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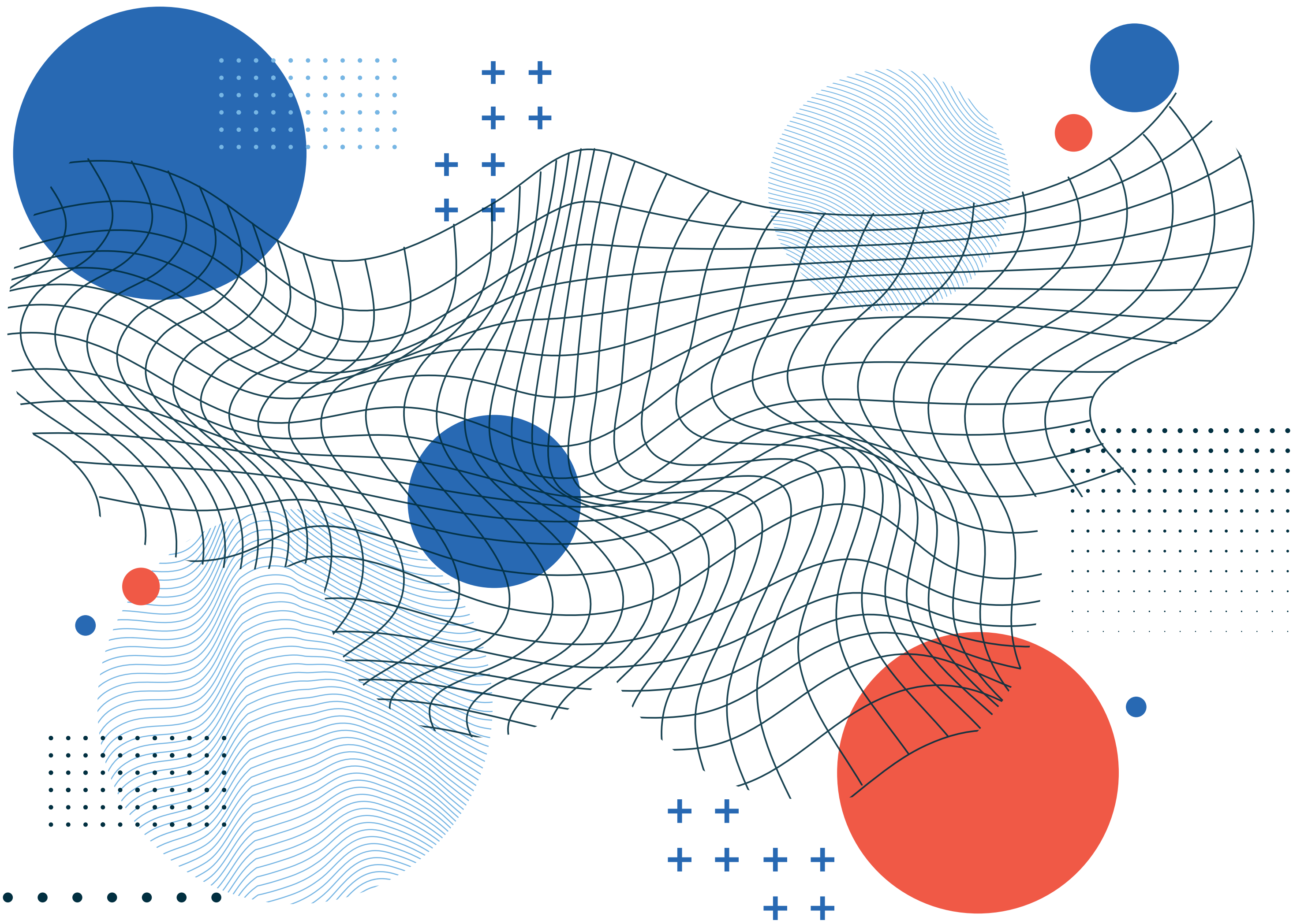

