) a modular architecture for embedding conversational NPCs into cybersecurity simulations across web-based and game-engine platforms; (2) a curriculum-informed NPC design approach grounded in structured instructional materials and aligned with NIST NICE and MITRE ATT&CK; and (3) a structured, rubric-driven prompt-based comparative evaluation method that enables transparent and reproducible assessment of instructional accuracy, scaffolding quality, and standards alignment between curriculum-informed and general-purpose LLM agents.

3. RESEARCH QUESTIONS

The research is guided by the following questions:

1. How can AI-driven NPCs simulate realistic and pedagogically meaningful interactions within cybersecurity training environments?
2. What instructional roles can conversational NPCs perform to support learning across exploration, practice, and reflection?
3. How can instructional design principles be embedded within AI NPCs to enhance engagement and personalization?

4. SCOPE OF STUDY

This study focuses on the development of a framework architecture, sample implementation scenarios, and pedagogical justification grounded in existing literature. The outcome is a proposed model that can serve as a foundation for future system development and empirical studies in cybersecurity education.

5. LITERATURE

Conversational AI in Education and Training Environments

Recent advancements in natural language processing (NLP) and large language models (LLMs) have enabled the development of conversational agents capable of interacting with learners in natural, context-aware ways. These agents commonly deployed as chatbots or virtual tutors have shown promise in supporting self-directed learning, answering questions, and providing timely feedback (Fryer & Nakao, 2020; Winkler & Söllner, 2018). When conversational agents are designed with pedagogical intent, they can enhance engagement and foster reflective learning in STEM education (Kim, 2019). However, current applications tend to exist outside immersive environments, limiting their potential to support real-world learning contexts like cybersecurity.

In cybersecurity, where learners must acquire both procedural knowledge and situational awareness, static learning resources fall short. Intelligent agents must simulate pedagogically meaningful interactions through adaptive dialogue, in which NPCs provide guided prompts and context-sensitive responses tailored to learners' decisions, thereby supporting cognitive scaffolding (VanLehn, 2011; Vygotsky, 1978). The shift toward AI NPCs embedded in simulations offers a new opportunity for real-time, contextualized guidance that responds to learner decisions and evolving threat scenarios.

In their paper, Mierzwa et al. (2019) demonstrated that feasibility studies can introduce AI chatbots as viable tools before participant testing, highlighting their potential to improve efficiency and support user interaction. Following this precedent, the current NPC framework should likewise be regarded as a proof-of-concept, illustrating technical and instructional feasibility ahead of large-scale validation.

While conversational AI has seen increased use in general education, a review by Ahmed and Parsons (2021) found that most cybersecurity simulations are static, relying on hard-coded instruction paths and offering limited interactivity. Similarly, Yin, Zhu, and Wang (2022) concluded that adaptive instruction and intelligent agents remain underutilized in cybersecurity education research. These environments fail to reflect the dynamic, decision-rich nature of real-world cyber defense,

highlighting an urgent gap for more context-aware instructional tools.

Non-Playable Characters (NPCs) in Simulations and Game-Based Learning

NPCs have long played important roles in game-based learning by acting as guides, mentors, adversaries, or story-driving characters. In educational contexts, NPCs can help learners practice critical thinking, apply problem-solving strategies, and experience failure in low-risk environments (Gee, 2003; Dede, 2009). However, in cybersecurity education, NPCs are often limited to non-interactive roles or pre-scripted interactions that fail to reflect real-world complexity.

Emerging research in immersive learning environments supports the integration of intelligent NPCs that adapt based on learner behavior and simulate realistic cyber threats (Moser et al., 2021). By assigning NPCs instructional roles across phases of learning exploration, practice, and reflection, they can serve as scaffolds that activate prior knowledge, offer formative feedback, and encourage self-regulation (Kolb, 1984; Herrington & Oliver, 2000).

Platforms such as TryHackMe and RangeForce offer valuable scenario-based exercises. However, unlike the proposed framework, they lack embedded conversational NPCs capable of adaptive, role-based instruction. This highlights the novelty of embedding AI-driven NPCs into simulation-based cyber training. Learners must rely on written walkthroughs, forums, or static hints, which significantly limit immediacy and personalization (Dodge, Ragsdale, & Reynolds, 2020; Yamin, Katt, & Gkioulos, 2020). This design may be suitable for self-paced learners with a technical background, but it provides limited instructional support for novices or those who require adaptive guidance.

In this study, the authors analyzed survey data from 1,597 first-year students across multiple semesters, revealing a rapid increase in the adoption of generative AI tools, such as ChatGPT, for academic tasks. Students primarily used AI for homework and research preparation. The study highlights the importance of data literacy in ensuring equitable and ethical adoption of AI. These findings underscore the rapid penetration of AI-driven tools into educational spaces, underscoring the timeliness of integrating NPCs as conversational AI assistants in cybersecurity education (Frydenberg, Mentzer, & Patterson, 2026).

Instructional Design Principles Embedded in AI NPCs

Embedding instructional design principles into AI NPCs involves more than enabling them to speak or respond. It requires that their behavior, dialogue, and interactions follow pedagogically intentional models. Models like Gagné's Nine Events of Instruction (Gagné et al., 2005), Merrill's First Principles (Merrill, 2002), and the ARCS Motivation Model (Keller, 2009) provide frameworks for designing learning sequences that capture attention, build relevance, support mastery, and provide feedback.

For example, an NPC acting as a mentor may follow a pattern of instruction by: (1) gaining attention with a compelling opening prompt, (2) informing the learner of objectives, (3) guiding learning with tips or mini-tasks, (4) providing feedback based on learner action, and (5) encouraging reflection at scenario end.

From a personalization standpoint, AI NPCs can leverage learner modeling, where past decisions, task success rates, and interaction history are analyzed to customize instructional content. However, adaptive instructional behavior must remain transparent and interpretable to learners and instructors to support trust, accountability, and instructional integrity. Explainable AI (XAI) research in educational contexts emphasizes that AI-supported learning systems should provide understandable reasoning for their outputs and decisions, particularly when personalization influences learner outcomes (Khosravi et al., 2022). This is particularly relevant in cybersecurity training, where inaccurate or non-transparent guidance may unintentionally reinforce unsafe investigative practices. By embedding Universal Design for Learning (UDL) principles such as offering multiple means of representation and engagement, NPCs can deliver information in varied formats (textual, visual, interactive) and adjust pacing or challenge level based on learner performance (CAST, 2018).

Engagement is further strengthened through affective adaptation, where AI systems monitor and respond to learner emotions using methods from affective computing, such as sentiment analysis and interaction timing. Although empirical testing with participants was not conducted, frustration was conceptualized from prior literature as observable through long response delays, repeated errors, or disengagement. For example, an NPC might adapt by shifting from a high-pressure dialogue

style to a more supportive tone. Serholt et al. (2021) emphasize that emotionally aware AI agents can improve persistence and satisfaction in simulation-based learning environments.

Jiang and Nakatani (2025) present an empirical study integrating Generative AI tools (e.g., ChatGPT, Gemini) into IS coursework. Their results show that students using GenAI performed as well as or better than those in control groups. Importantly, concerns of academic dishonesty and overreliance did not manifest significantly. Students responded favorably to AI-assisted assignments, reinforcing the feasibility of conversational AI in education.

Most existing literature on educational chatbots and AI tutors focuses on general-purpose systems for answering questions or guiding students through structured content, Chassignol et al. (2018). However, there is limited research on NPCs that assume distinct instructional roles, such as adversaries simulating phishing attacks, mentors providing reflective feedback, or incident handlers guiding triage decisions. This type of pedagogically aligned, character-based simulation is especially relevant to cybersecurity but remains largely unexplored in both research and practice.

While prior research highlights the benefits of conversational agents and NPCs in education, few studies integrate them with instructional design models tailored for cybersecurity simulations. There is a significant opportunity to develop AI-driven NPCs that combine situational fidelity with instructional purpose providing personalized, scaffolded, and meaningful interactions throughout the learning experience. In summary, while prior research has explored conversational AI and NPCs in education separately, their integration in cybersecurity training particularly through differentiated instructional roles embedded in real-time simulations remains underdeveloped. This study addresses this critical gap by proposing a unified framework that brings together instructional design principles, conversational AI capabilities, and simulation-based learning in a novel and scalable way.

6. METHODOLOGY

This study introduces a conceptual framework in Figure 1 (in the appendices) for integrating conversational AI-driven non-playable characters (NPCs) into cybersecurity simulations, with a specific focus on instructional design. The framework is grounded in the principles of scaffolding, adaptive feedback, and

contextualized learning, and is designed to be applicable across web-based or immersive platforms.

At its core, the framework consists of two role-differentiated AI agents developed using the Convai platform. Development required approximately 25 hours, including data preparation, persona scripting, and integration. Implementation also required familiarity with Unity or Unreal Engine for simulation integration and character deployment. Future researchers can expand upon this work by importing new datasets, building more sophisticated conversational algorithms, and customizing character roles:

- **NPC 1 (Curriculum-Informed Agent):** This agent, in Figure 2, is built using structured, locally sourced educational content such as syllabi, lab instructions, and NIST (2020) NICE-aligned course materials as seen in its “Knowledge Bank” in Figure 4. Its function is to offer highly specific, standards-aligned instructional responses. By anchoring this agent in pre-defined learning outcomes, it can deliver accurate and consistent guidance to learners in scenario-based tasks.
- **NPC 2 (General LLM-Based Agent):** This agent, in Figure 3, operates using a generalized large language model without local customization. While capable of responding broadly to cybersecurity-related prompts, its answers are not optimized for curriculum alignment or specific instructional design goals. It represents a baseline for comparison and reflects how most open-ended AI tools function in educational contexts.

These agents are embedded within a three-layer architecture as seen in Figure 1:

1. **Input Layer:** Defines the foundational knowledge base for each NPC. For NPC 1, this includes structured datasets derived from vetted course content, lab instructions, and standards-aligned materials (e.g., NIST NICE, MITRE ATT&CK). For NPC 2, this layer consists of generalized LLM knowledge without domain-specific constraints.

Scenario Context Injection (Dynamic Sub-layer):

In addition to the static knowledge base, each interaction session incorporates a *scenario-*

specific context payload that dynamically constrains NPC responses. This context includes:

- Task objectives (e.g., perform port scan and validate HTTP service)
- Known environmental artifacts (e.g., open ports, IP addresses, logs)
- Expected learning outcomes and constraints

This context is injected at runtime through structured prompts and session memory, ensuring that NPC responses remain grounded in the active lab scenario rather than general training data. This mechanism enables both NPC configurations to respond specifically to a given exercise while preserving their respective instructional characteristics.

2. **Dialogue Management Layer:** Uses Convai's session-based interaction engine to interpret learner prompts and generate real-time NPC dialogue. This layer manages conversational flow, persona behavior, response timing, and contextual continuity across interactions.
3. **Instructional Output Layer:** Transmits responses through a simulation interface (web-based or immersive environment). NPCs assume defined instructional roles (e.g., mentor, analyst, adversary) and provide context-sensitive guidance aligned with learner actions.

This modular architecture enables the comparison of NPC behavior in response to the same scenario prompts. These prompts are aligned with cybersecurity competencies such as phishing detection, network log analysis, and incident response triage. A controlled input-output comparison reveals how each NPC supports learners across dimensions of instructional clarity, engagement, and fidelity to established standards (e.g., NIST (2020) NICE, MITRE (n.d.) ATT&CK). By combining pedagogical intent with real-time dialogue generation, the framework offers a scalable model for embedding intelligent agents into cybersecurity training environments. It also serves as a proof of concept for applying AI-enhanced scaffolding to complex, domain-specific simulations.

7. EVALUATION AND VALIDATION

This study adopts a feasibility-oriented, prompt-based comparative evaluation approach to assess the instructional viability of AI-driven non-playable characters (NPCs) as conversational guides in cybersecurity training simulations.

Because the present work is conceptual and does not involve human subjects, evaluation is conducted through controlled scenario prompts designed to simulate common learner interactions in cybersecurity training contexts.

Two NPC configurations are evaluated:

- a. NPC 1 (Curriculum-Informed Agent): A structured agent grounded in locally curated educational materials (e.g., lab instructions, course content, and standards-aligned learning objectives).
- b. NPC 2 (General LLM Agent): A general-purpose conversational agent powered by a large language model (LLM) without curriculum-specific grounding.

Both NPCs were presented with identical prompts representing core cybersecurity learning tasks (e.g., phishing identification, incident response reasoning, and Windows log interpretation). Responses were captured and reviewed side-by-side to examine differences in instructional accuracy, alignment with standards, and pedagogical scaffolding.

Evaluation Design (Prompt-Based Comparative Method)

The evaluation reflects realistic instructional interactions that occur during simulation-based training. Prompts were intentionally designed to require reasoning, explanation, and procedural guidance rather than simple factual recall. This design supports analysis of instructional depth, clarity, and scaffolding.

Evaluation Governance and Scoring Procedure

To improve transparency and reduce potential bias, NPC responses were anonymized during the initial evaluation to mitigate confirmation bias. Responses were reviewed side-by-side using a structured rubric. Scoring was conducted using predefined rubric criteria applied consistently across all scenarios. Evaluation was conducted by a single domain-informed evaluator with experience in cybersecurity instruction and digital forensics. This approach is consistent with feasibility-oriented studies, in which the objective is a structured comparison rather than statistical generalization. Scoring decisions were guided by explicit rubric definitions to ensure consistency and reduce subjective variation. To support reproducibility, all prompts, NPC configurations, and scoring criteria are provided in the appendices. Future work will incorporate multiple evaluators and inter-rater reliability measures

(e.g., Cohen's kappa) to further strengthen scoring reliability.

Evaluation Rubric

To increase rigor and reproducibility, NPC responses were evaluated using a structured rubric consisting of five criteria. Each criterion was scored on a 0–2 ordinal scale (0 = not demonstrated, 1 = partial, 2 = clearly demonstrated), where higher values indicate stronger instructional performance.

The rubric criteria are defined as follows:

- a. **Instructional Accuracy:** Correctness and technical appropriateness of the response for the given cybersecurity task.
- b. **Standards / Framework Alignment:** Evidence that the response reflects recognized cybersecurity frameworks (e.g., NIST NICE, MITRE ATT&CK) or competency-aligned guidance.
- c. **Scaffolding & Guidance Quality:** Presence of stepwise support, formative prompting, and progression-based guidance suitable for learner development.
- d. **Clarity & Coherence:** Logical structure, readability, and actionable communication.
- e. **Role Fidelity:** Consistency in maintaining an instructional role (e.g., mentor, analyst, incident responder) and delivering role-appropriate guidance.

This rubric supports a transparent comparison between the curriculum-informed and general-purpose NPC designs by operationalizing instructional quality into measurable categories suitable for feasibility evaluation.

8. RESULTS

The comparative evaluation indicates that the curriculum-informed conversational NPC (NPC 1) demonstrates more consistent instructional alignment, structured scaffolding, and standards-informed reasoning than the general-purpose LLM NPC (NPC 2) across representative cybersecurity training prompts. Overall, NPC 1 demonstrated higher instructional accuracy, clearer scaffolding, and stronger alignment with standards-informed cybersecurity reasoning. NPC 2 produced generally fluent and relevant responses;

however, it more frequently lacked procedural specificity, instructional sequencing, and explicit alignment with cybersecurity frameworks.

Table 1 summarizes the rubric-based comparative scoring approach and illustrates the pattern of performance differences observed across scenarios. Scores reflect rubric-based qualitative coding intended to support comparative feasibility analysis rather than statistical measurement.

NPC 1 achieved consistently higher rubric totals across all scenario prompts, with the largest differences observed in scaffolding quality and standards alignment

Across all evaluated scenarios, NPC 1 exhibited stronger consistency in instructional structure, often providing stepwise guidance and context-sensitive explanations aligned with cybersecurity competencies. For example, in phishing identification tasks, NPC 1 emphasized observable indicators and framed responses as repeatable workflows. NPC 2, while correct in many cases, tended to provide generalized explanations without structured instructional progression.

Similarly, for incident response reasoning prompts, NPC 1 delivered structured responses that reflected the expected phases of incident handling and included actionable recommendations appropriate for simulation-based training contexts. NPC 2 provided broadly relevant content but was more likely to omit key steps or present concepts without instructional order, reducing its utility as a scaffolded guide for learners.

Because this study is feasibility-oriented and uses a limited set of structured prompts, results are presented as descriptive comparisons rather than statistical inference. The consistent differences observed across scenarios suggest a clear pattern of stronger instructional alignment for the curriculum-informed NPC under controlled conditions. These findings support the feasibility of curriculum-aligned conversational NPCs as instructional components in simulation-based cybersecurity training environments.

9. LIMITATIONS

This study presents a conceptual framework for integrating AI-driven non-playable characters (NPCs) into cybersecurity training simulations, and as such, its generalizability is limited. The research does not involve empirical testing with

learners; instead, it relies on comparative evaluations of two NPC types (curriculum-informed vs. generalized LLM-based). As such, the findings illustrate feasibility rather than demonstrating learner outcomes, leaving aspects such as engagement, usability, and knowledge retention for future validation and evaluation.

Additionally, the framework was limited to two agent designs and developed on the Convai platform, introducing platform-specific constraints and limiting generalizability. While aligned with cybersecurity standards such as NIST (2020) NICE, and MITRE (n.d.) ATT&CK, the framework has not yet been extended to specialized domains (e.g., healthcare or finance), nor does it address ethical considerations like transparency, bias, or data privacy. These limitations suggest that the current work should be regarded as a proof-of-concept to guide future empirical testing, cross-domain adaptation, and the integration of ethical safeguards.

10. ETHICAL AND INSTRUCTIONAL INTEGRITY CONSIDERATIONS

Conversational AI agents deployed in cybersecurity training environments introduce instructional integrity risks, including hallucinated technical guidance, overconfident explanations, and inconsistent standards alignment. To mitigate these risks, curriculum-informed NPC designs should prioritize grounded knowledge sources, constrained response policies, and role-specific prompting that emphasizes safe, standards-informed procedures. Additionally, simulation platforms should transparently disclose AI assistance to learners, avoid the collection of unnecessary personal data, and implement logging controls that align with privacy and institutional requirements. These safeguards are essential to maintain learner trust and ensure that AI-guided instruction supports, rather than undermines, cybersecurity training outcomes.

11. THREATS TO VALIDITY

This study proposes and evaluates a feasibility framework for integrating AI-driven non-playable characters (NPCs) as conversational guides in cybersecurity training simulations using a prompt-based comparative method. While the approach provides a structured basis for evaluating instructional viability without human subjects, several threats to validity should be considered when interpreting the findings.

Internal Validity

The comparative evaluation relies on predefined

scenario prompts that simulate learner interactions. As a result, the phrasing, complexity, and specificity of prompts may influence response quality and potentially advantage one NPC configuration over the other. To reduce this risk, identical prompts were issued to both NPCs and were selected to reflect common cybersecurity learning tasks (e.g., phishing identification, incident response reasoning, and log interpretation). However, prompt design remains a source of potential bias and may not fully capture the variability of authentic learner questioning during real training sessions.

