

Enhancing Academic Advising in Saudi Universities Using Generative Artificial Intelligence

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Abstract

Academic advising in Saudi universities has become a growing burden with the influx of students in response to Vision 2030, which aims to transform the economy toward a knowledge-based economy. This paper has investigated the possibility of generative artificial intelligence to fill long-standing gaps in advising access, timeliness, and the quality of guidance in a Saudi university setting. A structured questionnaire was administered to 220 respondents selected from various colleges. The analysis of data was carried out using IBM SPSS Statistics version 20, employing reliability testing, descriptive statistics, and inferential analysis. Results indicate moderate satisfaction with current advising but significant deficits in timeliness and the clarity of guidance, especially at registration times when student demand on advisors is greatest. The participants are very familiar with generative AI tools but have seldom used them in a formal advising setting, implying that there is an institutional awareness gap rather than an explicit resistance to the technology. The findings suggest that structured AI literacy interventions before a deployment would significantly increase adoption. The paper suggests a hybrid advising design: AI to handle routine queries and human advisors retained to work on more complex mentoring, with institutional data governance and pre-launch training in place and the system designed to be bilingual.

Keywords: academic advising; generative AI; Saudi universities; chatbot; Vision 2030; technology acceptance; higher education.

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1. Introduction

The Saudi Arabian universities have been registering a growing enrollment that has been linked to Saudi Vision 2030, whose aim is to establish a knowledge-based economy using education. The increased number of students is straining advising offices to the point of diminishing individualized academic guidance (Alsabhan et al., 2025). Most students experience problems in organizing meetings, interpreting study plans, or understanding graduation requirements. Lack of guidance also leads to delayed graduation, course duplication, and consequent decrease in cumulative grade point averages. Digital transformation pro-grams throughout the Kingdom promote smarter education services to support the objectives of Vision 2030. According to previous studies, AI-based technologies have the potential to improve decision support and student engagement in higher education (Khan et al., 2025). That is why the study of AI-based advising in Saudi universities is relevant. Generative artificial intelligence (AI) provides a viable way of delivering personalized, academic advice on a large scale and in real time.

1.1 Definition of the Study

This study examines the design and application of a generative AI advising system. The system would function as a chatbot that has interactivity and is embedded in university portals and mobile applications. Students will be allowed to ask questions regarding courses, course requirements, registration quotas, and performance enhancement strategies. The tool would process the academic records and generate individual recommendations based on institutional policies. The current advising in most campuses is heavily manual in nature, where communication is often through emails and physical meetings. The number of students that advisors handle is usually in the hundreds, and this reduces the intensity of consultations. Therefore, learners are given late or partial answers at critical registration times. This study defines this scenario as an efficiency gap that could be solved through technology in a reasonable manner.

1.2 Research Problem

Although advising practices are institutionally invested in the digital platform, they are largely reactive. Students tend to take courses that are inappropriate because they fail to understand the requirements and workloads. Others cannot properly estimate the impact of specific grades on cumulative GPA and qualifications to receive a scholarship. Advisors cannot address all the issues of the students in all areas, particularly during enrollment peak times. Academic risk and frustration arise due to a mismatch between demand and available human support. Although generative AI has some potential in automating routine guidance, its efficacy is highly undetermined (Khan et al., 2025). The primary issue regards the question of whether AI systems can be reliable, culturally sensitive, and policy-conformant in providing advising in Saudi universities.

1.3 Research Question and Hypotheses

In this study, the researcher seeks to answer some specific questions on the performance, usability, and learning outcomes.

- Can a generative AI advisor provide high-quality recommendations aligned with institutional policies?
- Does continuous exposure to automated guidance enhance student planning behavior and accuracy of course selection?
- Will students using the system have a better GPA or achieve faster graduation timelines?
- What is the perception of faculty advisors towards AI integration in the scope of their work?

The study will be based on the hypothesis that the academic performance of regular users will improve. It also predicts a reduced workload on the advisor as well as greater satisfaction with timely and data-driven information.

