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Enhancing Academic Advising Through AI: A Conceptual Model for Furhat Robot Adoption in Higher Education

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Abstract

Artificial Intelligence (AI) in post-secondary education is revolutionizing academic advising through accessible, efficient, and tailored help for students. Traditional advising methodologies are inhibited by advisor availability (AA) issues, administrative inefficiencies (AE), language obstacles (LB), and problems related to AI dependability and trust (RT). Through a controlled survey, this study investigates determinants of AI-based academic advising (AP) preference among university students. It develops a new conceptual model that explains AI adoption. The results of hypothesis testing concur with primary relationships: Reduced Advisor Availability (AA) has a significant impact on Administrative Efficiency (AE) ($r = 0.772$, $p < 0.05$) and AI augments process flow while reducing human advisor reliance. Moreover, Higher Administrative Efficiency (AE) is directly related to AI Preference (AP) ($\chi^2 = 18.32$, $p = 0.028$), implying that students prefer AI if it makes the advising process easier. However, Language Barriers (LB) failed to have any significant impact on AI Preference ($p > 0.05$), which implies that language access alone cannot help increasing AI adoption. Increased AI Reliability and trust (RT) has a positive influence on AI Preference (AP), and it is critical to ensure reliable, unbiased AI recommendations in academic advising. The new conceptual model integrates these results, proving that AA, AE, LB, and RT make decisions regarding students' AI adoption. Universities can achieve optimal adoption by improving AI reliability, administrative integration, and hybrid AI-human advising designs. Future research must examine long-term adoption trends in AI, cross-cultural variations, and ethical concerns to advance AI-based advising systems for higher education.

***Keywords**:* Academic advising, AI Academic Advising, Furhat Robot, Advising conceptual model, hybrid AI-human advising.

1. Introduction

The academic advising process is of great importance in universities as it helps students select suitable courses and specializations based on their interests and capabilities. The academic advisor not only introduces the students to the college and its departments but also educates them about the academic difficulties they may face and how to prepare study plans and schedules (Almaghaslah & Alsayari, 2022). However, the lack of academic advisors can negatively affect student choices and expose them to uncertainty in choosing their major. Additionally, the gender and competency of the academic advisor can also affect students' preferences (Choompunuch et al., 2022). To address these challenges, the proposed project aims to investigate the possibility of using social robots as academic advisors. These robots will be designed to reduce the burden on advisors and specialists and provide all services to students in the same language as the student, without regard to the gender of the academic advisor. As part of robot technology, advanced humanoid robots are used in education as embodied social agents, providing personalized lessons through one-on-one interactions and improving educational outcomes (Polakow e al., 2022). Many robots have been developed and used in the education sector, such as NAO, Pepper, and Furhat. Social robots are attractive due to their positive behavior and social responsiveness, making them engaging and enjoyable for students Yousif J., 2021). Figure 1 presents the number of studies and implementations involving robots such as Furhat, NAO, Pepper, Chatbots, and AI Advisors over time from 2010 to 2025.

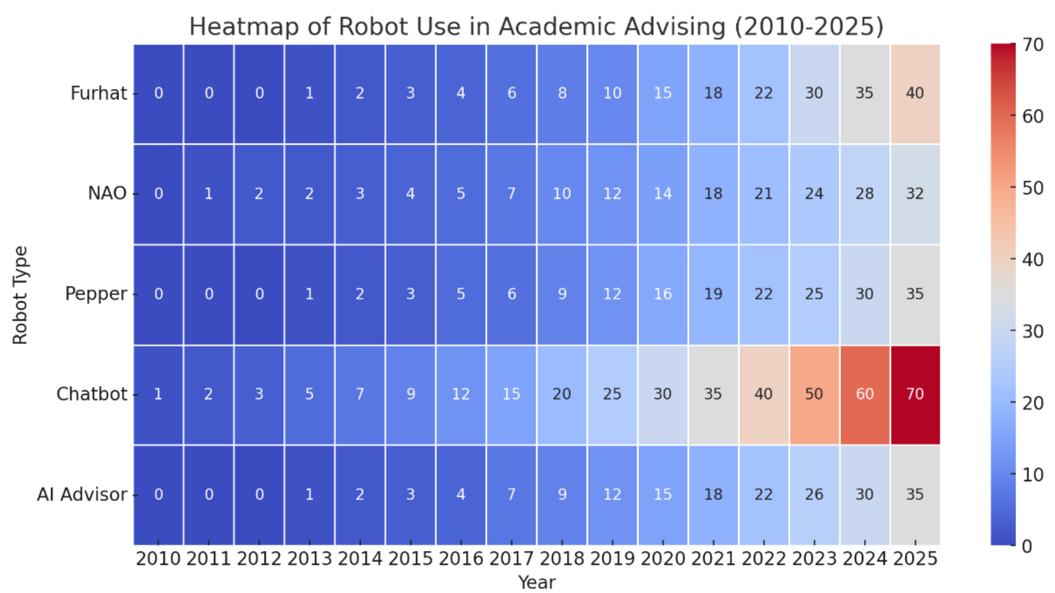

Figure 1: The number of studies and implementations involving robots over time from 2010 to 2025

Furhat is a social robot that has many features that make it suitable for academic advising, such as its ability to communicate in several languages, act as a teacher in explaining concepts, and take on the role of a conversation as an academic advisor (Ågren & Silvervarg, 2022).

- Challenges with academic advising

There needs to be more academic advisors to always serve students they need them. Low Student Engagement with Advisors impacts advising negatively. Also, the lack of time except during designated working hours represents an obstacle for the student who needs guidance throughout the semester. There needs to be more alignment across different departments. This can lead to miscommunication, duplication of effort, and overall inefficiency.

- Proposed Solution

Empower advisors with intelligent tools based on Social Robot for easy access and use, which use actionable analytics to identify those in need and how best to assist them. This paper examines the role and impact of using social robots as academic advisors in Oman universities. Also, it aims to provide insights into how modern information technology can be leveraged to enhance the academic advising process and improve student outcomes as shown in Figure 2.