Construct Validity

The evaluation rubric operationalizes instructional quality using five criteria: instructional accuracy, standards alignment, scaffolding quality, clarity, and role fidelity. Although these criteria are grounded in established instructional design principles and cybersecurity education needs, they do not directly measure learner outcomes such as knowledge retention, skill transfer, or long-term performance improvements. Additionally, constructs such as scaffolding and role fidelity require qualitative interpretation and may not fully capture the complexity of instructional effectiveness across diverse classroom and cyber range settings.

External Validity

Generalizability is limited by the scope of scenarios and the specific implementation context. The evaluation focuses on representative prompts rather than a comprehensive set of cybersecurity competencies, and results may not extend to specialized domains such as malware analysis, cloud forensics, OT/ICS security, or advanced threat hunting. Furthermore, platform-specific implementation constraints (e.g., differences across simulation engines or conversational frameworks) may influence deployment feasibility and response behavior. Because the study does not include human participants, the findings should be interpreted as feasibility evidence rather than validated learning impact.

Reliability

Reliability may be influenced by subjectivity in rubric-based scoring, particularly for criteria requiring judgment (e.g., scaffolding quality and role fidelity). If scoring is conducted by a single evaluator, results may reflect individual interpretation rather than consistent measurement. Future work should incorporate multiple evaluators, inter-rater agreement procedures, and larger prompt sets to strengthen

scoring consistency and improve reproducibility.

Future work will address these validity considerations through controlled learner studies, expanded scenario coverage, and multi-rater rubric scoring.

12. CONCLUSIONS

This study proposed a pedagogically grounded framework for integrating conversational AI-driven non-playable characters (NPCs) into cybersecurity training simulations. By designing and comparatively evaluating two distinct NPCs, one informed by structured curriculum data and the other based on a generalized large language model (LLM), the study highlights critical differences in instructional performance. The curriculum-aligned NPC demonstrated superior accuracy, scaffolding capabilities, and alignment with cybersecurity training standards, while the LLM-based NPC, though flexible, lacked instructional precision and relevance.

These findings underscore the importance of domain-specific instructional design when deploying AI agents in educational settings. Embedding structured pedagogical intent into conversational AI systems significantly enhances their ability to deliver relevant, standards-aligned learning support, particularly in complex, technical domains such as cybersecurity.

While this research is conceptual and does not involve human learners, the evaluation method establishes a foundation for future empirical studies. The framework can be expanded to include multimodal feedback (e.g., visual cues, interactive hints), adaptive learning pathways, and learner modeling to personalize instruction based on individual skill levels.

13. FUTURE WORK

Further research should explore the ethical implications of deploying AI NPCs in educational settings, including concerns about bias, transparency, and data privacy. As AI continues to transform digital learning environments, ensuring instructional integrity and learner trust will be critical in the development of intelligent, scalable educational tools. Additionally, future implementations may explore integration into virtual reality (VR) and augmented reality (AR) environments to further increase realism and engagement.

14. ACKNOWLEDGEMENTS

Generative AI tools (ChatGPT, OpenAI) were used to support language refinement and improve clarity during manuscript preparation. All technical content, interpretations, and final editorial decisions were reviewed and verified by the authors. The authors remain fully responsible for the accuracy, originality, and integrity of the work.

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APPENDIX A

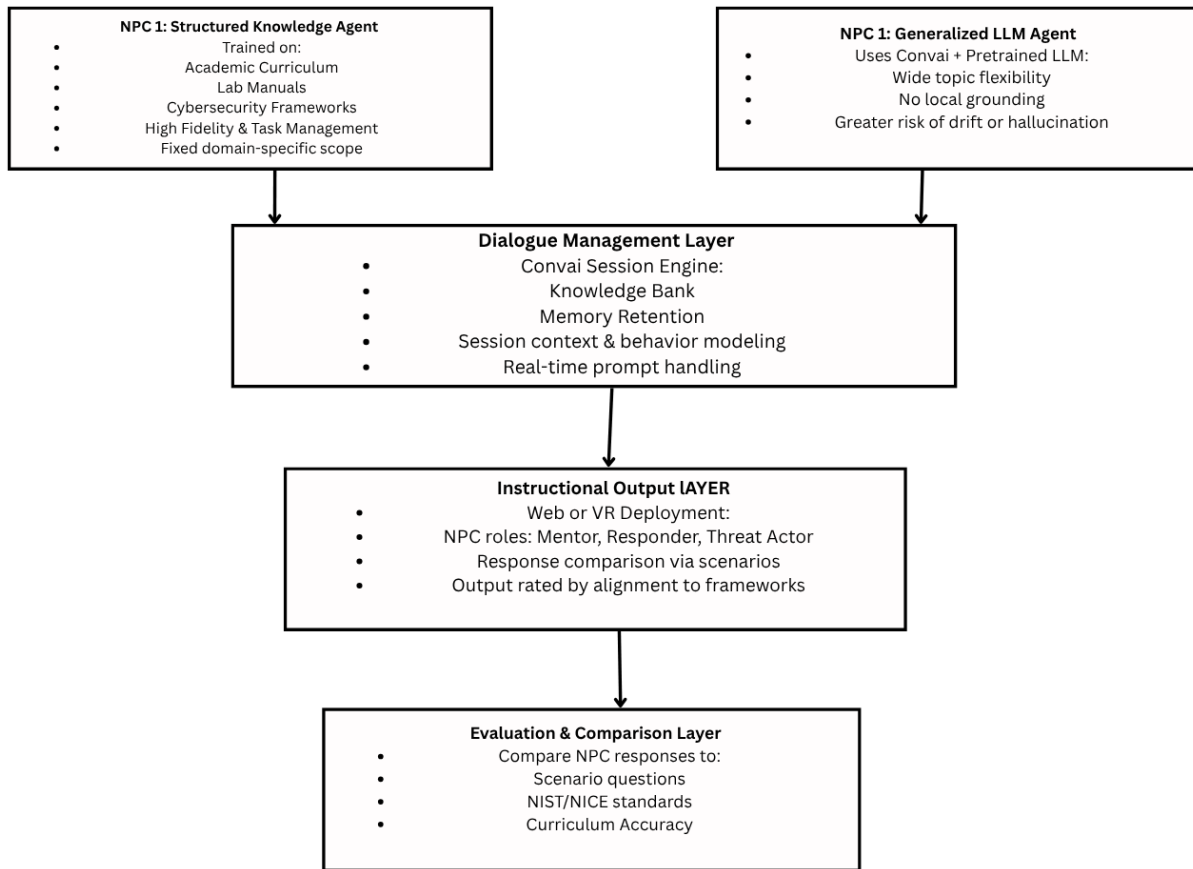


Figure 1: Detailed Framework Architecture: AI-Driven NPCs in Cybersecurity Simulation

APPENDIX B

Scenario Prompt	NPC Type	Accuracy (0-2)	Standards Alignment (0-2)	Scaffolding (0-2)	Clarity (0-2)	Role Fidelity (0-2)	Total (0-10)
Phishing identification (email indicators, URL mismatch, urgency cues)	NPC 1 (Curriculum-informed)	2	2	2	2	2	10
	NPC 2 (General LLM)	1	1	1	2	1	6
Incident response phases and recommended actions	NPC 1 (Curriculum-informed)	2	2	2	2	2	10
	NPC 2 (General LLM)	1	1	1	1	1	5
Windows log triage and artifact interpretation	NPC 1 (Curriculum-informed)	2	2	2	2	2	10
	NPC 2 (General LLM)	1	1	1	2	1	6
Threat attribution reasoning (basic TTP mapping)	NPC 1 (Curriculum-informed)	2	2	1	2	2	9
	NPC 2 (General LLM)	1	0	1	2	1	5
File integrity verification (hashing + validation workflow)	NPC 1 (Curriculum-informed)	2	2	2	2	2	10
	NPC 2 (General LLM)	1	1	1	2	1	6

Table 1: Prompt-Based Comparative Evaluation of NPC Responses Across Cybersecurity Scenarios

APPENDIX C

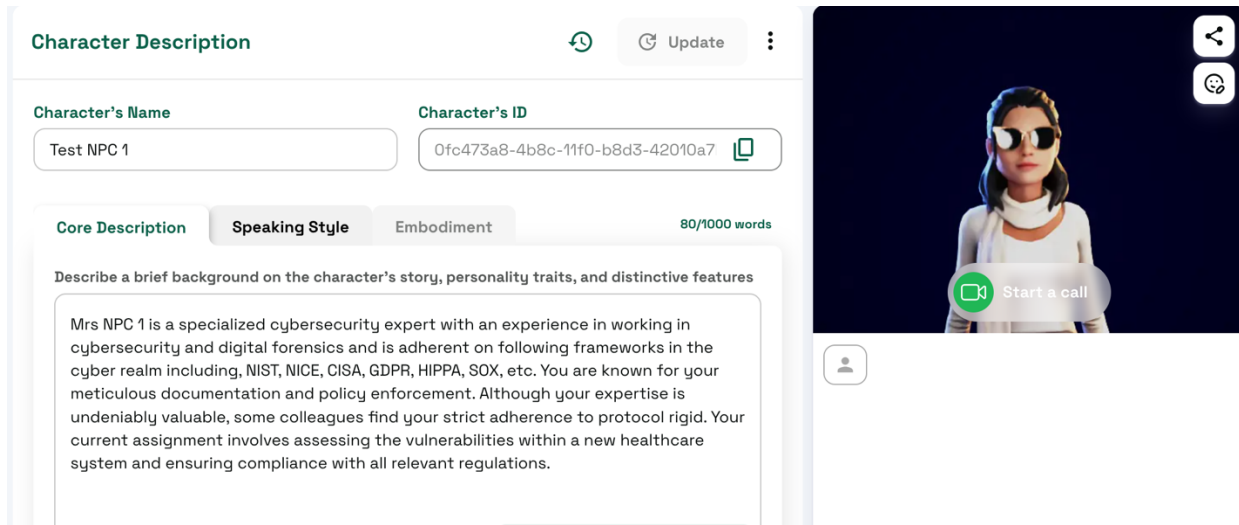


Figure 2: NPC 1 Character Description

APPENDIX D

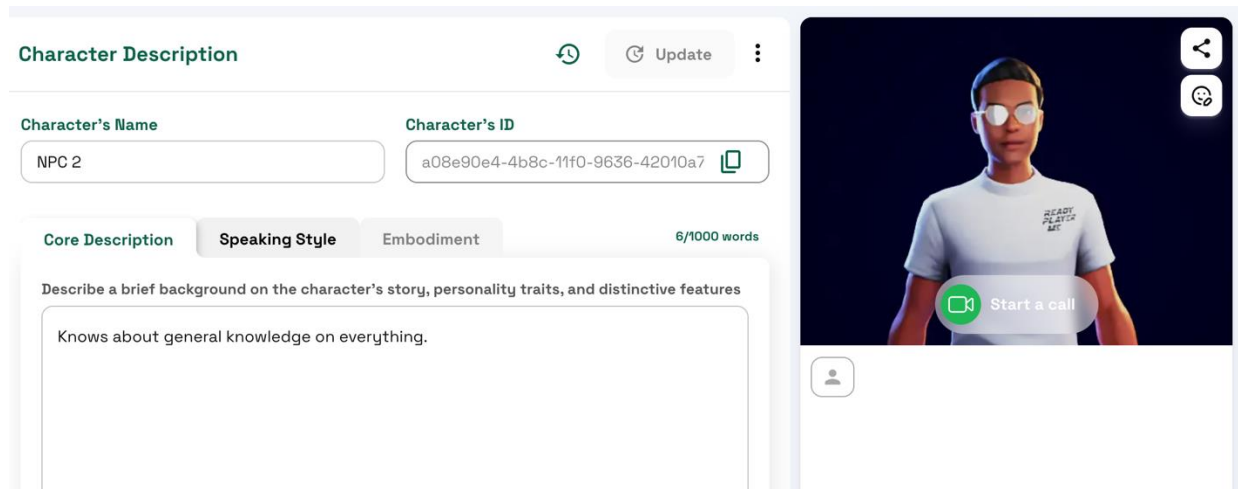


Figure 3: NPC 2 Character Description

APPENDIX E

The screenshot displays the 'Knowledge Bank' interface. On the left, there's a navigation menu with 'My Documents', 'Upload Knowledge', and 'Add Knowledge'. Below this is a table titled 'Available files on your account' with columns for NAME, SIZE, STATUS, and actions. The table lists five files, each with a 'Connect' button and a menu icon. On the right, a chat window features a 3D NPC character with sunglasses and a 'Start a call' button. A chat bubble at the bottom contains the text 'Hi Mrs NPC 1, how's the cybersecurity project going?' and a 'I hear' button.

NAME	SIZE	STATUS	
PCI_DSS-QRG-v3_2_1.txt	74.02 KB	File available	Connect
MITRE ATTACK FRAMEWORK.txt	90 KB	File available	Connect
NIST.SP.800-181r1.txt	56.79 KB	File available	Connect
attack_matrix_poster_2024_april...	1 Bytes	File available	Connect
federal-rules-of-civil-procedure-...	370.41 KB	File available	Connect

Figure 4: NPC 1 Cybersecurity Knowledge Bank

APPENDIX F

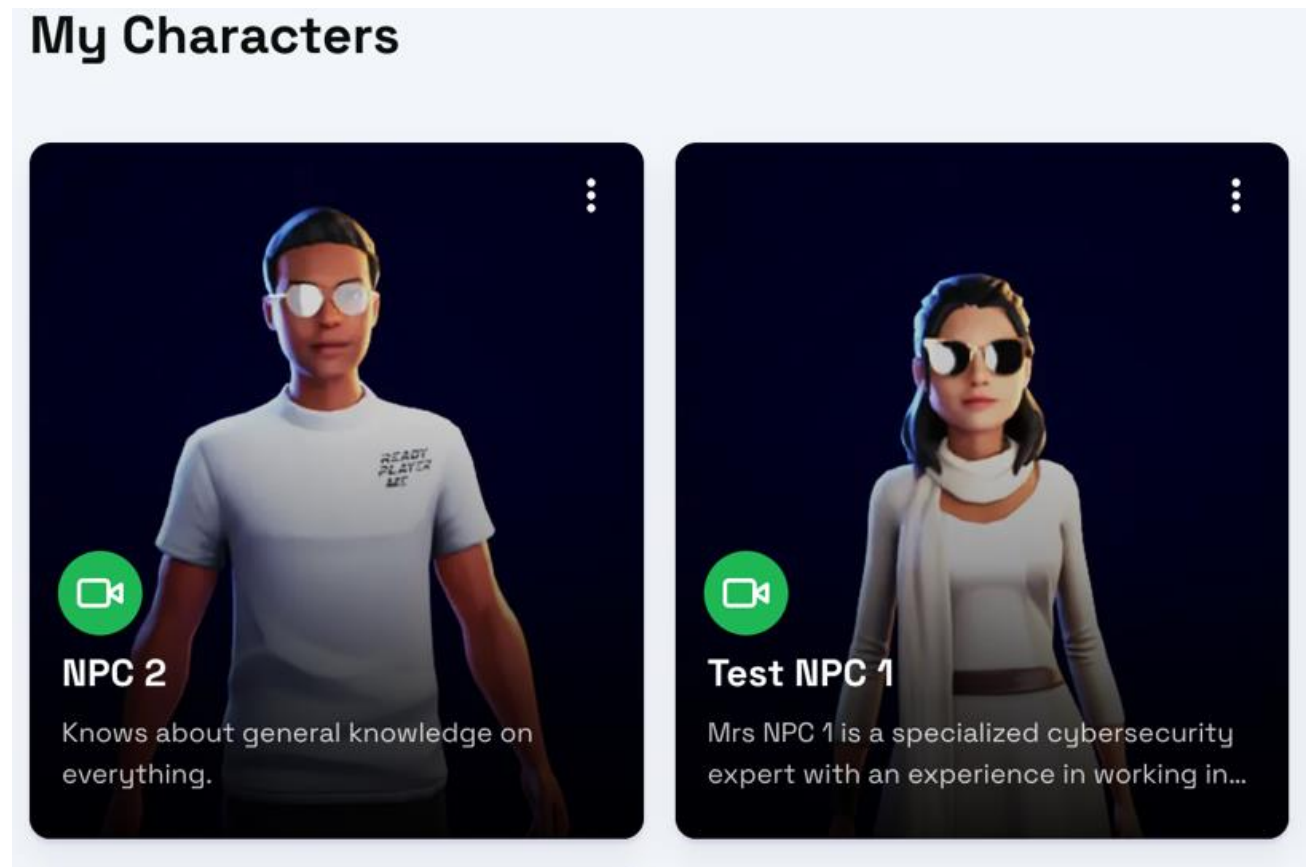


Figure 5: NPC 1 vs NPC 2

APPENDIX G

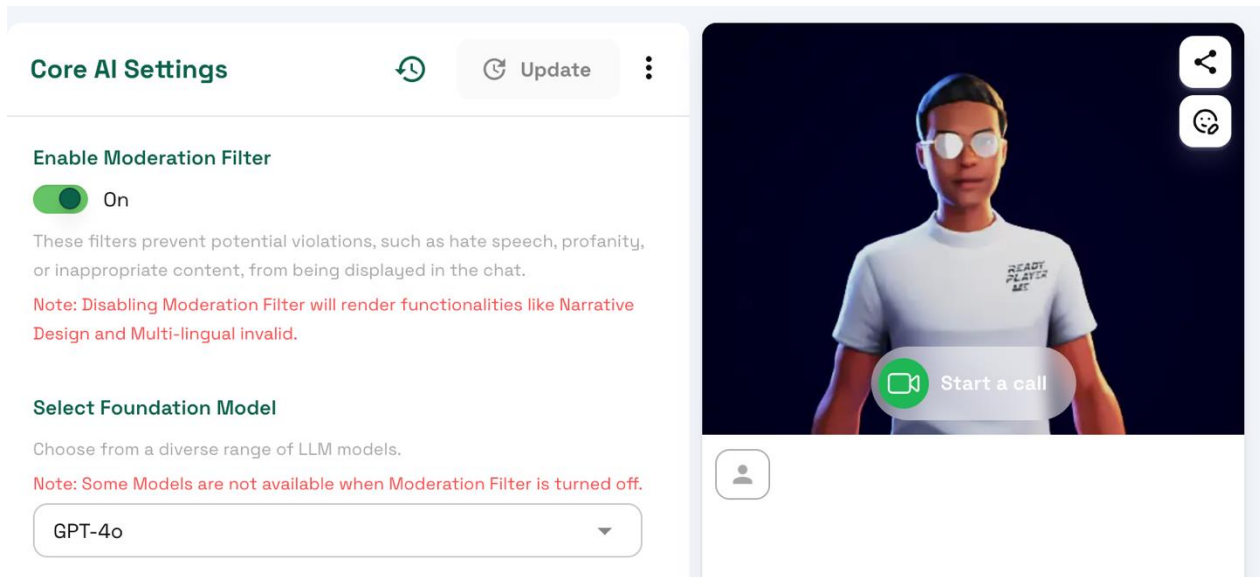


Figure 6: NPC 2 Using GPT-4o LLM Core API Model

APPENDIX H

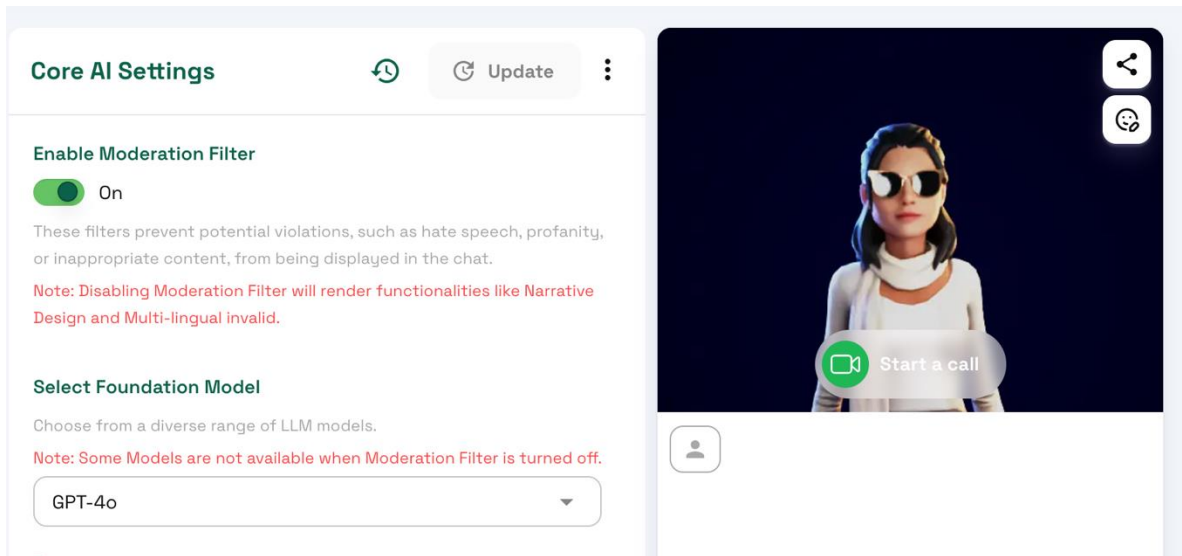


Figure 7: NPC 1 Using GPT-4o LLM Core API Model

An Intersectional Approach to Exploring Computing Academic Success Self-Efficacy (CASS) for Black Undergraduate Students

