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From chatbots to agentic AI: a comparative use case of generative AI for student advising

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Abstract

Universities are increasingly adopting generative artificial intelligence (GenAI) to support student advising, primarily through chatbot-based systems that provide on-demand responses to student inquiries. While these systems improve access to advising information, they remain largely reactive and place substantial responsibility on students to integrate information and manage academic planning. Despite growing interest in agentic AI, little research has examined how increasing levels of AI agency influence advising workflows and decision-support capabilities.

This study employs a design science–based comparative use-case analysis to evaluate two advising artifacts: a chatbot-based advising system and an agentic AI–based advising system. Using two representative advising scenarios, the study compares how the artifacts support planning, decision-making, cognitive effort, and academic risk identification.

The findings suggest that chatbot-based systems are effective for routine information delivery and improving accessibility, whereas agentic AI systems provide stronger support for complex academic planning, proactive risk identification, and self-regulated learning. By examining advising through a workflow and decision-support lens, this study contributes to emerging research on agentic AI by illustrating how differences in AI agency translate into distinct advising capabilities and student support outcomes. The paper concludes with implications for the design and governance of AI-supported advising systems in higher education.

Keywords: agentic AI; generative AI; conversational agents; academic advising; design science research; higher education; decision support

Introduction

Generative artificial intelligence is now a regular part of daily digital life. It changes how people look for information, handle tasks, and make choices. Tools like writing assistants and chatbots are becoming

common, helping people interact with complex information. This shift affects higher education, where students face complicated systems, changing degree requirements, and important academic decisions.

AI systems are already changing how students find and use information in higher education. Research shows that tools like ChatGPT are shifting student habits, often taking the place of traditional search engines because they are fast and feel more personal (Karunaratne & Adesina, 2023; Filson & Atuase, 2024). While these tools can make access easier, educators worry that relying too much on AI may affect students' critical thinking, planning, and independence (Sullivan et al., 2023; Aghaee et al., 2024). This highlights the need for AI literacy and careful system design in education. Academic advising is central to these issues. Good advising helps students stay in school, succeed academically, and graduate on time (Kalamkarian & Karp, 2017). Advisors guide students through degree requirements, course planning, workload management, and understanding the impact of their choices. However, advising takes a lot of resources, and many universities are dealing with more students, fewer advisors, and higher demand for personalized help.

To address these challenges, universities are using AI-powered chatbots to help with advising. Chatbots quickly answer common questions about registration, degree requirements, deadlines, and policies. They are available outside office hours and reduce routine questions, making them a practical option for schools with limited resources (Adamopoulou & Moussiades, 2020). Even with these benefits, chatbot advising systems are mostly reactive. They answer questions but do not guide students through complicated academic planning. Students need to know what to ask, remember earlier answers, and connect information from different conversations. This can be hard for students who are new to higher education, especially first-generation students, and may reduce the usefulness of advising.

Recent developments in AI have led to systems commonly described as agentic AI. Unlike chatbots, agentic AI systems can pursue user-defined goals, decompose complex tasks, retrieve relevant information, generate plans, and monitor progress over time (Wooldridge, 2020). These capabilities align closely with the planning, monitoring, and decision-support activities that characterize academic advising.

Although prior research has examined chatbots in higher education and emerging applications of agentic AI, limited research has compared how these two classes of AI artifacts support advising workflows and student decision-making. Existing studies largely focus on information access, user acceptance, or technology capabilities in isolation, providing limited insight into how increasing levels of AI agency influence planning support, cognitive effort, and academic decision-making. This gap is particularly important because advising involves complex, multi-step decisions that extend beyond information retrieval and require ongoing planning and monitoring.

Accordingly, this study examines how two information systems artifacts—a chatbot-based advising system and an agentic AI-based advising system—address the same advising challenges. Using a design science perspective, the study compares the artifacts with respect to workflow design, planning support, cognitive effort, and decision-support capability. The objective is not to benchmark predictive performance, but rather to evaluate how differences in AI agency shape advising processes and student support.

