Future-Ready AI-Empowered Academic Advising: An Adaptive and Sustainable Tool for Student Success

Kaijie Yu
Claremont Graduate University
kaijie.yu@cgu.edu

Xu Chen
Claremont Graduate University
xu.chen@cgu.edu

Shengjie Qian
Claremont Graduate University
shengjie.qian@cgu.edu

Samir Chatterjee
Claremont Graduate University
samir.chatterjee@cgu.edu

Abstract

Choosing an academic pathway remains a daunting challenge for students (Welding, 2024), with traditional advising systems struggling to deliver adaptive and personalized guidance due to data sparsity and static recommendations. This paper introduces a Generative AI-powered advising system that leverages large language models (LLMs), alumni-driven insights, real-time trending information, and stories of prominent individuals to provide tailored, explainable, and context-rich recommendations. The initial evaluation phase, involving five students and three academic advisors, is currently in progress to assess AI-generated suggestions in structured advising scenarios. Our proposed Two-Stakeholder Evaluation Framework systematically assesses both advisor usability metrics and student recommendation relevance, with detailed quantitative and qualitative measures for each group. This work highlights the potential of AI to transform advising, empowering students to make confident, informed decisions.

Keywords: Generative AI, Recommender System, Academic Advising, Collaborative Filtering, Higher Educational Technology

1. Introduction

The landscape of higher education is experiencing a significant challenge: despite the availability of academic resources and advising services, students face mounting uncertainty in their academic pathways(Harper et al., 2023). Recent research indicates that over half of students express doubt about their major choices, with 53% citing concerns about post-graduation salaries, 48% worried about job prospects, and 43% concerned about student loan debt (Welding, 2024). This uncertainty not only affects students' confidence but also has significant implications for their academic performance and long-term career trajectories(Jenkins et al., 2024).

Traditional academic advising systems, while offering personalized human interaction, are increasingly struggling to address modern challenges(Papastratis et al., 2024). These systems face fundamental limitations:

1. **Data Sparsity and Cold Start Issues:** Current systems lack mechanisms to effectively utilize historical student success patterns and outcomes, particularly for new students or emerging fields (Ayemowa et al., 2024).

2. **Limited Contextual Understanding:** Advisors face difficulties staying current with rapidly evolving industry trends and integrating real-world insights into their guidance.

3. **Scalability Constraints:** The traditional one-on-one advising model struggles to provide consistently deep, personalized guidance across large student populations.

To address these challenges, this research proposes integrating generative AI, specifically LLMs, into academic advising systems. Our solution aims to augment human advisors' capabilities while maintaining their central role in the guidance process. This approach aligns with recent advances in LLM applications for personalization (Wu et al., 2024) (Zhao et al., 2024) and educational support (Lekan & Pardos, 2024).

The research is guided by three key questions:

1. How can generative AI enhance the personalization, adaptability, and transparency of academic advising?

2. What role does explainability play in fostering trust and engagement in AI-driven recommendations?

3. How can generative AI accommodate diverse student backgrounds and educational goals?

2. Background Literature and Kernel Theory

Our research builds upon three key theoretical foundations that inform our artifact design and align with the Design Science Research (DSR) methodology.

The Large Language Models Enhanced Collaborative Filtering framework (Sun et al., 2024) provides our core theoretical basis for integrating LLM capabilities with recommendation systems. This framework demonstrates how LLMs can enhance collaborative filtering by incorporating world knowledge and reasoning capabilities through in-context chain of thought learning. This approach directly informs our system's architecture for processing student profiles and generating personalized guidance.

Recent work on user profile personalization in LLMs (Wu et al., 2024) offers crucial insights into how historical user data can be effectively leveraged for personalization. Their findings reveal that personalization success relies more heavily on user-specific response patterns than on input-mapping accuracy. This insight fundamentally shapes our approach to utilizing alumni profiles and student data, suggesting that focusing on successful outcome patterns may be more valuable than exact path replication.

Iatrellis et al. (2024) work on sustainable academic advising through AI demonstrates the practical viability of AI-augmented advising systems while highlighting the importance of maintaining human advisors' central role. Their findings on advisor acceptance and system integration provide valuable guidance for our implementation approach, particularly in designing interfaces and workflows that complement rather than replace human expertise.