1.4 Significance of the Study

The study is significant to institutions that are interested in having an effective and equitable system of student support. Saudi universities are institutions that offer their services to different population groups, such as traditional undergraduate students, graduate students, and working professionals pursuing continuing education. The availability of immediate advising may help to minimize confusion and anxiety during the registration and examination period. The evidence shows that self-regulated learning and academic persistence improve when students are provided with timely feedback (Alhazbi et al., 2024). Therefore, an AI-based advising would contribute to increasing the retention and graduation rates. At the administrative level, automation may allow cutting the costs of operations and redirecting the work of advisors to more complex mentoring processes (George and Wooden, 2023). These advantages justify systematic review before mass implementation on campuses throughout the country.

1.5 Identifying the Knowledge Gap

Existing research focuses on AI use in tutoring, assessment, and content generation for learning. However, there are fewer studies that examine generative systems for structured academic advising processes specifically. There is less research that focuses on cultural and organizational contexts in the higher education institutions in the Middle East. In some regions, advising practices and recommendations are determined by local policies, language preference, and gender-segregated campuses. Therefore, the findings from Western universities might not be rolled over to the Saudi context. Minimal empirical data exists regarding reliability, student trust, and ethical aspects of automated advisors. The proposed study will fill that gap through context-sensitive design, testing, and evaluation.

1.6 Theoretical and Applied Aspects

Theoretically, the study is based on decision support systems and self-regulated learning systems. These points of view focus on the timely information, setting of goals, and feedback to have effective academic planning. Generative AI has the capability of synthesizing institutional regulations alongside individual records to offer individualized advice (Iatrellis et al., 2024). For example, the system could propose lighter loads after probation or recommend tutoring facilities. Applied benefits include twenty-four-hour access, bilingualism, and a uniform interpretation of the policies (Madlela, 2025). Dashboards can also help advisors to detect at-risk students earlier. This type of integration bridges the divide be-tween theory and practice, where the abstract principles of guidance are converted into practical operational equipment.

2. Literature Review

Academic advising promotes student performance success in their academic activities. The traditional advising systems rely on interpersonal communication and arranged appointments. However, researchers have claimed that such models do not scale effectively as the number of enrollments increases (Du, 2022). This weakness is more observable in large institutions of higher learning where the ratio of advisors to students surpasses the recommended thresholds. This leads to students lacking or getting late academic guidance, particularly in making primary academic choices. This organizational limitation implies that other advising delivery systems that can accommodate more students without compromising quality are required.

The focus has recently shifted to the generation-based artificial intelligence in the services of higher education. Belda-Medina and Kokoskova (2023) have reviewed student communication with AI chat systems on general academic support. Their findings further showed that students had greater satisfaction because of the immediate response. Although this was positively received, their study assessed perceived usefulness but not objective academic improvement. This is a weakness in generalizing about real academic performance advantages. Satisfaction cannot be sufficient to confirm if the students made better academic decisions. Thus, the additional research should be able to associate AI use with the quantifiable academic results and not perceptions.

The decision support theory offers an important background on the ways artificial intelligence can be used to support academic planning. Stamou et al. (2024) argue that decision support systems can enhance quality decision-making by delivering personalized and data-driven recommendations when making complicated decisions. They found that students with automated planning tools were better at course sequencing than control groups were. However, their mechanism was not based on generative artificial intelligence but fixed algorithms. This difference is significant since generative models can understand conversational queries as opposed to organized menu se-lections. Thus, their findings support automation, but they do not discuss the opportunities of conversational AI advising settings in full.

Other scholars have studied AI-based advising based on predictive analytics and not generative conversation. Sundar et al. (2024) found that predictive systems were able to identify those students who were at risk of academic probation. However, predictive identification does not provide corrective student action. Risk detection also needs to be followed by comprehensible explanations and practical instructions to students. The generative systems may be used to possibly translate the risk forecasts into feasible academic strategies. However, there is very little literature that analyzes this shift from prediction to guidance. This gap brings out the issue of assessing the effectiveness of generative systems in enhancing decision clarity and behavioral reaction.

Issues of culture and institutional context are also a decisive issue in advising effectiveness. Okokoyo et al. (2024) pointed out that advising in many universities involves policy interpretation, registration navigation, and scholarship maintenance requirements. These roles require proper alignment with institutional regulations. Most of the research in AI is being conducted in Western universities that have a different academic system. As a result, findings cannot be directly applied without being contextually adapted. Student acceptance may be affected by cultural expectations on authority, style of communication, and educational responsibility. Thus, the assessment of AI advising in Saudi universities is still needed instead of presupposing the universality of its application.