以學生學習歷程檔案支援大學科系探索之概念驗證研究

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摘要

對許多高中生而言，升大學是人生中第一個重要的決策。此一決策歷程仰賴學生整合其個人學習經驗與未來的學術目標之資訊處理能力。本研究旨在發展一套遷入大型語言模型之 AI 升學指導系統，以協助學生建立申請大學所需的個人學習歷程檔案。在系統開發之前，我們先進行了先導訪談（pilot interviews）並進行概念驗證（proof-of-concept）。本研究以五位大學生在高中階段製作並用於大學申請的學習歷程檔案進行測試。結果顯示，該系統具備提供個人化建議以及預測學生所感興趣之科系類別的潛力。此外，我們亦邀請了四位來自教育產業與學術界的專家參與評估。本研究未來將進一步將此系統應用於真實教育情境進行實地測試。未來貢獻在於協助高中教育機

構更有效地管理學生的學習歷程，並幫助學生檢視自身學習表現，進而為其未來發展做出適切的決策。

關鍵字：決策支援系統、大學申請、學習歷程檔案、個人化學習

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Supporting University Major Exploration through Student Learning Profiles: A Proof-of-Concept Study

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ABSTRACT
A transition from high school to higher education is the first important life decision for many high school students. This decision-making process requires their ability to process information to integrate personal learning experience with future academic goals. The current study aims to develop a system with a Large Language Model to assist students in making their personal profiles for applying to university. We conducted pilot interviews before designing the system. The proof-of-concept is tested by 5 undergraduate students' profiles that they had made when they were high school students and applied to a university. The results showed that the system has the potential to provide personal suggestions and predict the major categories that the students are interested in. Furthermore, we also invited 4 experts from the educational industry and academia. The future work of this study is to apply this system to real-world testing. The contribution of this study is to help high school education institutions effectively manage students' learning process and help students assess their learning and make an appropriate decision for their future.

Keywords
Decision support system, University Application, Learning Profile, Personalized Learning

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1. Introduction

For a high school student, the transition to higher education is a high-stakes and complex information-processing behavior. It requires students to integrate internal self-understanding with massive amounts of external institutional data. According to the Iloh Model of College-Going Decisions, this process is heavily influenced by information availability, timing, and opportunity (Trinh et al., 2025). The whole process is often the high school students’ first attempt at constructing a comprehensive "self-narrative," necessitating the alignment of their academic performance, personal interests, and extracurricular achievements into a cohesive portfolio.

Recent studies indicate that students face multifaceted challenges ranging from psychological barriers to information overload. For instance, Sümer and Yılmaz (2025) highlight that for high school students in Turkey, career decision-making is significantly negatively correlated with anxiety, emphasizing the urgent need for support systems that bolster self-efficacy. Similarly, Chien (2024) found that Taiwanese students often perceive the preparation of learning portfolios as a significant burden and lack belief in their immediate benefits. In the US, Price (2025) notes that the complex framing of financial costs remains a barrier to application behavior. In fact, every student has different considerations, making personalized guidance essential.

However, the current operational model faces significant structural challenges. Student learning records, notes for course materials, school project outcomes, and consulting history with tutors and parents are often fragmented across disparate files, instant messaging apps, and legacy systems. This fragmentation makes it difficult for career tutors to comprehensively track the students' long-term growth trajectory. The students also find it difficult to systematically reflect on their learning processes. Parents, meanwhile, are often limited to receiving piecemeal information, preventing them from gaining a holistic view of their child's progress. Therefore, this study aims to develop an “AI agency coach” to help students, parents, tutors integrate all their personal learning data. We first conducted a pilot study of interviews to understand the needs of those stakeholders, and secondly developed a system. Finally, to evaluate the system performance, we used four real sample cases to verify the functions.