Traditional collaborative filtering approaches face limitations in educational contexts due to data sparsity and the cold start problem (Ayemowa et al., 2024). Recent advancements in LLM-based recommendation systems show promise in addressing these limitations through enhanced contextual understanding and reasoning capabilities (Xi et al., 2024). Lekan and Pardos (2024) demonstrated that GPT-4 recommendations align with human advisor suggestions approximately 33% of the time, indicating both potential and room for improvement in combining AI capabilities with human expertise.

Ma et al. (2024) emphasize the crucial role of explanation generation in recommendation systems, particularly in high-stakes decisions like academic planning. Their XRec framework provides insights into generating context-aware explanations that enhance user trust and engagement, which informs our approach to providing transparent and explainable recommendations.

Our research extends these foundations by addressing three key gaps in current literature. First, while existing work demonstrates the potential of both LLMs and recommendation systems separately, there is limited research on effectively combining these approaches for academic advising. Second, current systems often fail to incorporate real-world context such as alumni outcomes and industry trends into their recommendations. Third, most existing solutions focus either on fully automated systems or traditional human advising, with limited exploration of hybrid approaches.

The Design Science Research methodology provides an ideal framework for addressing these gaps through iterative artifact development and evaluation. Following Hevner's guidelines, our research creates an innovative artifact that addresses specific problems in academic advising while ensuring problem relevance through direct stakeholder engagement. This theoretical foundation guides our artifact development toward a solution that advances both technical capabilities and practical value in academic advising contexts.

3. Solution Design and Artifacr Details

Our primary artifact is a web-based Generative AI-powered Academic Advising System designed to support and enhance traditional advising through advanced AI capabilities. Accessible through a secure login, academic advisors can use this web platform to input student information and receive tailored recommendations for majors, courses, and career pathways. The system combines AI-driven insights with the advisor's own expertise, providing a collaborative interface that supports advisors rather than replacing them.

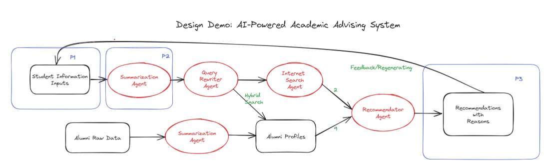

Figure 1. System Architecture Diagram

Key Components of the System: Generative AI Integration The system combines LLMs with collaborative filtering techniques to create a hybrid recommendation system. Specifically, it utilizes a multi-agent Retrieval-Augmented Generation (RAG) architecture, where AI agents retrieve relevant alumni data and integrate it with generative AI outputs to optimize recommendations. This approach allows the system to pull in specific, context-rich data segments dynamically and combine them with generated student profiles and other pertinent information. The RAG architecture enhances recommendations by ensuring seamless alignment between data retrieval and generative processes, supporting accurate, context-aware matches.