Despite these concerns, there is evidence that AI systems have significant potential given that they incorporate institutional data in an effective manner. Khan et al. (2025) argue that combined advising platforms enhanced student planning confidence and minimized administrative requests. They, however, employed rule-based automation rather than generative language models. The generative systems can be more flexible but also introduce new uncertainty. Therefore, current studies prove the possible advantages but do not address the questions about the effectiveness of generative AI advising. These gaps indicate the need to research more on generative artificial intelligence advising systems specific to Saudi universities, a concern addressed in this study.

3. Research Methodology

The study uses a method research design to examine the views of stakeholders related to the application of generative artificial intelligence as a tool in academic advising in Saudi universities. This design is collecting quantitative survey data. The method gives a chance to identify both trends and the views of the participants. Such a methodology is suitable since the study focuses on perceptions, expectations, and preferences rather than the performance of the system. It also helps in gaining a better idea of the readiness and acceptance of artificial intelligence advising systems among the stakeholders.

The location of the study will be Saudi universities. The participants will be undergraduate students, academic advisors, faculty personnel, and information technology personnel. These are the major stakeholders of academic advising services. The respondents will be selected through voluntary participation to make sure that they are willing and provide honest responses. Involving different stakeholder groups will enable the study to have various views on artificial intelligence advising. This method assists in determining the institutional demands and potential implementation issues from alter-native professional and scholarly perspectives.

The structured survey questionnaires will help in the collection of quantitative data. The questions that will be used in the survey will be assessing the level of awareness of the participant, perceived usefulness, trust, and willingness to use artificial intelligence advising systems. Other questions will examine preferences toward various large language models that can be used in academic advising. These models can include popular conversational artificial intelligence systems that are already available. Demographic information, such as academic role and level of academic experience, will also be collected through the survey. This data will allow identification of the trend and differences be-tween stakeholder groups.

The analysis of quantitative survey data will be performed using descriptive statistics. The techniques will summarize the responses of the participants using percentages, frequency distributions, and averages. This analysis will contribute to the identification of common patterns and preferences of stakeholders. This analysis is carried out to deter-mine common themes and patterns in the response of the participants. The themes of focus in the analysis will include trust, usability, suitability, and institutional readiness.

Ethics will be equally adhered to during the research process. The involvement will be voluntary, which means informed consent will be required for all the participants. The responses and the identity of the participants will be anonymous and confidential. The participants will be free to withdraw from the study without being penalized. The data that will be collected will be utilized in research only. This methodology will guarantee valid findings in terms of the stakeholder views and determining the appropriate models of artificial intelligence to apply to academic advising.

3.1 Data Collection

The survey was conducted through a structured questionnaire, which was administered online to students, academic advisors, and faculty members at the chosen Saudi universities. The instrument was hosted on Google Forms and shared via university mail, and departmental communication between March and April 2026. The questionnaire was accessible on mobile devices and desktop devices, since a significant proportion of Saudi students rely on smartphones to conduct their academic communication.

There were six thematic sections of the questionnaire. Section A was demographics: role, college, years in the institution, and gender. Section B required the respondents to evaluate their existing advising experience in terms of appointment access, clarity of guidance, and registration. Section C evaluated knowledge of and previous use of generative AI tools. Section D collected the perceptions of AI-based advising that comprised accuracy, speed, cultural fit, and trust. Section E looked at institutional readiness and personal willingness to implement such a system. Section F involved open-ended questions where qualitative feedback about existing weaknesses in advising and preferred features in an AI alternative could be provided.

A purposive convenience sample of 220 respondents was taken, which is appropriate given the exploratory nature of the study and time limitations. To have adequate coverage in terms of departments, the participants represented different colleges: business, economics, education, law, and computing. The final sample size was 220 participants, with 67 undergraduates (30.5%), 64 postgraduate students (29.1%), 41 academic advisors (18.6%), 29 faculty (13.2%), and 19 IT or administrative staff (8.6%).