This study makes three contributions to information systems research and AI-supported advising. First, it provides a structured comparison of chatbot-based and agentic AI-based advising artifacts, illustrating how differences in AI agency influence advising workflows and user support. Second, it extends the discussion

of AI in higher education beyond information delivery by examining advising as a planning and decision-support problem. Third, it offers practical guidance for institutions considering layered advising architectures in which chatbots support routine inquiries while agentic AI systems assist with more complex planning and risk-management tasks.

The remainder of the paper reviews prior work on chatbots, agentic AI, and academic advising, describes the design science comparative approach, presents two advising use cases, and discusses implications for theory, practice, and governance of AI-supported advising systems.

Background and Related Work

Chatbots

Chatbots are AI systems that interact with users using natural language. They are commonly used to give information, answer questions, and help with routine tasks in areas like customer service, banking, healthcare, and e-commerce. Their main advantage is providing quick, consistent answers to many users at once, which often reduces the need for people to handle simple, repetitive requests (Winkler & Söllner, 2018). Most chatbots are designed to react to user prompts and usually work within a narrow conversation. Even though natural language processing has made their replies smoother, chatbots do not usually plan ahead or make decisions on their own. They work best when tasks are simple and can be solved through single question and answer exchanges.

In higher education, chatbots are now widely used, especially for administrative help, learning support, and academic advising. They are popular because they can answer student questions right away, at any time, which makes services easier to access and lightens the load for staff (Adamopoulou & Moussiades, 2020). As more students enroll and advising resources stay limited, chatbots give schools a way to handle routine questions on a larger scale.

In advising, chatbots are mainly used to answer questions about degree requirements, registration, academic calendars, deadlines, and school policies. Research shows that these systems can make students happier with how they get information and can greatly speed up answers to common questions (Mughal et al., 2025). For simple information needs, chatbots usually work well and save time. However, from an information systems point of view, chatbot-based advising still has important limits. These systems rely on students to start the conversation, ask the right questions, and connect information from different chats. Since chatbots usually remember little beyond one conversation, the support they give can feel broken up. This can make things harder for students, especially when advising involves several steps, prerequisites, or long-term goals (Goel & Polepeddi, 2018; Nadarzynski et al., 2021).

Agentic AI

Agentic AI is a new type of intelligent system that acts on its own to achieve goals set by users. From an information systems perspective, these systems extend beyond information retrieval and conversational support by incorporating planning, reasoning, monitoring, and decision-support capabilities within the artifact itself. In this paper, “agentic AI” means systems that can break down an advising goal into steps, find needed information, make and improve plans, and track progress over time. These abilities go beyond just generating responses or retrieving information (Wooldridge, 2020). Unlike chatbots, which handle each

conversation separately, agentic AI systems see each interaction as part of a larger task or goal. Based on early work in artificial intelligence and autonomous agents, these systems can set goals, break tasks into parts, reason, remember, and take action (Wooldridge, 2020).

Agentic AI has been used in areas like healthcare coordination, project management, and complex decision support. In these fields, tasks take place over time and depend on many factors, so simple reactive systems are not enough. Agentic AI systems do more than just respond to input. They also help users by organizing tasks, finding useful information, and tracking progress toward goals (Rai et al., 2019). In higher education, agentic AI is especially useful for student services that require long-term planning and must follow school rules. Tasks like degree planning, choosing courses, and tracking progress build on each other and depend on policies, prerequisites, and what students want to achieve. Agentic AI can help by breaking down these complex tasks into smaller steps and managing information over time.

For academic advising, agentic AI systems can pull data from school databases or APIs, create organized academic plans, and adjust their advice as students' situations change (Belda-Medina & Calvo-Ferrer, 2022). From a design science view, agentic AI is a unique type of tool that handles planning and monitoring within the system itself, instead of leaving these tasks to students. Early research shows that shifting some of the thinking from students to the system can lower mental effort, help students make better decisions, and offer clearer guidance over time, especially when decisions are important and limited by rules (Nadarzynski et al., 2021).