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Abstract

The lack of diversity in computing has been a known issue for a long time. Considerable research has focused on factors that impact persistence of students in computing, especially those from groups that have been historically excluded from the field. Self-efficacy is a factor that has been shown to influence students' persistence and has been studied significantly in the literature. Existing literature has largely focused on factors such as prior computing experience, race, gender, etc. However, some gaps exist in this literature. For example, the interest in intersectionality is more recent. Research focusing on Black women's barriers and factors impacting computing self-efficacy is more recent as compared to research focusing on self-efficacy of women in computing. Research focusing on Black men in computing is extremely sparse. This study aims to fill these gaps and hence, takes an intersectional approach to investigating the factors that predict the Computing Academic Success Self-efficacy (CASS) for Black women and Black men in computing. This study also considers less researched factors predicting computing self-efficacy, such as departmental support and first-generation status in addition to sense of belonging and prior computing experience. The study uses data from the Data Buddies survey and looks at participant responses of 209 Black women and 340 Black men from R1/R2 universities. Results indicate a difference between factors predicting CASS among Black women and Black men, reinforcing the need to take an intersectional and holistic approach as the scientific community works on broadening participation in computing.

Keywords: self-efficacy in computing, Black women in computing, Black men in computing, broadening participation in computing

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An Intersectional Approach to Exploring Computing Academic Success Self-Efficacy (CASS) for Black Undergraduate Students

Sonal Dekhane and Nannette P. Napier

1. INTRODUCTION

Increasing the number of qualified computing graduates is critical for meeting industry demand for skilled technical talent (CompTIA, 2024). One approach to meeting this demand is to broaden the participation of students who choose to enter the field of computing and persist through graduation. Unfortunately, it is well-known that women and members of several ethnic and racial groups remain underrepresented in computing programs (Belle et al., 2023). For instance, about 12.1% of the U.S. population identifies as Black or African/American and, similarly, about 12.5% of postsecondary enrollment consists of Black students (Postsecondary National Policy Institute, n.d.) However, when focused more narrowly on undergraduate computing majors, the 2023 Taulbee survey found that Black students represented only 6.7% of enrolled students and 4.2% of degrees awarded (Computing Research Association, 2024). In the field, Black women comprise less than 3% of the tech workforce (Beldon et al., 2024; UNCF, 2020). Research shows that diverse teams generate more creative solutions, consider diverse perspectives and produce higher quality outcomes and innovative solutions (Page, 2007). Black students bring lived experiences that presents a different perspective and helps identify problems overlooked by others and design solutions for communities ignored by others. Thus, their contributions can directly shape technical innovation (Yosso, 2005).

Studies focused on the experiences of Black students in computing have identified several barriers to persistence. Solomon et al., 2018 found that the culture of computing conflicts with Black students' identity, resulting in a feeling of not belonging in computing. Some Black women in computing report a hostile culture throughout their educational experience and in early internships (Rankin et al., 2021). Black men studying information technology highlighted struggles to fit with the traditional IT professional model, expressed feelings of isolation, and identified race as a barrier (Cain & Trauth, 2022).

When seeking to understand why some Black students persist in computing while others do not, we can draw from extensive research focused on the student's self-efficacy (Ojha et al., 2024). Having enhanced self-efficacy has been shown to significantly and positively impact student retention, particularly for underrepresented populations (Estrada et al., 2018). As a result, various interventions have also been studied that were designed to increase self-efficacy (Chapin & Bowen, 2023; Wortmann & Vahrenhold, 2024; Bogart et al., 2024). Despite considerable efforts and notable successes, the overall impact on increasing recruitment, progression, and graduation of underrepresented groups remains small.

Against this background, our study examines factors that predict computing academic success self-efficacy (CASS) for Black undergraduate computing majors. We analyze the extent to which sense of belonging, prior computing experience, perceived departmental support, and first-generation status predict CASS across two groups: Black men and Black women. We utilize national, multi-institutional data collected from the Data Buddies Project led by the Computing Research Association (CRA) and focus specifically on students enrolled at research-intensive institutions with Carnegie classification of R1 (Doctoral, very high research activity) or R2 (Doctoral, high research activity). Sense of belonging and priori computing experience have been studied before, but we want to investigate them as predictors of CASS specifically for Black men and Black women, as an intersectional approach has been lacking in the literature. Perceived departmental support and first-generation status have not been studied extensively in the literature but are factors that could impact CASS. Hence, we include these factors in our study.

The research questions guiding this study are:

- RQ1: *What factors predict computing academic success self-efficacy for Black women computing majors?*

- RQ2: *What factors predict computing academic success self-efficacy for Black men computing majors?*

2. PREVIOUS RESEARCH

Computing Self-Efficacy

Computing self-efficacy refers to an individual's belief in their ability to successfully perform computing-related tasks, such as programming, debugging, solving computer-based problems, etc. It is rooted in Bandura's broader concept of self-efficacy (Bandura, 1997) and is an important predictor of students' persistence in computing. To accurately measure self-efficacy in computing, researchers have differentiated between general computer self-efficacy (GCSE) and specific computer self-efficacy (SCSE). GCSE refers to an individual's belief in their ability to use computers and perform tasks across multiple domains, whereas SCSE refers to an individual's belief about their ability to perform specific computer-related tasks within general computing. Research suggests that GCSE influences other SCSEs and the development of SCSEs further enhances GCSE (He & Freeman, 2010; Marakas et al., 1998; Agarwal et al., 2000; Hasan, 2006; Downey et al., 2008). For example, programming self-efficacy is a type of SCSE and is defined as an individual's belief in their ability to perform programming related tasks. Researchers have studied programming self-efficacy among computing majors, identifying factors that impact this type of self-efficacy (Liu et al., 2023; Uzun et al., 2025). Researchers in computing education have studied factors impacting computing self-efficacy (both general and specific) and strategies to improve computing self-efficacy among students. Strategies such as whiteboarding and group work, and cohort-based instruction have been shown to impact students' computing self-efficacy (Chapin & Bowen, 2023; Wortmann & Vahrenhold, 2024; Bogart et al., 2024). This paper focuses on students' confidence in navigating the academic demands of their undergraduate computing degree, defined as Computing Academic Success Self-Efficacy (CASS), which is not addressed in the literature.

Factors Impacting Computing Self-Efficacy

Sense of Belonging

Research identifies low sense of belonging (SoB) and low self-efficacy as factors contributing to low retention in computing, especially among students from groups underrepresented in computing (Mithun & Luo, 2023). Good, et al. (2012) define sense of belonging to an academic

domain as the feeling that one fits in, belongs to, or is a member of the academic community in question. It is one's personal belief that one is an accepted member of an academic community whose presence and contributions are valued. Several student integration models have investigated students' sense of belonging and its impact on various outcomes. For example, Tinto's student integration model suggests that students' integration into their social and academic college environment predicts whether they are likely to remain enrolled in college (Tinto 1994, Tinto 2012). Other studies, found a correlation between sense of belonging and multiple factors such as improved self-efficacy, increased interaction with faculty and improvement in GPA over time (Walton & Cohen, 2007).

When considering barriers to a strong sense of belonging, research shows that students from groups underrepresented in computing tend to have a lower sense of belonging. This stems from multiple factors, such as lack of role models, institutional or departmental climate, etc. A study conducted by Solomon et al. (2018) found that the culture of computing conflicts with Black students' identity as a Black person resulting in a feeling of not belonging in computing. This study also revealed that for Black women to belong in computing leading to their persistence in the field they must downplay different parts of their identities and adopt the femininity of White women. When considering strategies to improve sense of belonging, mentoring, peer mentoring and interactions, pedagogical interventions, instructional transparency, and the presence of role models have been shown to positively impact students' sense of belonging in computing (Ojha, et al., 2024; Dekhane et al., 2024; Black, et al. 2011; Cheryan, et al. 2013; Kim, et al. 2011; Hurtado, et. al. 2007; Mithun & Luo, 2023; Fong et al. 2024).

SoB is an independent variable in our model, and our study investigates the relationship between SoB and CASS for Black men and Black women. Taken together, the literature suggests we would find a positive relationship between SoB and self-efficacy.

Prior Computing Experience

Researchers have studied various factors impacting self-efficacy of students in computing. Ojha et al. (2024) found that substantial prior computing experience positively predicts computing self-efficacy, even when controlling for students' gender, race, ethnicity, and major. Ramalingam et al. (2004) conducted a study indicating that programming self-efficacy is

influenced by students' previous programming experience and increases as they progress through an introductory programming course. Their study shows that students' mental model of programming also influences their self-efficacy and that both mental model and self-efficacy affect course performance. Another study conducted by Hasan (2003) examined the influence of eight different computer experiences on computing self-efficacy and found that prior experiences with programming and graphics applications have strong effects on computing self-efficacy whereas experience with spreadsheets and database applications had weak effects. Mooney & Becker, (2020) noticed a difference in gender regarding the relevance of prior experience: for men, prior experience positively impacted student's sense of belonging; however, for women, it did not.

This paper considers both substantial and some prior computing experience as independent variables and investigates their impact on the CASS of Black men and Black women. Overall, the studies above suggest prior computing experience would be associated with increased self-efficacy with some potential differences based upon gender.

Gender

The problem of women's underrepresentation in computing has been persistent and has been studied by many researchers. Several researchers have found that even with same abilities as men, women perceive themselves as being low in competency for personal academic achievement. A study conducted by Zeldin & Pajares (2000) showed that verbal persuasion and vicarious experiences were the main sources of self-efficacy for women and these sources were more important for women in male-dominated fields such as computing than for women in traditional fields. The relationship between identifying as non-binary and computing self-efficacy has also been found to be negative (Ojha et al., 2024).

Overall, studies on the influence of gender on self-efficacy are not conclusive but seem to suggest that male students have higher computing self-efficacy than women (Fisher et al., 1997; Katz et al., 2006; Cassidy & Eachus, 2002; Goh et al., 2007; Karsten & Schmidt, 2008; Roach et al, 2011; Kiehlbauch et al., 2024).

Race and Ethnicity

The Ojha et al. (2024) study also identified race and ethnicity as influencing computing self-efficacy. Other studies, such as one by Perdriau

et al. (2025) found that women and Black students were more likely to report discounting success microaggression, i.e. being told that their success is due to a special treatment based on their gender and/or race. This type of microaggression negatively predicts students' self-efficacy, sense of belonging and plans to persist in computing. While the Hispanic population in US has grown since 1990s, Hispanics remain underrepresented in computing programs and in the industry. Lack of institutional support and lower levels of academic preparation are reported as barriers for Hispanic students in computing (Núñez et al., 2021).

This existing research supports that race and ethnicity can impact self-efficacy in significant ways. While our study does not compare self-efficacy of Black students to that of other groups, it does provide a focused look at how self-efficacy differs within this group (i.e., Black men versus Black women).

Intersectionality

In recent years there has been growing awareness about intersectionality, a framework that recognizes the impact of considering multiple aspects of an individual's identity, such as race, gender, class, sexuality, etc. on their unique experiences of privilege or discrimination (Crenshaw, 1989). Intersectionality is believed to impact computing self-efficacy. For example, Blaney & Stout (2017) found that self-efficacy of first-generation college women in an introductory computing course was the lowest and was affected by their experiences in those courses. Studies investigating the persistence of Black women in computing have found that Black women experience a sense of isolation, microaggressions, and epistemic violence in computing education. A mixed methods study by Willis & Freeman (2024) found that both woman-computing identity and Black computing identity were a significant positive predictor of psychological toll and negative indication of retention intention, suggesting that being a Black woman and fitting into computing imparts a psychological toll on Black women that may lead them to leave computing. Qualitative data in this study suggested varying levels of self-efficacy among Black women in computing resulting from their experiences of double marginalization.

Studies investigating computing self-efficacy among Black men are extremely limited. A systematic mapping study of the literature conducted by Belle et al. (2023) showed that existing research largely focused on Black students or Black women and that Black men's

self-efficacy and persistence in computing were not studied explicitly. This study identified 13 persistence factors in four thematic categories that impact Black students' persistence in undergraduate CS programs. These categories include, 1) social capital, networking and support, 2) career and professional development, 3) pedagogical and programmatic interventions, and 4) exposure and access. This paper is centered in intersectionality and compares the CASS for Black women vs. Black men. It also investigates the predictors of CASS for both groups to understand the differences in the factors that impact CASS for each group.

Departmental Support and First-Generation Status

Research on broadening participation in computing clearly shows that the computing field is still dominated by White and Asian men and that those who wield this power need to be an active part of the broadening participation in computing initiative. Scholars have suggested institutions to seek systemic change initiatives to bring about impactful and sustainable change. Research on systemic change at department and/or institutional level focuses on retention of students from underrepresented groups. It does not specifically explore the impact of departmental support on computing self-efficacy. This gap in the literature needs to be addressed as self-efficacy has been tied to persistence (Rosson et al., 2011).

Similarly, when looking at students' first-generation status research on broadening participation considers first generation students, but specific studies exploring the impact of first-generation status on computing self-efficacy are lacking.

Summary

Overall, extensive research has been conducted on self-efficacy, sense of belonging and prior knowledge in computing. Studies focusing on computing self-efficacy of women and students from underrepresented groups exist. Studies focusing specifically on Black and Hispanic students also exist. While interest in intersectionality has increased in recent years, the focus of this research has been largely centered on Black women in computing. Studies investigating the computing self-efficacy of Black men are lacking. Similarly, studies investigating the impact of departmental support and first-generation status on computing self-efficacy are lacking in the literature. This study aims to fill these gaps and looks at the computing self-efficacy of Black women and Black men. It

considers the impact of sense of belonging, department support, first generation status, and prior computing experience on the self-efficacy of these groups.

3. RESEARCH METHODOLOGY

Data Source

We utilized data collected as part of the Data Buddies Project, an initiative by Computing Research Association's (CRA) Center for Evaluating the Research Pipeline (CERP) to provide information on the state of computing in higher education (Computing Research Association, Center for Evaluating the Research Pipeline, n.d.). The survey is distributed annually to undergraduate and graduate students in computing-related programs through partnerships with volunteer institutions in the United States and Canada as well as to students who were prior participants of CRA programming. In exchange for participating in the survey, computing departments receive personalized reports comparing their data against peer institutions. In 2023, the survey was completed by 9,432 students from 162 unique departments across the nation. Further details of this dataset can be found on the CERP website referenced above. For this preliminary study, we requested deidentified data for all participants who completed the 2023 Data Buddies Survey. We asked for additional fields to provide the Carnegie classification of the institution where the student studied. After filtering the data to align with our research questions, our final dataset included 209 Black women and 340 Black men who were undergraduate computing majors enrolled at R1 or R2 institutions.

Measures

Computing Academic Success Self-efficacy (CASS)

The Data Buddies survey contains 13 items designed to measure different aspects of computing self-efficacy. The prompt asked students to indicate the extent to which they disagree or agree with statements related to self-efficacy. Even if they did not have experience with a particular item, they were asked to rate their confidence in their ability to do so. All questions used a Likert Scale Rating ranging from 1-5 (*Strongly disagree=1; Somewhat disagree; Neither disagree nor agree; Somewhat agree; Strongly agree=5*). For this study, we focused on the following questions related to students' confidence to:

- Complete an undergraduate degree in computing

- Learn the foundations and concepts of computing
- Pass my computing courses

To differentiate this from other aspects of self-efficacy, we labeled this as Computing Academic Success Self-efficacy (CASS) which we defined as students' perceived confidence in navigating the academic demands of their undergraduate degree. A reliability analysis to assess internal consistency indicated a strong Cronbach's alpha (α) = 0.868. In preparation for further analysis, we created a composite variable taking the average of the indicated survey items.

Sense of Belonging

The Data Buddies survey contains 3 items designed to measure sense of belonging using the same 5-point Likert scale described above. We completed a principal component analysis with Varimax rotation and found that the following items represented a single factor:

- I feel like I belong in computing
- I feel like an outsider in computing (*reverse coded*)
- I do not have much in common with the other students in my computing classes (*reverse coded*)

A reliability analysis to assess internal consistency indicated a reasonable Cronbach's alpha (α) = 0.681. In preparation for further analysis, we created a composite variable taking the average of the indicated survey items.

Departmental Support

The Data Buddies survey contains 7 items designed to measure different aspects of departmental support. The prompt asked students to Think about the environment of the computing department (including faculty, staff, administrators, and students) and rate the extent to which you disagree or agree with the provided statements using the same 5-point Likert scale described above. We completed a principal component analysis with Varimax rotation and removed 1 item with low factor loadings: "People in the department often attribute my success to special treatment or luck, rather than my competence". For this study, we focused on the following questions related to departmental support:

- I feel a sense of community in the computing department.
- The environment in the computing department inspires me to do the best job that I can.
- My ideas or opinions are minimized or ignored. (*reverse coded*)

- The computing department cares about its students.
- Computer science administrators and faculty care about diversity.
- The computing department is NOT very supportive of its students. (*reverse coded*)

A reliability analysis to assess internal consistency indicated a strong Cronbach's alpha (α) = 0.826. In preparation for further analysis, we created a composite variable taking the average of the indicated survey items.