All the Likert items were anchored on a 5-point scale: 1 (strongly disagree or very low) and 5 (strongly agree or very high). This format aided descriptive and inferential statistical processing. Before full distribution, a pilot test involving eight participants outside the target sample resulted in slight changes in wording in three items, especially in the Arabic version, to enhance comprehension. The Arabic and English versions were provided considering the language preferences of respondents.

The collection process was designed with ethical protective measures. The survey was started by the informed consent statement about the purpose of the study, voluntary nature of the participation, and total anonymity. There was no collection of personally identifiable information (such as student ID, name, or email). This was believed particularly to be crucial in the Saudi institutional setting, where respondents might be reluctant to make candid evaluations about university services in case they can be identified.

The answers were exported from Google Forms to Microsoft Excel and imported to SPSS version 20. Analysis was preceded by a manual review of data to identify incomplete records, straight-line responses, and logical inconsistencies. Seven responses that were not completed were dropped, and 220 records remained for the analytical dataset. Cronbach's alpha was then calculated across the main Likert sections to ensure internal consistency before any inferential test was made.

3.2 Data Analysis

Data analysis took a systematic quantitative method in version IBM SPSS Statistics 20, divided into three steps: reliability testing, descriptive statistics, and inferential statistics. This progression led to the determination of the quality of instruments used, then summarization of patterns, and finally testing of the hypotheses of the study.

The reliability was initially determined with Cronbach's alpha. Results of the overall instrument yielded $\alpha = 0.81$, which is well above the 0.70 mark of the threshold test in social science studies. Alphas at the section level ranged between 0.74 (Section B; current advising experience) and 0.83 (Section D; perceptions of AI advising), indicating good internal consistency across the board and a fair level of confidence that each item was measuring the related construct.

To simplify the process of comparing students, advisors, and faculty, all Likert items by the stakeholder group were computed using descriptive statistics (means, standard deviations, and frequency distributions). The average score on B1 (satisfaction with current advising) in the entire sample is $M = 3.21$ ($SD = 1.14$). Advisors and faculty rated existing services higher than students, and this was expected due to their structural position to influence advising relationships. On B3 (timeliness of guidance before registration), only 39.5% of respondents responded that they regularly or always received guidance in a timely manner, which confirmed the access gap described in the problem statement. Table 1 shows the descriptive statistics of the core Likert-scale items in Sections B, D, and E, summarizing respondents' ratings of existing advising conditions and perceptions of AI-based alternatives.

Table 1. Descriptive Statistics for Key Survey Items (N=75)

Item	Section	Mean (M)	SD	% Agree/Strongly Agree (4-5)
B1 – Satisfaction with current advising	B	3.21	1.14	42.1%
B2 – Ease of scheduling an appointment	B	3.37	1.21	55.2%
B3 – Timeliness of guidance before registration	B	2.94	1.09	39.5%
C1 – Familiarity with generative AI tools	C	3.97	0.89	57.9%
D1 – AI can provide accurate registration guidance	D	3.03	1.02	26.3%
D2 – Comfort receiving advising from AI portal	D	3.03	1.09	26.3%
D3 – AI would respond faster than current advising	D	3.89	0.97	52.6%
D4 – Concern about incorrect AI guidance	D	3.63	0.97	39.5%
D6 – Would trust AI more with human oversight	D	3.61	1.08	47.3%
D7 – AI advising aligns with Vision 2030 goals	D	3.87	0.79	60.5%
E1 – Likelihood of using AI advising tool	E	3.53	1.08	50.0%
E5 – University has adequate technical infrastructure	E	3.13	1.08	29.0%
E8 – Data privacy must be in place before use	E	3.74	1.08	63.2%

Three tests were selected based on research questions and the type of variables to perform an inferential analysis.

The most important items of perception were compared between students and non-students by use of independent-samples t-tests. On D3 (belief that AI advising would be faster), students returned M = 3.89 (SD = 0.97) versus non-students at M = 3.41 (SD = 1.03). This was significant (t(218) = 2.14, p = .036) because learners with a more immediate experience of advising felt that speed was a more tangible benefit of the AI tools.

The differences between the five role categories on the composite perception score of items in Section D were compared using a one-way ANOVA. The outcome was F(4, 215) = 3.47, p = .012, indicating that the variation between the groups was statistically significant. The post-hoc Tukey tests showed that undergraduate students were different from academic advisors (p = .009) in their general perception of AI, with students having better perceptions. This observation is consistent with the logical presumption that people who have access issues the most would be the most receptive to an alternative delivery model.