Academic Advising as a Planning Problem

Academic advising provides a useful context for comparing chatbot and agentic AI systems because it requires more than information retrieval. Effective advising involves helping students navigate complex academic requirements, evaluate alternatives, anticipate future consequences, and monitor progress toward long-term goals. Consequently, advising can be viewed as both an information problem and a planning problem. This perspective creates a natural connection among the three concepts discussed in this section. While chatbots primarily support information access and question answering, agentic AI systems are designed to support planning, coordination, and decision-making activities that are central to the advising process.

Academic advising has moved well beyond simply providing students with information. At its core, advising is a planning and self-regulation process that requires students to set academic goals, plan course sequences, monitor their progress, and reflect on outcomes. Research on self-regulated learning consistently shows that these processes are central to academic success, particularly in complex educational environments where decisions are cumulative and constrained (Panadero, 2017; Zimmerman, 2008). Zimmerman's self-regulated learning framework, in particular, highlights the cyclical nature of learning, emphasizing that students must actively plan, monitor, and adjust their actions over time to achieve desired outcomes (Zimmerman, 2008; Russell et al., 2020). Advising systems that focus primarily on information delivery risk overlooking these critical planning and monitoring stages. Traditional chatbot-based advising systems often assume that students are able to independently manage self-regulatory tasks, such as integrating information across semesters or anticipating downstream consequences of academic decisions. Without explicit support for planning and progress monitoring, these systems may provide correct answers without meaningfully improving student decision-making (Yin et al., 2020; Fan et al., 2024). This limitation is particularly consequential for students who are unfamiliar with institutional structures or lack prior experience navigating complex academic pathways.

Agentic AI systems offer a different approach by embedding planning and monitoring directly into the advising artifact itself. By supporting goal decomposition, structured planning, and ongoing evaluation, agentic AI can create a more adaptive and supportive advising environment that evolves alongside students' academic journeys (Dwivedi, 2025; Neumann, 2025). Rather than treating advising interactions as isolated exchanges, these systems engage students in a continuous process that aligns more closely with how academic decision-making unfolds in practice. Emerging research suggests that AI systems designed around these principles can actively foster self-regulated learning. Studies show that AI-assisted applications can support all three phases of self-regulated learning—planning, monitoring, and reflection—leading to improvements in learner outcomes, self-efficacy, and overall satisfaction (Ou, 2025; Afzaal et al., 2023). Through tailored feedback and adaptive guidance, agentic AI systems help students not only set academic goals but also follow through on them over time (Afzaal et al., 2021).

Viewed through this lens, the distinction between chatbot-based and agentic AI advising systems becomes clearer. Chatbots are effective at delivering relevant information efficiently, but they often lack the interactivity and continuity required to support deeper self-regulatory processes (Yin et al., 2020). Agentic AI systems, by contrast, are designed to play a more proactive role throughout the advising process, supporting planning, progress monitoring, and reflection—key components of successful self-regulation (Dwivedi, 2025; Schwabe, 2021). Framing academic advising as a planning problem therefore provides a useful foundation for comparing these two system designs. It helps explain how differences in artifact capabilities translate into differences in cognitive support, decision quality, and advising outcomes. Prior studies indicate that students who engage with systems that encourage structured planning and reflection report higher levels of motivation and academic achievement (Wild & Grassinger, 2023; Wang & Li, 2024). Together, these findings highlight the potential for agentic AI-based advising systems to meaningfully enhance student decision-making and learning outcomes, forming the basis for the comparative use-case analysis presented in this study.

Taken together, the literature suggests that chatbot-based and agentic AI systems represent different approaches to supporting advising activities. Chatbots are primarily designed to facilitate information access and transactional interactions, whereas agentic AI systems are designed to support more complex planning, monitoring, and decision-support functions. This distinction provides the conceptual foundation for the comparative analysis presented in this study and motivates the examination of how varying levels of AI agency influence advising workflows and student support.

