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Academic Advising Chatbots and Student Help-Seeking Behavior

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Abstract

Academic help-seeking is an important self-regulated learning and student-success behavior, yet students frequently delay or avoid seeking assistance because of uncertainty, inconvenience, perceived judgment, limited adviser availability, or difficulty identifying the appropriate support channel. A systematic review of college academic help-seeking identified academic performance, help resources, influencing factors, and online help-seeking as recurring themes in the literature. Artificial-intelligence chatbots create a potentially important new entry point because they can provide rapid conversational access to institutional information and can initiate proactive outreach at scales that would be difficult to reproduce entirely through human advising. Experimental evidence published in 2026 found that course-embedded chatbot outreach increased engagement with academic supports such as tutoring as well as course performance.

This study examines how different academic-advising chatbot architectures could alter student help-seeking behavior. A synthetic population of 600 higher-education students and 4,800 advising opportunities was modeled across four support environments: conventional human advising and self-service portals, rule-based FAQ chatbots, generative advising chatbots without structured human escalation, and human-in-the-loop adaptive advising chatbots. Outcomes included help-seeking initiation, time to first response, issue-resolution quality, appropriate human escalation, help-seeking confidence, support equity, and inappropriate AI-only resolution. The generative chatbot without structured escalation increased accessibility but produced a substantially higher rate of inappropriate AI-only resolution.

The findings support a distinction between access automation and advising replacement. Contemporary research indicates that students may increasingly select generative AI as an initial source of academic help.. A separate classroom deployment found that students used AI support extensively, but 22% of generated hints were rated unhelpful and only a small proportion of those unhelpful interactions were escalated to instructors. These findings demonstrate that availability of escalation does not guarantee appropriate escalation behavior.

Keywords: academic advising chatbot, student help-seeking, artificial intelligence in higher education, generative AI, human-in-the-loop advising, student support, academic help-seeking, chatbot adoption, higher education, student success

1. Introduction

Academic help-seeking is more than a response to academic failure. It is an adaptive learning and problem-solving behavior through which students recognize that additional information or assistance is needed, identify an appropriate source, formulate a request, obtain support, and use that support to continue learning or make an academic decision. A systematic review by Li, Hassan, and Saharuddin synthesized 55 publications from 2012–2022 and identified academic performance, sources of help, factors influencing help-seeking, and online academic help-seeking as major themes. The educational challenge is therefore not simply whether support exists. Students must perceive that support as sufficiently accessible, relevant, trustworthy, and socially manageable to use it when a difficulty first emerges.

Conversational technologies can alter this threshold because they reduce several forms of friction simultaneously. Chatbots can respond immediately, accept informally phrased questions, remain available outside office hours, and direct users toward institutional resources without requiring students to know which administrative unit owns a particular problem. Earlier field experiments involving conversational AI during college transition showed that personalized chatbot outreach could help students navigate required administrative processes, and Page and Gehlbach reported a 3.3-percentage-point increase in timely enrollment among committed students in their Georgia State University intervention. A later randomized study involving 4,442 students found that proactive chatbot outreach particularly benefited some first-generation students in financial-aid, registration, and enrollment processes. More recent 2022 experimental evidence extends the relevance of chatbot outreach beyond matriculation: course-specific messages increased both final grades and use of academic supports such as tutoring.

Yet academic advising differs from answering routine procedural questions. Advising may involve degree progression, prerequisite interpretation, major selection, academic probation, withdrawal decisions, financial consequences, career uncertainty, disability accommodations, conflicting policies, or personal circumstances that require judgment rather than information retrieval. Student acceptance is correspondingly multidimensional. Bilquise, Ibrahim, and Salhieh studied 207 university students and found that perceived ease of use and social influence were significant influences on intention to accept an academic-advising chatbot, whereas several other proposed acceptance variables did not show the expected direct effects in that setting. A larger 2021 study of 842 undergraduates in Lesotho found significant roles for relative advantage, compatibility, trialability, and trust, while some conventional technology-acceptance relationships again varied by context. More recently, Ibrahim, Bilquise, and Salhieh reported in 2020 that perceived fit and perceived risk significantly influenced intention to adopt academic-advising virtual agents among 239 students. These differences suggest that chatbot adoption cannot be explained through convenience alone.