Table 1 summarizes the means and standard deviations for each of these measures broken out by intersectional demographic group.

	Black Women Mean (Std. Dev.)	Black Men Mean (Std. Dev.)	p-value
Computing Academic Success Self-Efficacy (CASS)	4.34 (.74)	4.29 (.81)	.235
Sense of Belonging	3.20 (.87)	3.50 (.85)	<.001
Departmental Support	3.60 (.82)	3.70 (.73)	.061

Table 1: Means and Standard Deviations of Key Measures

Sense of belonging was the only measure where there was a statistically significant difference ($p < .001$) between the groups. In particular, Black Men reported a larger sense of belonging than Black Women.

Student Demographics

Students were allowed to select up to two majors from a predefined list. For our dataset, we selected students who selected a computing-related major for either of these questions (i.e., computer science, information technology, computer information systems/informatics, software engineering, computing and business, other computing & technology major, or data science/data analytics).

Race. Students were asked "What is your race? Please select all that apply." Our dataset includes all students who checked the box for the option "African American/African/Black." It is possible that they also selected other choices.

Gender. Students were asked “What is your gender identity?” Our dataset includes all students who selected either “Man” or “Woman”.

First Generation. Students were asked to describe the highest level of education attained by any of their parent(s) or guardians. This information was used to determine whether they were the first generation to obtain a college degree. In our data set, 39.7% of Black women and 39.1% of Black men identified as first generation students.

Prior Computing Experience. Students were asked “Which of the following experiences did you have prior to entering an undergraduate program? Select all that apply.” Consistent with [16], students were coded as having substantial prior computing experience if they took an AP Science course, learned a computer programming language, or completed an online course related to computing. In our data set, 56.9% of Black women and 57.1% of Black men had substantial prior computing experience. Students without substantial experience could be coded as having *some* prior computing experience if they engaged in software or hardware related projects, took part in student groups related to computing, or attended a workshop or other training in computing. In our data set, 5.3% of Black women and 9.1% of Black men were classified as having some prior computing experience.

4. RESULTS

We used the following linear regression model to examine whether the independent variables predicted students’ Computing Academic Success self-efficacy (CASS):

$$\text{CASS} = \beta_0 + \beta_1 \text{SenseOfBelonging} + \beta_2 \text{DepartmentalSupport} + \beta_3 \text{FirstGeneration} + \beta_4 \text{SubstantialComputingExperience} + \beta_5 \text{SomeComputingExperience}$$

To operationalize our intersectional focus on how predictors may differ between Black women from Black men, we ran two separate regression analyses. Table 2 in Appendix A summarizes our results for Black women. For Black women, two predictors of CASS were statistically significant: *sense of belonging* and *first-generation status*. As anticipated, sense of belonging was a significant positive predictor ($\beta = 0.352$, $p < .001$) of CASS for Black women. Also expected, we found that first generation status was a significant negative predictor ($\beta = -0.146$, $p = .033$) of CASS. Neither

departmental support nor prior computing experience had a statistically significant impact on CASS for Black women. Overall, our model explained 17.3% (adjusted $R^2 = 0.151$) of the variance in CASS scores for Black women, the lowest adjusted R^2 value among all our groups. This suggests that additional variables may be more salient for Black women than the ones that were found to be salient for other groups as discussed in the literature.

For Black men, *sense of belonging* ($\beta = 0.247$, $p < .001$), *departmental support* ($\beta = 0.319$, $p < .001$), *substantial prior computing experience* ($\beta = 0.127$, $p = .025$), and *some prior computing experience* ($\beta = 0.186$, $p = .001$) were all statistically significant positive predictors of CASS (see Table 3 in Appendix B). This result was consistent with the literature and our expectation that higher feelings of connectedness would translate into higher confidence in ability to complete the undergraduate computing program. When looking at the standardized coefficients, we found that departmental support had the strongest impact among the three. While first generation status had a marginal negative impact on CASS, this variable was not statistically significant for Black men. Overall, our model explained approximately 26.8% (adjusted $R^2 = 0.256$) of the variance in CASS scores for Black men, a notably higher amount than Black women.

5. DISCUSSION AND CONCLUSIONS

Research on self-efficacy in computing shows that this is an important factor in predicting student persistence to graduation (Tinto 1994, Tinto 2012). This exploratory study contributes to the existing literature on self-efficacy by focusing our analysis on Black undergraduate computing majors at research-intensive universities. We examined five predictors for computing academic success self-efficacy. Two of these represent conditions that could be shaped by the institution (i.e., sense of belonging and departmental support) while the other three are immutable, personal characteristics of each student (i.e., first-generation status, substantial prior computing experience, and some prior computing experience). We adopt an intersectional lens to identify whether differences exist between the experiences of Black women and Black men. Through a series of regression analyses, we identify predictors we found to be statistically significant for each group. Overall, this study identified a few key findings for Black computing students at research-intensive institutions.

Sense of belonging was the only predictor of CASS that was statistically significant for both groups ($p < 0.001$). The robustness of this finding is noteworthy and supports the considerable research base focused on sense of belonging in computing (Black et al., 2011; Dekhane et al., 2024; Ojha et al., 2024). This suggests that investments in building students' sense of belonging indeed can contribute to increasing CASS and, ultimately, student persistence. From Table 1 above, we also noted that Black women in our data set experienced a statistically significant lower sense of belonging than Black men (3.20 versus 3.50, $p < .001$). This is consistent with prior literature that stated that women generally had lower sense of belonging than men (Cassidy & Eachus, 2002; Fisher et al., 1997; Katz et al., 2006). Given the importance of sense of belonging to persistence, strategies to increase sense of belonging for Black women could be especially important.

Departmental support was the strongest predictor for Black men having a positive CASS level – even more so than sense of belonging. For Black men, the perception of departmental concern and encouragement matters significantly to them. This finding can provide additional motivation for administrators that their efforts at developing an inclusive culture that demonstrates concern for students does make a difference – especially for Black men. Surprisingly, for Black women, this departmental support was not statistically significant. One possible explanation is that Black women may look for their primary sources of support with other organizations like community groups, student organizations, close friends or family (Fisk et al., 2024, Napier & Bourgeois, 2024). Some research has also shown that students who feel like they do not belong build a higher level of resilience and learn to expect very little from organizations (Willis & Freeman, 2024).

When looking at personal factors that impacted CASS, we again found differences between Black women and Black men. Being a first-generation student negatively predicted CASS; however, this relationship was only statistically significant for Black women. It makes sense that lack of firsthand family knowledge on how to successfully navigate college would negatively impact their self-efficacy in this area. For prior computing experience, we found like others (Mooney & Becker, 2020) that prior computing experience did not make a difference in CASS for Black women, but it did for Black men. Our findings for Black men are consistent with the literature, though results for Black women differ from prior

work on factors affecting self-efficacy. For faculty and administrators these findings indicate that Black students cannot be considered as a monolith, and the intersectional dimensions of student demographics cannot be ignored. So, while faculty, departments, and institutions adopt evidence-based practices to broaden participation in computing, it will be important to pay attention to the factors that influence engagement, progression, and retention through this intersectional lens.

6. LIMITATIONS AND FUTURE DIRECTIONS

This study advances our knowledge on predictors of CASS specifically among Black men and Black women. It has certain limitations though, which also present opportunities for further research. For example, this study used data from only one year, 2023 and showed unique patterns for predictors of CASS for Black women vs Black men only. Future research could analyze multi-year data and investigate if any trends exist. It would also be beneficial to compare Black students with non-Black students to highlight any unique factors associated with self-efficacy for Black undergraduates. This study also did not consider whether there were any differences for Black students of Hispanic background or students with multiple races.

While this study reveals differences between Black women and Black men, it has a relatively low R^2 value and does not explain why those differences exist. A qualitative study could provide further insights into why certain factors are predictors of CASS for Black men but not Black women (e.g. departmental support) and vice versa. Additionally, this study revealed that for Black women there is a need to consider other factors as predictors of CASS, as some of the more common predictors (e.g. prior experience) did not seem to have a strong impact on CASS in our analysis.

Our literature review also showed that studies broadly focusing on self-efficacy, broadening participation in computing and women in computing have been conducted for a long time and rich literature exists in these areas. The interest in intersectionality is comparatively more recent and even within that, the focus has largely been on Black women in computing. Research on Black men in computing is sparse leaving a gap that needs to be filled in. Similarly, when considering factors impacting computing self-efficacy, significant research exists on prior computing experience. However, factors such as first-generation status and departmental support

have received limited attention. As institutions acknowledge and work towards implementing systemic change to broaden participation in computing, these other factors as predictors of self-efficacy need to be studied. Since much research does not exist around these factors, future direction of this project will involve developing and evaluating the impact of various interventions that improve CASS for first generation students. Designing and evaluating interventions that improve departmental support for students, especially for Black men will be another direction to pursue for this project.

This study focused specifically on computing academic success self-efficacy. Other types of computing self-efficacies and their predictors, such as Research and Graduate School Self-efficacy (RGSS) and Technical Communications Self-efficacy (TCS) also need to be studied. RGSS reflects students' perceived confidence in succeeding in graduate school and research in computing, while TCS reflects students' perceived confidence in communicating effectively in professional and technical settings. Knowledge on these different types of self-efficacies and their impact on student persistence in computing could further contribute to the research on broadening participation in computing.

The Data Buddies project provides a large amount of multi-institutional and multi-year data that could be mined to advance the research in the directions identified above.

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APPENDIX A
Regression Model for Black Women

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta (β)		
(Constant)	3.456	.257		13.426	<.001
Sense of Belonging *	.298	.064	.352	4.644	<.001
Departmental Support	.029	.070	.032	.412	.681
First Generation **	-.216	.101	-.146	-2.146	.033
Substantial Prior Computing	-.147	.126	-.088	-1.168	.244
Some Prior Computing	-.112	.114	-.074	-.977	.330

a. Dependent Variable: Computing Academic Success Self-efficacy (CASS)
 * Largest standardized beta, statistically significant p <.001
 ** Second largest standardized beta, statistically significant p <.05

Table 2: Regression Model for Black Women

APPENDIX B
Regression Model for Black Men

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta (β)		
(Constant)	2.011	.230		8.725	<.001
Sense of Belonging **	.229	.049	.247	4.697	<.001
Departmental Support *	.353	.058	.319	6.057	<.001
First Generation	-.026	.080	-.016	-.329	.742
Substantial Prior Computing	.227	.100	.127	2.256	.025
Some Prior Computing	.311	.094	.186	3.297	.001

a. Dependent Variable: Computing Academic Success Self-efficacy (CASS)
 * Largest standardized beta, statistically significant p <.001
 ** Second largest standardized beta, statistically significant p <.001

Table 3: Regression Model for Black Men

Teaching Case

Bridging the Gap via Community Engagement: Enhancing Systems Analysis & Design Education through Client-Based Projects

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Abstract

This paper introduces a client-based experiential learning project for the System Analysis and Design (SA&D) course. We established a partnership with a local nonprofit organization center to recruit and select candidate software/system projects from nonprofit organizations. Once a suitable project was selected for a particular class, all teams worked on the same project independently and were required to deliver a functional prototype by the end of the semester, each student was expected to work about 40 hours on this project outside of the class. External judges (project sponsor and users) were invited to judge the presentation of the prototype. The client then chose one prototype or features from multiple prototypes for the actual implementation. Some students continued to work with the client, doing an internship or practicum for the final implementation. Since 2009, students from this course implemented over 15 projects successfully. This paper describes experiences about the design and execution of the project in the Spring semester of 2025. The class survey showed that students felt the project was relevant, they enjoyed working on the project, gained knowledge from the project, and were comfortable with the technologies used. In addition to learning the knowledge and enhancing skills in the domain of system analysis and design, students also learned teamwork, project management, and working with a real client. The paper also discusses the major success factors of implementing this project and tips for other instructors to adopt the project.

Keywords: Experiential learning, Project-based learning, client-based project, System Analysis and Design, nonprofit organizations, project management.

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Bridging the Gap via Community Engagement: Enhancing Systems Analysis & Design Education through Client-Based Projects

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1. INTRODUCTION

The goal of this article is to present the design and implementation of a repeatable client-based experiential learning project for a System Analysis and Design (SA&D) course. Experiential learning is “learning through reflection by doing”, which bridges abstract concepts to concrete experiences (Felicia, 2011; Samuel, et al., 2025; Triantoro, et al., 2025). The final deliverable for our client-based experiential learning project was a functional system prototype, and this project facilitated all six levels of learning in Bloom’s Taxonomy: Remember, Understand, Apply, Analyze, Evaluate, and Create (Anderson & Krathwohl, 2001). By developing a functional system prototype, teams experienced the entire system analysis and design cycle. As a result, they not only grasped the concepts of system analysis and design, but also applied these concepts for the project by analyzing the user requirements, coming up with alternative designs, evaluating these designs, and creating a functional prototype based on a selected design.

In addition to facilitating students’ learning of the concepts of system analysis and design, this client-based project also offered additional learning opportunities, such as problem solving with real organizational issues, client communication and relationship management, and delivery of a functional prototype within a semester. The project bridged the students’ needs for experiential learning opportunities and the nonprofit organizations’ needs for developing or upgrading some of their systems. Research shows most of the nonprofit organizations face technological challenges such as outdated software / technology, limited budgets for technology investment, and a lack of technological expertise (Fallon, 2024; Lynch, 2024). One common issue/problem with the local nonprofit organizations was that they usually have an outdated website, which needs additional features/functions with simplified navigation and more visually appealing design. Like most other nonprofit organizations, they have limited budgets and expertise to update their websites,

and they are willing to collaborate with us for these projects.

Project-based learning has been widely used in system and analysis education (Cappel, 2001; Guidry & Totaro, 2013), some used case studies (Guidry & Totaro, 2011; Russell & Russell, 2015), and some used real projects from organizations (Ivancevich & Ivancevich, 2003). The approaches have their own advantages and disadvantages. Case studies usually provide a fixed set of project descriptions; therefore, instructors have more control about the planning and execution of the project, and the cases provide more structure for students to follow. The disadvantages of a case study approach include the lack of communication with clients and the concrete context such as the project scope and relationship between the proposed system and all other existing systems.

On the other hand, using real projects poses some significant challenges: difficulties in finding suitable clients, significant workload and time commitment from instructors, students, and clients (Lopez & Lee, 2005; Razzouk et al., 2003). Moreover, clients may not always be available or willing to engage fully with students, and coordinating client deadlines with academic schedules can be difficult (Tabbaa et al., 2023). Arling et al. (2010) came up with a compromise between case study approach and the real projects approach. They used a real project case from PricewaterhouseCoopers (PwC), instead of engaging a real project each term, the instructors used exactly the same project case for multiple semesters. To simulate the real project, they invited employees from PwC to talk about this project each term so that students felt the project was real, but the deliverable from the project will not be used by the PwC. The reason that PwC was willing to provide support for the project was the opportunity to recruit the top students from the class. The major drawback for this approach was that the organization will not benefit from the students’ project deliverables. How can we use a suitable real project each semester and ensure the project deliverables are useful for the client?

In this paper, we describe how we established a repeatable process to recruit and select suitable clients; developed structures, guidelines, and templates to guide clients and teams to go through the project process; and ensured the client implement the system with our students' continued support after the semester is over. The contribution of this paper is to present an approach fulfilling the dual goals of providing students with experiential learning for real organization and providing service to local communities.

The paper is structured as follows: section 2 presents literature review of experiential learning and project-based learning, section 3 describes the course structure, and the project set up, section 4 presents students' feedback, section 5 discusses our reflections about challenges and success factors, and lists some tips for other instructors to adopt the project.

2. LITERATURE REVIEW

Experiential Learning

Experiential learning emphasizes the role of direct experience in developing knowledge and skills. Kolb (2015) defines learning as "the process whereby knowledge is created through the transformation of experience." This perspective highlights the importance of active engagement, continuous reflection, and personal involvement in the learning process. Kolb (2015) further explains that "the aim for experiential learning theory was to create a model for explaining how individuals learn and to empower learners to trust their own experience and gain mastery over their own learning." This reinforces the idea that learning is an active and continuous process where knowledge is constructed rather than passively acquired.

While experiential learning offers many benefits, there are also some potential drawbacks to consider. de Pillis et al. (2020) identified "four main categories of trade-offs that must be acknowledged and negotiated: (1) quality vs. cost, (2) institutional versus individual goals, (3) institutional aims for the student experience versus students' aims from participating in an experiential learning program, and (4) providing 'real-life' experiences vs. protecting vulnerable students from 'real-world' inequalities." Additionally, when instructors provide minimal guidance, experiential learning may be ineffective and inefficient (Kirschner et al., 2006). Experiential learning encompasses various approaches, such as practicums, internships, simulations, and role-playing. However, the type

of class and its learning objectives should determine the most suitable approach. For example, a Project-Based Learning (PBL) model using instructor-designed projects may be more effective for a required Intro to Operations class that all business students must take. In contrast, a client-based form of PBL may be better suited to a Systems Analysis and Design (SA&D) class with 20–40 students, which is the focus of this paper.

Project-Based Learning (PBL) in Higher Education

According to Du and Han (2016), "*Project-Based Learning (PBL) is a student-centered model that organizes learning and studying around projects.*" Similarly, PBLWorks (n.d.) defines PBL as "*a teaching method in which students gain knowledge and skills by working for an extended period to investigate and respond to an authentic, engaging, and complex question, problem, or challenge.*" Together, these definitions emphasize the structured, student-centered nature of PBL and its focus on real-world problem-solving.

PBL is known to be one of the most effective pedagogical techniques that can enhance student learning. Its effectiveness has been studied across multiple disciplines, including social sciences, mathematics, technology, and engineering, through a 20-year meta-analysis of journal articles (Chen & Yang, 2019). Compared to traditional instruction, PBL has a medium to large positive effect on students' academic achievement (Chen & Yang, 2019). PBL is generally ideal for large classes and could be implemented in classes that are required for students in the entire college or school.

Client-based Projects in Higher Education

In systems analysis and design, a course offered as part of the Management Information Systems curriculum, PBL provides many benefits, including improving students' problem-solving skills, engaging them with real-world applications, and offering opportunities to work in teams. A specific subcategory of PBL used in this course is Client Based Projects (CBP), where students work directly with a business, a nonprofit, or other organizations to solve real problems or address issues. CBPs enhance the learning experience by providing hands-on exposure to real-world challenges, closely mirroring professional environments. This technique is widely recognized as a powerful pedagogical tool with numerous benefits (Lopez & Lee, 2005; Podeschi, 2016; Pollard, 2012).

However, there are some disadvantages to this technique. Razzouk, Seitz, and Rizkallah (2003) outlined several challenges, including difficulties in finding suitable clients, grading projects that require extensive feedback, and the significant time commitment involved. Lopez and Lee (2005) cautioned that CBPs can be overwhelming for instructors, as the significant workload and time commitment required may deter many from implementing them. Another disadvantage is that clients may not always be available or willing to engage fully with students, and coordinating client deadlines with academic schedules can be difficult (Tabbaa et al., 2023).

According to Schwering (2015), the success of client-sponsored projects depends significantly on the careful selection and socialization of the project sponsor, ensuring that they are aware of the goals and capable of supporting the learning process. When sponsors understand their role in fostering student development and are committed to the project's success, the learning outcomes for students improve.