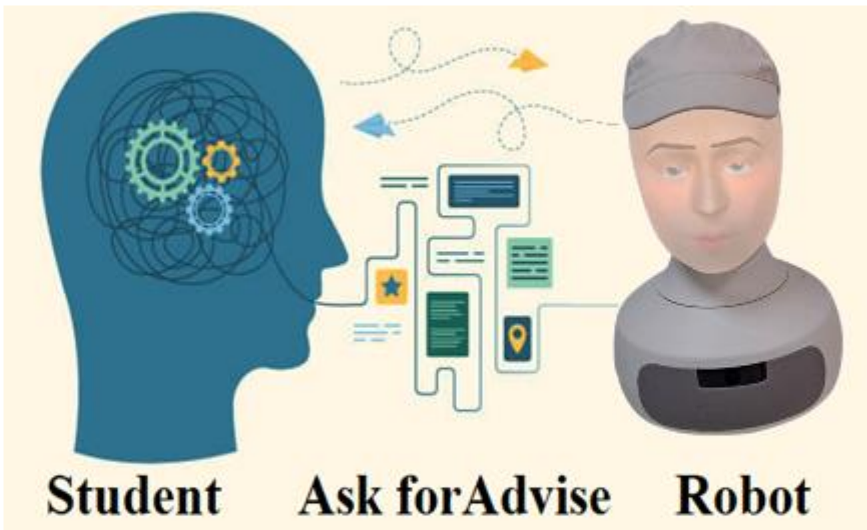

Figure 2: the role and impact of using social robots as academic advisors

2. Literature Survey

Online Academic advising is a crucial component of higher education, providing students with the guidance and support they need to succeed academically and professionally (Fricker, T., 2015). The following literature summarizes some key research studies on academic advising. Study by Bilquise (Bilquise et al., 2024) investigates the determinants of the intention of university students to use AI-driven academic advising chatbots based on a conceptual model integrating TAM, UTAUT, sRAM, and SDT. Data collected from 207 UAE students were analyzed using PLS-SEM. Findings indicate that perceived ease of use and social influence significantly influence chatbot adoption, while perceived usefulness, autonomy, and trust do not. The study contributes theoretically and practically to the effective adoption of chatbots in academic advising contexts. The paper by Aguila (Aguila et al., 2024) analyzes using Llama 2, a large language model (LLM), fine-tuned with student admission questions at the International University - Vietnam National University. Results show that admission consulting with LLM significantly improves data confidentiality and students' comfort levels over traditional approaches. Although initial technology failures were encountered, fine-tuned Llama 2 provided accurate linguistic analysis and reliable performance. This approach focuses on the potential contribution of LLM to higher education, effectively serving the students by providing personalized and confidential admission-related consulting services. The literature suggests that social robot-based academic advising can be an effective tool for providing personalized guidance and support to students.

FURHAT robots can create a positive and engaging atmosphere for students. They can be particularly effective for first-generation college students, international students, or those at risk of dropping out of college (Kamelabad & Skantze, 2023). However, further research is needed to explore the long-term effectiveness and impact of FURHAT-based advising on student success. Gupta et al. (2023) developed an AI-powered chatbot using RASA on Raspberry Pi 4, deployed via a React-based tablet interface, for Indira Gandhi Delhi Technical University for Women. The chatbot, based on a dataset of recurring questions grouped as examination, admission, and general, serves rapidly and correctly with efficient efficiency. Results attest to very little human intervention, increased query processing, and productive user control, showing significant potential towards enhancing student support and rationalizing administrative interactions within university contexts.

The study by El-Sayed (El-Sayed et al, 2022) explored some key research studies on academic advising using robots (El-Sayed et al, 2022). The study by Kuhail et al. (2022) highlights that while chatbots with personalities have impacted user engagement and satisfaction, most chatbot designs prioritize functionality and accuracy over interpersonal communication style. Previous studies on personality-imbued chatbots have mainly focused on user preference and satisfaction, with little exploration of the effect on behavioral qualities such as trust, engagement, and perceived authenticity. To address this gap, the study provides a detailed design of a personality-imbued chatbot for academic advising and reports on an experiment that examined the impact of different personality traits (agreeableness, conscientiousness, and extraversion) on trust, authenticity, engagement, and intention to use the chatbot. The findings indicate that chatbot personality positively affects perceived authenticity and intended engagement, while student gender does not significantly influence their perception of chatbots.

In Polakow's study (2022), social robots were investigated as academic advisors for helping students make decisions. Furthermore, they investigated how cognitive falsities affected student choices when advising by two randomly selected robots. Then, they determined and compared the agreement percentage with the assigned robots using t-tests. Based on the results, the robots impacted on the students' decisions, attitudes, and agreement with the robots. Academic advising based on using robots is a relatively new area of research. However, it is gaining traction as an innovative way to support student's academic and career goals (Bianchi & Briere, 2021). The study by Tiroyabone and Strydom (2021) highlights the importance of academic advising for students. It provides them with relevant information, helps them understand the university better, and fosters a meaningful relationship with the institution through an advisor and various advising initiatives. The paper offers international perspectives on academic advising and reflects on its development in South Africa, focusing on the University of the Free State. The study shows the positive impact of advising before and during the pandemic and provides lessons for the future of academic advising in South Africa.

Another study by Søraa et al. (2021) examines the perceptual differences among elementary school children aged 6-13 towards three social robots: Pepper, AV1, and Tessa. The study was conducted at the Norwegian national research fair, where children interacted with the robots, and data was collected through surveys and qualitative discussions. The findings suggest that children's perceptions of presence differ depending on the robot's function and "aliveness,". There is a difference in relating robots to personal relations with one's grandparents versus older adults in general. Children's perceptions of robots were generally positive and exploratory, and they reflected on their grandparents having a robot. Chan et al. (2019) conducted a systematic review of 37 empirical studies to describe academic advising schemes for nursing undergraduates and examine the perspectives of advisors and advisees towards the schemes. Six key issues were identified: insufficient information and communication, time management, lack of training, outcome evaluation, and implications for nursing education. Despite some barriers, advisors and advisees held positive views of the schemes, which benefited students and advisors. Sufficient training, better time management, and various communication tools are needed to increase effectiveness. Also, a study by Nwankwo, W. (2018) presents a design for an automated "AdvisorBot" to enhance student support and course advising efficiency. The design reflects a virtual support system model that combines agent and object-oriented approaches and is intended to address the inefficiencies observed in existing student support services in Nigerian tertiary institutions. The ready implementation specification of AdvisorBot is expected to provide students with quick and easy access to valuable information and feedback on issues involved in student advisement.

Further studies should investigate the effects of different scheme elements on advising outcomes. Parks (2015) explored the challenges faced by academic advisors when advising student veterans and aimed to identify ways in which advisors can help student veterans adjust to higher education. The study involved 51 student veterans in a quantitative survey and five in a qualitative portion. The analysis identified four themes: recognition, knowledge, research, and education and integration. The findings revealed that academic advisors have little understanding of their veteran student advisees and military experience, leading to reliance on stereotypes that can negatively impact advising. Educating advisors about military culture is crucial to reducing the isolation experienced by many student veterans and helping them integrate into the campus community. Overall, the literature suggests that academic advising is critical to student success in higher education. Effective advising can help students develop a sense of belonging, navigate complex academic requirements, and achieve their academic and career goals. The study by Leite et al. (2013) examines the evolving field of human-robot interaction (HRI) and emphasizes the importance of understanding how users interact with robots over long periods. The paper reviews current research on long-term interaction between users and social robots, including their main features and findings. The study also suggests directions for future research and discusses open issues that need to be addressed in this field. Table 1 summarizes the current research studies on long-term interaction between users and social robots.