Research Methodology and Design Science Framing

This study uses a comparative use-case approach grounded in design science research (Hevner et al., 2004; Peffers et al., 2007). Rather than testing causal relationships or predictive performance, the objective is to evaluate how alternative information systems artifacts address the same advising problem. Consistent with design science principles, the focus is on artifact utility and how different design choices influence planning, decision-making, and advising support.

To maintain realism while avoiding institution-specific assumptions, the study uses a generic U.S. university setting. Two advising artifacts are examined: (1) a chatbot-based advising system and (2) an agentic AI-based advising system. The chatbot artifact represents current AI-supported advising systems that primarily provide information through reactive question-and-answer interactions, whereas the agentic

AI artifact represents an emerging class of systems capable of planning, monitoring, and goal-oriented reasoning. Comparing these artifacts within a common advising context enables a structured examination of how increasing levels of AI agency influence advising workflows and decision-support capabilities.

The comparison focuses on four evaluation dimensions derived from advising, decision-support, and design science literature: planning capability, context retention, cognitive support, and proactive risk identification. These dimensions are consistent with prior work on decision-support systems, self-regulated learning, and design science artifact evaluation (Hevner et al., 2004; Zimmerman, 2008; Rai et al., 2019). They were selected because they capture key differences in how advising artifacts support student decision-making. The analysis examines how each artifact structures advising workflows, manages information across interactions, supports planning activities, and assists students in identifying and responding to academic risks.

The use case scenarios, detailed below, were selected because they represent common advising situations encountered across higher education institutions and require students to coordinate information across multiple constraints and time horizons. The first scenario focuses on degree planning and graduation pathway optimization, while the second focuses on workload management and academic risk detection. Together, these scenarios provide an appropriate context for evaluating planning and decision-support capabilities.

Following design science principles, the advising workflows and outcomes associated with each artifact are compared across the two scenarios. The purpose of this evaluation is not to determine which system is universally superior, but rather to identify how differences in artifact design influence advising support, student cognitive effort, and decision-making processes.

The following scenarios illustrate how the two advising artifacts address common advising challenges and demonstrate differences across the evaluation dimensions identified above.

Use Case Scenario 1: Early Graduation and Course Planning

Scenario Description

In this example, a second-year undergraduate student wants to finish their degree in less than four years. They are seeking advice on three things: if early graduation is possible with their current progress, which courses to take next semester to stay on track, and whether their course load is too heavy. This is a common advising situation where students must think about degree requirements, prerequisites, course order, and workload. Because these decisions are interconnected and influence future academic options, this scenario is particularly useful for evaluating planning capability, context retention, and decision-support effectiveness across advising artifacts.

Chatbot-Based Advising Flow

In a chatbot-based advising system, the process begins when a student asks a question like, “Can I graduate early?” The chatbot responds with general information about graduation requirements, such as the

minimum credits or typical time needed to finish a degree. If the student needs more details, they must ask follow-up questions about completed credits, major requirements, prerequisites, and available courses.

In this system, each question and answer is handled separately. For example, after learning how many credits are needed to graduate, the student must ask on their own which major courses remain, what prerequisites those courses have, and if the workload is manageable. The chatbot does not put this information together into a full academic plan. As a result, the student has to gather the answers, track different requirements, and create their own course schedule. While the chatbot provides accurate information, it does not help with overall planning or decision-making.

Agentic AI Advising Flow

In contrast, the agentic AI advising system sees the student's request to "graduate early" as a planning task, not just a simple question. When it gets this goal, the system starts a multi-step process. First, it gathers degree requirements and the student's completed courses. Then, it checks prerequisite structures, course order rules, and which courses are offered each term. Finally, the system creates a semester-by-semester plan that shows how early graduation could be possible.