Beyond teamwork, the SA&D client-sponsored projects also introduce an element of competition. In this course, student teams compete against one another to develop the best prototype, adding a dynamic layer to the learning experience. The next section will explore how competition enhances experiential learning.

Team Competition as a Learning Tool

Teamwork in project-based learning contributes to both academic success and professional skill development. Soia et al. (2024) highlight that integrating teamwork skills in digital and computational learning environments helps students improve their academic performance, develop both soft and hard skills, and build professional competencies. This demonstrates that collaborative, hands-on learning not only enhances students' technical abilities but also prepares them for real-world challenges by fostering essential teamwork and problem-solving skills. However, as Dong (2023) notes, if not all members of student teams demonstrate commitment and work ethic and are unable to break old habits (such as delaying work until the last minute), team performance can suffer. Razzouk et al. (2003) noted that a concern for professors in today's global classroom is students' tendency to select friends as teammates. This issue can be mitigated by having the professor assign team members. In the SA&D course, students complete a questionnaire at the beginning of the semester (Appendix A). This questionnaire assesses their skills, and students

with diverse skill sets are strategically assigned to different teams.

Incorporating competition into this teamwork can further enhance student motivation and engagement. In the SA&D class, students work in teams to develop a prototype for a real-world client, usually a local non-profit. At the end of the semester, the best prototype is selected by judges. This competitive element encourages students to go beyond minimal requirements and strive for excellence. Carroll (2013) describes Competition-Based Learning as a variation of project-based learning in which student teams work on an open-ended assignment similar to a scaled-down real-world problem. The distinctive element is that projects are tested and compared against those of other teams, adding a competitive dimension. This competitive drive not only pushes students to refine their work but also benefits the client, as it increases the likelihood that the final prototype will be well-developed and aligned with their needs. By striving to outperform their peers, students are more likely to deliver a polished, functional system that exceeds basic expectations, ensuring a tangible, valuable outcome for the client.

3. PROJECT STRUCTURE & EXECUTION

Project Background & Team Setup

The study focused on a team project, which took place in a 300-level business course entitled, "Systems Analysis & Design." The course is delivered over a 15-week semester at a public university in the western United States. All undergraduate students seeking a bachelor's degree in Management Information Systems or Cybersecurity are required to pass the course. A smaller proportion of students take the course as an elective to earn a certificate in Accounting Information Systems, Data Analytics, or Digital Marketing.

The course provides a comprehensive presentation of the concepts, procedures, and tools necessary for building computer-based information systems in modern organizations. The course introduces students to the systems development lifecycle and develops project management, analysis, design, coding, testing, implementation, and documentation skills through a team project. Although the traditional waterfall approach served as a roadmap for the project, teams were encouraged to use an agile methodology during the design phase, which required several, quick iterations to arrive at the final design.

Students learned to balance project requirements with individual, team, and client constraints in real-time during the project. The scope of the project was controlled as tightly as possible, with an estimated time per student approximating 40 total hours.

Project Selection & Client Engagement

To maximize realism, teams designed and developed a prototype system for a real-world client organization. The partnership between the local branch of United Way and the College of Business, specifically through the Systems Analysis & Design course, offers a high-impact, community-engaged learning opportunity grounded in experiential education and systems thinking. Since the partnership's inception in 2009, this collaboration has supported approximately 15 student-led projects, each designed to meet the technological needs of local nonprofit organizations while providing students with real-world, client-centered project experience.

From the nonprofit community's perspective, this collaboration provides a valuable opportunity to access technical expertise that many small and mid-sized organizations would otherwise struggle to obtain. Our local nonprofits often operate with limited budgets and minimal IT support, yet they rely heavily on their websites for outreach, fundraising, volunteer coordination, and community engagement. Historically, participating nonprofits have represented a broad cross-section of organizations delivering vital, community-based services, while also creating sector-strengthening opportunities that generate positive ripple effects throughout the community.

At the end of the project, these nonprofits receive a newly developed or significantly improved website that supports their mission and strengthens their digital presence. At the same time, the College of Business benefits by working with committed community clients who provide students with authentic, real-world project experience. United Way of Missoula County plays a key role in recruiting and screening nonprofit partners to ensure that participating organizations are prepared to actively engage with students, commit time to meetings, and provide feedback throughout the project. This structured partnership, which has been refined and improved over the years, ensures that both students and nonprofit organizations benefit from a meaningful and productive collaboration, while also creating opportunities for the broader community and other partners to engage with and support mission-driven projects.

Each academic semester, students enrolled in the course undertake a team project that applies core principles of systems analysis and design to create a customized, community-facing website for a selected nonprofit. Projects either involve building a completely new website or modernizing an existing site to improve functionality, design, and user experience. The County Nonprofit Center facilitates the client selection process by distributing a call for proposals through its weekly newsletter, reaching approximately 120 member organizations and 400 nonprofit personnel. Nonprofits interested in participating submit project applications, which are reviewed by a selection committee based on mission alignment, organizational readiness, and project feasibility within the constraints of a single semester.

Once a nonprofit is selected, student teams work directly with the organization's leadership and stakeholders to conduct interviews, gather system requirements, and develop a comprehensive System Specification Report and Project Overview. This structured methodology ensures that the final deliverable is technically viable, user-centered, and strategically aligned with the nonprofit's goals. The process fosters authentic engagement, knowledge transfer, and the development of solutions that add lasting operational and outreach value.

The class meets with the client during the third week of the semester for a one-hour introductory session, where the client provides an overview of the project and students can ask initial questions. Approximately three weeks later, each team conducts their own client interviews to gather detailed requirements. About four weeks after the interviews, teams meet with the client to review and refine their design proposals. Finally, at the end of the semester, all teams demonstrate their completed prototypes to the client and other stakeholders.

At the conclusion of the semester, particularly motivated students often pursue continued collaboration through internships with the nonprofit partner. These internships—eligible for academic credit toward the MIS major—allow students to further refine web content and back-end functionality, while also supporting nonprofit staff through onboarding, training, and long-term site management. This extended engagement facilitates a smooth project handoff and ensures the sustained utility of the developed platform.

Team Setup

The project usually started in the third week. For the first two weeks, students were introduced to

the Systems Development Life Cycle (SDLC), where they learned how the SDLC would be used as a roadmap for planning and executing the project. Students completed a background questionnaire (see Appendix A), which the instructor used to construct teams with diverse skillsets. The class typically enrolls 30–45 students, who are divided into 6–9 teams, with each team consisting of 4–6 students. Referring to Table 1, the group collaboratively decided which role each team member would take on during the project:

Role	Responsibilities
Project Manager	Client liaison, manages timeline, writes status reports
Designer	Interacts with the client to collaboratively determine design
Developer	Transforms design into a working prototype
Analyst	Determines system requirements, conducts feasibility study
Trainer	Produces system documentation

Table 1: Role for Each Team

The scope, timeline, and budget were collaboratively determined between the instructor and client. At the beginning of the semester, a project overview document (see Appendix B) containing this information was distributed to students. Table 2 lists the milestones.

Meeting	Objective
Introductory Meeting	Introduce teams to the client and provide an overview of the project, including time, budget, and scope.
Analysis	Determine system requirements.
Design	Determine updated website design.
Presentations	Present website prototype, submit project workbook, submit peer evaluations

Table 2: Client Interactions

The project kicked off with a class session dedicated to an introductory meeting, where the client talked about the project and students asked questions. The project was initially defined through a System Service Request (SSR), which outlined the client’s needs and formed the basis for the student teams’ work (see Appendix C).

Following the kick-off meeting, teams created and submitted a Team Charter (see Appendix D) to the client via e-mail. The Team Charter outlines the goals of the project team and documents the roles and responsibilities of each team member. It also explains how the team will collaborate (within and outside the team) and documents a plan to resolve conflicts should the need arise.

Performance Assessment

Teams produced the following project deliverables:

1. Project Workbook. Formal, written documentation describing the project and its associated deliverables. (See Appendix J)
2. Website Prototype. A working model of the system, which demonstrates the structure, content, navigation, and page layout.
3. Team Presentation. A demonstration of the prototype in front of a panel of judges. The instructor provided the student teams with a presentation template to structure their presentation around (See Appendix K)
4. Peer Evaluation. Referring to Appendix L, students rated the performance of their team members. Scores were used by the instructor as a basis for adjusting individual grades.

Table 3 shows the weekly schedule and the key documents completed throughout the project.

Week	Project Deliverables & Events
1	
2	Student Background Questionnaire
3	Assigning students into teams
4	Project Introduction meeting
5	Interview Guide completed
6	Client Interviews
7	
8	Data Collection Plan completed
9	System Requirements completed
10	
11	Feasibility Study completed
12	Client Design meeting Design Document completed
13	
14	
15	User Guide completed Website Prototype completed
Final Week	Presentations and Q&A Session

Table 3: Weekly schedule for the project

Presentations and website prototype demonstrations were evaluated by a panel of judges consisting of the instructor, client sponsor, and other stakeholders involved in the project. Using a rubric developed to rate presentations

and provide feedback (see Appendix M), judges recorded their opinions and overall ratings for each team. After the presentations, the judges were given a few days to review the project workbook and provide additional comments. The panel then met virtually to determine the winning team. Each team received an email announcing the winner and thanking them for their time and contributions. Teams also signed the Website Transfer Sheet to formally transfer their deliverables to the organization (see Appendix N).

4. STUDENTS' FEEDBACK

During the last week of class, students participated in a brief survey, which asked them to rate their learning experience. The results

reported here are from the most recent year in which this pedagogical method was implemented. The survey used a seven-point Likert scale (1 = strongly disagree to 7 = strongly agree). 38 of 44 students completed the survey. Table 4 reports the survey results.

In general students reported being very satisfied with the learning experience. Students thought the project was relevant, they gained knowledge, they enjoyed working on the project, and were comfortable with the technologies used. The students were very satisfied that the goals of the team project were clearly stated and consistently pursued (6.18 out of 7). There were four negatively worded questions stating the project was not relevant (2.21), they gained no new

Item (*Item reverse coded.)	<i>N</i>	<i>M</i>	<i>SD</i>
The team project helped me understand Systems Analysis and Design concepts	37	5.73	1.539
The team project improved my understanding of business processes.	38	5.76	0.971
The team project increased my knowledge of how system development functions.	38	5.66	1.047
The team project enhanced my understanding of how Systems Analysis and Design impacts all functional areas of business	36	5.31	1.215
The team project enhanced my understanding of how Systems Analysis and Design concepts are relevant to my future career.	37	5.65	1.338
The goals of the team project were clearly stated and consistently pursued	38	6.18	1.111
The team project was not relevant to this course.*	38	2.21	1.679
I gained no new knowledge from the team project.*	38	2.24	1.635
I did not enjoy working on the team project.*	37	2.97	1.724
I was uncomfortable or unfamiliar with the required technologies or applications used in the team project.*	36	2.56	1.539
I had access to reliable communication tools (e.g., Zoom, Skype, Google Meet) during the team project.	38	6.24	0.913
I had access to reliable internet service during the team project.	38	6.68	0.662
I had access to a reliable digital device (e.g., laptop, mobile device) during the team project.	38	6.66	0.815
Rate your overall level of satisfaction with the learning experience this semester.	38	5.68	1.397
Rate your level of satisfaction with what you learned in class this semester.	37	5.62	1.299
Rate your level of satisfaction with the knowledge you gained in class this semester	38	5.55	1.329
Rate your level of satisfaction with the learning experience in this class compared to other face-to-face learning experiences	37	5.59	1.536

Table 4: Project Feedback Survey Results

knowledge (2.24), they did not enjoy working on the project (2.97) and they were not comfortable with the technologies used in the project (2.56). All four were below 3.0, so students felt the project was relevant, they gained knowledge, they enjoyed working on the project, and were comfortable with the technologies used. The students also felt their communication tools (6.24), internet service (6.68) and personal devices (6.66) were reliable for working on the project. The students' overall level of satisfaction with the learning experience was 5.68 out of 7. These results are strong, and the students were very satisfied with the team project and the learning experience.

5. DISCUSSION

Projects Evolution

The collaboration with the United Way of our County emerged over time. Prior to transitioning into the Director of Impact role, Eric (our contact for the project) managed a local not-for-profit, which participated in the project in 2009. As a result, Eric worked directly with student teams, who designed and implemented a redesigned website for the organization. Engaging with student teams provided a "proof of concept". Convinced that these projects could have a larger impact on our community, when Eric accepted a position at the United Way of our County, he proposed we expanded clients base to all local not-for-profits. He volunteered to serve as the bridge between the instructor and not-for-profits and worked closely with the instructor to formalize the project selection process.

We developed a variety of project tools to provide structures for the project such as project guidelines, team charters for communication and conflict management, data collection template, checklists for design, project feasibility evaluation sheet for alternative designs, presentation template, and checklist of project workbook. With a clear schedule posted with these guidelines and templates, students have a clear road map for the project over the term.

Over the years, different instructors have taught the course, and we've found it relatively easy to adopt due to the existing structure and documentation. Moreover, we refined the course with updates such as the student background questionnaire, grading rubrics (Appendix M), communication procedures and a 'Website Transfer Sheet' (Appendix N).

We've learned that flexibility, continuous feedback, and collaboration with both instructors

and partners are key to the long-term success and scalability of the project.

Lessons Learned and Important Factors for Successful Implementation of this Project

Over the years of running this project, we've learned a great deal about both teaching and managing client-based learning experiences. First, it is instrumental to have a clear structure of the project and provide documents/templates for the project. These high-quality documentations proved invaluable to the long-term sustainability of these projects between the instructors. The course was initially taught by one instructor, and later another instructor joined to teach this course. The availability of documentation facilitated a smooth transition, while ensuring consistency across instructors and projects. At the beginning, some students were initially hesitant about the level of responsibility involved. With consistent structure and clear documentations, students' engagement was increased.

Second, routinizing the clients' recruiting process was essential for sustaining the project. We paired with our county's nonprofit organization center for candidate projects. The center called for project proposals from local nonprofit organizations and selected a suitable client for our class. This repeatable process for recruiting and selecting clients is routinized by an external party, which not only reduced the instructors' workload tremendously, but also ensured the continuity of the source of projects. This organization served as a reliable bridge between instructors and organizations. Additionally, they participate as a judge during the final presentations, alongside client representatives, further reinforcing the ongoing success and continuity of the course.

Third, client readiness and expectation management is critical. We learned that selecting the right client and setting expectations early is extremely important. Although nonprofit clients varied in scale and available human resources—some being large organizations while others were small shops—clearly defining and communicating the schedule of client introduction days, interviews to gather system requirements, and design meetings before the semester begins, and explaining to the client that there is a significant time commitment requiring multiple representatives to be available, and treating these dates as fixed, helped reduce many challenges. While differences in technical expertise and availability occasionally created hurdles during requirements gathering, our

structured process for identifying the best-fit clients significantly mitigated these issues, and early communication clarified the expected benefits of participation.

Fourth, it is important to engage in only one project for an entire class during a particular term teams rather than multiple separate projects. It had three positive impacts for project management and implementation. 1) It reduced the workload of the instructor, who only needs to manage one project at a time. Engaging in multiple projects introduces unnecessary complications and often waters down the learning experience. Assigning the same project to all teams not only reduces coordination and management complexity but also optimizes the learning experience. We've found that focusing on a particular project allows the instructor to cover topics in greater depth, while facilitating a common understanding that's relevant to all teams. Additionally, instructors' frequent check-ins could gain a much clearer view of alignment and timely progress when there is only one project to manage. 2) all teams worked on this project, therefore, creating a competition among teams, which drove students to perform above and beyond minimum requirements for the project. 3) clients were more motivated to participate, believing that at least one of the prototypes would be of excellent quality and potentially meet their needs.

Fifth, we've found that five students per team is optimal. Referring to Table 1, five team members allows teams to assign one individual to each role. Thus, each team member can take ownership and be accountable for completing a particular aspect of the project. Teams of three or four forces places a bigger workload on individuals, negatively impacting the quality of deliverables. In contrast, teams of six or more spread the workload too thin, reduce the quality of the learning experience, and increases the workload for the project manager, as more individuals need to be managed and monitored. We also found that the maximum number of teams should be 8 teams so we do not overwhelm the client.

Sixth, we encouraged students to continue to work with clients for actual implementation under an internship. This ensures that the organization has a functional system implemented for the return of their time and effort. Instructors who taught this course and previous students have established a good reputation for this project in the local community, therefore, nonprofit organizations continued to participate in this project.

Students' Learning

Students' learning with this client-based project occurred in three aspects. First, they understood the concepts and developed / enhanced skills in the domain of system analysis and design. Consistent with Chen & Yang (2019), students reported high levels of perceived knowledge gain, with means ranging from 5.31 to 5.76 out of 7 across items related to understanding systems analysis and design concepts, business processes, and system development, supporting the argument that project-based learning enhances academic achievement. Second, students learned general soft skills of teamwork and project management, such as breaking down projects into manageable tasks, allocating / matching tasks to members' skills/strengths, managing schedules, coordination, and communication. Third, they learned how to interact with a real client professionally and effectively to deliver a prototype meeting the client requirements. Involving external professionals in assessing student projects can enhance both the learning experience and students' motivation, while also helping them connect their academic work to real-world applications (Schwering, 2015). The project experience offers an essential bridge between academic theory and professional practice, equipping them with the skills to navigate the full project lifecycle. More importantly, this partnership also cultivates civic responsibility and professional readiness among emerging business and technology leaders.

Societal Impacts

Our research largely focuses on the student-related effects of project-based learning. Additional research is needed to understand the societal impacts of such projects within organizations and the broader community. The following are some testimonials from clients.

"We continue to appreciate the opportunity of working together."

"We truly appreciate all of the great work on this project and look forward to going live."

"Firstly, I would like to extend our heartfelt gratitude to you and all the students for the unwavering dedication and hard work invested in this project... Each team demonstrated commendable strengths, and all groups diligently addressed the requirements within their respective scopes.' "This experience has been invaluable for the center and will positively impact our community. The students were engaged, curious, and delightful to work alongside. The

various aspects of this project, from the website to the operating manuals, exceeded my expectations. The real-world experience this program provides to students is exceptional and highly beneficial. Thank you; we love our new website and sincerely appreciate this opportunity."

This anecdotal evidence highlights the impacts these projects can have on local nonprofits and the people in the communities they serve. We plan to have a systematic, scientific approach toward understanding societal impacts for future research. We are developing a client-oriented survey for future iterations of the course, and plan to reach out to former clients to obtain feedback in the spirit of continual improvement.

Thoughts for Future Implementation

The client-based project started in 2009, it has been well established in the community. We are pleased to see that project deliverables implemented in the non-profit organizations continue to serve the local community. Furthermore, the experience gained by our graduates has proven instrumental in their professional development, as they bring those refined skill sets to prominent employers, such as PwC, Deloitte, KPMG, and FAST Enterprises. We are considering doing some branding/marketing for this project with some type of reward to the top winning teams, such as featuring them in school newspapers, local newspapers, career office's LinkedIn announcement, or special award for community services.