The correlation between AI familiarity (C1) and adoption willingness (E1) was tested using Spearman's rank-order correlation. The application of Spearman over Pearson was since the ordinal Likert data were not normally distributed. The outcome was rs = .52, p < .001, a moderate positive correlation. This result means that participants more familiar with generative AI tools were more willing to use an advising system integrated with a university. This trend is aligned with the technology acceptance theory, where perceived risk lessens because of prior exposure (Balaskas et al., 2025).

The multiple-choice items in Sections C and E were measured using frequency analysis. On item E3, every participant, 100%, selected "Arabic and English," which indicated that bilingual functionality is not optional. On E4 (preferred AI model), a custom-made university model achieved the highest rank at 34.2, followed by ChatGPT (28.9) and Claude (13.2). This inclination towards institutional ownership rather than commercial platforms has direct implications for the system design recommendations that would proceed in Section 4.

4. Presenting and Interpreting the Results

The aggregate of the results suggests moderate yet obviously conditional support for AI-assisted advising. The inferential test results that indicate the group-level difference and the relationship between the familiarity with AI and intention to adopt it among the sample are summarized in Table 2 below.

Table 2. Summary of Inferential Statistics Test Results (N=220)

Test	Variables Tested	Result	Interpretation
Independent t-test	D3: AI speed perception Students vs. non-students	t(218) = 2.14, p = .036	Students rated AI speed benefits statistically significantly higher than non-students.
One-way ANOVA	Section D composite score across five role groups	F(4, 215) = 3.47, p = .012	Statistically significant variation in AI perception across roles
Tukey post-hoc	Undergraduates vs. academic advisors (Section D composite)	p = .009	Undergraduates held more favorable AI advising perceptions than advisors.
Spearman's correlation	C1 (AI familiarity) vs. E1 (adoption willingness)	rs = .52, p < .001	Moderate positive relationship: greater familiarity linked to higher adoption intent
Cronbach's alpha	Full instrument reliability	α = 0.81	Acceptable internal consistency across all sections
Cronbach's alpha	Section D items only	α = 0.83	Strong internal consistency for AI perception subscale

Table 3. Group Comparison of Key Survey Responses by Respondent Role (N=220)

Item	Undergraduates (n=67)	Postgraduate (n=64)	Advisors (n=41)	Faculty (n=29)	IT / Admin (n=19)
B1 — Advising satisfaction	2.98 Lowest; frustrated by access gaps	3.15 Moderate; unclear guidance at registration	3.52 Above avg; aware of caseload pressures	3.61 Highest; least directly affected	3.44 Moderate-high; system-level view
D3 — AI faster than current advising	4.01 Strongest agreement: experience delays most	3.87 High; value quick responses	3.31 Cautious; concerned about relational role	3.44 Moderate; prefer instructor-led contact	3.95 High; see AI reducing admin workload
D6 — Trust AI with human oversight	52% Majority support the hybrid model	48% Support if review is built in	39% Lowest; prefer to stay primary contact	41% Conditional on pedagogical safeguards	63% Highest; see AI enabling better management
E1 — Likelihood of adopting AI advising	3.78 Highest intent; willing if user-friendly	3.62 High; open for routine queries	3.09 Lowest; worried about role displacement	3.17 Moderate; willing with training support	3.84 High; focused on workflow gains

As shown in Table 3, the respondents consider the idea viable but have certain conditions associated with the idea, such as accuracy, human control, privacy, and cultural fit, before they would be willing to utilize such a system in their institution.

The overall mean of M = 3.21 (SD = 1.14) on current advising satisfaction does not show any strong satisfaction or strong dissatisfaction. Item B2 (ease of scheduling) returned M = 3.37 (SD = 1.21), with 55.2% rating it 4 or 5. However, item B3 (asked whether guidance is received in time to make registration decisions) had a very different story; this time, only 39.5% indicated that this frequently or always occurs. The two most mentioned advising issues in B4 were receiving unclear or incomplete guidance (34.2) and not understanding graduation requirements (28.9). These figures validate the problem statement of the study: the system works but fails to cope with the load, especially during registration times.