Along with creating a detailed plan, the agentic AI also checks how heavy the workload is and points out possible risks with a faster schedule. For example, it might highlight semesters with several demanding courses or spot prerequisite issues that could slow progress. The student gets a complete advising report that explains which courses to take and why the plan is either practical or risky. This process makes planning easier and gives advice that matches the student's goal.

Use Case Scenario 2: Academic Risk and Course Load Balance

Scenario Description

The second use case focuses on academic risk detection and course load balance. In this scenario, a student is enrolled in multiple high-intensity courses within a single semester, such as advanced quantitative, technical, or writing-intensive classes. The student seeks advice on whether the current schedule is manageable and whether changes should be considered to reduce academic risk. Because students may not recognize potential overload until academic performance begins to decline, this scenario is particularly useful for evaluating proactive risk identification, cognitive support, and monitoring capabilities across advising artifacts.

Chatbot-Based Advising Flow

Within the chatbot-based system, the student asks a question such as *"Is my course load too heavy this semester?"* The chatbot responds by offering general advice about workload management or suggesting that students balance difficult courses across semesters. In some cases, the chatbot may recommend consulting a human advisor for personalized guidance.

However, the chatbot does not evaluate the student's full course schedule as a combined workload. It does not assess interactions among courses, consider historical patterns of academic difficulty, or anticipate cumulative risk. As with the first use case, the chatbot provides generic information but does not engage in proactive or context-aware analysis. The responsibility for recognizing overload and deciding whether to adjust the schedule remains with the student.

Agentic AI Advising Flow

The agentic AI system approaches this scenario by treating academic risk assessment as a continuous monitoring task. After retrieving the student's full course schedule, the system evaluates workload intensity based on course characteristics, prerequisite difficulty, and known performance patterns. It identifies potential overload conditions, such as multiple demanding courses scheduled concurrently, and estimates the likelihood of academic strain.

Rather than waiting for the student to ask additional questions, the agentic AI proactively surfaces concerns and offers alternative scheduling options. For example, it may recommend deferring one high-intensity course, suggest substituting an elective, or propose a revised plan that maintains degree progress while reducing risk. This proactive intervention represents a key distinction in artifact capability, highlighting how agentic AI supports anticipatory decision-making rather than reactive information delivery.

Contrasting Advising Workflows: Chatbot and Agentic AI Use Cases

Together, the two use case scenarios illustrate how differences in AI agency fundamentally shape advising workflows and decision-support capabilities. Across both scenarios, the chatbot and agentic AI artifacts address the same advising challenges but distribute planning, monitoring, and information-integration responsibilities differently between the student and the system. These differences provide a basis for evaluating how artifact design influences cognitive support, decision-making, and advising outcomes. As shown in Figure 1, chatbot-based advising systems follow a largely reactive workflow in which guidance is provided only after a student initiates a question.

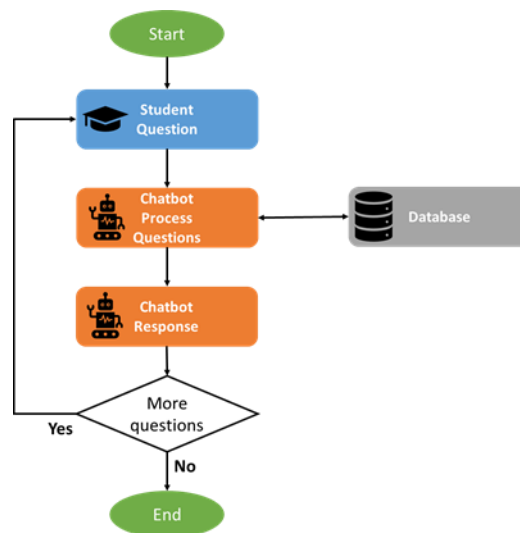


Figure 1. Basic Workflow for Chatbot

In this setting, the interaction can be summarized as: Student Question → Chatbot Response → Repeat. While such systems can deliver accurate and timely information, the guidance they provide is often fragmented. Key cognitive tasks—such as planning, integrating information across requirements, and assessing academic risk—remain externalized to the student. As a result, effective use of chatbot-based advising systems depends heavily on student initiative and sustained cognitive effort. From an advising

perspective, this workflow positions the chatbot primarily as an information-access artifact rather than a decision-support artifact. While students can obtain accurate answers, they remain responsible for integrating information, evaluating alternatives, and developing actionable academic plans.