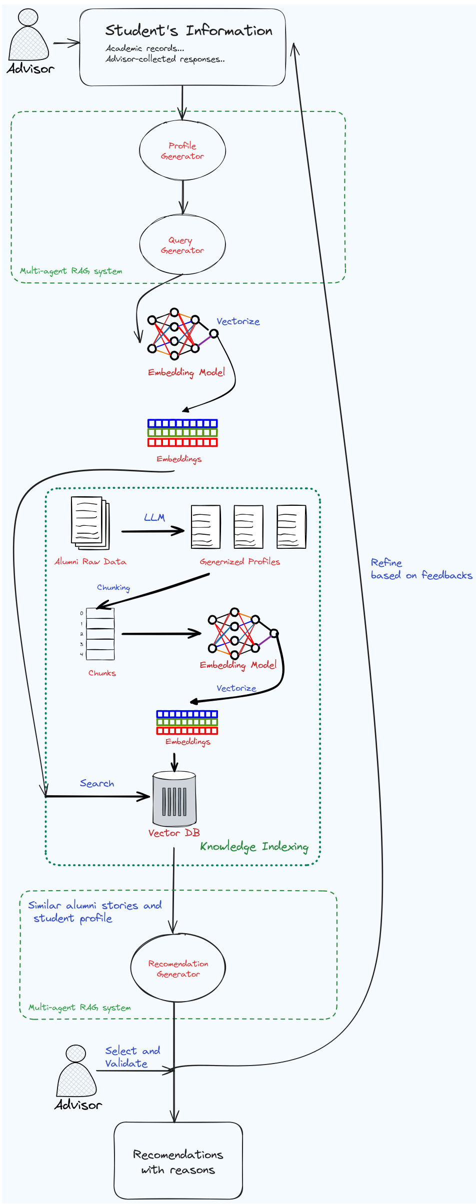

Figure 2. RAG Architecture Flow Diagram

Dynamic Profile Generation Upon gathering raw data from both students and alumni, whether from existing academic records, advisor-collected responses, or alumni data sources, the system uses an LLM to synthesize this information into cohesive, narrative-style profiles. For students, the profile captures academic background, interests, and goals in a readable paragraph format. For alumni, it organizes majors, degrees, career paths, skills, and relevant experiences. These dynamically generated profiles standardize diverse data formats, forming the basis for accurate matching and bypassing the rigid structure typical of traditional recommendation systems.

Explainable Recommendations A key feature of the system is its ability to provide context-rich, explainable recommendations. Using the multi-agent RAG system, the generated student profile is matched with similar alumni stories, which have also been generated and summarized by the LLM from raw alumni data. By drawing on these comparable alumni experiences and career outcomes, the system delivers recommendations that are not only personalized but also accompanied by clear reasoning. This context helps both students and advisors understand the alignment between academic choices and potential career paths, fostering trust in the AI-driven suggestions.

Case Scenario In a typical advising scenario, an academic advisor logs into the web-based system and initiates a session with a student to discuss their academic and career goals. The advisor inputs relevant background details, such as the student's declared interests, current major, and any specific academic concerns into the tool. The system processes this input and draws upon a range of data sources to generate recommendations. For example, the tool might suggest potential majors or career paths, supported by success stories from alumni who followed similar pathways. The advisor can review these AI-generated insights and selectively incorporate them into their recommendations, blending AI-driven advice with their own professional judgment.

4. Proof of Concept and Development

The proof of concept for our generative AI-powered academic advising system focuses on demonstrating its technical viability and collecting initial stakeholder feedback. The system prototype has been developed as a web-based platform, combining modern frameworks to ensure responsiveness, scalability, and real-world adaptability. It features a Next.js frontend for an intuitive user interface and a Python/FastAPI backend to process inputs efficiently. A PostgreSQL database with vector extensions, such as pgvector, enables semantic