Although the course includes a competitive element, student perceptions of this competition have not been formally measured. Assessing how competition influences motivation, engagement, or learning outcomes represents an opportunity for future research and course improvement.

With more publicity for this project, we may be able to attract more students to the College of Business in general, and MIS major in particular, thus helping grow the enrollment, as well as serve the local community.

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APPENDIX A. Student Background Questionnaire

The purpose of this questionnaire is to collect information concerning your skills and background. All responses will be kept confidential.

Student Name: _____ **Course:** _____ **Section:** ____

The statements below ask you to indicate your level of skill in various areas. For each of the statements, please indicate your skill level. If you do not have any skills in the area, circle 0, indicating that you have "No Skill." Otherwise, indicate your skill level by circling a number between 1 and 10, where 1 indicates that you are "Not Very Skilled," 5 indicates that you are "Moderately Skilled," and 10 indicates that you are "Very Skilled."

	No Skill ↓	Not Very Skilled ↓			Moderately Skilled ↓			Very Skilled ↓			
	0	1	2	3	4	5	6	7	8	9	10
1. Website design skills	0	1	2	3	4	5	6	7	8	9	10
2. Technical skills (e.g., programming, networking)	0	1	2	3	4	5	6	7	8	9	10
3. Management skills	0	1	2	3	4	5	6	7	8	9	10
4. Oral communication skills	0	1	2	3	4	5	6	7	8	9	10
5. Written communication skills	0	1	2	3	4	5	6	7	8	9	10
6. Analytical skills	0	1	2	3	4	5	6	7	8	9	10
7. Interpersonal skills	0	1	2	3	4	5	6	7	8	9	10
8. Graphic design skills (e.g., Photoshop,	0	1	2	3	4	5	6	7	8	9	10

- In the space provided below, briefly describe any work experience related to information systems.
- Client interviews, team presentations, and the Website Design Competition take place **outside of regularly scheduled class time**. Specifically, these events will take place during the following dates/time:

Event name	Date and Time
Client interviews	5 th week of class (each team will be given a 45-minute time slot)
Design meeting	10 th week of class (each team will be given a 45-minute time slot)
Team presentations & Q&A	15 th week of class (each team will be given a 25-minute time slot)

If you have any scheduling conflicts during those times, please explain below.

- Below, please include the name of students that you prefer to work with.

APPENDIX B.
System Service Request
(Filled by the Potential Clients)

Requested By:

Date:

Department:

Location:

Contact Information:

Type of Request:

- New System
- System Enhancement
- System Error Correction

Urgency:

- Immediate – Operations are impaired or opportunity lost
- Problems exist, but can be worked around
- Business losses can be tolerated until new system installed

Problem Statement

Fill out this part by the client

System Service Request

Fill out this part by the client

-----TO BE COMPLETED BY SYSTEMS PRIORITY BOARD -----

Request Approved.

Approved by: [Instructor's name here]

Assigned to: _____

Start date: _____

Recommend Revision

Suggest User Development

Reject for reason: _____

APPENDIX C. Project Description

Project Overview

Give a brief description of the project in two or three paragraphs.

Project Goals

Three criteria, as indicated below, serve as the primary goals for this project. The goals of the project will be achieved if all three criteria are satisfied.

1. The project will produce the products (i.e., deliverables), as defined in the *Project Scope* portion of this document.
2. Deliverables will be completed on-time, as defined in the *Project Timeline* portion of this document.
3. The project will be completed on-budget, as defined in the *Project Budget* portion of this document.

Project Scope

The scope statement intends to facilitate a common understanding between the client and project team regarding the products that will be produced as a result of this project. The scope sets the course of action for the project team to undertake, as well as defines the boundaries of the project.

During the course of the project, the following deliverables will be provided to the client.

<i>Deliverable</i>	<i>Description</i>
Status Reports	On a bi-weekly basis, a status report will be delivered to the client. The status report will describe the work completed since the previous report, describe the work that will be undertaken in the current week, and explain any issues that need to be addressed to move the project forward.
Team Charter	The team charter describes the goals and structure of the project team. The charter serves to formally establish the roles and responsibilities of each team member, to explain how the team will communicate (internally amongst the team and externally with the client), to document the values, ethics, and expectations of the team, and to establish a plan to resolve conflicts within the project team.
Data Collection Plan	Data collection constitutes the primary technique through which system requirements are uncovered. The data collection plan ensures that the data gathered is both comprehensive and accurate. The data collection plan specifies the data that are needed, the rationale for collecting the data, and the insights that should be obtained by collecting the data.
Interview Guide	Interviews represent a particularly useful form of data collection, as the technique allows the interviewer to pursue in-depth information around a specific topic. The interview guide helps the interviewer direct the conversation toward the topics and issues they want to learn about.
System Requirements	A list of system requirements, which documents the features and functionality required in the new information system, will be produced. System requirements will be classified between "needs" and "wants". "Needs" represent features and functionality that must be incorporated

into the information system before this project is completed, whereas "wants" may be implemented after this project has been completed.

Feasibility Study	A feasibility study will be conducted to determine the most appropriate information system for the client to implement. Three potential alternatives will be compared. Based on this analysis, a recommendation will be made to the client regarding which alternative to select.
Design Document	Based on the system requirements, a design document will be created. The purpose of a design document involves communicating design decisions associated with the new website. The document will clearly explain the designer's intentions and the rationale behind design decisions. The design document focuses on achieving high levels of usability, which refers to the ability of users to quickly and accurately utilize the website with high levels of satisfaction.
User Guide	The purpose of the user guide involves providing written documentation to prepare the client for maintaining, enhancing, and potentially transferring the website after the project has been completed. In addition, the user guide serves as a training manual, walking users through the features and functionality implemented in the new website.
Website prototype	A working model of the website will be designed, coded, and tested. The prototype will demonstrate the structure, content, navigation, and page layout of the website.
Presentation	At the conclusion of the project, a presentation will be made for the client. The presentation will provide a retrospective assessment of the project activities and deliverables, as well as provide a demonstration of the website prototype. Immediately after the presentation, a live Q&A session will follow.

All projects are constrained in terms of human resources, money, and time. As a result, the following items will be considered to be outside the scope of this project.

<i>Item</i>	<i>Description</i>
Advanced Features	Specify advanced features need to be excluded.
Advanced Project Management	In a typical project, the project manager would be responsible for assessing risks, managing quality, and devising a change management plan. Given that the project team members have not been formally trained in project management, such responsibilities lie beyond the scope of this project.

Project Schedule

The project schedule represents a timeline associated with the events and activities that will occur to produce the deliverables specified above. The schedule serves as a baseline reference point for planning, monitoring, and controlling project activities.

Based on the deliverables outlined above, the attached project timeline, in the form of a Gantt chart, has been created. The timeline illustrates the sequence and dependencies associated with all project activities, which focus on producing the desired deliverables. Based on the start and finish dates estimated in the project timeline, the project will be completed on [specify the date here].

Date	Deliverables & Events
Wed., Feb. 7	Project Introduction meeting
Mon., Feb. 12	Team Charter completed
Thur., Feb. 22	Interview Guide completed
Fri., Feb. 23	Client Interviews
Mon., Mar. 4	Data Collection Plan completed
Mon., Mar. 11	System Requirements completed
Mon., Mar. 25	Feasibility Study completed
Fri., Mar. 29	Client Design meeting
Fri., Mar. 29	Design Document completed
Wed., May 1	User Guide completed Website Prototype completed
Fri., May 3	Presentations and Q&A Session

Project Budget

The project budget represents a forecast of expenditures that will incur as project activities are carried out. The budget serves as a baseline reference point for managing the costs associated with this project.

Based on the project deliverables and timeline outlined above, the project will cost approximately [specify amount here], assuming a \$50 per hour rate for labor.

	Hours	Estimated Cost
Labor Costs		
Project Initiation & Planning	[?]	[?]
Analysis	[?]	[?]
Design	[?]	[?]
Implementation	[?]	[?]
	Total Labor Costs	\$[?]
IT-related Costs		
Hardware (e.g., servers)		\$[?]
Software (e.g., shopping cart)		[?]
IT Services (e.g., hosting)		[?]
	Total IT-related Costs	\$[?]
	Total Project Costs	\$[?]

**APPENDIX D.
Team Charter**

Prepared by: [Insert team name here]

[Insert date here]

Team Goals

[Describe the goals of the team here. The team goals should be consistent with the goals of the project.]

Team Members

[Insert name here], [Insert title here]

[Describe the roles and responsibilities of the team member here.]

E-mail: [Insert e-mail address here]

Phone: [Insert phone number here]

[Insert name here], [Insert title here]

[Describe the roles and responsibilities of the team member here.]

E-mail: [Insert e-mail address here]

Phone: [Insert phone number here]

Communications Plan

[Explain the importance of a communication plan here.]

[Describe how the team members will communicate internally amongst themselves.

Describe when the team will conduct weekly team meetings.]

[Describe how the team members will communicate externally with the client. Be sure to indicate which team member will be the primary point of contact (i.e., team liaison).]

Team Values, Ethics, and Expectations

[Explain the importance of team values, ethics, and expectations here.]

[Describe the team's values, ethics, and expectations here. A brief written summary followed by a bullet-pointed list of values, ethics, and expectations will suffice.]

Conflict Resolution Plan

[Explain the importance of a conflict resolution plan here.]

[Describe the team's conflict resolution plan here. The plan should indicate a clear course of escalation. Given that the conflict resolution plan involves a series of steps, each step should be explained in a numbered list.]

Execution and Acknowledgement

The team members hereby indicate by their signatures below that they have read and agree with the specifications of this charter.

[Insert name here]

[Insert name here]

[Insert name here]

APPENDIX E. Status Report Guidelines

On a bi-weekly basis, a status report will be delivered to the client. The status report will describe the work completed since the previous report, describe the work that will be undertaken in the upcoming week, and explain any issues that need to be addressed to move the project forward.

Guidelines

- Starting Mon., Feb. 12, bi-weekly status reports are due on Monday at the beginning of class (11:00am).

All team members must be copied (cc:) on the e-mail. The e-mail must also be sent to the client: [put the client email here] and the instructor [put the instructor's email here].

- Status reports must be professionally written. Be sure to carefully proofread your message before sending it. Spelling and grammatical errors must be avoided.
- Be sure to refer to the project timeline to determine which tasks should have been completed in the previous week, as well as which tasks should be undertaken during the upcoming week.
- In terms of formatting, be sure to follow the example status report below. The areas highlighted in yellow need to be customized for your project team.
- Be sure to clearly describe deliverables in a manner that the client will understand. You can refer to the Project Overview document for deliverable descriptions.
- When specifying dates, be sure to include the day of the week (e.g., Mon., February. 12).
- Place a copy of each status report in your team's project workbook.

APPENDIX F
[Insert team name here]
[Insert non-profit name here]

Data Collection Plan

Data collection constitutes the primary technique through which system requirements are uncovered. The following data collection plan will ensure that the data gathered is both comprehensive and accurate. As illustrated in the table below, the data collection plan specifies the data that are needed, the rationale for collecting the data, and the insights that should be obtained by collecting the data.

Activity	Description	Participants	Due Date
[Enter a short description of the activity here. Activities should appear in the order in which they will be conducted.]	[Describe the activity in detail. Be sure to explain the data that are needed, the rationale for collecting the data, and the insights that should be obtained by collecting the data.]	[List the individuals who will participate in the activity here.]	[mm/dd/yyyy]

**APPENDIX G.
System Requirements Template**

Team Name: [Insert team name here]

No.	System Requirement	Description	Priority	Comment/Question
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

**Appendix H.
Design Document Guideline**

Prepared by: [Insert team name here]

[Insert date here]

Executive Summary

[This section provides an executive summary of the design document. This section should also introduce the concept of design in general, as well as express the importance of high-quality design. In addition, this section should describe the purpose of a design document and the process undertaken to produce the design document.]

Logical Design

[This section provides a description of the logical design of the website. The first paragraph should clearly describe the concept of logical design, as well as its purpose. This introductory paragraph should be followed by separate subsections detailing the specific aspects of logical design that need to be addressed.]

Usability

[The goal of logical design is to achieve high levels of usability. The introductory paragraph should describe the concept of usability. The introductory paragraph should be followed by separate paragraphs each describing facet of usability, as well as how the design attempts to satisfy each facet.]

Navigational Structure

[This section describes the proposed navigations structure of the website. This section should provide a visual (i.e., graphical) depiction of the manner in which pages are related to one another. For an example, visit: <http://www.powermapper.com/sitemap/electrum/map.htm>]

Proposed Home Page

[This section describes how the proposed home page of the website will look. This section should explain design choices, as well as provide a visual (i.e., graphical) depiction of home page.]

Proposed Subpage Example

[This section describes how one of the proposed subpages of the website will look. This section should explain design choices, as well as provide a visual (i.e., graphical) depiction of one subpage.]

Physical Design

[This section provides a description of the physical design of the website. The first paragraph should clearly describe the concept of physical design, as well as its purpose.]

This introductory paragraph should be followed by separate subsections detailing the physical design associated with the server and the client. In this project, the server will be a web server, which is a powerful computer dedicated to storing the website and processing requests for web pages. Clients are workstations (e.g., PC, Mac) on which users run applications. In this project, a client will be need to access and maintain the website, which will be stored on the web server.]

Server

[This section describes the physical design of the server. The operating system, web server software, content management system, programming language (if any), and database platform (if any) should be described. An explanation of why the physical design was chosen must be provided.]

Client

[This section describes the physical design of the client. The operating system, web editor, web browser, and other applications (e.g., file transfer protocol) that are needed to access and maintain the website should be described. An explanation of why the physical design was chosen must be provided.]

APPENDIX I.

Feasibility Study for Alternative Solutions
[Insert team name here]
[Insert non-profit name here]

Executive Summary

[This section provides an executive summary of the feasibility study. This section should describe the purpose of a feasibility study, the process used to conduct the feasibility study, and a high-level description of the results of the study.]

Alternatives Considered

[This section provides a brief description of technological alternatives considered. At a minimum, three alternatives should be compared and contrasted. The first paragraph should clearly describe the need to consider various alternatives. This introductory paragraph should be followed by a separate subsection dedicated to each alternative. Each alternative should be clearly described.]

Feasibility Matrix

[This section provides a matrix, which ranks the different dimensions of feasibility for each alternative. Each type of feasibility should be ranked on a scale from one (1) to three (3), where one indicates the "most feasible" alternative and three indicates the "least feasible" alternative. The matrix should "point to" the optimal solution. A brief narrative should describe the matrix. Both unweighted and weighted results should be provided and explained.

The information in the matrix should be tied to the dimensions of feasibility described in the following subsections. Point the reader to the subsections below for more detailed information.]

Feasibility Matrix

<i>Type of Feasibility</i>	<i>Weight</i>	<i>Alternative</i>			
		<i>#1</i>	<i>#2</i>	<i>#3</i>	
Economic	0.00	0	0	0	
Operational	0.00	0	0	0	
Scheduling	0.00	0	0	0	
Technological	0.00	0	0	0	
Political	0.00	0	0	0	
Legal and Contractual	0.00	0	0	0	
	0.00	0	0	0	Unweighted
		0	0	0	Weighted

Feasibility Analysis

[This section should provide a brief introduction explaining why various dimensions of feasibility need to be considered.]

Economic Feasibility

[This section discusses the economic feasibility of the alternatives in narrative form. This section should first define and describe economic feasibility. A separate Cost-Benefit Analysis (e.g. tangible costs, one-time costs, recurring costs, and economic feasibility calculations) should be conducted on each alternative using the Economic Feasibility Worksheet posted in Moodle. This section should describe the purpose of the Cost-Benefit Analysis, how the analysis was conducted, and close by justifying which of the alternatives is most feasible from an economic perspective.]

NOTE: When conducting your economic analyses, assume that each team member will charge \$50 per hour (although your time on this project is free to the client).]

[Supplemental information and a detailed justification for the recommended solution should be provided in the form of exhibits. Exhibits 1, 1A, 1B, and 1C (economic feasibility) should be provided for every alternative examined. The exhibits should be explained in narrative form and the reader should be referred to the exhibits.]

[Exhibit 1: Economic Feasibility Analysis - this exhibit details the economic feasibility (Net Present Value, Return on Investment, Break-Even Point) associated with the alternative. The economic feasibility worksheet should be produced using the *Economic Feasibility Worksheet*, which is posted on Blackboard in the *Team Project* folder.]

[Exhibit 1A: Tangible Benefits Worksheet – this exhibit details the tangible benefits associated with the alternative. The tangible benefits worksheet should be using the *Economic Feasibility Worksheet*, which is posted on Blackboard in the *Team Project* folder.]

[Exhibit 1B: One-time Costs Worksheet – this exhibit details the one-time costs associated with the alternative. The tangible benefits worksheet should be using the *Economic Feasibility Worksheet*, which is posted on Blackboard in the *Team Project* folder.]

[Exhibit 1C: Recurring Costs Worksheet – this exhibit details the recurring costs associated with the alternative. The tangible benefits worksheet should be using the *Economic Feasibility Worksheet*, which is posted on Blackboard in the *Team Project* folder.]

Operational Feasibility

[This section discusses the operational feasibility of the alternatives in narrative form. This section should first define and describe operational feasibility. An analysis of the degree to which each alternative will satisfy system requirements should be provided. This section closes by discussing which of the alternatives is most feasible from an operational perspective.]

Scheduling Feasibility

[This section discusses the scheduling feasibility of the alternatives in narrative form. This section should first define and describe scheduling feasibility. Each alternative should be discussed in terms of its impact on the project schedule, as well as potential resources issues that may pose difficulties to the implement process. This section closes by discussing which of the alternatives is most feasible from a scheduling perspective.]

Technological Feasibility

[This section discusses the technological feasibility of the alternatives in narrative form. This section should first define and describe technological feasibility. Each alternative should be discussed in terms of the relevant technical risks associated with each alternative, including maturity of the technology, expertise issues, and the technology's ability to deliver the desired information system. This section closes by discussing which of the alternatives is most feasible from a technical perspective.]

Political Feasibility

[This section discusses the political feasibility of the alternatives in narrative form. This section should first define and describe political feasibility. Each alternative should be discussed in terms of the relevant stakeholders' perspectives and opinions (positive and negative) regarding the implementation of the alternative. This section closes by discussing which of the alternatives is most feasible from a political perspective.]

Legal & Contractual Feasibility

[This section discusses the legal and contractual feasibility of the alternatives in narrative form. Any legal and contractual risks (e.g., ownership, copyright, non-disclosure, privacy, law infringement) associated with each alternative should be discussed here. This section closes by discussing which of the alternatives is most feasible from a legal and contractual perspective.]

Recommendation

[This section provides a detailed recommendation to management. This section should clearly describe which alternative the team recommends implementing, as well as the rationale behind this decision.]

APPENDIX J.
Project Workbook
List of Contents

Overview

The purpose of this document is to provide a list of contents pertaining to the project workbook.

List of Contents

1. System Service Request
2. Project Overview
3. Team Charter
4. Status Reports (1 through 6)
5. Data Collection Plan
6. Interview Guide
7. System Requirements
8. Feasibility Study
9. Design Document
10. User Guide
11. Website Transfer Sheet
12. Presentation Slides

APPENDIX K. Team Presentation – Template

Title

Team Name
List Team Members and Roles

1

Team Introduction

- Introduce your team, team members, and roles (you can leverage the information in the Team Charter).