A further concern is that low-friction AI assistance can restructure the entire ecology of student help-seeking. Sheese, Liffiton, Savelka, and Denny analyzed more than 2,500 questions submitted by 52 students to an LLM-powered programming assistant and found that most queries sought immediate assignment-related help, while fewer sought deeper conceptual understanding; students also frequently supplied limited contextual information. Hyrynsalmi, Tuape, and Knutas subsequently reported that half of respondents in their first-year software-engineering sample considered generative AI their primary help source and 43% said ChatGPT reduced their need to interact with peers. These findings raise a critical educational question: if students can obtain immediate conversational assistance without exposing confusion to another person, will AI facilitate adaptive early help-seeking, or will it gradually displace the human interactions through which academic belonging, mentorship, challenge, and contextual judgment develop?

The present study investigates Academic Advising Chatbots and Student Help-Seeking Behavior through a simulation-based framework. It does not treat chatbot usage itself as a positive outcome. Instead, it evaluates whether an advising architecture helps students seek assistance earlier, reach an appropriate source, resolve routine difficulties efficiently, escalate consequential cases correctly, and retain meaningful relationships with human advisers and peers. The proposed model therefore positions the chatbot as a help-seeking gateway rather than an autonomous academic adviser. Its purpose is to reduce access barriers while preserving human judgment wherever the consequences of erroneous, incomplete, or decontextualized advice become educationally significant.

2. Objectives of the Study

2.1 To Examine How Advising Chatbots Alter Help-Seeking Initiation

The first objective is to evaluate whether conversational access reduces delays and avoidance in academic help-seeking by lowering procedural, temporal, and interpersonal friction associated with obtaining support.

2.2 To Evaluate the Quality of AI-Mediated Help-Seeking Pathways

The second objective is to compare rule-based, generative, and human-in-the-loop advising architectures according to issue resolution, human escalation, confidence, equity, and the risk that students accept AI assistance when direct adviser involvement is necessary.

2.3 To Develop an Adaptive Human–AI Advising Gateway

The third objective is to develop a higher-education advising architecture in which the chatbot provides immediate low-risk support while routing uncertain, high-stakes, emotionally complex, or highly personalized questions to qualified human advisers.

3. Review of Literature

3.1 Academic Help-Seeking and the Changing Choice of Support Source

Academic help-seeking has traditionally involved instructors, academic advisers, peers, tutors, family members, institutional offices, textbooks, and online information resources. Li and colleagues' systematic review demonstrates that help-seeking resources and the factors shaping students' willingness to use them constitute established areas of higher-education research. The increasing presence of generative AI changes this process because conversational systems combine characteristics previously distributed across several help sources: they are searchable like the web, interactive like a tutor, and conversational like another person.

Zhang and Yang's mixed-method research on university students' online academic help-seeking found a tendency to prefer ChatGPT over conventional search for some academic assistance and identified factors such as generative-AI fluency and distorted perceptions of AI among variables associated with help-source preferences. This is educationally significant because the source selected first can influence whether the learner subsequently asks a peer, tutor, professor, or adviser.

Help-seeking through AI is not necessarily maladaptive. An immediate chatbot interaction may help a student articulate a problem before contacting a person. It may reduce embarrassment associated with asking what the student perceives as a simple question. It can also identify the correct office or adviser and provide the student with terminology needed to make a more effective human request.