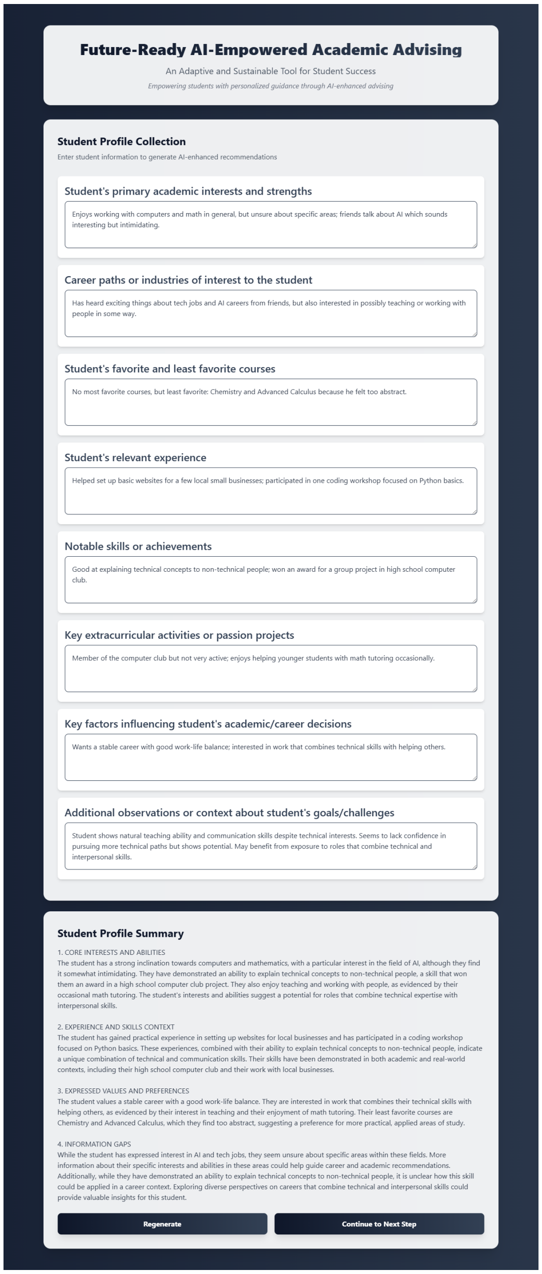

Figure 3. Profile Generation Interface Screenshot

similarity searches across structured alumni profiles, facilitating personalized academic recommendations.

To address the limitations of static advising systems, we have incorporated an internet search module that retrieves real-time information on industry trends, emerging job markets, and the career trajectories of prominent individuals, similar to some other researches that use open-world knowledge (Xi et al., 2024). This dynamic integration complements historical alumni data and ensures that recommendations remain contextually

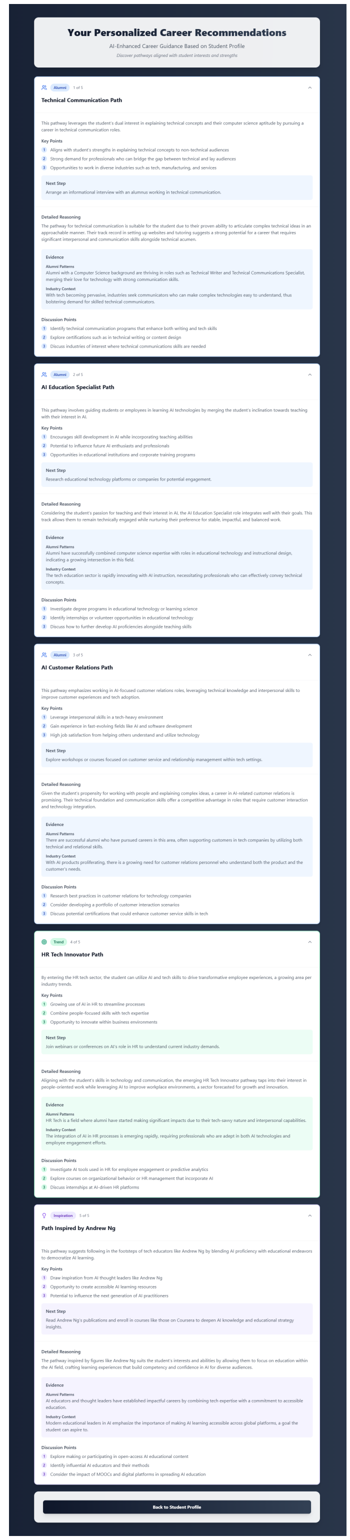

Figure 4. Recommendation Interface Screenshot - Extended View

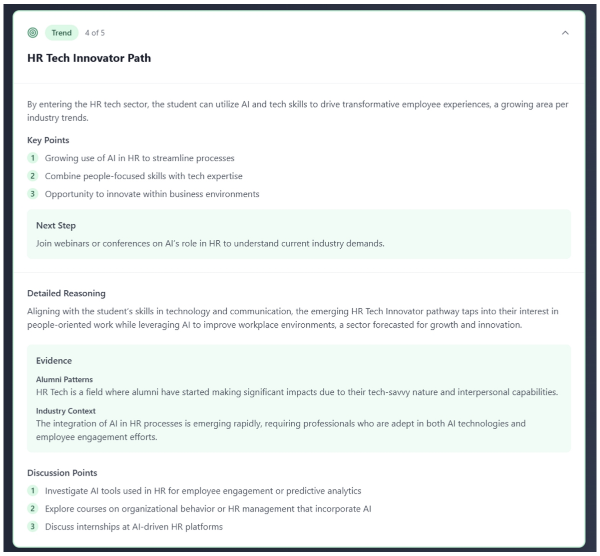

Figure 5. Recommendation Interface Screenshot - One Example

relevant and forward-looking. At the core of the system lies a multi-agent RAG framework. The RAG architecture combines retrieval and reasoning processes: it pulls alumni profiles, integrates real-time information, and synthesizes cohesive, explainable academic pathways tailored to students' interests, strengths, and goals.