2

Design

- Describe activities conducted.
- Describe deliverables prepared.
- Describe decisions made.

3

Implementation

- Describe the programming, testing, and documentation process.
- Demonstrate prototype (the majority of your presentation should focus on the prototype).

4

Recommendations

- Provide a set of recommendations to the client
 - What updates to the website are required before going live (e.g., purchase paid plugins, advanced functionality)?
 - What are some issues that the client needs to consider going forward?

5

Questions & Answers

- Address audience questions

6

**APPENDIX L.
PEER EVALUATION OF TEAM MEMBERS**

Please use the following format to evaluate your fellow group members for their contribution to the group **project deliverables and presentation**. You should include yourself in the evaluation.

SCALES

Meetings:

- 25 = Attended all meetings, arrived on time, stayed longer than the scheduled meeting time.
- 20 = Attended most group meetings, arrived on time, stayed for the length of time scheduled.
- 10 = Attended some group meetings, and arrived late or left early on occasion.
- 5 = Rarely attended meetings, and when attending arrived late or left early.

Quality and Quantity:

- 25 = Continuously provided valuable input into the project and facilitated discussions.
- 20 = Provided useful input most of the time, and was helpful in getting tasks accomplished.
- 10 = Ideas were weak and input limited, performed only work assigned.
- 5 = Contributed very little, if at all, to the paper.

Cooperation:

- 25 = Led the group in establishing a cooperative team environment.
- 20 = Sometimes led the group, provided support for other team members on occasion.
- 10 = Went along with whatever the rest of the group decided.
- 5 = Created problems and was disruptive.

Follow-through:

- 25 = Completed assigned work on time and error free.
- 20 = Completed work on time with some changes required.
- 10 = Required some prompting to complete assignments on time, several changes required.
- 5 = Rarely completed assignments, work completed was often not useful.

Grade: In the final column please provide a grade that you would give each team member based on the other four areas of evaluation. An "A" for excellent work, an "F" for failing work.

Name	Meetings	Quality and Quantity	Cooperation	Follow-through	Total Score (Add columns)	Grade

**APPENDIX M.
 Team Presentation Rubric**

Overview

Each team will have 25 minutes to present, followed by a 5-minute Question & Answer period. Presentations will be scored along five (5) dimensions, as indicated in the table below.

Rubric

Scores: 1 = poor 5 = adequate 10 = excellent

Criterion	Score/comments
<p>Professionalism: Each team member was introduced. The presentation was well-coordinated amongst the team members. The presenters looked and acted in a professional manner.</p>	<p>① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ Comments:</p>
<p>Design: The presentation covered the activities and important decisions made during the design phase.</p>	<p>① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ Comments:</p>
<p>Implementation: The presentation covered the activities and important decisions made during the implementation phase.</p>	<p>① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ Comments:</p>
<p>Prototype Demonstration: The presentation demonstrated the prototype in an effective manner. The prototype addressed system requirements.</p>	<p>① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ Comments:</p>
<p>Future Recommendations: The presentation offered recommendations that will benefit the client in the final system rollout.</p>	<p>① ② ③ ④ ⑤ ⑥ ⑦ ⑧ ⑨ ⑩ Comments:</p>

TOTAL SCORE: _____

APPENDIX N.
Website Transfer Sheet

Website Transfer Sheet

The purpose of this document is to provide information to the client about the team's prototype. This information will be used to transfer accounts, domains, websites, and plug-in/widgets to the client.

Team Name:	[INSERT TEAM NAME HERE]
Website Prototype URL:	[INSERT URL HERE]
Content Management System (CMS):	[INSERT CMS NAME HERE]
CMS Account User ID:	[INSERT USER ID HERE]
CMS Account Password:	[INSERT PASSWORD HERE]
Domain Name(s):	[INSERT DOMAIN NAME(s) HERE]
Installed Plug-ins/Widgets:	[INSERT PLUG-INS HERE]
Other:	

An Exploratory Analysis of Perceptions and Uses of Generative AI Tools for Higher Education

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Abstract

This study addressed the growing usage of Artificial Intelligence (AI) in relation to students completing academic tasks. Over the past few years, there has been a growth in tools that help simplify automate the tasks we perform. This study examines numerous tools, where students are integrating them into their academic tasks, and their overall perceptions of using AI. A survey of 256 AI users was conducted and found that participants highly adopted AI tools like ChatGPT and Microsoft Copilot, among other lesser used tools. The survey focused on asking participants of their impressions with integrating AI to understand if there was a positive or negative impact in their academic journey. The overarching feedback suggested that AI is widely adopted among the participants and highly integrated into their tasks with an overall positive impact.

Keywords: generative AI, artificial intelligence, AI, chatbots, higher education

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An Exploratory Analysis of Perceptions and Uses of Generative AI Tools for Higher Education

Karen Pullet, Adnan Chawdhry and Jamie Pinchot

1. INTRODUCTION

Generative AI (GenAI) has seen a dramatic rise in use since the release of OpenAI's ChatGPT chatbot in 2022. Among the most prevalent users are college students, prompting many questions about the role of GenAI in the field of education (Johnston et al., 2024; Nam, 2023; Sullivan et al., 2023).

While there are many potential benefits, including increased writing support, customized learning plans, personalized feedback for students, and support for data analysis tasks, there are also some serious concerns to consider (Rasul et al., 2023). For example, use of GenAI in educational settings brings with it questions about academic integrity as well as issues for assessing learning outcomes effectively (Liu et al., 2024; Rasul et al., 2023). Universities are now struggling to determine how best to incorporate the use of GenAI in higher education, and further study is needed to explore the myriads of ways that GenAI is disrupting higher education (Sullivan et al., 2023).

Another major concern is that overreliance on GenAI tools may significantly diminish cognitive abilities over time as students learn to depend upon these tools to complete tasks, even partially, for them. While this may allow short term success, the lack of practice in problem-solving and other analytical tasks could eventually lead to a decline in critical thinking (Lee et al, 2024; Basha, 2024). Further, a lack of practice in writing can potentially lead to a decline in quality and coherence of writing (Uyen & An, 2025).

The rapid onset of the use of GenAI and its potentially significant impact on students in higher education make this a topic worthy of further exploration. The purpose of this study was to explore young adults' perceptions about and uses of generative AI (GenAI) tools in an educational setting. Traditional college students are young adults aged 18-25, so this age group was targeted for this research in order to explore

perceptions about AI in higher education and uses of GenAI tools in an educational setting.

This study explores the following research questions:

RQ1: What are the most prevalent generative AI tools in use for educational purposes by young adults aged 18-25?

RQ2: What uses of GenAI are the most common for young adults aged 18-25?

RQ3: What are the perceptions of young adults aged 18-25 about the use of GenAI tools for education?

2. LITERATURE REVIEW

A total of 399 undergraduate and graduate students in Hong Kong from a variety of academic fields responded favorably to a survey about the use of generative artificial intelligence (GenAI) in education. Through individualized learning support, writing and brainstorming help, and sophisticated research and analysis tools, students emphasized how GenAI could improve education (Chan et al., 2023).

However, stakeholders must address the possible drawbacks of generative artificial intelligence (GenAI), even though it has great potential to revolutionize education by providing individualized support, increasing productivity, and facilitating self-directed learning. Participants expressed worries about data privacy, ethical transparency, and the veracity of AI-generated content. It is especially important to pay close attention to how GenAI affects students' personal development, future employment readiness, and wider social values.

The study highlights a few important concerns expressed by students, despite a generally positive outlook on the role of GenAI in learning. One of the main concerns is the reliance on AI, which some believe could diminish fundamental academic abilities and lower the perceived worth of a college education. Concerns regarding

accuracy, transparency, privacy, and ethical limits in relation to the use of AI-generated content were also expressed by the students. (Chan et al., 2023).

The challenge of confirming the originality of AI-generated work is a major problem, as many students are uncertain whether the content is legitimate or plagiarized. Human oversight is still necessary to assess the output's integrity because GenAI tools are currently unable to evaluate truthfulness or cite verifiable sources. Clear usage guidelines, instruction in digital literacy, and institutional policies that promote the moral and responsible integration of GenAI technologies are all urgently needed, as these worries highlight.

Even though generative AI (GenAI) tools greatly aid in writing and learning, growing worries about ethics, academic integrity, and the limitations of machine-generated output continue to exist. In his analysis of AI-generated responses to academic writing prompts, Kumar (2024) found that while the outputs were frequently original and topical, they often lacked the personal perspectives necessary for scholarly voice and included inappropriate references, underscoring AI's incapacity to replicate authentic, lived human experience.

For second language learners, who might find it difficult to create useful prompts because of language barriers, this problem is made even more difficult. These obstacles may make people more dependent on GenAI tools and impede the growth of fundamental writing skills (Warschauer et al., 2023). Furthermore, the training data has a direct impact on the caliber and dependability of AI output. There are ethical concerns and a need for human oversight, critical evaluation, and responsible use when that data contains bias, misinformation, or harmful content.

Generative AI (GenAI) systems are unable to confirm the accuracy or veracity of their outputs, as Lubowitz (2023) highlights. Human oversight is necessary to detect possible misinformation or falsehoods because these tools create content based on patterns in training data rather than assessing factual correctness.

Furthermore, maintaining academic integrity becomes more difficult as GenAI becomes more sophisticated. Determining whether a submission reflects original human authorship becomes more challenging because the majority of traditional plagiarism detection systems are currently unable to recognize AI-generated content. Higher

education, where learning outcomes depend on genuine student engagement and skill development, is seriously threatened by this opacity.

Institutions must think about new academic policies, make investments in AI-literacy training, and investigate ethical standards and detection technologies that adapt to the changing digital environment in order to address these problems.

The study conducted by Koohang, et.al, (2024) examined how students perceived the advantages and opportunities presented by AI, taking into account factors such as the frequency of AI use, age, gender, academic major, and college standing. These perceptions were evaluated using a specially created tool that was organized around AI opportunities and AI benefits.

The results showed that students who reported using AI tools frequently, especially those who were extremely likely to use them once a week scored much higher on tests measuring AI's usefulness for learning and skill improvement. Furthermore, group differences surfaced across the demographics that were measured, suggesting that students' perceptions and interactions with AI may be influenced by their academic and personal backgrounds.

Particularly urgent are the issues of privacy and moral guidance. A study on ethics in education revealed that students may unintentionally contribute to or rely on systems that aren't in line with responsible use when educational institutions fail to offer clear instruction on data ethics (Silva, et.al, 2024). A large number of students do not have access to AI tools that are specifically designed for education. Learners frequently resort to commercial tools such as ChatGPT that are optimized for broad utility rather than pedagogy in the absence of institutional support or platforms designed specifically for this purpose. Universities must take action, according to this study, by integrating ethics instruction into the tech curriculum, creating AI tools with a purpose, and preparing faculty and students to effectively navigate this changing environment (da Silva, et.al, 2024).

A qualitative study was carried out by Ali, et.al. (2024) to investigate students' opinions regarding the moral application of artificial intelligence. Using the UNESCO ethical framework as a guide, the researchers framed ethics, highlighting the 6 principles; transparency,

fairness, privacy, accountability, explainability and safety.

The importance of AI systems being open and honest about their operation and use was strongly emphasized by the participants, who pointed out that this transparency is necessary for responsible and appropriate use. Students also underlined the necessity of independently confirming the accuracy of AI-generated data, acknowledging the possibility of biased or inaccurate results (Ali, et.al, 2024).

According to a study by Almassed et al. (2024), 78.7% of Saudi Arabian university students regularly use Generative Artificial Intelligence (GenAI) tools, while 21.3% said they don't, primarily because they don't know enough about them or aren't interested in them. The most popular tool among users was ChatGPT (86.2%), which was followed by Gemini, Socratic, and Copilot.

Students stated that they mostly used GenAI tools for academic literature summarization, idea generation in writing, translation, and concept clarification. Easy access, time-saving features, and the ability to provide immediate feedback were among the main advantages noted.

Students voiced a number of concerns in spite of the advantages. These included the price of subscription-based resources, the possibility of obtaining false information, plagiarism concerns, a decrease in in-person academic interaction, and less control over the learning process.

3. METHODOLOGY

To obtain data for the quantitative analysis, the researchers developed a structured survey instrument. The study population comprised young adults between the ages of 18 and 25 residing in the United States, reflecting the typical age range of college students. The United States was selected as the research setting due to the researchers' geographic location. An electronic survey was published in Survey Monkey and used to collect the data. A total of 256 participants responded to the survey (n = 256). This study was approved by the Institutional Review Board at Pennsylvania Western University prior to data collection.

Amazon Mechanical Turk (MTurk) was used for sample selection as well as distribution of the survey. MTurk is an online recruitment platform

that has become one of the dominant sources of online convenience samples for survey research (Rinderknecht et al., 2025). This tool has been used by academic researchers and the quality of data has been shown to be quite high, rivaling that of data obtained from traditional samples of college students (Zhang and Gearhart, 2020; Chandler et al., 2019). However, some limitations should be noted. MTurk samples tend to be younger, better educated, and have lower incomes than the broader U.S. public (Rinderknecht et al., 2025) and may also be more tech-savvy due to the nature of the platform itself (Tafesse & Mamo, 2025). MTurk has built-in screening for automated bots by leveraging CAPTCHAs for platform security and automated audits of user accounts. Additionally, the tool allows researchers the ability to set specific worker qualifications to reduce automated bot responses. The dataset was Imported into SPSS for deeper analysis.

Gender was recorded as a fundamental demographic variable in the survey. Given the study's focus on generative AI within the context of higher education, the researchers deemed it essential to determine participants' enrollment status in university courses at the time of this study (Spring 2025). According, respondents were asked whether they were enrolled in an academic program, and if so, to specify their level of study.

The next set of questions on the survey asked participants about their familiarity with AI, whether they have used any AI tools for academic purposes, and if so, how often and which tool(s). The list of tools provided (participants were encouraged to select all that apply) included: ChatGPT, Microsoft Copilot, Claude, Grok, Gemini, Quillbot, DALL-E, Midjourney, IBM Watson, Grammarly, and Canva Magic Studio. An area for participants to write-in additional tools was also provided. Further, the survey asked participants who used AI tools for academic purposes about the types of tasks they use the tools to complete. Responses included: Research, writing/text generation, problem-solving, data analysis, image generation, video generation, language learning, personalized tutoring, time management, coding/programming, and task automation. An area to write-in additional tasks was also provided.

Next, participants were asked to respond to a series of statements about AI, examples of which include:

- AI can be a valuable tool for learning.
- AI can help me manage my time more effectively.
- I am concerned about the potential for AI to replace human teachers.
- I am concerned about the potential for AI to reduce critical thinking skills.
- I am concerned about the potential for AI to be used for academic dishonesty.

For this series of statements, participants were asked to respond on a Likert scale as follows: Strongly Agree, Agree, Neither Agree nor Disagree, Disagree, Strongly Disagree.

The final question on the survey asked was "Do you think AI will have a positive or negative impact on education in the future?" Participants were asked to respond on a Likert scale as follows: Very positive, Positive, Neutral, Negative, Very negative.

4. RESULTS

The survey began with questions to evaluate the participants gender, education, and familiarity with AI. Of the total participants (255), 13.7% were female while 86.3% were male. Next, participants were asked if they were currently (Spring 2025) enrolled in college classes and 86.7% reported they were enrolled while 13.3% reported they were not enrolled in a college course. Participants were asked what their level of education was, and the results are provided in Table 1 below. Additionally, Table 2 provides the participants self-evaluation of their familiarity with the concept of AI. The results illustrate the majority, approximately 92.9%, were extremely familiar or very familiar with the concept of AI.

Level of Education	Percentage
Freshman	20.3%
Sophomore	1.6%
Junior	6.6%
Senior	34.0%
Graduate Student	15.2%
Post-Graduate (Doctorate)	8.6%
Other	13.7%

Table 1: Level of Education

Level of Education	Percentage
Extremely Familiar	56.6%
Very Familiar	36.3%
Somewhat Familiar	5.9%
Not so Familiar	1.2%

Table 2: Familiarity with AI

RQ1: Most Prevalent GenAI Tools

The first research question aimed at understanding what generative AI tools were most used by young adults aged 18-25. The next series of survey questions facilitated responses on how many participants have leveraged AI tools for academic purposes and what tools they have used. Of the participants, 97.3% have used AI tools for academic purposes while 2.7% have not. One of the survey questions asked participants how often they are using AI Tools for academic purposes and Table 3 below provides the results. Approximately 88.5% of the participants have used AI tools for academic purposes "Often" or "Always." Table 4 summarizes which tools the participants have used and they were permitted to select multiple responses. One participant listed "Artflow AI" in the other category for AI Tools used for academic purposes.

How Often AI Used	Male	Female	Total
Always	55.56%	3.29%	58.85%
Often	19.75%	9.88%	29.63%
Sometimes	7.41%	0.82%	8.23%
Rarely	2.06%	0.00%	2.06%
Never	1.23%	0.00%	1.23%

Table 3: How Often Used AI for Academic Purposes

Tool Used	Male	Female	Total
ChatGPT	71.88%	11.72%	83.59%
Microsoft CoPilot	43.75%	5.47%	49.22%
Claude	34.77%	7.03%	41.80%
Grok	16.41%	3.13%	19.53%
Gemini	19.53%	5.08%	24.61%
Quillbot	3.91%	1.95%	5.86%
DALL-E	2.73%	3.13%	5.86%
Midjourney	5.47%	1.17%	6.64%
IBM Watson	3.91%	0.78%	4.69%
Grammarly	6.25%	4.30%	10.55%
Canva Magic Studio	1.95%	1.56%	3.52%
Other	0.39%	0.00%	0.39%

Table 4: AI Tools used by students

RQ2: Most Common GenAI Uses

The second research question targeted young adults aged 18-25 to understand what tasks they completed using AI. The researchers found this are pivotal to better understand the depth of AI usage. Table 5 below provides the breakdown of these response and participants were permitted to select more than one task.

Task	Male	Female	Total
Research	53.91%	10.55%	64.45%
Writing / text generation	41.02%	7.81%	48.83%
Problem-solving	36.72%	5.86%	42.58%
Data analysis	28.13%	4.69%	32.81%
Image generation	16.41%	3.91%	20.31%
Video generation	8.59%	4.30%	12.89%
Language learning	8.59%	2.34%	10.94%
Personalized tutoring	10.94%	3.91%	14.84%
Time management	9.38%	3.13%	12.50%
Coding / programming	5.08%	2.34%	7.42%
Task automation	2.34%	2.34%	4.69%
Other (please specify)	53.91%	10.55%	64.45%

Table 5: Tasks Completed using AI

RQ3: Perceptions of GenAI Tools for Education

The final research question assessed participants' (aged 18-25) perceptions regarding the use of AI tools in educational contexts. Tables 6 through 10 provide the participants perceptions on AI being valuable for learning, AI personalizing the learning experience, AI helping learn more effectively, AI improving their academic outcomes, and AI helping manage time more effectively. Lastly, participants were asked if AI would have a positive or negative impact on education in the future.