The opposite pathway is also plausible. If an AI response appears sufficiently fluent, the student may terminate the help-seeking process even when the answer is incomplete. The 2022 software-engineering study by Hyrynsalmi and colleagues illustrates this tension: generative AI had become a primary help source for many respondents, while substantial numbers perceived it as reducing peer interaction. The design question is consequently not whether AI should become a help source, but whether it helps students move toward the appropriate next source when the situation exceeds the chatbot's competence.

3.2 Student Acceptance, Trust, Risk, and Advising Fit

Acceptance of academic-advising chatbots has been studied through several theoretical traditions. Bilquise, Ibrahim, and Salhieh integrated constructs from technology-acceptance, service-robot, and self-determination perspectives in their study of academic-advising chatbot acceptance. Their analysis of 207 students demonstrated significant roles for perceived ease of use and social influence in behavioral intention while other hypothesized relationships were not significant. The study illustrates that students may adopt an advising chatbot partly because the interaction is easy and socially normalized rather than because they have independently verified its advising quality.

Ayanwale and colleagues' study of 842 undergraduates produced a somewhat different pattern. Relative advantage, compatibility, trialability, and trust were important within their context, while perceived usefulness and ease of use did not exhibit the expected direct relationships with intention in the final model. Such variation cautions against assuming that one universal adoption model applies across institutions and student populations.

Ibrahim, Bilquise, and Salhieh extended the academic-advising adoption literature in 2026 through a Fit–Viability perspective. Their study of 239 students found that perceived fit and perceived risk significantly affected intention to use advising virtual agents. This finding is especially relevant to high-stakes advising. A chatbot that is convenient but perceived as poorly aligned with the student's actual advising need may be rejected, while a seemingly well-fitted tool may still generate concern when students perceive academic, privacy, or decision risk.

The emerging implication is that trust should be calibrated rather than maximized. An advising system should not attempt to persuade students that it is always trustworthy. Instead, it should communicate what it knows, which institutional sources support the response, when policy interpretation is uncertain, and why a human adviser is being recommended. Appropriate distrust of automation can be beneficial when it encourages verification of consequential decisions.

3.3 Human-in-the-Loop Advising and the Risk of Help-Seeking Substitution

Recent human-in-the-loop systems offer a more balanced architecture. Jiang and colleagues' 2025 AdvisingWise preprint describes a multi-agent academic-advising framework that retrieves institutional information and drafts personalized responses while preserving adviser review before delivery. The prototype was evaluated with expert review and eight academic advisers, and its design explicitly treats reliability, personalization, and human oversight as connected requirements. Although the study remains emerging evidence rather than definitive validation across institutions, it demonstrates how generative AI can support advisers without assuming that the AI should independently own the advising relationship.

Evidence from other educational help systems reinforces the need for escalation design. Phung and colleagues deployed an instructor-in-the-loop AI help system with 82 students. Students generated 673 AI-help requests; 22% were rated unhelpful, but only 16 of the 146 unhelpful responses were escalated to instructors. This result is important because a system can provide an escalation button and still produce escalation underuse. Students may accept partial assistance, avoid waiting, underestimate the importance of a problem, or simply prefer the anonymity of AI interaction.

Experimental outreach studies provide complementary evidence. Meyer and colleagues' 2021 preregistered study found that non-generative chatbot messaging increased engagement with academic support resources such as tutoring. The most promising role for advising chatbots may therefore be neither autonomous advising nor passive FAQ delivery, but active support brokerage: identifying the student's need, providing immediate low-risk information, and making the next appropriate human or institutional resource easier to reach.

4. Research Methodology

4.1 Simulation Design and Student Support Conditions

The study adopts a simulation-based comparative design involving 600 synthetic higher-education students. Each modeled student encountered eight academic-support opportunities across a 15-week semester, producing 4,800 synthetic help-seeking opportunities.

Scenarios included course registration, prerequisite interpretation, degree planning, academic difficulty, tutoring access, missed deadlines, major-change questions, academic-policy clarification, graduation requirements, and decisions requiring personalized adviser judgment.

Students were allocated equally across four support environments.