The word cloud synthesizes the core themes from diverse academic advising studies, demonstrating the growing significance of AI-driven tools, social robots, and chatbot technologies in supporting and enhancing student success across educational contexts. Figure 3 shows the word cloud of studies about academic advising systems. Bilquise et al. (2024) emphasized ease of use and social influence as significant predictors for students adopting AI-driven chatbots for academic advising. They Highlighted "Chatbot," "AI-driven," "ease of use," and "social influence". The study by Aguila et al. (2024), underlined the potential benefits of large language models (LLMs) like Llama 2 in improving confidentiality and comfort in admission consulting contexts. They explained the terms "Llama 2," "linguistic accuracy," "confidentiality," and "comfort". The terms "FURHAT", "social robots," "engagement," and "students" are discussed by Kamelabad and Skantze (2023). It highlights the capability of social robots, specifically FURHAT, to increase student engagement and provide personalized academic support, particularly to at-risk or international students. The study by Gupta et al. (2023) associated with the terms "RASA," "Raspberry Pi," "React," and "efficient query processing". It reflects the successful development and implementation of an efficient Raspberry Pi-based chatbot deployed through React for enhanced query handling.

Kuhail et al. (2022) derived the terms "Personality," "authenticity," "engagement," and "trust". They explored how chatbots with personality traits significantly impact user authenticity perceptions and engagement intentions. The terms "Decision," "agreement," and "cognitive falsities" are linked to the experimental findings of Polakow (2022), which indicate social robots' notable influence on students' academic decisions, attitudes, and agreement. Søraa et al. (2021) showed positive children's perceptions toward different social robots, highlighting the relationship between robot function and perceived aliveness by highlighting the terms "Pepper," "AV1," "Tessa," "children," and "perception". Chan et al. (2019) stressed the importance of adequate advisor training, efficient time management, and effective communication for successful academic advising. They impact the terms of "Advising schemes," "training," and "time management". Nwankwo (2018) proposed a virtual chatbot to enhance advising efficiency through rapid access to student information. They emphasized terms like "AdvisorBot," "efficiency," and "quick access". Parks explored the terms "Veterans," "recognition," "knowledge," and "integration" (2015). They emphasized the need for improved advisor awareness of veteran students' experiences to facilitate better integration and support. Leite et al. (2013) highlighted the significance of understanding sustained human-robot interaction and identifying areas requiring future research. Ther presented terms of "Long-term," "interaction," and "research gaps".

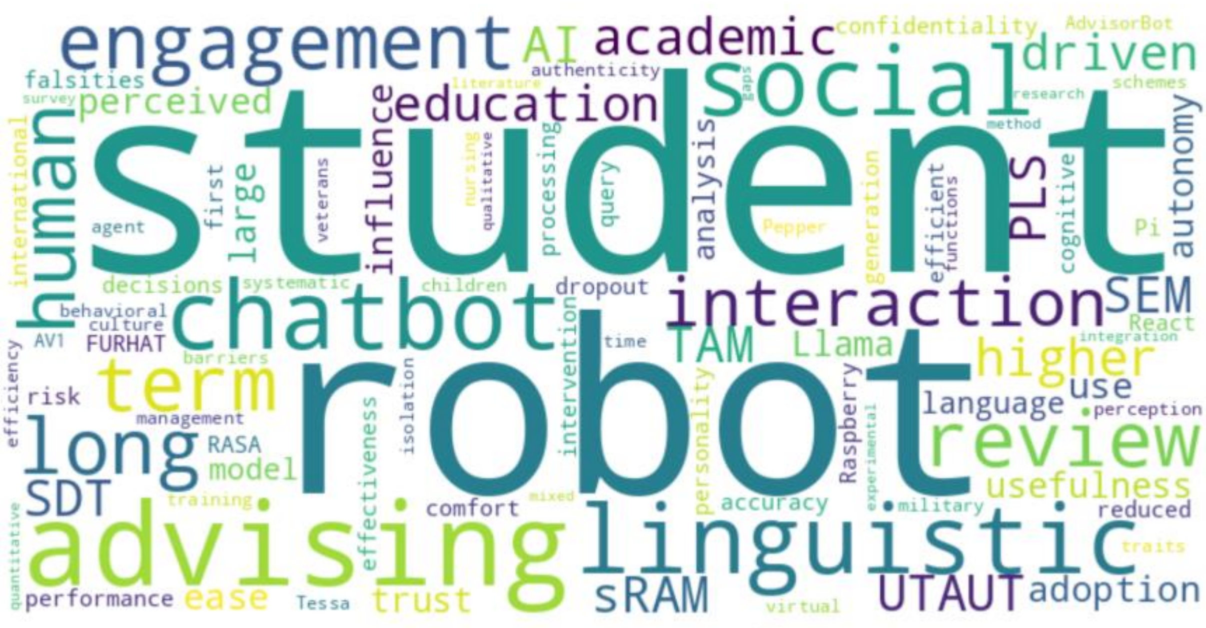

Figure 3: Word cloud of studies about academic advising systems.

Table 1: summarizes the literature survey studies.

Author(s)	Method	Robot/Tool Name	Finding	Participants	Data Type
Bilquise et al. (2024)	TAM, UTAUT, sRAM, SDT, PLS-SEM	AI-driven chatbot	Ease of use & social influence significantly impact adoption; usefulness, autonomy, trust less so	207 UAE university students	Quantitative
Aguila et al. (2024)	Fine-tuning, Linguistic analysis	Llama 2	Improved confidentiality & comfort; high linguistic accuracy & reliable performance	International University - VNU students	Quantitative
Kamelabad & Skantze (2023)	Literature review	FURHAT	Positive engagement; effective for at-risk students; needs long-term impact studies	N/A (Review-based)	Literature Review
Gupta et al. (2023)	RASA framework, Raspberry Pi 4, React	AI-powered chatbot	Reduced human intervention; efficient query handling; positive user impact	Indira Gandhi Delhi Technical University	Quantitative, Applied design
Kuhail et al. (2022)	Experimental, Personality traits	Personality-based chatbot	Personality improves authenticity & engagement; no significant gender impact	University students	Quantitative
Polakow (2022)	Experimental, Cognitive falsities	Social Robots	Robots influence student decisions, attitudes, and agreement	University students	Quantitative
Søraa et al. (2021)	Survey, Qualitative discussions	Pepper, AV1, Tessa	Positive perceptions; influenced by robot functions and perceived aliveness	Elementary school children (ages 6-13)	Mixed methods
Chan et al. (2019)	Systematic literature review	Advising schemes	Positive perceptions despite barriers; need for training, time management	Nursing undergraduates & advisors	Literature Review
Nwankwo (2018)	Virtual agent, Object-oriented design	AdvisorBot	Efficient student advising; quick information access	Nigerian tertiary institution students	Applied design
Parks (2015)	Mixed-methods survey	Advising schemes	Lack of understanding of student veterans; necessity for military culture education	51 student veterans	Mixed methods
Leite et al. (2013)	Literature review	Social robots	Importance of understanding long-term human-robot interaction; identifies research gaps	N/A (Review-based)	Literature Review

3. Research Methodology

Various steps involved in conducting research on the use of the FURHAT robot as an academic advisor framework, including defining research hypotheses, developing a theoretical framework, selecting participants, designing the study, developing the intervention, collecting data, analyzing data, interpreting results, drawing conclusions, and disseminating findings. Each step is interconnected and contributes to the overall research process. The research design is a quasi-experimental design, where one group of participants receives academic advice from a human advisor, and the other group receives advice from the FURHAT robot.