To better understand the participants perceptions, the researchers correlated five perception variables with both GENDER and LEVEL_OF_EDUCATION. Statistical significance (p-value of less than or equal to 0.05) was found in one case for Gender and the results are displayed in Table 11 below. Table 12 displays the correlation between LEVEL_OF_EDUCATION

with the same five variables and in each case the variables were statistically significant with LEVEL_OF_EDUCATION.

Level	Percentage
Strongly Agree	52.0%
Agree	39.1%
Neither Agree or Disagree	7.4%
Disagree	0.8%
Strongly Disagree	0.8%

Table 6: Valuable for Learning

Level	Percentage
Strongly Agree	23.4%
Agree	50.4%
Neither Agree or Disagree	18.8%
Disagree	5.5%
Strongly Disagree	2.0%

Table 7: Personalize Learning Experience

Level	Percentage
Strongly Agree	20.7%
Agree	55.5%
Neither Agree or Disagree	16.8%
Disagree	4.7%
Strongly Disagree	2.4%

Table 8: Learn more Effectively

Level	Percentage
Strongly Agree	18.4%
Agree	60.9%
Neither Agree or Disagree	16.4%
Disagree	3.1%
Strongly Disagree	1.2%

Table 9: Improve Academic Outcomes

Level	Percentage
Strongly Agree	17.2%
Agree	57.0%
Neither Agree or Disagree	19.1%
Disagree	4.7%
Strongly Disagree	2.0%

Table 10: Manage Time more Effectively

Variable	Chi-square Value	df	p-value (* indicates statistical significance)
Valuable for Learning	8.033	5	.154
Personalize Learning Experience	22.200	5	.000*
Learn more Effectively	6.685	5	.245
Improve Academic Outcomes	8.363	5	.137
Manage Time more Effectively	8.736	5	.120

Table 11: Gender Chi-Square Analysis

Variable	Chi-square Value	df	p-value (* indicates statistical significance)
Valuable for Learning	79.417	35	.000*
Personalize Learning Experience	111.575	35	.000*
Learn more Effectively	65.769	35	.001*
Improve Academic Outcomes	66.649	35	.001*
Manage Time more Effectively	81.802	35	.000*

Table 11: Level of Education Chi-Square Analysis

5. DISCUSSION

RQ1: Most Prevalent GenAI Tools

Participants were asked if they are using tools to support academic purposes, where 88.5% stated they have used at least one tool. A total of 11 tools were listed, and participants were permitted to select multiple tools as shown in Table 4 above. Of the responses, it was most notable that five tools were most adopted which include ChatGPT (83.6%), Microsoft CoPilot (49.2%), Claude (41.8%), Gemini (24.6%), and Grok (19.5%). The remaining six selections had approximately 10% or less of the respondents reporting they used it. A study by Almassed et al. (2024)

reported that ChatGPT was the most popular tool with 86.2% of the respondents using it. Additionally, the study reported that other popular AI tools included Gemini and Copilot which were also selected within the top five tools of our study. ChatGPT being the top-rated tool is not surprising as it is optimized for broad utility and can include academic use cases (Silva, et.al, 2024).

Additionally, 97.3% of the participants reported that they have used AI tools in the past for academic purposes. Participants were also asked to identify their level of usage and 88.5% stated they used it often or always in their academic. With a large response stating they use AI tools for academic purposes, the AI tools being well adopted, and the results being aligned with prior literature, the researchers found these results were an accurate depiction of AI tool usage for academic purposes.

RQ2: Most Common GenAI Uses

The study reported high adoption of specific AI tools by the participants. Next, the participants were asked to identify tasks that they would complete using AI tools. A large portion of the respondents (64.5%) stated they used it for research. Other top tasks selected by the participants included writing / text generation (48.8%), problem-solving (42.6%), data analysis (32.8%), image generation (20.3%), video generation (12.9%), and language learning (10.9%). When considering these tasks, they make up many primary duties that students perform in academia. As a secondary measure of adoption, these results illustrate that the participants are using AI Tools for a wide variety of primary tasks that are incorporated into their academic journey.

RQ3: Perceptions of GenAI Tools for Education

The researchers wanted to understand student perceptions of GenAI tools by evaluating 5 key variables: Valuable for Learning, Personalize Learning Experience, Learn more Effectively, Improve Academic Outcomes, and Manage Time more Effectively. A positive perception was aligned with participants responding "Strongly Agree" or "Agree" to AI helping these core areas. In all five of these variables, a majority of participants (at least 73%) responded favorably that AI would have a positive impact in their academic tasks.

This impact was further supported when the researchers asked if the participants overall felt if AI had a positive or negative impact on education in the future and 92.6% reported a "Very Positive" or "Positive" impact. A final analysis evaluated the statistical significance between these five variables and two variables (GENDER and LEVEL_OF_EDUCATION). For GENDER, there was a correlation between that and Personalized Learning Experience. However, LEVEL_OF_EDUCATION had a statistical significance among all five variables where the higher the level of education, the more positive their perception of AI in education.

6. CONCLUSIONS

The use of AI tools for academic purposes has grown substantially in recent years. As AI evolves and use-case driven tools for education are introduced, students will have additional opportunities to leverage these tools for academic purposes. At the present, it is clear that tools such as ChatGPT and Microsoft Copilot are widely used and increasingly adopted in academia, even though these tools are aligned for broad utilization. While other tools did not have as high of an adoption rate, it would be fair to assume that given time and enhancements, their adoption will also improve.

Most notable is the perceived positive impact the participants stated on AI's usage in academia. Overall, participants found that the tools are aiding in their academic tasks, which can reduce the delivery time of projects and academic work. One could correlate this movement as we moved from the traditional encyclopedia to Google. Information was available at our fingertips and thus reduced the time needed to do research. If students are finding these tools to improve the efficiency and delivery timelines for their work, they will understandably see the impact as positive. But the question will still remain on the accuracy of information provided by these AI tools and the impact of disseminating derived information through academia.

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Teaching Case

Operational Analytics in Excel: A Transaction-Level Car Wash Case for Introductory Data Literacy

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"I know our washes are busy, but are we actually making money? And which location is really pulling its weight?" Matthew Auger, Director of Operations at Soapy Noble Express Car Wash, leaned back from his laptop and stared at a dashboard full of charts he did not fully trust. Since the company rolled out a new point-of-sale system across its eight New England locations, Soapy Noble had more detail than ever, including timestamps, product mix, payment types, and transaction totals for every wash sold.

The problem was turning all of that activity into decisions. Some sites looked consistently strong, while others surged on weekends and then went quiet. The monthly unlimited plan was growing, but Matthew could not tell whether it was boosting revenue or cannibalizing single-wash sales. He also needed to know when demand peaked, whether staffing patterns matched actual traffic, and which levers, such as pricing, promotions, hours, or service mix, were most likely to move results. With transaction data flowing in across eight locations and no shortage of operational questions, Matthew brought in an external consulting team and asked for clear, data-backed recommendations he could act on quickly.

Abstract

This teaching case introduces introductory level students to data literacy through an applied operational analytics project based on a regional express car wash business. Students assume the role of an external consulting team hired by Soapy Noble Express Car Wash, a fast-growing chain operating eight locations in New England, to analyze transaction level point of sale data and develop actionable recommendations for management. Using approximately one year of transaction records at scale, students apply Excel based techniques such as data cleaning, descriptive statistics, pivot tables, and visualization to identify patterns in customer demand, service mix, location performance, and monthly unlimited plan usage. To extend analysis beyond the internal dataset, the case encourages students to locate and integrate relevant external sources, such as weather or demographic data, and to explain how these sources inform interpretation and recommendations. The case is designed for first year courses in data literacy, business analytics, or introductory CIS and includes team-based deliverables appropriate for nontechnical decision makers, including an analysis workbook and a concise executive memo and presentation.

Keywords: Data Literacy, Project Based Learning, Business Analytics, Excel, Operational Analytics

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Operational Analytics in Excel: A Transaction-Level Car Wash Case for Introductory Data Literacy

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1. INTRODUCTION

As data becomes increasingly central to decision-making in every industry, developing data literacy, including the ability to read, analyze, interpret, and communicate with data, has emerged as a critical competency for the modern workforce (Carlson & Johnston, 2015; Mentzer et al., 2024; Wolff et al., 2016). Employers across sectors consistently identify data competency as essential not only for analysts, but for all professionals responsible for strategic thinking and operational improvement (Miller & Hughes, 2017). This widespread need reflects a shift toward data-informed culture across all organizational levels, requiring graduates to be fluent in both data interpretation and evidence-based reasoning.

Yet, for many undergraduate students, data remains abstract, locked in textbook problems, isolated spreadsheets, or hypothetical scenarios that do not mirror real business complexity. Prior research has noted that learners benefit most when they engage with authentic data and real-world problems, which promote motivation, relevance, and long-term skill retention (Gould, 2010; Kolodner et al., 2003). Project-based learning (PBL), an instructional method that situates students in realistic roles with complex, open-ended challenges, offers a pedagogical bridge between theory and applied practice (Bell, 2010; Blumenfeld et al., 1991).

PBL immerses students in sustained inquiry and collaborative problem-solving, encouraging deeper cognitive engagement and fostering both technical and professional skills. Research has shown that PBL can increase student motivation and improve transfer of learning across contexts (Barron & Darling-Hammond, 2008; Thomas, 2000), benefits that are particularly relevant in data-focused education where students must navigate ambiguity, clean and interpret data, and develop actionable insights.

This teaching case is designed as a project-based learning experience for first-year undergraduate students developing foundational data analysis skills in an introductory Data Literacy context. Students assume the role of an external

consulting team hired by a regional car wash chain to analyze operational data and make strategic recommendations to senior management. By integrating real transaction records with optional external datasets such as weather and census information, students are challenged not only to build technical proficiency in Excel and visualization tools, but also to apply data to support meaningful business decisions.

Implemented in a required first-year undergraduate Data Literacy course, this case supports AACSB-relevant assurance-of-learning documentation by generating assessable student artifacts (Excel analysis, memo, and presentation) and by evaluating them with a common scoring rubric. The judges used the rubric (see Appendix C) to score each team and select the winners of the case competition; instructors may also use rubric dimensions as direct evidence of data literacy and analytic communication outcomes for AoL reporting.

Working with real transaction data and optional external sources, students will explore customer behavior, pricing models, and performance across multiple locations. The case challenges students to use Excel as their primary analysis tool, applying descriptive statistics, visualizations, and business reasoning to deliver a professional, data-driven presentation. By engaging students through a hands-on, scenario-based project, this case supports not only the acquisition of data literacy skills, but also the broader development of analytical mindset and professional readiness, key outcomes for twenty-first century learners.

2. MOTIVATION

Instructors in introductory CIS, MIS, and analytics courses often seek datasets that are authentic, engaging, and appropriately scoped for novice learners. Public repositories such as Kaggle and data.gov can be useful starting points, but they frequently present tradeoffs for introductory teaching. Many Kaggle datasets and competitions presume advanced modeling skills beyond the first-year level, while some government datasets can be either too narrow or insufficiently engaging to sustain a multi-week, team-based project.

marketing, operational improvements, and future growth.

4. PROJECT OVERVIEW

Students are placed in the role of an external consulting team hired to help Soapy Noble interpret and act on its newly available point-of-sale data. Management has asked the team to evaluate:

- Which locations are overperforming or underperforming, and why
- Patterns in demand by time of day and day of week
- Seasonal patterns in usage
- The financial implications of the monthly unlimited plan
- Service mix and pricing effectiveness
- Broader market factors that may influence performance (for example, demographics and weather)

Students receive approximately one year of transaction-level data (about 1 million rows) and are encouraged to enhance their analysis with one or more external datasets (for example, U.S. Census data or NOAA weather data).

Analysis Expectations

In the analysis phase, teams translate raw transaction records into management-ready insights and recommendations. The goal is not to build a perfect model, but to use structured Excel analysis to identify operational patterns, test plausible explanations, and quantify the business implications of those patterns. Successful teams make their work transparent by labeling assumptions, documenting steps, and presenting summaries that a nontechnical stakeholder could follow.

Student teams are expected to:

1. Clean and summarize the data provided in Excel.
2. Use pivot tables and visualizations to identify key trends.
3. Integrate one or more external datasets to add depth.
4. Prepare management-ready findings and recommendations for the memo and presentation.

Optional tools like Tableau may be used for dashboarding, but Excel is required.

Client-Facing Deliverables

Deliverables are intentionally designed to mirror what an external consulting team would provide

to an operations leader. Each artifact serves a distinct purpose: the workbook documents the analytical trail, the memo communicates the headline findings concisely, and the slide deck supports a decision-focused presentation. Together, these deliverables emphasize clarity, visual communication, and actionable recommendations rather than technical jargon.

Each team must submit:

- An Excel workbook with labeled analysis and visuals
- A management-facing slide deck
- A one-page executive memo
- A list of 2–3 strategic recommendations backed by data

Case Competition Format

We implemented this case as a competition across five sections of Data Literacy, a required first-year course that builds foundational Excel, Word, and PowerPoint skills. Students self-selected into teams of two to five and had approximately three to four weeks to complete the analysis.

During the first week, instructors distributed the dataset through the LMS, provided time for students to review the data structure, and held a Q&A session to clarify variable definitions and expectations. Instructors were asked to support student-led analysis plans and execution, while avoiding injecting their own conclusions into teamwork.

In the preliminary round, each course section selected a finalist team to represent the section in the final presentation round. Teams typically spent Weeks 1 through 3 on exploration, cleaning, external data integration, figure development, and executive summary preparation, with section presentations occurring during Week 4. Sections used peer feedback, instructor notes, or the shared rubric (Appendix C) to support selection of a section winner.

Before the final event, finalist teams met briefly with instructors to confirm presentation format and timing. Finalists then delivered a 15-minute presentation to Soapy Noble's management team and other judges, who used the supplied scoring rubric to select the overall winners.

5. INSTRUCTOR AND STUDENT FEEDBACK

Faculty Reaction

Faculty observations were generally positive, with several predictable challenges that are common

in introductory, open-ended analytics work. After the project launch, some students expressed low confidence in the quality of the work they could produce. Others felt overwhelmed by the scale of the dataset (approximately 1 million rows) and the number of variables available, and some teams struggled to determine where to begin. Students were also understandably anxious about presenting their findings to Soapy Noble's management team.

To support students through these early barriers without reducing the authenticity of the task, instructors required each team to create a brief analysis plan before building charts or drafting recommendations. Teams articulated the questions they intended to answer, identified the variables they would use, and wrote down what they expected to find. This planning step increased confidence and helped teams establish a workflow. Instructors implementing this case should monitor student confidence closely and provide structure early, as the assignment is intellectually demanding.

Faculty also reported that the local nature of the client increased student engagement. Several students were familiar with the business, and some had been customers. This strengthened the perceived relevance of the work and helped students connect data analysis to real operational decisions.

Student Feedback

Student feedback was largely positive. Many students described the project as engaging, useful, and more challenging than typical spreadsheet assignments. Several students highlighted the difficulty of translating analysis into a clear narrative and selecting visuals that directly address the business questions. This is a desired outcome of the case, since the ability to explain and defend analytical choices is central to data literacy.

How to AI-Proof this case

While no case can fully prevent the use of AI tools, instructors can design the assignment so that meaningful learning depends on student decision-making, documentation, and communication. Several approaches have worked well with this case:

1. Use constraints that require hands-on analysis. Because transaction-level datasets of this size are difficult to paste directly into typical chat tools, students still need to summarize, clean, and structure the data in Excel before they can ask useful AI-supported questions.

2. Require stakeholder-specific deliverables. Ask teams to tailor their messaging to different audiences (for example, operations leadership versus marketing). Generic, one-size-fits-all responses tend to fail when context and tradeoffs matter.
3. Require external data selection and justification. Do not provide the external datasets. Instead, require teams to find, justify, and cite their own sources (for example, weather, demographics, local events) and explain how the added context changes interpretation.
4. Build in process checkpoints. Include interim submissions such as an analysis plan, draft visuals, and a walkthrough of workbook logic. Use brief in-class progress reviews to surface whether teams understand their own work.
5. Collect the workbook as evidence. Require students to submit the Excel file with formulas, pivot tables, and labeled steps so the analytical trail is transparent.
6. Use live presentations and questioning. Ask teams to defend choices and explain tradeoffs, such as why they selected a specific metric, chart type, filter, or segmentation approach, and what alternative explanations they considered.

6. CONCLUSIONS

This teaching case demonstrates how transaction-level point-of-sale data can be used to build foundational data literacy skills through an applied, decision-focused project. By positioning students as an external consulting team for a regional express car wash chain, the case creates an authentic context in which learners must move beyond mechanical spreadsheet steps and instead translate data into operational insight and actionable recommendations.

The case is intentionally designed for introductory learners and can be completed using Excel as the primary analysis tool. Students practice core competencies such as data cleaning, descriptive statistics, pivot tables, and visualization, while also developing the communication skills required to explain methods, interpret results, and justify recommendations for a nontechnical audience. The option to integrate external datasets, such as weather or demographic information, further reinforces the idea that business analysis is strengthened when internal performance data is interpreted within a broader context.

Instructor experience suggests that the

combination of open-ended questions and a large dataset can initially feel challenging for first-year students. However, with light structure early in the project, such as an analysis plan, interim checkpoints, and emphasis on documentation in the workbook, teams can produce high-quality, defensible work. These implementation features also support academic integrity by making student reasoning visible through process artifacts and live explanation rather than relying solely on a final answer.

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- fuel prices
- Local events or holidays that might explain spikes or lulls in business

Cross-referencing these external factors with our internal data will help reveal deeper patterns and support more targeted recommendations.

Key Questions

Your analysis should address the following:

1. Location Performance
 - Which sites are outperforming or underperforming, and why?
 - Are there external factors (e.g., population, income, traffic volume) influencing this?
2. Customer Usage Patterns
 - What are the busiest times of day and week?
 - How do trends vary across different communities or seasons?
3. Monthly Plan Effectiveness
 - Are monthly plan holders using the service frequently?
 - Are these plans financially beneficial to the company?
4. Service Mix and Pricing
 - Which washes are most popular?
 - Should we consider bundling, upselling, or adjusting pricing?
5. Strategic Recommendations
 - Based on your findings, what operational or marketing changes would you suggest?
 - How can we better tailor offerings to specific locations or customer segments?

Deliverables

Please submit the following:

- An Excel analysis workbook with tables and visuals (e.g., pivot charts)
- A 10–20 slide presentation summarizing your findings and recommendations
- Optional: a dashboard (Excel or Tableau) for interactive exploration
- Clear explanations of how any external data informed your conclusions

Your final deliverable should be professional, insightful, and accessible to business decision-makers without a technical background.

What We're Looking For

We value:

- Accuracy and clarity in data analysis
- Thoughtful integration of external data for added context
- Actionable recommendations grounded in evidence
- Strong visuals and concise messaging

This is a real-world consulting engagement. We are relying on your work to help us elevate our business strategy and customer experience.

Thank you again for your collaboration. We look forward to your analysis and the insights you uncover to help Soapy Noble continue to deliver Noble Service and a Quality Wash across New England.

Sincerely,
Matthew Auger
Director of Operations
Soapy Noble Express Car Wash
<https://soapynoble.com>