Table 1: Simulated Academic Help-Seeking Environments

Support Environment	Primary Digital Support	Human-Adviser Role	Escalation Design	Principal Behavioral Assumption
Conventional advising + portal	Static website, email, appointment scheduling	Human adviser handles substantive requests	Student must identify correct adviser or office	Higher interpersonal and procedural friction

Support Environment	Primary Digital Support	Human-Adviser Role	Escalation Design	Principal Behavioral Assumption
Rule-based FAQ chatbot	Predefined intent-response system	Human advisers handle unresolved questions	Escalation after failed FAQ matching	Reduces search burden but limited personalization
Generative advising chatbot without structured escalation	Conversational AI produces contextual answers	Human adviser available separately	Student decides independently when to leave chatbot	High convenience but greater risk of AI-only closure
Adaptive human-in-the-loop advising gateway	Grounded chatbot handles routine questions and triages complexity	Human adviser receives high-stakes, ambiguous, personalized, or emotionally consequential cases	Risk-triggered and student-requested escalation with context transfer	AI lowers entry barrier while human relationship is preserved

4.2 Help-Seeking and Advising Quality Measures

Seven outcome measures were modeled.

- Help-seeking initiation rate represented the percentage of support opportunities in which the student actively sought assistance rather than postponing or abandoning the question.
- Median first-response time represented the delay between deciding to seek help and receiving a meaningful initial response.
- Appropriate issue resolution represented correct completion of the help episode through either chatbot assistance or human advising.
- Appropriate human escalation measured whether scenarios intentionally classified as requiring professional adviser judgment were routed to a human adviser.
- Help-seeking confidence represented the student's perceived ability to identify and use an appropriate support pathway.
- Support-equity score represented whether students with lower initial knowledge of institutional processes could access assistance without disproportionately greater navigation burden.
- Inappropriate AI-only resolution represented high-stakes or uncertain cases in which a student terminated the help-seeking process after chatbot interaction when human verification was required. Lower values are preferable.

The measures were standardized for methodological comparison. They are synthetic constructs rather than validated institutional indicators.

4.3 Adaptive Triage, Escalation, and Ethical Boundaries

The human-in-the-loop condition classified requests according to consequence and uncertainty rather than topic alone.

Low-risk requests included office hours, routine deadline lookup, location of forms, tutoring availability, and straightforward explanation of published procedures. The chatbot could answer these directly when information was grounded in authoritative institutional content.Moderate-risk requests included course-selection comparisons or interpretations requiring student-specific context. The chatbot could collect information and explain options but would encourage adviser verification before action.

High-risk requests included possible delayed graduation, academic standing, exceptions to regulations, withdrawal decisions, financial or immigration consequences, disability-related accommodations, conflicting degree requirements, or circumstances involving significant personal distress. These scenarios required human escalation.The chatbot was modeled to transfer conversation context to the adviser so that the student did not have to repeat the entire problem. Students could also request a person at any time.

The simulated chatbot did not diagnose mental-health conditions, determine academic misconduct, authorize policy exceptions, or make binding progression decisions. Student conversations were assumed to follow data-minimization and institutional governance requirements.No inferential p-values are reported because the observations are synthetic. Empirical validation should use randomized or quasi-experimental deployment, behavioral logs, independent advising-quality review, student interviews, equity analysis, and longitudinal tracking of whether chatbot use strengthens or weakens subsequent human help-seeking.

5. Analysis

5.1 Comparative Help-Seeking and Advising Outcomes

The conventional advising condition produced a simulated help-seeking initiation rate of 58%. Its major strength was human oversight: high-stakes questions that reached advisers were handled by people. Its weakness was access friction, with a median modeled first-response time of 9.6 hours and a support-equity score of 63.