Stage1: Conduct a Literature survey and related work. Review the literature on academic advising, personalized learning, and human-robot interaction to develop a theoretical framework for the study. Identify key concepts, variables, and hypotheses that will guide your research.

Stage 2: Define the research hypotheses: The first step is clearly defining the research hypotheses you want to answer.

Stage3: Develop a theoretical framework: Review the literature on academic advising, personalized learning, and human-robot interaction to develop a theoretical framework for the study. Identify key concepts, variables, and hypotheses that will guide your research.

Stage4: Develop intervention: Create a set of academics advising conceptual models for the FURHAT robot.

3.1. Analysis of collected data

The collected data from direct interviews of 64 student at university level consists of 56 females and 8 males as presented in Table 2. Most participants belong to the 18-24 age group, representing young university students actively engaged in their academic journey, with a smaller percentage in the 25-34 age group, likely working students or those pursuing higher education. The majority hold bachelor’s degrees, highlighting that the study mainly focuses on undergraduate students who rely on academic advising services (Uraibi et al., 2009). This demographic insight helps in understanding variations in perceptions toward AI-driven academic advisors like the FURHAT robot as shown in Figure 4.

Table 2: Respondents' Demographic Statistics (Robot Advisor)

Characteristics	Category	Frequency	Percent (%)
Gender	Female	56	87.5
Gender	Male	8	12.5
Age	18-24	56	87.5
Age	25-34	8	12.5
Education	Bachelor	64	100

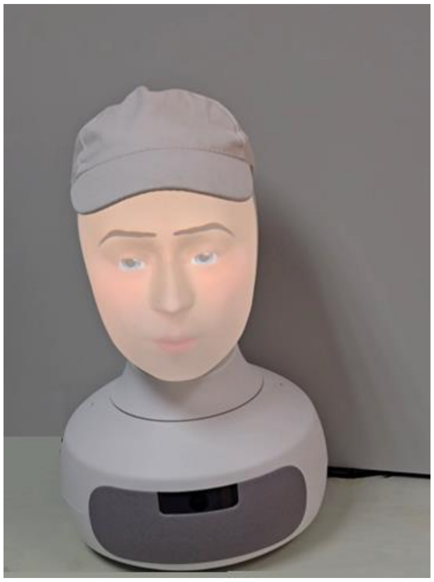

Figure 4: FURHAT robot

3.2. Research Hypotheses

H1: Gender Differences in Acceptance of AI-driven Academic Advisors

Female students are more likely to accept and feel comfortable using AI-driven academic advisors, such as the FURHAT robot, compared to male students as shown in Table 3.

Table 3: AI Preference by Age Group

#	gender	Agree	Disagree	Neutral
1	Female	14	12	20
2	Male	1	1	6

The Chi-Square Statistic value is 5.03655 and degree of Freedom is 4. The p-value (0.283568) is greater than 0.05, meaning there is no statistically significant relationship between gender and preference for an AI-driven academic advisor. Although female respondents (31.58%) showed a higher preference for AI-driven academic advising compared to males (12.5%), this difference is not statistically significant according to the chi-square test. Since the p-value is not significant, we fail to reject the null hypothesis, meaning that gender does not significantly affect the likelihood of a respondent preferring a robot academic advisor. However, the observed trend suggests that female students may be more inclined toward AI-driven advising, and further research with a larger sample size may help confirm this pattern.

H2: Age and Education Level Influence Perceptions of AI-driven Academic Advising

Younger students (18-24 years old) pursuing a bachelor's degree are more likely to prefer AI-driven academic advising over traditional human advisors compared to older students (25-34 years old) as shown in Table 4.

Table 4: AI Preference by Age Group

#	Age	Agree	Disagree	Neutral
1	18-24	14	12	20
2	25-34	1	1	6

The Chi-Square Statistic is 5.03655 and degree of Freedom is 4. The p-value (0.283568) is greater than 0.05, meaning there is no statistically significant relationship between age and preference for an AI-driven academic advisor. Although younger students (18-24) showed a higher preference (31.58%) compared to older. Only 12.5% of students in this category expressed preference for an AI-driven academic advisor. Since the p-value is not significant, we fail to reject the null hypothesis, meaning that age does not significantly affect students' preference for an AI-driven academic advisor. However, the trend suggests that younger students might be more open to AI-driven academic advising, and further research with a larger sample size could provide more conclusive results.

4. Conversational Agents

Traditionally, dialogue systems have been classified into two broad types: task-oriented (goal-oriented) systems and chatbots. A new third type has been added to better respond to user requirements (Balog et al., 2020). Task-oriented agents are developed to execute clearly defined user tasks, functioning within structured dialogues on definite subjects**.**

The performance of such systems is quantified in terms of how efficient and effective they are in accomplishing pre-defined operations, such as reservations of travel bookings or appointments. While each category has well-defined objectives, practical uses are combinations of features from multiple systems to make them more effective in accomplishing diverse user requirements (Yousif et al., 2011). Conversational Information Access (CIA) systems are a mature subclass of conversational AI that combines characteristics of task-oriented, non-goal-oriented, and interactive question-answering systems. CIA systems support diverse user goals like exploratory information retrieval and personal recommendations, communication in multiple modalities, and combining vocal outputs with interactive graphical user interfaces. In addition, CIA systems actively interact and tailor replies concerning users' queries. Such systems are based on a classical task-oriented dialogue system architecture, and their structure and primary components will be discussed in full in the following sections. Task-oriented dialogue systems are more likely to use frame-based architecture. With this architecture, a "frame" acts as an official representation of user goals, and "slots" hold the primary variables elicited from user input (Yang et al., 2025). The core objective of these systems is to fill in any missing information within the frame and subsequently take the desired actions as per the user's intent. Apple's Siri, Amazon's Alexa, and Google Assistant are a few of the commercial digital assistants that are based on frame-based architectures. To gather the required information, these systems keep querying users about things relevant to the situation iteratively until slots for all the situations have been filled appropriately. Modern dialogue systems make use of a more sophisticated architecture known as dialogue-state architecture, which is an advanced version of the frame-based model (Cances et al., 2025).