2. Pilot Study

To design a localized solution tailored to this specific educational context, we conducted a comprehensive user needs survey involving tutors, students, and parents. The survey included 6 student questionnaires, 5 parent questionnaires, and 3 tutor interviews. Based on the results of the questionnaires and interview, this paper proposed a novel framework centered on developing a student personalized knowledge profile and adaptive learning content via a Large Language Model (LLM) agency coach. Focusing on the context, the LLM agency coach primarily serves middle and high school students aiming for admission to foreign universities, which require more effort in information processing for the students. Using students’ individual profiles, the system should deliver tailored questions and revision prompts to scaffold learning within the zone of proximal development. This design will reduce tutors’ workload while fostering self-regulated learning and mitigating AI dependency and academic dishonesty observed in the user survey.

3. System Design

The AI Agency Coach System is a support platform designed to assist students in completing their learning overview reports that reflect students' learning portfolio, which is based on their long-term accumulated learning process data. The role of our proposed system positions AI as a "coach" rather than a content writer. Through structured questioning, feedback, and reflection, it guides students step-by-step toward autonomous learning and career planning. The proposed system has several features, including prompt optimization in the user interface, a personal material retrieval model, and professional support based on the institution’s teaching experience.

3.1 User Interaction and Information Transformation

The point of our system lies in positioning AI as a "coach" that supports active thinking rather than a tool for generating results., but a partner that supports active thinking. The system usage begins with the student inputting questions, ideas, or real-time files through the user interface, which are then transformed into structured prompts and integrated into a Large Language Model (LLM). Through this approach, structured guiding questions help students reduce their psychological burden when facing a blank page and retain their control over the content. This embodies the following core principles: the central role of AI in education, therefore, is to facilitate learning and teaching processes (Toussaint et al., 2026), ensuring that process record should truly reflect personal thinking, and simulated questioning should be used to promote self-regulation.

3.2 Personal Material Integration and Retrieval

At the heart of our system design is the student learning database. The system extracts learning topics, problem-solving processes, and personal reflections by integrating structured data (personalized databases) with unstructured data (real-time conversational content). Through Large Language Models (LLMs), analyzed content analysis and summarized theme summarization into basic reference data that can be used for subsequent applications. Its operational essence is the same as the following principles: “hybrid intelligent systems aim to optimise the complementary strengths of human intelligence and AI, so that the two together behave more intelligently than the two separately” (Molenaar, 2022). This system does not directly score students' abilities and provide suggestions based on a single item. Instead, we focus on identifying students' strengths, tracking their long-term growth, and exploring their growth potential as the main analytical outputs. By constantly updating student profiles, we can tailor our coaching strategies in real-time. “Aspirations and level of effort strongly depend on individuals’ beliefs... which, in turn, are strongly dependent on the amount of available information” (Toussaint et al., 2026). Using a longitudinal data collection perspective, a more complete and contextualized student learning report is created. As a result, the system builds a comprehensive and contextualized learning overview report, no longer relying on a single test or short-term performance evaluation.

3.3 Organizational Knowledge and Professional Support

Another critical design feature of this system is the preservation and storage of internal institutional knowledge. Tutors can transform their tacit experience—including admissions insights, pedagogical expertise, and core curriculum materials—into structured prompts. This facilitates the process of knowledge externalization, as described by Nonaka and Takeuchi (1995): “tap the tacit and often highly subjective insights, intuitions, and hunches of individual employees and making those insights available for testing and use by the company as a whole.” Consequently, tutor expertise is retained within the system and delivered to students through interactive interfaces.