To validate the prototype, we initiated a structured feedback collection phase. Using Google Forms, we are gathering responses from two key stakeholder groups: academic advisors and students. Academic advisors are assessing the system's usability, recommendation accuracy, and potential integration into their workflows, while students evaluate the relevance, clarity, and overall utility of the AI-generated suggestions. At present, this data collection process is ongoing, and early responses indicate that students appreciate the relevance and explainability of the recommendations, while advisors recognize the system's potential to enhance their advising processes.

The current phase focuses on refining the system based on this feedback. Backend optimizations, improved alumni data integration, and adjustments to the real-time search module are ongoing to further enhance recommendation quality and system responsiveness. This iterative development process ensures that the system evolves in alignment with stakeholder needs, setting the stage for more comprehensive evaluations in subsequent phases.

5. Evaluation Method

The evaluation phase is pivotal in assessing the efficacy and impact of our AI-powered academic advising system. While the tool has been fully implemented, the current study focuses on evaluating its output using hypothetical student scenarios due to the limited time available to engage a larger pool of stakeholders. This approach enables us to gather targeted feedback on recommendation quality and usability while laying the groundwork for broader, real-world testing in future phases.

5.1. Initial Evaluation Phase

The initial evaluation phase, currently in progress, involves a pilot study with five students and three academic advisors. This phase is designed to assess the system's ability to generate relevant, actionable, and explainable recommendations that align with student profiles and advising workflows. Academic advisors evaluate the usability of the tool, its accuracy in generating suggestions, and the practical relevance of recommendations in advising sessions. Meanwhile, students focus on the clarity, personalization, and perceived usefulness of the recommendations in supporting their academic and career decision-making processes.

To collect meaningful feedback, we employ a mixed-methods approach. Participants rate their experiences across six evaluation dimensions on a 5-point Likert scale (1: Strongly Disagree to 5: Strongly Agree), supplemented with targeted qualitative questions to provide deeper insights.

For academic advisors, the evaluation questions include:

- "How well do the recommendations align with the student's academic and career goals?"
- "To what extent do the recommendations provide actionable and practical insights?"
- "How accurate and relevant do the generated recommendations seem based on the student profile?"
- "How clear and transparent is the rationale behind the AI-generated suggestions?"
- "How seamlessly could this tool integrate into your existing advising process?"

For students, the questions focus on their individual experience, including:

- "How relevant are the recommendations to your academic and career goals?"

- “How clearly does the system explain the reasoning behind its recommendations?”
- “To what extent did the recommendations inspire you to explore new academic or career options?”
- “How confident did the recommendations make you feel about your academic decisions?”
- “How diverse and creative were the options provided in the recommendations?”

Given the small sample size in this pilot study, the quantitative ratings primarily serve as descriptive indicators of trends and patterns. A larger participant pool in future evaluations would allow for the application of more robust statistical methods, such as inferential tests. At this stage, qualitative responses are analyzed using thematic analysis to extract recurring themes, actionable suggestions, and user experiences. This dual approach ensures that the feedback is both systematic and detailed, capturing measurable indicators alongside rich, user-centered insights.

The findings from this pilot study will directly inform the next iteration of the system. Specific areas of focus include enhancing recommendation accuracy, improving the clarity and transparency of explanations, and optimizing the overall user experience for both advisors and students.

5.2. Planned Comprehensive Evaluation

Building on the insights gained from the initial pilot study, we plan to conduct a comprehensive evaluation guided by a structured two-stakeholder framework. This phase will expand testing to a larger participant group, involving additional academic advisors and students. The comprehensive evaluation will focus on systematically assessing system functionality, recommendation quality, and overall user satisfaction in real-world advising contexts.

For academic advisors, the evaluation will emphasize key areas such as system usability, response time, profile generation accuracy, and the relevance of recommendations across diverse student profiles. Advisors will provide professional insights into how effectively the tool integrates into their workflows, supports their expertise, and enhances the advising process.

For students, the evaluation will assess the clarity, usefulness, and impact of the recommendations on their academic planning and decision-making confidence. Expanded testing will include more diverse student backgrounds to evaluate system adaptability and ensure its recommendations address a variety of academic interests and learning needs.