By contrast, agentic AI advising systems adopt a more goal-oriented and proactive workflow, as illustrated in Figure 2. Rather than responding to isolated queries, the agentic system treats advising as an integrated planning process aligned with the student's broader academic objectives.

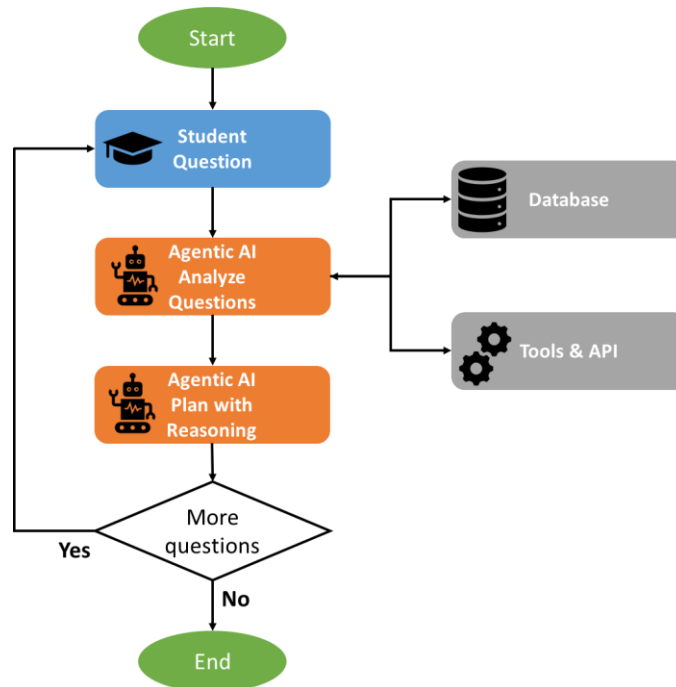


Figure 2. Basic Workflow for Agentic AI

This workflow can be summarized as: Student Question → Question Decomposition by Agentic AI → Targeted Data Retrieval via APIs (as needed) → Agentic AI Response with Reasoning → Repeat. Here, the agentic AI functions as a decision-support artifact that actively structures the advising process. It externalizes complexity, anticipates downstream consequences, and synthesizes information in ways that reduce cognitive burden on the student while maintaining alignment with long-term goals. This shift reflects a redistribution of cognitive effort from the student to the advising artifact. Rather than requiring students to coordinate multiple pieces of information independently, the agentic AI system assumes a more active role in planning, monitoring, and evaluating potential academic pathways.

From a design science research perspective, these workflow differences are central to evaluating the utility and effectiveness of advising artifacts. While chatbot-based systems primarily improve access to advising information by providing timely, on-demand responses, their underlying design limits their ability to support more complex advising tasks. As summarized in Table 1, chatbot advising systems rely on a reactive interaction style, responding only to student-initiated queries. Consequently, planning capability remains minimal, and memory is typically short-term, constrained to the immediate conversational context. These design characteristics shift much of the cognitive burden onto students, who must integrate fragmented information, anticipate downstream consequences, and independently manage academic risks.

In contrast, agentic AI advising systems are explicitly designed to support goal-oriented and multi-step advising processes. As shown in Table 1, agentic systems incorporate persistent memory and structured planning capabilities that allow them to reason across multiple constraints, academic requirements, and time horizons. By externalizing planning and synthesis tasks, agentic AI substantially reduces cognitive load on students, enabling them to focus on decision-making rather than information coordination. Moreover, proactive risk detection is embedded directly within the workflow, allowing the system to identify potential issues—such as course sequencing conflicts or unmet prerequisites—before they materialize.