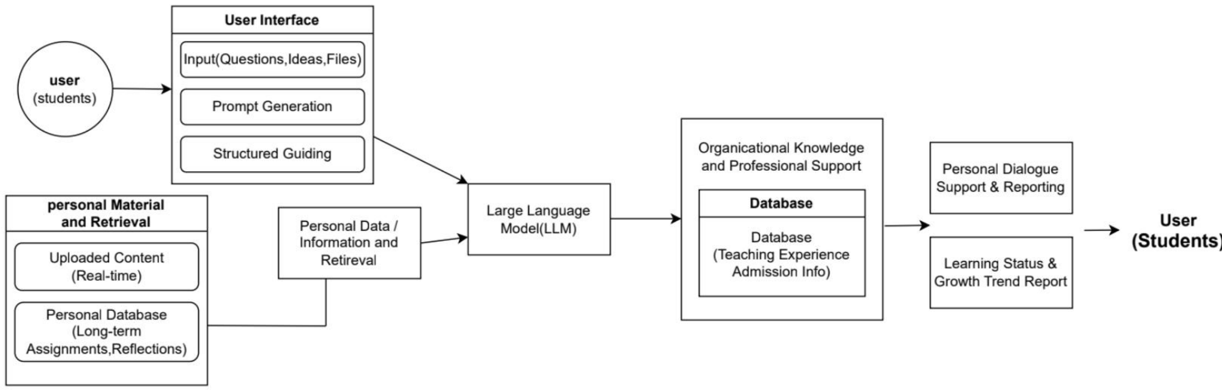

Figure 1 . The framework of the AI Agency Coach System

Leveraging these accumulated datasets, the system generates personalized performance analytics and career development advice. The AI coach integrates quantitative metrics (e.g., course completion rates) with qualitative analysis (e.g., depth of reflection, thematic distribution, and future orientation) to produce accessible and actionable reports. This institutionalized support is expected to “increase students’ level of information... their beliefs regarding the likelihood of success in their studies can change” (Toussaint et al., 2026). Through this framework, the system ultimately facilitates the “interplay between learners, tutors, and AI to optimize learning” (Molenaar, 2022), enabling institutional expertise to effectively guide students in understanding their own growth trajectories.

4. Proof of Concept

4.1 Expert consultation result and practitioner insights

To ensure the system's professional rigor and market viability, a panel of four experts was consulted on January 2, 2026. This panel consisted of:

Three Academic Professors specializing in Information Management and Educational Technology, who provided guidance on pedagogical accuracy and university admission standards.

One Industry Expert serving as a senior executive and veteran instructor in the private education and test-prep industry, who offered insights into market demands and student/parent communication.

1) **B2B Strategic Positioning and Industry Chain Integration:** Experts suggested that the system should be positioned as a B2B (Business-to-Business) tool designed for educational institutions and consulting firms rather than a general-purpose consumer app. It was emphasized that the system should serve as a "Professional Brain" for institutions, enabling them to preserve the proprietary teaching expertise and historical case data of their consultants. This ensures that the system acts as a high-value intermediary between students and consultants, rather than a replacement for human expertise.
2) **Domain-Specific Reliability and RAG Implementation:** A significant concern raised was the "hallucination" and lack of professional reliability in general-purpose Large Language Models (LLMs). Experts recommended the implementation of Retrieval-Augmented Generation (RAG) to create a "semi-closed knowledge loop." By feeding the system with specialized data—such as past successful portfolios and interview records from elite university admissions—the AI coach can provide precise, evidence-based recommendations that align with specific institutional standards (e.g., National Taiwan University or top-tier international colleges).

3) **User Interface and Accessibility for Guardians:** The panel highlighted a common pain point in the industry: the digital divide among parents. To increase adoption, experts advised deep integration with the LINE messaging platform. Since most parents are already familiar with LINE, embedding the AI coach within this ecosystem lowers the technical barrier and allows for real-time synchronization of student progress, summaries, and notifications.

4) **Human-AI Hybrid Interviewing Models:** For the mock interview module, experts recommended a hybrid design. The AI can learn from real mock interview sessions led by human tutors, which may help it ask more relevant questions and better reflect department-specific expectations.

These insights have been integrated into our current development cycle, shifting our focus toward building a specialized, RAG-enhanced B2B platform (for an educational institution and their teachers) that prioritizes professional credibility and seamless communication via existing social messaging infrastructures.

4.2 Case Study

To evaluate the practical efficacy of the AI-based University Application Guidance System, a pilot study was conducted using a retrospective data approach. This study tested five students' learning portfolios to evaluate the system's predictive accuracy. These students are current undergraduate students, but their high school learning portfolios, which had been prepared for university applications, were used as our testing sample.