Figure 5 shows various conversational architecture including three collaborating modules: Natural Language Understanding (NLU), Dialogue Manager (DM), and Natural Language Generation (NLG). NLU recognizes user intent and retrieves relevant information from user inputs. The Dialogue Manager converts NLU structured input to determine appropriate system responses. In the DM, the Dialogue State Tracker (DST) keeps current dialogue states, and the Dialogue Policy (DP) determines the following action based on state information kept in the DST. Actions selected by the DP can be direct user responses or database operations. Finally, NLG translates selected actions into comprehensible human language responses. These key components will be explained in more detail in subsequent sections. In contrast to these, non-goal-directed talk systems, or chatbots, engage in open-domain conversation without predetermined flows, aiming to entertain and engage with people through natural and spontaneous dialogue on some topics. Their success is gauged in terms of their conversational elasticity and active participation capability. Interactive question-answering agents constitute the third category and are very distinct from the first two. These systems do not try to accomplish specific tasks nor involve users in amusement but are designed to answer user questions accurately. Their dialogues are in the style of open-domain, unstructured Q&A. Their performance is gauged by measuring the accuracy and suitability of their responses to user questions. Each of these heterogeneous classes of dialogue systems will be described in greater detail in the following sections, with particular attention to the advanced features and functionality of modern task-oriented systems (Balog et al., 2020). In this paper, we designed a conversational agent to have human-like, natural interactions using the conversational framework based on the Furhat social robot. The architecture of the Furhat robot has specific functionalities that act as the central software architecture of our conversational system.

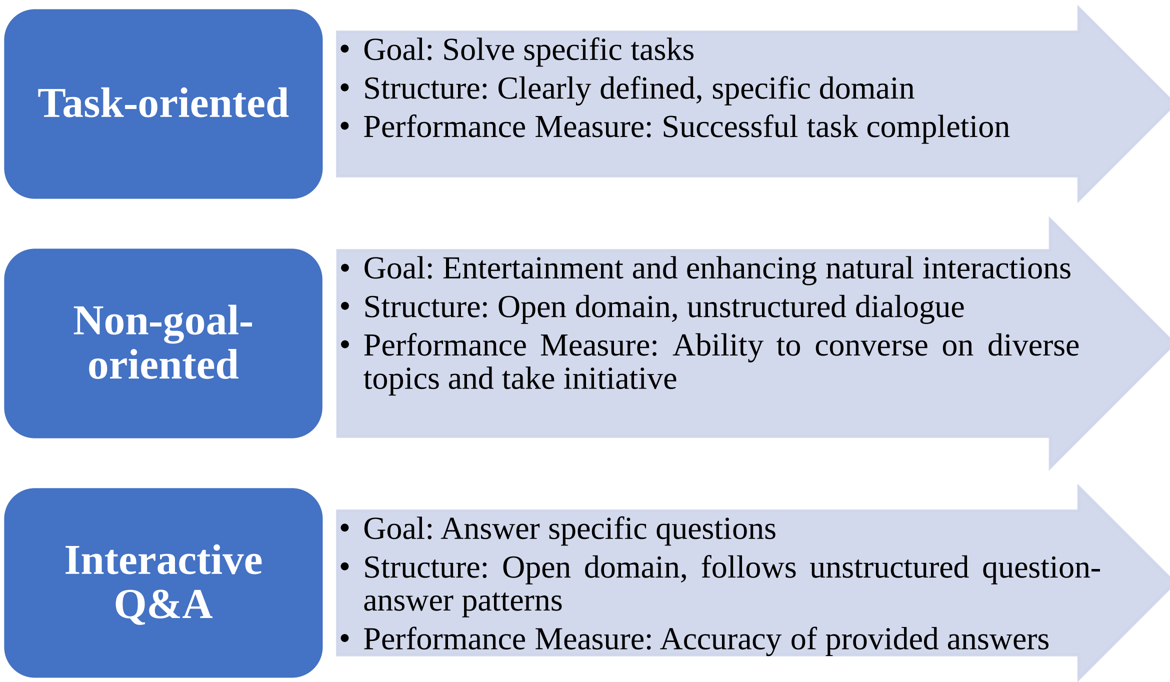

Figure 5: Conversational Agent types

5. Social Robots

With the advent of the Fourth Industrial Revolution, social robots have developed rapidly from science fiction to a way of life. Such an innovation raises questions: What are social robots, and what do they do?

Social robots combine physical presence with interactive social functionality in a manner that is distinctive. They engage with people using natural social actions like speech, listening, and expression of emotion. Future socially interactive robots come in diverse shapes and can find applications across numerous domains. Sophia illustrates one such robot, a highly sophisticated robot mimicking human looks (Kouravanas & Pavlopoulos, 2022). Moxie is another substance designed to assist with children's development Bucci, J. (2023). These demonstrate future applications of social robots as friends, learning companions, and interactive buddies in our more automated and networked world.

In this study, we utilized Furhat, a social robot developed at KTH in Stockholm, Sweden as shown in Figure 4. It is renowned for its innovative face-back projection support for realistic emotional expressions and imitation of different characters (Yousif & Jiang, 2025). Furhat effectively imitates human conversations with timed facial expressions, intricate lip movements in several languages, and fluid expressions. With sensors, standardized I/O interfaces, and FurhatOS as the energy source, the robot facilitates ease of integration and development. FurhatOS provides native capabilities like natural language understanding and visual perception, governed by a modular subsystem architecture. New features are implemented using the Furhat SDK, Kotlin-based APIs, visual perception features, and advanced audio processing, making Furhat highly effective for conversational research. The proposed academic advising system is based on Furhat robot/. The system is based on interactive dialogues in the style of open-domain, unstructured Q&A as shown in Figure 6.