The comprehensive evaluation will introduce additional dimensions, such as system scalability, consistency of outputs, and responsiveness to evolving user inputs. Data collection will combine structured surveys, follow-up interviews, and case studies, enabling us to gather both quantitative metrics and qualitative insights to guide further refinement.

5.3. Longitudinal Evaluation

While the immediate focus is on evaluating short-term usability and recommendation quality, future work will incorporate longitudinal evaluation to assess the system’s sustained impact. A longitudinal framework will involve tracking student outcomes, career progress, and decision-making over extended periods. By following students who have interacted with the system, we can evaluate how effectively the AI-generated recommendations translate into tangible academic success and career advancement.

Future phases will focus on expanding the scope of system enhancements through improved adaptability of recommendations to accommodate diverse learning styles, incorporation of broader data inputs for richer personalization, and refinement of explainability features to foster greater trust and engagement. Additionally, larger-scale studies will test the system’s performance across different institutions and advising contexts, ensuring its scalability and robustness in diverse educational settings.

Through this iterative evaluation process, we aim to develop a comprehensive, adaptive, and sustainable AI-powered advising tool that empowers students and advisors to make informed, confident decisions. By continually refining the system based on stakeholder feedback and real-world outcomes, we ensure its long-term value as a transformative tool for academic advising.

6. Preliminary Results and Discussion

While our evaluation is still in the planning phase, existing research highlights the potential of AI-enhanced academic advising systems to improve decision-making for students. Iatrellis et al. (2024) demonstrated that AI-generated recommendations provided unique insights and were considered highly relevant, though they received moderate scores in terms of acceptance and practicality. Similarly, Lekan and Pardos (2024) found that GPT-4 recommendations aligned with human advisor suggestions 33% of the time, revealing both promising potential and areas requiring further improvement.

Our approach extends beyond these baseline studies by addressing key limitations through three significant innovations. First, we employ multi-source recommendation generation that combines structured alumni data, real-time industry trends, and insights from notable figures, ensuring recommendations are both dynamic and contextually rich. Second, we adopt a Two-Stakeholder Evaluation Framework to systematically assess the system from the perspectives of both advisors and students, creating a more comprehensive understanding of usability and impact. Third, we leverage a RAG architecture to generate dynamic, personalized profiles that improve the quality and explainability of recommendations.

Despite these advancements, we recognize several challenges that need to be addressed in our development and evaluation strategy. Integrating diverse data sources effectively remains a technical hurdle, particularly in balancing accuracy and efficiency. Another key challenge is ensuring a smooth interplay between automated recommendations and advisor expertise, preserving the human-centered nature of academic advising. Additionally, achieving high levels of explainability without compromising recommendation quality will be critical for fostering trust among users. Finally, maintaining data privacy and security as the system scales is essential, especially when incorporating real-time external data.

These challenges will guide our ongoing system refinement and pilot study design. By addressing these issues systematically, we aim to create a robust, scalable framework that enhances academic advising through generative AI while preserving the indispensable role of human advisors.

7. Conclusion and Future Work

This research presents a comprehensive framework for enhancing academic advising through the integration of generative AI, structured alumni data, and real-time industry insights. Our contributions include a novel system architecture combining large language models with multi-source data inputs, a systematic evaluation approach through the Two-Stakeholder Framework, and an emphasis on explainable, context-rich recommendations that address the limitations of static advising systems.

The planned evaluation methodology will provide critical insights into the system's performance, usability, and effectiveness. Our immediate focus is implementing the pilot study with five students and three academic advisors, validating system recommendations and identifying areas for refinement. Based on these findings, the system will undergo iterative improvements to ensure better alignment with user needs and address challenges identified during early testing.

In subsequent phases, we will expand testing to larger and more diverse groups of students and advisors to evaluate the system's scalability, adaptability, and robustness in real-world advising contexts. Additionally, longitudinal tracking mechanisms will measure the sustained impact of AI-generated recommendations on student outcomes, including academic performance, major choices, and career trajectories.