4.2.1 Quantitative Summary of Pilot Results

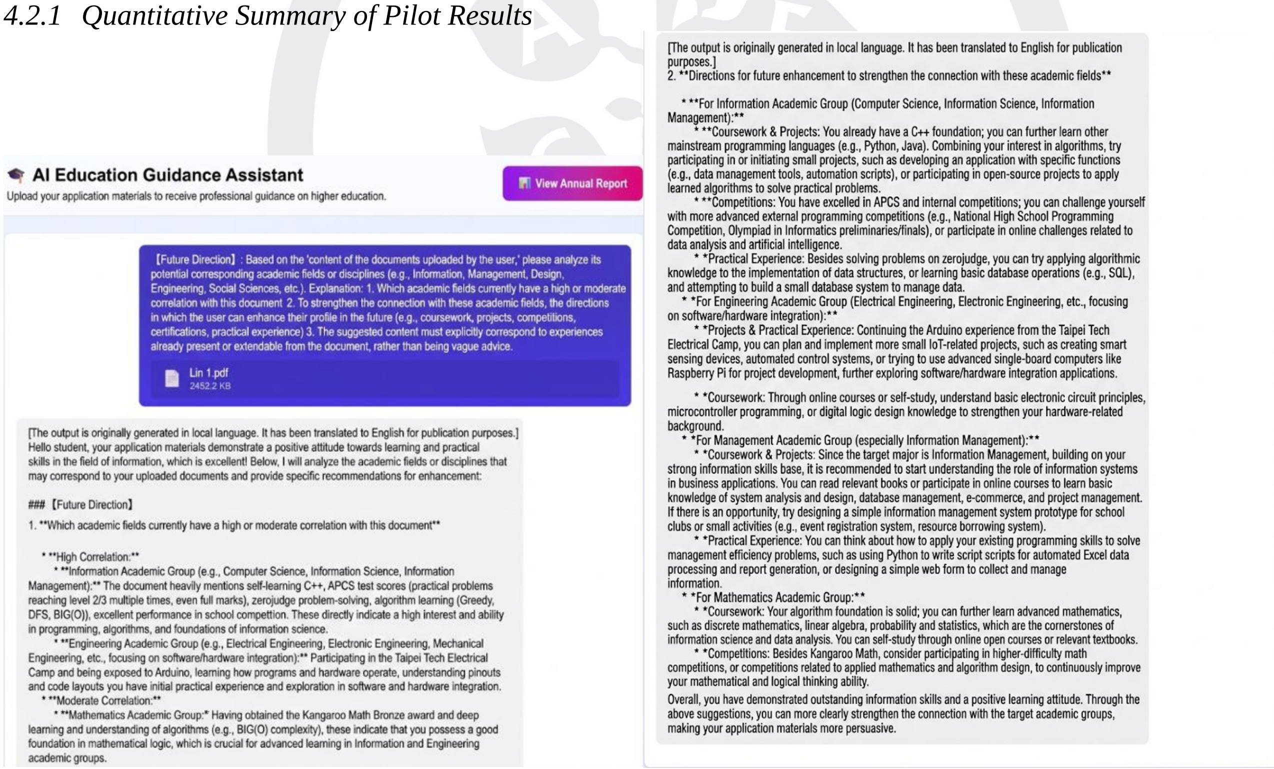

Figure 1 . The output generated by AI coach. (The output is originally generated in Mandarin. It has been translated into English for publication purposes.)

Overall, the pilot study demonstrated significant reliability in academic alignment. Out of the five cases analyzed, four cases (80% accuracy) yielded recommendations that perfectly matched the students' actual university majors. The system successfully identified interdisciplinary intersections such as "Information

+ Design" (Case: Chao) and "Information + Management" (Case: Lin, Chi, Lyu). Even in cases with highly diverse portfolios (Case: Yu), the system provided actionable insights that mirrored the student's actual academic transition from Educational Technology to Information Management.

4.2.2 Primary Case Illustration: Retrospective Validation

The researcher's own portfolio (Case: Lin) serves as the primary demonstration of the system's deep reasoning capabilities. As illustrated in Figure X, the AI analyzed the uploaded documents and identified a High Correlation with the Information Management and Computer Science clusters.