The FAQ chatbot increased help-seeking initiation to 69% and reduced first-response time substantially. However, its limited conversational capacity produced lower resolution for personalized questions.The unstructured generative chatbot generated an initiation rate of 82%, illustrating the behavioral effect of immediate conversational support. Appropriate resolution increased to 81%, but inappropriate AI-only closure reached 27% in cases designated as requiring adviser involvement.

The adaptive human-in-the-loop model produced the strongest balance.

Table 2: Simulated Student Help-Seeking Outcomes

Support Environment	Help-Seeking Initiation	Median First Response	Appropriate Resolution	Appropriate Human Escalation	Help-Seeking Confidence	Support Equity	Inappropriate AI-Only Resolution ↓
Conventional advising + portal	58%	9.6 h	71%	100%	68	63	0%*
Rule-based FAQ chatbot	69%	1.8 min	74%	47%	72	72	18%
Generative chatbot without structured escalation	82%	0.7 min	81%	58%	80	80	27%
Adaptive human-in-the-loop advising gateway	88%	0.9 min	91%	94%	88	89	7%

5.2 Immediate Access Can Increase Help-Seeking but Also Produce Premature Closure

The most significant improvement from chatbot introduction appears in help-seeking initiation. The model suggests that conversational interfaces can lower the threshold for asking a question before the issue becomes severe.

This mechanism is consistent with experimental outreach research. Meyer and colleagues found that chatbot messaging increased student engagement with academic supports, providing causal evidence that conversational technology can affect support-seeking rather than simply answer questions after students independently request assistance.

The generative-only condition reveals the corresponding risk. Immediate answers make it easier to seek help but also make it easier to stop seeking help prematurely.

This distinction is supported by Phung and colleagues' real classroom deployment. Although students could escalate unhelpful AI assistance to instructors, only a minority of unhelpful interactions were escalated.

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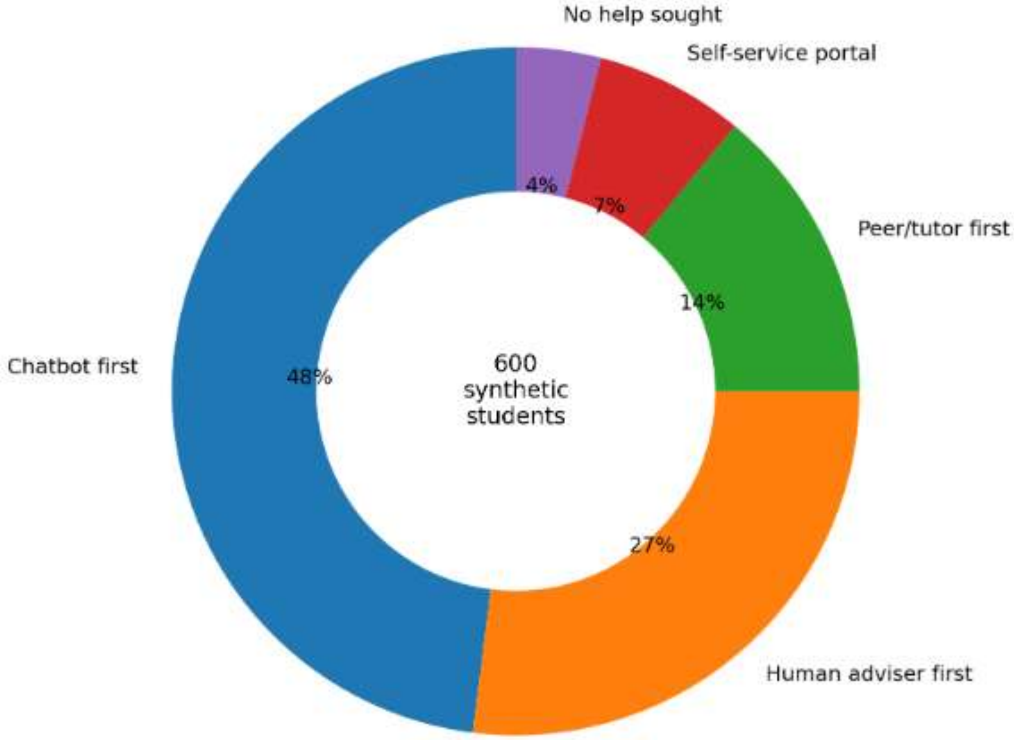
The strongest advising architecture therefore cannot assume that students will always identify when AI assistance is inadequate. The system itself must detect high consequence, low confidence, conflicting evidence, or missing context and actively recommend human review.