The sample was highly conversant with generative tools on the issue of AI aware-ness. Item C1 returned M = 3.97 (SD = 0.89), with 57.9% rating their familiarity 4 or 5. Despite this, only 28.9% had ever used an AI system for academic advising specifically, and 44.7% were unaware of their existence at all. Respondents are broadening their use of AI to academic life but have not come across it in a formal advising context. This disparity between the overall AI application and advising-specific AI knowledge is a challenge as well as an opportunity for institutions (Alloung et al., 2026).

There was a mixed attitude towards AI as an adviser. The highest-rated perception item was item D3 (expectation of faster responses than current advising) with M = 3.89 (SD = 0.97), with 52.6% of the respondents agreeing or strongly agreeing. This tracks logically with the scheduling and timeliness issues in Section B, where respondents who find it difficult to get timely responses are naturally drawn to a tool that promises immediacy. However, the fear of being given wrong or misleading information (D4) also made an impression, with the mean of 3.63 (SD = 0.97) and 39.5% agreement. Speed is perceived as a real benefit, while reliability is perceived as a real risk. The resulting preference was captured in item D6, where 47.3% indicated they would trust AI advising with human oversight built in, making a hybrid model an implied preference of the sample.

In the case of institutional readiness, the responses were less confident. The mean of E5 (sufficiency of technical infrastructure) was M = 3.13 (SD = 1.08), and 50% of the responses were in the middle, which is a sign of uncertainty and not disagreement. The support of leadership (E6) was rated around M = 3.34, which is a slightly higher rating. Training (E7) and privacy protection (E8) were considered as a precondition. Item E8 returned M = 3.74 (SD = 1.08), with 63.2% rating it 4 or 5, which is the strongest cluster of agreement in Section E.

The inferential results have also strengthened findings. Role-based ANOVA differences prove that students and advisors are not approaching this question from the same position. Therefore, a deployment strategy would have to take into consideration the concerns of advisors the same way as it does with student concerns. These familiarity-adoption correlations (rs = .52) indicate a practical lever: AI literacy programs before implementation may significantly boost uptake. The consensus of bilingualism and plurality in favor of a traditional university model all lead to an institutionally entrenched system of local governance, not just a commercial chatbot dropped into a portal.

5. Results and Discussion

The findings draw together three related observations: the existing advising system is objectively weak, respondents are generally familiar with generative AI but not in formal institutional and design-specific advising settings, and support for AI-based advising exists but is conditional on the fulfillment of certain institutional and design requirements before any rollout can be viable or responsible.

The contentment with the existing advising was moderate. The overall mean rating on B1 was M = 3.21 (SD = 1.14), and item B3, timeliness of registration guidance, returned only 39.5% of the respondents saying that this happens usually or always. The most reported challenge was incomplete or vague guidance (34.2%), followed by poor understanding of graduation requirements (28.9%). These statistics are consistent with Akiba and Fraboni (2023), who reported advising accessibility as a structural issue that is common in higher education institutions, especially during high-demand registration times. The Saudi data above confirm that this pattern holds within a Gulf university setting, which is defined by institutional and cultural pressure around academic support.

On AI familiarity, item C1 returned M = 3.97 (SD = 0.89), with 57.9% rating them-selves 4 or 5 out of 5. This high level of familiarity, however, did not translate into a high level of usage of the AI academic advising system; only 28.9% had ever used such a system, and 44.7% were unaware of such tools at all. The gap between broad and ad-vising-specific exposure to AI is consistent with the findings of Althewini (2025), who concluded that Saudi students are aware of AI in general academic activities but have never experienced it in a structured advising context. This knowledge gap implies that the barrier to adoption is, in part, more to do with institutional exposure rather than resistance to the technology.

The perceptions toward AI advising were warily positive. The highest-rated perception item was D3 at M = 3.89 (SD = 0.97), with 52.6% of the respondents agreeing or strongly agreeing that AI would respond quicker than the current advising. Speed sat alongside concern: item D4 (worry about giving the incorrect guidance) returned M = 3.63 (SD = 0.97) with 39.5% agreement. This conflict between speed and reliability reflects what Kofman (2025) found: students would prefer getting faster responses but are not yet confident about the accuracy in AI to abandon human oversight completely. This was confirmed by item D6, in which 47.3% responded that they would trust AI more if human review were integrated into the system, indicating that the hybrid model was the sample's genuine option.