The system provided specific, actionable recommendations that align with real-world requirements:

1) Technical Skill Advancement: Enhancing Python and Java proficiency based on existing C++ foundations.
2) Interdisciplinary Integration: Applying programming skills to solve business efficiency problems, which is the core of Information Management.
3) Strategic Goal Alignment: Suggesting further exploration of database management and system analysis.

These results are highly consistent with the subject's actual academic trajectory, as the researchers are currently third-year students majoring in Information Management at Fu Jen Catholic University. This alignment confirms that the system effectively achieves its primary objective: providing personalized guidance that reflects real-world admission standards and career paths.

4.2.3 Synthesis of Secondary Cases

The remaining four cases further corroborated the system's effectiveness:

1) Case Chao: Correctly identified the intersection of coding and creativity, leading to a 100% acceptance rate across Information and Design departments.
2) Case Chi & Lyu: Validated the system's ability to pinpoint "Information Management" from unstructured data, including research on financial systems and IoT.
3) Case Yu: Demonstrated the system's ability to translate socially oriented topics into information-system requirements (e.g., privacy ethics and risk management).

5. Discussion

5.1 Interpretation of Findings

The primary contribution of this study is the development of an intelligent learning hub that integrates Learning Management Systems (LMS) with an AI-driven career coach. Our preliminary implementation and pilot testing results indicate that integrating scattered learning records, such as course progress, project reflections, and external competition results, into a unified "Personalized Knowledge Profile" reduces the administrative burden on tutors and enhances parents' visibility into their children's progress. Unlike traditional LMS which focuses solely on content delivery, our system's "AI Coach" module successfully guides students to transform fragmented experiences into coherent narratives suitable for study abroad applications. This addresses the critical pain point identified in our user requirements survey: students often struggle with self-reflection and fear that using AI for writing might lead to plagiarism or loss of personal voice. By positioning the AI as a "Coach" that asks guiding questions rather than a "Generator" that writes for them, we have observed an improvement in students' willingness to engage in self-regulated learning (SRL) and reflection. This aligns with findings by Luo, Wang, and Hew (2026), who argue that well-designed AI scaffolding can significantly enhance SRL strategies, such as goal setting and metacognitive monitoring, provided the system avoids the "illusion of competence" by encouraging active information transformation rather than passive acquisition.

5.2 Comparison with Related Works

Our work aligns with and extends recent advancements in educational technology. Heras et al. (2020) proposed an argumentation-based conversational recommender system that provides explanations to justify learning object recommendations. While their work emphasizes the transparency of recommendations, our system takes a step further by using Large Language Models (LLMs) not only to recommend content but also to co-construct knowledge with the student. Our system engages in a dialogue to help students articulate why a specific learning experience is valuable to their career goals, effectively moving from "recommendation explanation" to "metacognitive scaffolding."

Furthermore, Mittal et al. (2024) provided a comprehensive review highlighting the potential of Generative AI (GenAI) in creating personalized learning experiences while cautioning against data privacy and bias issues. Our system implements the "structured pedagogical frameworks" called for by Mittal et al. (2024), by constraining the AI's role within a "coaching" boundary. We utilize the student's own uploaded data as the primary context (RAG), thereby mitigating hallucinations and maintaining the authenticity of the student's portfolio.

In the domain of LLM-based agents, Yang et al. (2025) surveyed the architecture of educational agents, identifying a shift towards agents with sophisticated memory and reasoning capabilities. Our system includes a long-term memory module that keeps track of a student’s learning history over time. This is especially useful for study abroad preparation, where students often need to show evidence of long-term development. This contrasts with many existing agents that focus on episodic, short-term task completion without retaining a longitudinal "Growth Experience" (Yang et al., 2025).