5.3 First Help-Seeking Destination in the Hybrid Advising Environment

Graph 1: Simulated First Help-Seeking Destination in a Human-in-the-Loop Advising Environment



In the strongest simulated environment, 48% of students selected the advising chatbot as their first help destination. This supports the gateway function: the chatbot becomes the most common entry point because it is immediate and low friction.However, 27% approached a human adviser directly and 14% first sought assistance from a peer or tutor. Another 7% used a self-service portal, while 4% did not seek help.

The distribution is deliberately not designed to maximize chatbot usage. An effective student-support ecosystem should permit students to select the source most appropriate to their preferences and needs.The substantial continued use of human advisers and peers is particularly important given emerging evidence that heavy generative-AI use may reduce some peer help-seeking. Hyrynsalmi and colleagues found that 43% of students in their sample perceived ChatGPT as reducing their need for peer interaction.

The key analytical finding is therefore that chatbot adoption should be evaluated according to whether it increases successful help-seeking across the whole support ecosystem, not according to the percentage of questions the chatbot prevents from reaching humans.

6. Discussion

6.1 The Best Advising Chatbot Reduces the Threshold for Asking for Help Without Reducing the Value of Human Advising

The present analysis suggests that one of the strongest contributions of an advising chatbot is behavioral rather than informational. Students may know that advisers, tutors, and academic offices exist but still delay contact because the request feels too small, the correct office is unclear, an appointment is inconvenient, or asking another person exposes uncertainty. Conversational interfaces can reduce these initiation costs. Historical chatbot experiments around college transition already demonstrated that personalized conversational outreach could help students navigate complex institutional requirements, and the 2021 experimental study by Meyer and colleagues showed that chatbot communication can increase engagement with academic support during enrolled coursework. The educational value of the chatbot therefore lies partly in making support easier to begin.

This advantage should not be confused with evidence that human advising is obsolete. Academic advising is relational as well as informational. A student deciding whether to change a major may technically need information about course requirements but also need help interpreting uncertainty, professional identity, prior performance, family expectations, financial constraints, and long-term goals. Emerging work on AdvisingWise explicitly recognizes this distinction by using AI for information-intensive work while preserving adviser review and human connection. The model is particularly relevant because a chatbot can retrieve rules quickly while an experienced adviser can recognize what the student's question means within a broader academic trajectory.

A successful chatbot should therefore make human advising more focused rather than less available. Routine questions can be resolved before an appointment, allowing the student and adviser to spend limited meeting time on planning, interpretation, trade-offs, and personal context. The chatbot can also prepare the student by summarizing the issue, identifying relevant rules, and suggesting questions to discuss with the adviser. In this arrangement, automation removes clerical friction while preserving the higher-value functions of advising.

6.2 Chatbot Availability Can Shift Students From Adaptive Help-Seeking Toward Help-Seeking Substitution

The second implication concerns substitution. Generative AI can become so convenient that students use it before considering whether another human being might provide a more valuable form of support. Hyrynsalmi, Tuape, and Knutas found that 50% of their first-year software-engineering respondents used generative AI as a primary help-seeking source and 43% believed ChatGPT reduced peer interaction. Although this study focused on software-engineering learning rather than academic advising, the behavioral mechanism is relevant: an always-available conversational system can change which support source students approach first.