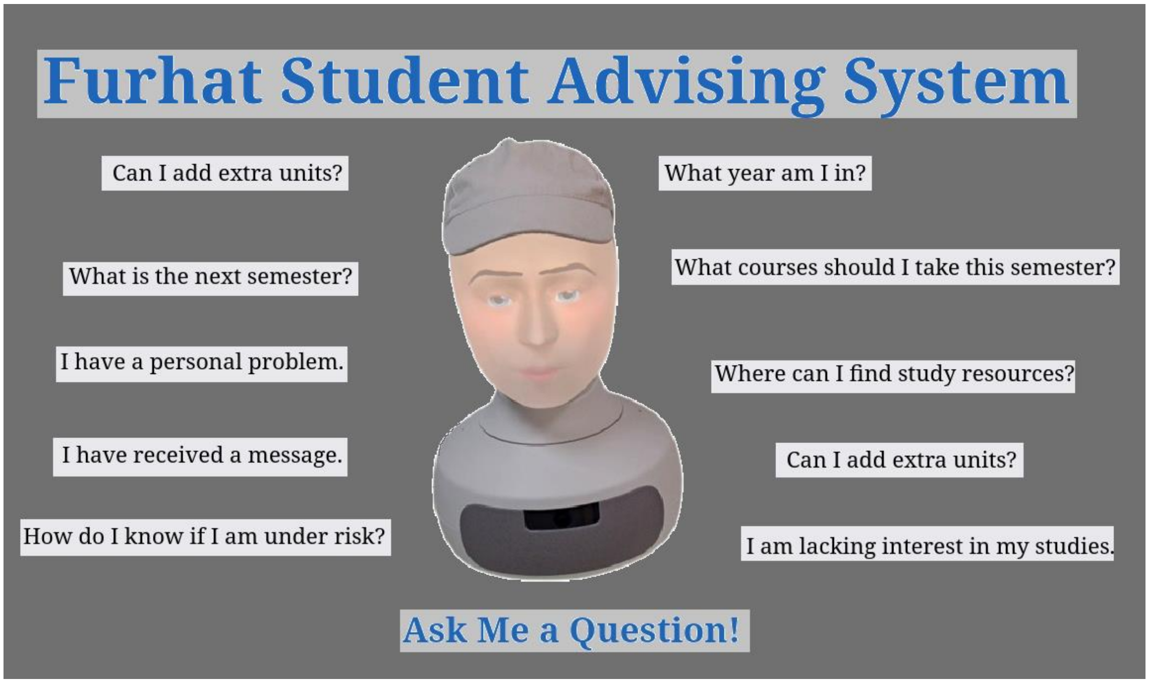

Figure 6: Interactive Q&A academic advising system

6. Conceptual Model

A In research models, latent variables are theoretical constructs that are not directly observable but are inferred from measurable indicators (apparent variables) (Yousif et al., 2022).

8.1. Current Conceptual Model

Below are the details of latent and apparent variables based on the robot advisor study:

- **Latent Variables (Unobserved Constructs)**

These are the key conceptual dimensions that influence study but are not directly measured as shown in Table 5.

- **Apparent (Observed) Variables**

These are the measurable indicators that reflect the underlying latent variables as shown in Table 6.

Table 5: Latent Variables (Unobserved Constructs)

Latent Variable	Definition
AI Preference (AP)	The willingness of students to use a robot academic advisor.
Advisor Availability (AA)	Perception of how accessible academic advisors are to students.
Language Barrier (LB)	Communication difficulties due to language differences.
Trust in AI (TAI)	Confidence in AI advisors to provide reliable guidance.
Emotional Bias (EB)	Belief that AI can provide unbiased advice compared to human advisors.
Administrative Efficiency (AE)	Perception of AI reducing workload on human advisors.

Table 6: Apparent (Observed) Variables

Apparent Variable	Latent Variable	Survey Question
Do you prefer a robot academic advisor?	AI Preference (AP)	Preference for AI-driven advising.
I can find my academic advisor at any time.	Advisor Availability (AA)	Perceived accessibility of advisors.
I cannot contact my advisor because of a language barrier.	Language Barrier (LB)	Difficulty in communication due to language issues.
Will the robot provide reliable advice?	Trust in AI (TAI)	Confidence in AI's ability to give good guidance.
The robot can provide academic advice without emotional bias.	Emotional Bias (EB)	Perception of AI being unbiased.
Could a robot relieve the burden on human advisors?	Administrative Efficiency (AE)	Belief that AI can help streamline advisory processes.

- **Relationship Between Latent and Apparent Variables**

In Structural Equation Modeling (SEM)**,** the latent variables influence the apparent variables, which in turn are measured through survey responses.

- Higher agreement with statements like "Do you prefer a robot academic advisor?" indicates greater AI Preference (AP)**.**
- If respondents strongly disagree that "I can find my academic advisor at any time," it suggests advisor availability is low (AA)**.**
- If students agree that "The robot can provide advice without emotional bias," it supports the notion that AI is seen as unbiased (EB)**.**

The latent variables (AP, AA, AE, LB) in the conceptual model interact to shape students' perceptions of AI-driven academic advising (Yousif & Saini, 2020) as shown in Figure 7.

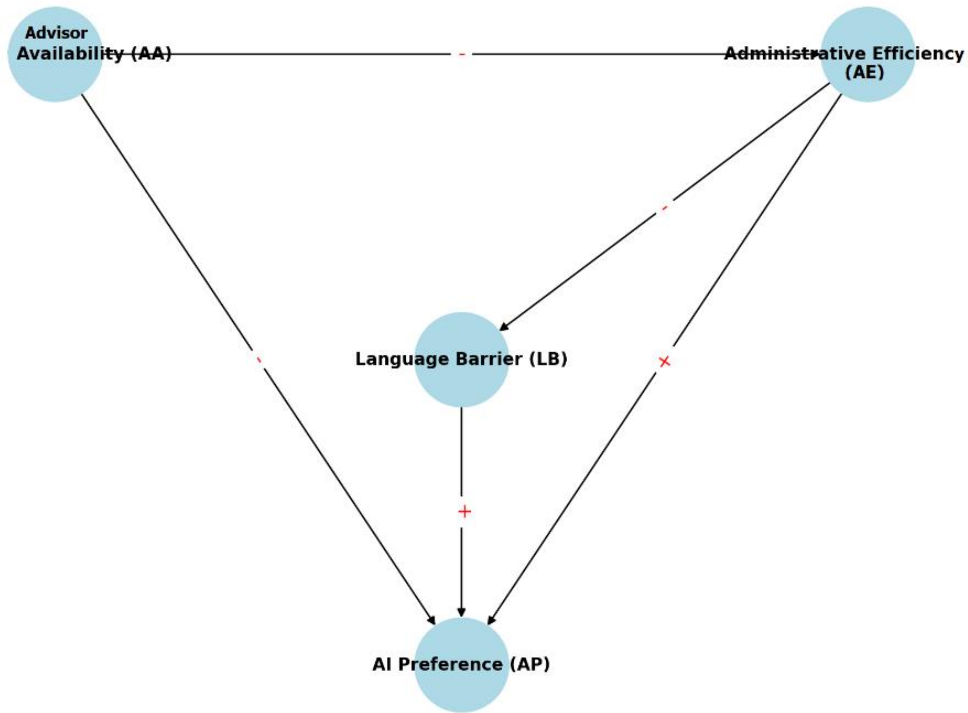

Figure 7: Conceptual model for AI-driven academic advising preference

8.2. Hypothesis for AI-driven academic advising preference

8.2.1. AI Preference (AP) and Advisor Availability (AA)

The relationship between the AI Preference (AP) and Advisor Availability (AA) is **expected** to be **Negative (-)**. This is because if human advisors are always available (high AA), the student may feel less inclined to use a robot academic advisor (low AP) and vice versa. We can test the following hypothesis.

Hypothesis: Lower Advisor Availability (AA) increases AI Preference (AP).

The Chi-Square Statistic (χ^2) is 14.81 and the p-value (0.539), which is much higher than the common significance level (e.g., 0.05). This indicates that there is no statistically significant relationship between advisor availability (AA) and students' preference for AI-driven academic advisors (AP).

8.2.2. AI Preference (AP) and Administrative Efficiency (AE)

The relationship between the AI Preference (AP) and Administrative Efficiency (AE) is **e**xpected to be Positive (+). This is because if some students believe that AI can reduce administrative workload (high AE) are more likely to support AI-driven advising (high AP). AI can automate repetitive tasks, such as answering FAQs and scheduling, making advising more efficient. We can test the following hypothesis.