Finally, compared to the recent work by Luo et al. (2026), who developed a GenAI-based recommender system to improve self-regulated learning and academic performance, our system shares the goal of enhancing self-regulation. However, while Luo et al. focus primarily on academic performance metrics, our system uniquely targets "Narrative Coherence" (McAdams, 2001). We argue that for students aiming for overseas higher education, the ability to synthesize learning outcomes into a compelling personal statement is as critical as academic grades. Our system demonstrates that AI agents can be effectively deployed in this high-stakes, niche domain of "Admissions Coaching" to preserve authentic student voice (Austin, 2025).

5.3 Implications and Future Applications

Our system demonstrates that GenAI can be effectively used to digitize and scale the "tacit knowledge" of experienced study abroad consultants. By encoding the logic of profile building into the AI Coach, educational institutions can offer high-quality, personalized guidance to a larger number of students without proportionally increasing human labor. This touches upon the "knowledge transfer paradox" described by Levy Yeyati (2024), where AI is used to augment rather than replace the nuanced intuition of human mentors. Future applications of this system could extend beyond study abroad preparation to other "portfolio-based" domains, such as art school applications or internship resume building, where storytelling and evidence integration are key (Nguyen, 2013). Additionally, the accumulated data on student-AI interactions offers a valuable resource for institutions to analyze learning behavior patterns and optimize curriculum design.

5.4 Limitations and Future Research

Current validation of the system relies on pilot testing with a limited number of students and qualitative feedback from experts. As noted by Yang et al. (2025), subjective evaluation remains dominant in assessing LLM agents, which can introduce bias. Future research should incorporate longitudinal studies to track the actual admission success rates of students using our system compared to a control group, providing objective evidence of its efficacy. Furthermore, while we currently analyze text-based reflections, future iterations will aim to integrate multimodal capabilities—such as analyzing students' oral presentation videos or project diagrams—to provide more holistic coaching. Recent developments in open-source multimodal feedback systems, such as OpenOPAF (Ochoa & Zhao, 2024), suggest that analyzing nonverbal cues like gaze and pacing could significantly enhance the "mock interview" features of our agent, addressing the complex nature of real-world problem-solving.

6. Conclusion

An intelligent learning reflection and career navigation system is proposed in this paper. The system aims to establish a comprehensive learning ecosystem by integrating generative AI to support students' transition from daily video-based learning to long-term career planning. The key contribution of the system is that it functions not merely as a passive recording tool but as a proactive learning coach: while students watch courses, it provides real-time knowledge reinforcement and, through a structured guidance process, transforms fragmented learning experiences into high-quality portfolios. These portfolio data are further leveraged to generate quantitative performance reports, which help persuade and guide students toward more informed decisions regarding higher education and career pathways.

The proposed system spans multiple stages of the learning cycle, and its modular functions have been validated. During the learning phase, the system enables video-synchronized note-taking with AI feedback to promptly correct misunderstandings. In the reflection phase, through the "Single-Activity Record Assistant," the system offers automated prompts and optimization suggestions to substantially lower the barrier to reflective writing and improve the professionalism of the content. In the planning phase, the "Career Advice" module provides data-driven pathway matching. In addition, the system introduces a "Self-Assessment System" that uses mock interviews to verify whether students have truly internalized the knowledge described in their portfolios, thereby enhancing the authenticity and consistency of learning records.

At present, the system serves as a proof of concept. Based on expert interviews and practical evaluations, we found that if the system relies only on generative large language models (LLMs), the guidance it provides may become too similar to common ChatGPT-style services, making it harder to show the project's unique value and strengths. This suggests that the AI's coaching capability may be limited when dealing with cross-domain or highly unstructured learning activities.

Accordingly, future work will focus on strengthening the system's technical architecture to address these challenges. First, we will build a semi-closed database and implement retrieval-augmented generation (RAG) by incorporating high-quality private datasets, including successful cases from hundreds of students who participated in international competitions and university applications, such as portfolios and competition records. This will enable the model to draw on validated examples when generating suggestions, making its guidance more precise and actionable than that of generative models. Second, we will adopt a human-in-the-loop framework and position AI as an assistant to tutors rather than a replacement for them. Future research will also collect and analyze real mock interview data to continuously refine and improve the model.

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