Substitution is not necessarily harmful. Asking a chatbot how to locate a degree audit or interpret basic terminology may be more efficient than waiting for an adviser. The concern arises when the chatbot begins replacing interactions that provide social, relational, or reflective value. A peer can normalize difficulty. A tutor can observe misconceptions over time. An adviser can connect one question to a pattern of academic choices. AI may respond conversationally, but it does not occupy the same institutional and interpersonal role.

The distinction between instrumental help-seeking and answer acquisition is therefore important. Sheese and colleagues found that many student queries to an LLM-powered programming assistant focused on immediate assignment problems rather than deeper conceptual understanding. Advising chatbots could exhibit a similar pattern if students use them only to obtain the fastest actionable answer.

6.3 Human Escalation Must Be Designed as an Active Safety Mechanism Rather Than an Optional Button

The third implication is that escalation cannot depend entirely on student judgment. The instructor-in-the-loop system evaluated by Phung and colleagues illustrates the problem clearly: 22% of AI hints were rated unhelpful, yet only a small fraction of those were subsequently escalated. Students may avoid escalation because it introduces delay, because they are uncertain whether the problem is important enough, or because the anonymity and convenience of AI are precisely what attracted them to the tool.

Academic advising can increase the consequences of such under-escalation. Incorrect interpretation of a prerequisite, degree requirement, withdrawal rule, or progression condition may not become visible until the student attempts to register or graduate. An AI response can also be technically accurate in general while inappropriate for an individual student because of transfer credits, program-specific regulations, financial conditions, immigration status, accommodation requirements, or an approved exception.

The adaptive model therefore treats escalation as a system responsibility. Certain request categories should automatically trigger human review. Other cases should trigger escalation when retrieval sources conflict, information is missing, model confidence is low, the student repeatedly rephrases the same unresolved question, or the consequences of error are high. The chatbot should explain the reason for escalation so that referral is experienced as competent service rather than failure.

Human review also needs to be efficient. Context transfer should allow advisers to see the student's question, relevant institutional sources, information already collected, and the chatbot's uncertainty without forcing the student to repeat everything. The emerging AdvisingWise architecture demonstrates one version of this principle by producing source-informed drafts for adviser validation. Such systems should still be evaluated carefully because adviser approval can become superficial if automation bias encourages reviewers to accept plausible drafts too readily.

7. Conclusion

Academic-advising chatbots can meaningfully change student help-seeking because they alter the cost of beginning a support interaction. Immediate conversational access can reduce search burden, uncertainty about where to ask, and the interpersonal discomfort associated with exposing confusion. Experimental evidence from both college-transition and enrolled-course contexts demonstrates that chatbot outreach can affect real support behavior, including navigation of institutional processes and engagement with tutoring or other academic resources.

The simulation developed in this study illustrates the potential consequences of different implementation choices. Conventional advising produced the lowest modeled help-seeking initiation rate but strong human oversight for students who reached the system. FAQ chatbots improved accessibility but remained limited for personalized issues. Generative advising without structured escalation produced much higher help-seeking initiation while also generating the highest risk of inappropriate AI-only closure. The adaptive human-in-the-loop model achieved the strongest balance, with an 88% simulated help-seeking initiation rate, 91% appropriate resolution, 94% appropriate escalation for high-stakes cases, and a 7% inappropriate AI-only resolution rate.

These values are synthetic and should not be interpreted as expected real-world effect sizes. The contribution instead lies in the distinction between chatbot usage and successful help-seeking. An institution could deploy a chatbot that handles thousands of conversations while simultaneously weakening peer interaction, delaying professional advising, or increasing student reliance on plausible but incomplete answers. Chatbot traffic is therefore an inadequate primary success measure.

The appropriate goal is an advising ecosystem in which AI increases access to human and institutional support rather than simply absorbing demand. Routine information retrieval can be automated. The chatbot can clarify vague questions, help students identify relevant policies, and provide immediate navigation. High-stakes, ambiguous, emotionally consequential, or personalized decisions should move smoothly toward qualified human advisers.

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