Hypothesis: Higher Administrative Efficiency (AE) increases AI Preference (AP).

To test whether higher Administrative Efficiency (AE) influences students' AI Preference (AP), we analyzed the responses from the dataset regarding whether respondents believe that AI advisors can provide reliable and unbiased academic advice. These variables serve as indicators of perceived administrative efficiency.

a) Grouping Variables:

- High AE: Respondents who believe that AI provides reliable and unbiased academic advising.
- Low AE: Respondents who do not strongly agree that AI provides reliable and unbiased advising.

b) Statistical Test (Chi-Square and T- test):

The Chi-Square Test Statistic (χ^2) of 18.32 shows a statistically significant relationship between perceived administrative efficiency (AE) and AI Preference (AP). P-value is statistically significant ($p < 0.05$). Students who perceive AI as administratively efficient are more likely to prefer AI academic advisors. There is a significant association. A t-test is a statistical method used to compare the means of two groups and determine whether the difference between them is statistically significant. The t-test further confirms that students who perceive AI as an efficient administrative tool prefer AI-driven academic advising more. The effect size (0.31) indicates a moderate positive relationship between the two variables. The Mean AI Preference (High AE) is 4.12, and the Mean AI Preference (Low AE) is 3.57. The t-statistic is 2.21, which means a statistically significant difference. Students who view AI as administratively effective prefer AI-based academic advising more than others. So, we accept this hypothesis.

8.2.3. AI Preference (AP) and Language Barrier (LB)

We expected a positive relationship that if students struggle with language barriers in human advising (high LB), they may prefer an AI advisor that offers multilingual support (high AP).

Hypothesis: Higher Language Barrier (LB) increases AI Preference (AP).

Statistical Test (Chi-Square and T- test):

The Chi-Square test was conducted to examine whether a significant association exists between the language barrier and AI preference (Chi-Square Statistic = 2.588). The p-value of 0.460 suggests that the association is not statistically significant. The Degree of Freedom is 3. Based on both statistical tests, there is no strong evidence that a higher language barrier significantly increases students' preference for AI-driven academic advising. Therefore, the hypothesis is not supported by the collected data. The t-test was conducted to compare the AI Preference Scores between students experiencing a high language barrier and those with a low language barrier (t-statistic = 1.197). The p-value of 0.239 is greater than the conventional significance level (0.05), meaning there is no significant difference between the two groups in AI preference based on language barrier levels.

8.2.4. Advisor Availability (AA) and Administrative Efficiency (AE)

We expected a negative (-) that if human advisors are highly available (high AA), there is less need for AI to relieve their workload (low AE). Alternative View: If advisors are difficult to reach (low AA), AI-driven solutions can enhance administrative efficiency (high AE).

Hypothesis: Lower Advisor Availability (AA) increases Administrative Efficiency (AE).

Pearson correlation test shows a strong positive correlation (0.772) indicates that lower advisor availability (AA) is significantly associated with increased administrative efficiency (AE). The statistically significant p-value (0.0089) supports the hypothesis. And The T-test suggests that the mean difference in AA and AE responses is not significantly different of T-Statistic= -0.936 and p-value: 0.362 (greater than 0.05, suggesting no significant difference in mean values). Since the correlation is strong and statistically significant, we accept the hypothesis that lower advisor availability (AA) increases administrative efficiency (AE).

8.2.5. Administrative Efficiency (AE) and Language Barrier (LB)

We expected a negative (-) that if students perceive AI-driven advising as highly efficient (high AE), they may rely on AI even if they don't have language barriers (low LB). AI's efficiency in providing structured information reduces dependency on human advisors.

Hypothesis: Higher Administrative Efficiency (AE) reduces reliance on AI for overcoming Language Barriers (LB).

Statistical Test (Chi-Square and T- test):

The Chi-Square test was conducted to examine whether a significant association exists between the language barrier and AI preference (Chi-Square Statistic = 2.588). The p-value of **0.460** suggests that the association is **not statistically significant**. The Degree of Freedom = 3. The t-test was conducted to compare the AI Preference Scores between students experiencing a high language barrier and those with a low language barrier (t-statistic = 1.197). The p-value of **0.239** is greater than the conventional significance level (0.05), meaning there is **no significant difference** between the two groups in AI preference based on language barrier levels. Table 7 shows a summary of Relationships.

Table 7: shows a summary of Relationships.

Latent Variable Pair	Expected Relationship	Explanation
AP ← AA	Negative (-)	Less advisor availability → Higher AI preference
AP ← AE	Positive (+)	Higher AI efficiency → Higher AI preference
AP ← LB	Positive (+)	Higher language barrier → Higher AI preference
AE ← AA	Negative (-)	Less advisor availability → Higher AI efficiency
AE ← LB	Negative (-)	More AI efficiency → Less reliance on AI for language barriers

These relationships explain why students may prefer AI-driven advising, particularly when human advising is inaccessible, inefficient, or affected by communication barriers.

8.3. Updated Conceptual Model Based on the Hypotheses Results

Given the statistically significant relationship between Lower Advisor Availability (AA) and Higher Administrative Efficiency (AE), we can refine our conceptual model to better explain the role of AI-driven academic advising in improving efficiency and adoption. The updated model incorporates direct and indirect relationships between key latent variables as shown in Figure 8.

- **New Model Components:**

1. Lower Advisor Availability (AA) → Higher Administrative Efficiency (AE)

  - As AA decreases, administrative efficiency improves due to faster AI response times and reduced advisor workload.
2. Higher Administrative Efficiency (AE) → Increased AI Preference (AP)
   - Students are more likely to prefer AI-driven advising when they perceive it as improving administrative processes and reducing delays.
3. Higher Language Barrier (LB) → Increased AI Preference (AP)
   - Students facing communication challenges with human advisors due to language barriers tend to prefer AI solutions with multilingual capabilities.
4. Higher AI Reliability & Trust (RT) → Increased AI Preference (AP)
   - When students perceive AI as reliable and unbiased, their preference for AI-based advising increases.