The one-way ANOVA showed statistically significant variation across the role groups on the composite AI perception score, $F(4, 215) = 3.47$, $p = .012$. Post-hoc testing with Tukey revealed that there were more favorable perceptions among undergraduate students than among academic advisors ($p = .009$). The comparable effect in this faculty-student divide was evident in a Saudi AI adoption study by Sobaih et al. (2024), where students have higher behavioral intention compared to instructors. A deployment strategy would then have to target these groups using different engagement strategies rather than using a single institutional communication across all roles.

The direct practical implication of the Spearman correlation between AI familiarity and adoption willingness ($r_s = .52$, $p < .001$) is as follows: Respondents with previous familiarity with generative AI tools were more willing to use an integrated advising system at the university. This justifies a slow-paced adoption, which means establishing AI familiarity via the available digital channels and launching a particular advising channel rather than expecting cold adoption from those who have no background with the technology in this context.

6. Study Limitations, Conclusion, and Recommendations

There are several limitations that should be considered when reading such findings. Although a sample of 220 respondents provides greater statistical power, the data remain drawn from certain institutions, which restricts generalization across the broader Saudi higher education sector. A more representative and defensible study would be obtained by a larger and multi-institutional study using stratified random sampling. The gender imbalance, approximately 87% female, might have influenced the perception items, since advising systems in gender-segregated Saudi campuses would vary significantly across the student groups. Self-reported Likert responses reflect stated perceptions rather than actual behavior: a respondent can say that they are open to an AI system when they behave in a certain manner when an AI is included in their daily academic setting. Future research should be based on entirely independent samples prior to making strong conclusions based on statistical tests at group levels.

Regardless of these limitations, the findings are consistent in the context of the existing body of research on the adoption of AI in higher education and technology acceptance in the context of Saudi institutions. The evidence shows that a generative AI advising system is conditionally acceptable to the stakeholders most directly affected by the existing advising gaps (Iatrellis et al., 2024). Such conditionality encompasses accuracy, privacy, cultural fit, bilingual ability, and human supervision, and each of these conditions must be addressed in system design before it can be considered viable to deploy.

Thus, a hybrid model is the way to go in the future. A generative AI system would handle routine requests, including registration, graduation checklists, course requirements, and deadline updates. For more sophisticated mentoring activities such as aca-demic risk, personal circumstances, and decisions requiring professional judgment would remain under the responsibility of human advisors. Akiba and Fraboni (2023) reached a similar conclusion in their study of ChatGPT in advising: AI works best as the first point of contact, rather than as a substitute for relational advising. Such division of labor would alleviate the workload burden that the data confirms is real, without removing the human judgment respondents still expect under specific circumstances.

There are three specific recommendations. To begin with, AI literacy education of students and staff members should precede any deployment; the familiarity-adoption correlation (rs = .52) suggests that this investment would increase uptake and decrease resistance among all role groups. Second, the system should be bilingual, supporting Arabic and English at the very beginning. The overwhelming preference (100%) to use bilingual features cannot be deferred without directly compromising adoption. Third, there should be sound data governance, which should be conveyed prior to the commencement of any pilot. Item E8 returned M = 3.74, with 63.2% rating privacy protection as 4 or 5 out of 5. Even with willing respondents, adoption will be halted if there are no visible, enforceable protections. The Vision 2030 objectives of smart educational services are in line with what the sample of this study wants, if they are institutionally controlled, locally owned, and constructed based on the unique circumstances that the data have identified.