Viewed collectively, the dimensions in Table 1 illustrate a progression from information-oriented support to planning-oriented support. The comparison suggests that increasing levels of AI agency do not simply improve information delivery but fundamentally alter how advising tasks are performed. In particular, planning capability, persistent context, and proactive monitoring enable agentic AI systems to function as decision-support artifacts rather than information-retrieval tools.

Table 1. Comparison of Chatbot-Based and Agentic AI Advising Systems

Dimension	Chatbot Advising	Agentic AI Advising
Interaction Style	Reactive	Goal-oriented
Planning Capability	Minimal	Multi-step
Memory	Short-term	Persistent
Cognitive Load on Student	High	Reduced
Proactive Risk Detection	None	Embedded
Design Complexity	Low	High

Although these advantages come at the cost of greater design complexity, the increased complexity reflects a deliberate trade-off in artifact design rather than a limitation. In design science terms, agentic AI systems exhibit higher utility for advising contexts characterized by uncertainty, interdependence, and long-term planning demands. Taken together, the workflow analysis demonstrates that differences in AI agency have implications beyond system functionality. They influence how advising knowledge is organized, how cognitive responsibilities are distributed between students and technology, and how effectively advising systems can support complex academic decision-making over time.

Discussion

The comparison between chatbot-based and agentic AI systems shows that the two approaches address different parts of the advising challenge rather than competing to solve the same problem. Chatbots are effective at improving access and efficiency. They make advising information easier to obtain and reduce friction for routine questions. However, because they rely on a reactive question-answer format, they provide limited support for more complex tasks such as long-term academic planning, course sequencing, or anticipating future risks.

Agentic AI systems, by contrast, are designed to take on a more active role in the advising process. By externalizing planning, reasoning, and monitoring activities, agentic systems shift some of the cognitive work away from students and into the system itself. This design aligns more closely with how self-regulated learning unfolds in practice, where goal setting, planning, and progress

monitoring are ongoing and interconnected rather than isolated actions. Instead of simply responding to individual questions, agentic AI supports students in navigating broader academic goals over time.

From a design science perspective, these findings highlight how seemingly small design choices—such as whether a system plans, remembers, or monitors progress—can lead to very different user experiences and outcomes. Importantly, this work does not suggest that agentic AI should replace chatbot-based systems. Rather, the findings point to the value of treating the two as complementary artifacts, each well suited to different advising needs. Chatbots excel at handling straightforward, high-frequency inquiries, while agentic AI is better positioned to support higher-order advising tasks that involve coordination, foresight, and decision-making.

Theoretical Implications

This study adds to IS and design science research by showing that AI agency is not simply present or absent, but develops through specific design choices. By comparing chatbot and agentic workflows, the analysis shows how features such as planning, memory, and proactive monitoring affect what an AI system can actually do. This shifts the conversation about agentic AI from abstract descriptions to observable differences in artifact behavior and user support.

The findings also provide a more practical way to think about self-regulated learning with AI support. Instead of expecting students to handle all planning and monitoring themselves, the results show that some of this work can be embedded within the advising artifact. This changes the focus from how students use AI tools to how students and technology share responsibility for planning, monitoring, and decision-making.

From a decision-support perspective, the findings suggest that increasing levels of AI agency expand the role of advising systems beyond information delivery. While chatbot-based systems primarily support information access, agentic AI systems function more as decision-support artifacts by integrating information, evaluating alternatives, and assisting with planning activities (Rai et al., 2019). This distinction contributes to emerging research on agentic AI by illustrating how differences in artifact capabilities translate into differences in workflow design and user support.

More generally, this study contributes to emerging research on agentic AI by showing its potential value in advising contexts where decisions unfold over time and involve multiple constraints. By directly comparing agentic AI with chatbot-based advising, the analysis helps clarify when additional system complexity may create meaningful value rather than simply adding technological sophistication.