Through this work, we establish a more data-driven, adaptive, and personalized approach to academic advising while preserving the critical role of human judgment. By systematically combining AI innovation with user-centered design and evaluation, this research provides a strong foundation for transforming advising practices and supporting students in making confident, informed decisions about their academic and professional futures.

8. Code and Resources

The project's code and supplementary materials can be accessed on the **GitHub repository**:
https://github.com/MSWinds/futureready-ai-advising

For feedback and participation, the following Google Forms are available:

Student Information Form:
https://docs.google.com/forms/d/e/1FAIpQLSdvzl52Zq-hR6d7hhuUfAX59ZPbLYgAtJHp4JGlxJHWEC7fog/viewform

Evaluation Form for Advisor Feedback:
https://docs.google.com/forms/d/e/1FAIpQLSdf1zZGpa8l3BsqC4e0EqE5nyOsBWNsYTttu8Ud_uPVMBtadA/viewform

Evaluation Form for Student Feedback:
https://docs.google.com/forms/d/e/1FAIpQLSf67zMM18jFAtdqNIXqMnMcLH3of3aV3w39V34cW1qAbz_CRw/viewform

9. References

References

Ayemowa, M. O., Ibrahim, R., & Khan, M. M. (2024). Analysis of recommender system using generative artificial intelligence: A systematic literature review. *IEEE Access*, *12*, 87742–87766. https://doi.org/10.1109/ACCESS.2024.3416962

Harper, C. E., Orr, R., & Stolzenberg, E. B. (2023). Demographics, purpose, and dreams: Predicting entering college as an undecided major student. *NACADA Journal*, *43*(2), 136–145. https://doi.org/10.12930/NACADA-22-42

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

Jenkins, D., Lahr, H., & Brock, T. (2024). *Lessons from two major evaluations of guided pathways*. Community College Research Center, Teachers College, Columbia University. https://ccrc.tc.columbia.edu/publications/lessons-two-major-evaluations-guided-pathways.html

Lekan, K., & Pardos, Z. A. (2024). Ai-augmented advising: A comparative study of gpt-4 and advisor-based major recommendations. In M. Ananda, D. B. Malick, J. Burstein, L. T. Liu, Z. Liu, J. Sharpnack, Z. Wang, & S. Wang (Eds.), *Proceedings of the 2024 aaai conference on artificial intelligence* (pp. 85–96, Vol. 257). PMLR. https://proceedings.mlr.press/v257/lekan24a.html

Ma, Q., Ren, X., & Huang, C. (2024). *Xrec: Large language models for explainable recommendation* [arXiv]. https://doi.org/10.48550/arXiv.2406.02377

Papastratis, I., Konstantinidis, D., Daras, P., et al. (2024). Ai nutrition recommendation using a deep generative model and chatgpt. *Scientific Reports*, *14*, 14620. https://doi.org/10.1038/s41598-024-65438-x

Sun, Z., Si, Z., Zang, X., Zheng, K., Song, Y., Zhang, X., & Xu, J. (2024). Large language models enhanced collaborative filtering. *Proceedings of the 33rd ACM International Conference on Information and Knowledge Management (CIKM '24)*, 2178–2188. https://doi.org/10.1145/3627673.3679558

Welding, L. (2024). *More than half of college students experience doubt about their choice of major: Survey results* [Accessed: 2024-10-16]. https://www.bestcolleges.com/research/college-students-doubt-major-choice-survey/

Wu, B., Shi, Z., Rahmani, H. A., Ramineni, V., & Yilmaz, E. (2024). *Understanding the role of user profile in the personalization of large language models* [arXiv:2406.17803 [cs.CL]]. https://doi.org/10.48550/arXiv.2406.17803

Xi, Y., Liu, W., Lin, J., Cai, X., Zhu, H., Zhu, J., Chen, B., Tang, R., Zhang, W., & Yu, Y. (2024). Towards open-world recommendation with knowledge augmentation from large language models. *Proceedings of the 18th ACM Conference on Recommender Systems (RecSys '24)*, 12–22. https://doi.org/10.1145/3640457.3688104

Zhao, Z., et al. (2024). Recommender systems in the era of large language models (llms). *IEEE Transactions on Knowledge and Data Engineering*, *36*(11), 6889–6907. https://doi.org/10.1109/TKDE.2024.3392335