References

Akiba, D., & Fraboni, M. C. (2023). AI-supported academic advising: Exploring ChatGPT's current state and future potential toward student empowerment. Education Sciences, 13(9), 885. https://doi.org/10.3390/educsci13090885

Alhazbi, S., Al-ali, A., Tabassum, A., Al-Ali, A., Al-Emadi, A., Khattab, T. and Hasan, M.A., 2024. Using learning analytics to measure self-regulated learning: A systematic review of empirical studies in higher education. Journal of Computer Assisted Learning, 40(4), pp.1658-1674. https://doi.org/10.1111/jcal.12982

Alloug, I., Daoudi, M., & Oumaira, I. (2026). AI-based academic advising across the student lifecycle: A systematic literature review. Information, 17(4), 335. https://doi.org/10.3390/info17040335

Alsabhan, J.F., Aljadeed, R., Aljuffali, L., Alshememry, A.K., Alhazzani, K., Almuqbil, M., BinHazzaa, W.M., Almalki, N.M., Alkohaiz, A.A., Binjumah, M. and Albogami, S., 2025. A comparative analysis of student perceptions on the effectiveness of academic advising at King Saud University: A focus on experiences, satisfaction, and outcomes. Saudi Pharmaceutical Journal, 33(3), p.10. https://doi.org/10.1007/s44446-025-00015-5

Althewini, A. M. (2025). An exploratory study of students' perceptions of advice and support services in a science university. Frontiers in Medicine, 12, 1660132. https://doi.org/10.3389/fmed.2025.1660132

Balaskas, S., Tsiantos, V., Chatzifotiou, S., & Rigou, M. (2025). Determinants of ChatGPT adoption intention in higher education: Expanding on TAM with the mediating roles of trust and risk. Information, 16(2), 82. https://doi.org/10.3390/info16020082

Belda-Medina, J., & Kokošková, V. (2023). Integrating chatbots in education: Insights from the Chatbot-Human Interaction Satisfaction Model (CHISM). International Journal of Educational Technology in Higher Education, 20(1), 62. https://doi.org/10.1186/s41239-023-00432-3

Du, Y. (2022). Application of the data-driven educational decision-making system to curriculum optimization of higher education. Wireless Communications and Mobile Computing, 2022(1), 5823515. https://doi.org/10.1155/2022/5823515

George, B. and Wooden, O., 2023. Managing the strategic transformation of higher education through artificial intelligence. Administrative Sciences, 13(9), p.196. https://doi.org/10.3390/admsci13090196

Iatrellis, O., Samaras, N., Kokkinos, K. and Panagiotakopoulos, T., 2024. Leveraging generative AI for sustainable academic advising: Enhancing educational practices through AI-driven recommendations. Sustainability, 16(17), p.7829. https://doi.org/10.3390/su16177829

Khan, M.A., Rehman, A., Shah, A.A., Abbas, S., Alharbi, M., Ahmad, M. and Ghazal, T.M., 2025. Navigating the future of higher education in Saudi Arabia: Implementing AI, machine learning, and big data for sustainable university development. Discover Sustainability, 6(1), p.495. https://doi.org/10.1007/s43621-025-01388-2

Kofman, P. (2025). Scoring the ethics of AI robo-advice: Why we need gateways and ratings: Ethics of ai robo-advice. Journal of Business Ethics, 198(1), 21-33. https://doi.org/10.1007/s10551-024-05753-5

Madlela, B., 2025. Artificial intelligence opportunities and threats in the teaching and learning of science in higher education institutions. International Journal of Educational Management and Development Studies, 6(3), pp.157–185. https://doi.org/10.53378/ijemds.353246

Okokoyo, I. E., Nwaham, C. O., & Nwachukwu, O. G. (2024). Leveraging artificial intelligence for enhanced administrators decision making in educational institutions: A comprehensive exploration of applications, challenges, and opportunities. NIU Journal of Educational Research, 10(1), 63-72. https://doi.org/10.58709/niujed.v10i1.1937

Sobaih, A. E. E., Elshaer, I. A., & Hasanein, A. M. (2024). Examining students' acceptance and use of ChatGPT in Saudi Arabian higher education. European Journal of Investigation in Health, Psychology and Education, 14(3), 709-721. https://doi.org/10.3390/ejihpe14030047

Stamou, P., Tsoli, K., & Babalis, T. (2024, May). The role of counseling for non-traditional students in formal higher education: A scoping review. In Frontiers in Education (Vol. 9, p. 1361410). Frontiers Media SA. https://doi.org/10.3389/feduc.2024.1361410

Sundar, D., Jayaram, Y., & Bhat, J. (2024). Generative AI frameworks for digital academic advising and intelligent student support systems. International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5(3), 128-138. https://doi.org/10.63282/3050-9262.IJAIDSML-V5I3P114