Practical Implications

For universities, the results suggest that the greatest value may come from deploying AI systems in a layered or hybrid manner. Chatbots can serve as an effective front line for intake and routine questions, ensuring accessibility and responsiveness at scale. Agentic AI systems can then be used to support more complex advising tasks, such as degree planning, identifying potential risks, and helping students stay aligned with long-term goals.

This layered approach has practical advantages for both students and institutions. Students receive timely answers to simple questions while also gaining structured support for more demanding decisions. At the same time, advisors and administrators can use agentic AI to reduce manual planning effort and improve consistency across advising interactions, particularly in resource-constrained environments.

For system designers and decision-makers, the findings emphasize the importance of matching AI capabilities to intended use cases. Deploying chatbots for complex planning tasks may unintentionally increase student cognitive burden, while introducing agentic AI without clear integration into advising workflows may limit its impact. Thoughtful alignment between system design and advising goals is therefore essential.

Governance and Ethical Considerations

As advising systems become increasingly autonomous, governance considerations become more important. Agentic AI systems may require access to sensitive student information, including academic records, degree progress, and performance indicators. Institutions must therefore ensure appropriate privacy protections, transparency regarding how recommendations are generated, and clear accountability for advising decisions.

Human oversight remains particularly important when recommendations may influence academic progression or graduation outcomes. Rather than replacing professional advisors, agentic AI systems should be viewed as decision-support tools that augment human expertise. Establishing appropriate governance mechanisms and review processes can help ensure that increasing levels of AI autonomy remain aligned with institutional policies and student interests.

Limitations and Future Research

This study has several limitations. First, the analysis is conceptual and relies on representative use-case scenarios rather than implemented advising systems. Consequently, the findings should be interpreted as a comparative evaluation of advising artifacts and workflows rather than as evidence of actual system performance. Accordingly, the results provide design-oriented insights into advising system capabilities rather than evidence of causal effects on advising outcomes. Second, the scenarios were intentionally designed to represent common advising challenges and do not capture the full diversity of advising contexts across institutions, programs, and student populations. Third, the study does not evaluate student perceptions, advising outcomes, or learning effectiveness through direct observation or experimentation.

These limitations create several opportunities for future research. Future studies should evaluate agentic AI advising systems through pilot implementations, user studies, controlled experiments, and field deployments involving both students and advisors. Such work would provide empirical evidence regarding usability, advising quality, cognitive load reduction, and academic outcomes. Longitudinal research may also help examine how students interact with agentic advising systems over time and whether these systems influence self-regulated learning, academic planning behaviors, and student success.

Conclusion

This paper compares chatbot-based and agentic AI systems for student advising using a design science approach. By examining how two advising artifacts address the same advising challenges, the study highlights how differences in AI agency influence advising workflows, cognitive support, and decision-making. Rather than focusing on predictive performance, the analysis evaluates artifact utility and explores how different design choices shape advising processes and student support.

The findings show that chatbot-based systems improve access and scalability by efficiently handling routine advising questions. However, because they primarily operate through reactive interactions, they are less effective for complex advising tasks that require planning, information integration, and ongoing progress monitoring. In contrast, agentic AI systems provide stronger decision-support capabilities by incorporating planning, monitoring, and proactive guidance into the advising process. These capabilities reduce the cognitive burden placed on students and support more goal-oriented academic decision-making.

Overall, the results suggest that chatbot-based and agentic AI systems should be viewed as complementary rather than competing approaches to AI-supported advising. By comparing these artifacts through a workflow and decision-support lens, this study contributes to research on agentic AI and illustrates how increasing levels of AI agency can transform advising systems in higher education. Understanding the strengths and limitations of these approaches will be important as institutions seek to balance scalability, personalization, and responsible AI use in student support services.

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Generative AI tools are used mainly for language improvement.

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