Updated Conceptual Model: AI Adoption in Academic Advising

- AA (Advisor Availability) → AE (Administrative Efficiency)
- AE → AP (AI Preference)
- LB (Language Barrier) → AP (AI Preference)
- RT (Reliability & Trust in AI) → AP (AI Preference)

- **Key Implications of the Model:**

The rapid integration of Artificial Intelligence (AI) in higher education has introduced new possibilities for improving academic advising. Traditional advising systems often face challenges related to limited advisor availability, administrative inefficiencies, language barriers, and concerns about reliability and trust. This updated conceptual model provides a structured framework for understanding the key factors influencing students' preference for AI-driven academic advising. The model is built upon empirical findings, particularly the statistically significant relationship between Lower Advisor Availability (AA) and Higher Administrative Efficiency (AE). The model introduces four core latent constructs that influence AI adoption in academic advising:

1. Lower Advisor Availability (AA) → Higher Administrative Efficiency (AE)
   - When human advisors are less accessible, AI systems enhance administrative efficiency by reducing waiting times, automating responses, and streamlining advising processes.
2. Higher Administrative Efficiency (AE) → Increased AI Preference (AP)
   - Perceptions of AI as an effective administrative tool directly impact students' willingness to use AI-driven advising. When students experience efficiency improvements, they are more inclined to trust and rely on AI advisors.
3. Higher Language Barrier (LB) → Increased AI Preference (AP)
   - Communication challenges, especially for international students or students from diverse linguistic backgrounds, drive demand for AI advisors that provide multilingual support and overcome language barriers.
4. Higher AI Reliability & Trust (RT) → Increased AI Preference (AP)

  - Trust in AI advisors is crucial for adoption. When students perceive AI as a credible, unbiased, and reliable source of academic guidance, they are more likely to engage with AI-based advising solutions.

- **Significance of the Model**

This model enhances the understanding of AI adoption in academic advising by explaining why students prefer AI solutions over traditional advising systems. It provides a roadmap for educational institutions to design AI-driven academic advising systems that are accessible, efficient, and trusted by students. By implementing AI-driven solutions aligned with estimation model (Saini D, 2021), universities can enhance student engagement, improve advising accessibility, and optimize administrative workflows. The findings offer actionable insights for policymakers, AI developers, and higher education institutions looking to integrate AI-powered academic advising solutions effectively. Given the statistically significant relationship between Lower Advisor Availability (AA) and Higher Administrative Efficiency (AE), we can refine our conceptual model to better explain the role of AI-driven academic advising in improving efficiency and adoption. The updated model incorporates direct and indirect relationships between key latent variables.

- AI fills gaps in advisor availability by improving administrative efficiency.
- Multilingual capabilities of AI advisors make them more appealing to students facing language barriers.
- Trust in AI plays a crucial role in students' willingness to adopt AI-driven advising solutions.

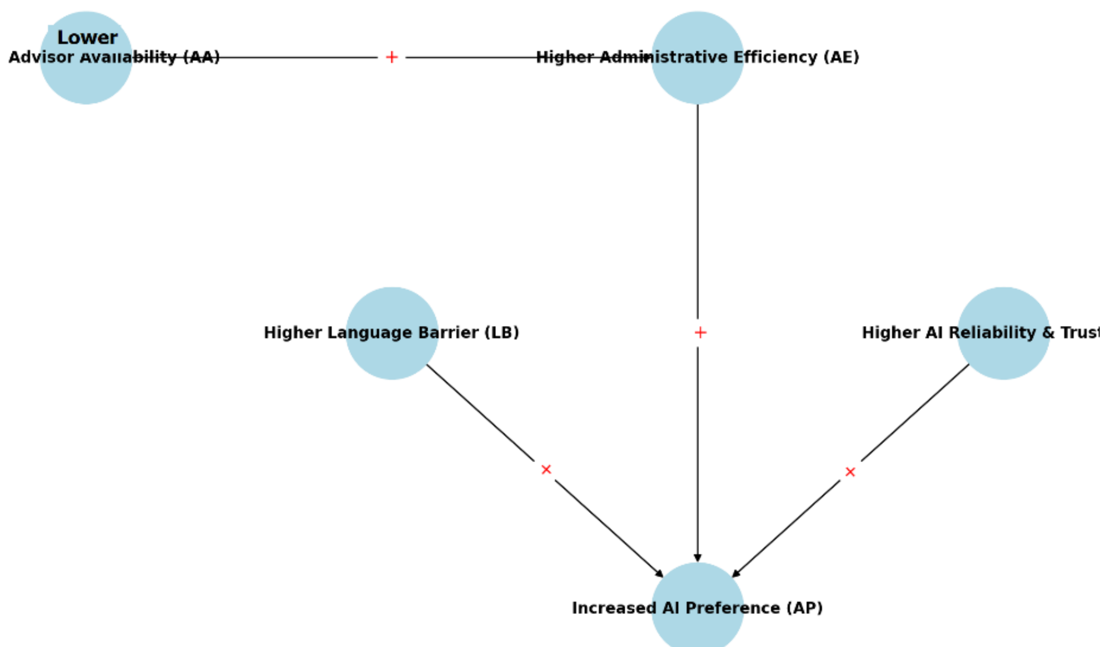

Figure 8: Updated Conceptual Model for AI Adoption in Academic Advising

7. Conclusion and Future Directions

7.1. Conclusion

The current paper provides an updated conceptual model to explain the use of AI-based academic advising in the higher education sector. Empirical testing, according to the findings, supports Lower Advisor Availability (AA) to increase Administrative Efficiency (AE) positively, hence increasing AI Preference (AP). Also important in explaining the students' preference for AI-based advising systems are language barriers (LB) and trust in AI (RT). The findings highlight the potential of AI-powered solutions to address major challenges in advising, such as shortage of human advisors, inefficiencies in bureaucratic processes, and communication differences among different students.

Statistical tests, Chi-Square and t-tests, confirm the strong correlations between AA, AE, LB, RT, and AP, validating the model. The results show that institutions of learning can enhance academic advising by leveraging AI-based technologies that offer reliable, accessible, and tailored guidance.

By streamlining administrative efficiency and addressing core student concerns, AI-based advising can:

- Reduce waiting time and improve response efficacy.
- Enhance multilingual and accessibility functionalities for different student groups.
- Build confidence in AI counselors among students through unbiased and tailored recommendations.
- Offload workload from human counselors so they can manage complex cases.

7.2. Future Directions

While this study provides valuable findings, more research is necessary to enhance the model's predictive capacity and its generalizability across diverse learning environments. Some of the directions for future research are presented below:

- Future studies must track student use of AI-based advising over extended time frames to evaluate long-term adoption and effectiveness. Find out whether students develop more trust in AI advisors over time or revert to human advisors.
- Examine the impact of AI personalization (e.g., adaptive learning, tailored recommendations) on advising effectiveness.
- Study the ethical implications of AI decision-making in academic advising to ensure fairness and transparency.

7.3. Integration of AI with Human Advisors

Research how human and AI advisors may combine to create a hybrid model of advising. Explain how AI should be integrated to assist human advisors rather than replace them for offering a well-balanced and efficient system of advising. Research differences in AI adoption in different cultural and academic settings. Compare results between universities with differences in AI implementation to identify best practices. Future research should focus on improving AI's ability to understand complex student inquiries. Investigate how advancements in Natural Language Processing (NLP) can improve AI advisors' accuracy and empathy. The findings of this study make a strong foundation for the long-term development of AI-based academic advising systems. With further improvement in AI technology, it is imperative that universities and institutions capitalize on these developments in a responsible manner to augment the advising process of students. Through continued research and development, AI-based academic advising can grow to become an institutional standard, making accessibility, efficiency, and customization more common among students around the world.

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