From Insights to Impact: An Agentic Learning Intelligence Framework for Student-Centred Success

Joel Weijia Lai(✉), Wei Qiu, and Fun Siong Lim

Institute for Pedagogical Innovation, Research, and Excellence,
Nanyang Technological University, 50 Nanyang Avenue, Singapore 639798, Singapore
{joellai,qiuwei,lim_fun_siong}@ntu.edu.sg

Abstract. Agentic artificial intelligence (AI) in education can reshape student success by fostering adaptive and personalized learning experiences. AI-powered systems are individually built to analyze academic records, career aspirations, and engagement with curricular and co-curricular activities to generate tailored recommendations that dynamically adjust learning pathways. While existing research has explored AI's role in education, its full potential in holistic student development remains under-examined. This practitioner report presents an agentic framework that leverages advances in learning analytics to propose a practical application of agentic AI, emphasizing its future role in integrating academic support, skill-building opportunities, and career preparation. By continuously refining recommendations based on real-time progress, AI-powered systems will enhance student engagement, optimize resource accessibility, and ensure education remains flexible and responsive to evolving career pathways. This ongoing work aims to provide perspective and advance discussions on the future of AI in education, positioning agentic AI as a transformative proponent for student-centered success.

Keywords: Agentic Artificial Intelligence · Learning Analytics · Personalized Pathways · Goal-Oriented Recommendations

1 Introduction

Artificial intelligence (AI) is transforming education by reshaping how students engage with learning and how institutions provide academic support. Learning analytics is one of its most impactful applications, which leverages data to enhance student success [4]. Traditionally, learning analytics has focused on tracking academic performance through structured data, such as grades, attendance, and participation metrics [12,20]. Early warning systems [14], predictive analytics [18], skills identification [7], and adaptive learning platforms [10] have enabled educators to make data-informed decisions to support students at risk

A. I. Cristea et al. (Eds.): AIED 2025, CCIS 2590, pp. 109–118, 2025.
https://doi.org/10.1007/978-3-031-99261-2_10

of failing or dropping out. However, these systems primarily function retrospectively, predicting risks based on past performance, and often do not consider students' personal learning goals. Since education is a dynamic and evolving process, AI-powered learning analytics must move beyond prediction-based intervention models toward a proactive, student-centered approach that continuously adapts to learners' evolving goals and needs.

Generative AI introduces a significant shift in learning analytics by enabling real-time analysis, guidance, and personalization of student experiences. Context-aware large language models and chain-of-thought reasoning play a crucial role in this transformation by synthesizing learning content, adapting instructional materials, and generating tailored goal-oriented recommendations [2]. Despite growing interest in generative AI for education, much existing research has focused on content generation, automated assessment, and personalized tutoring. Learning analytics remains primarily confined to academic monitoring and predictive modeling for student retention [2]. Recent studies have begun to explore generative AI's potential in understanding learning motivation and engagement [3,5,6], but a more comprehensive integration of AI in student development is still lacking.

Agentic AI is an emerging intelligence system demonstrating autonomy, goal-directed behavior, and the ability to take independent actions to achieve objectives. These systems can plan, make decisions, and execute tasks without constant human intervention [1]. Agentic AI expands the possibilities of AI in education by shifting from passive analytics to active guidance, empowering students with personalized learning trajectories that evolve in response to their real-time progress, skills development, and career aspirations. Unlike traditional systems that primarily identify struggling students for remedial interventions, agentic AI dynamically adjusts learning pathways for all students based on academic history, engagement with curricular and co-curricular activities, and emerging career trends. However, existing frameworks often fail to integrate essential non-academic factors such as internships, mentorship programs, and experiential learning, all critical for workforce readiness [13,17,19]. By advancing discussions on agentic AI, this paper highlights its potential to support student success through personalized, adaptive, and holistic learning experiences, positioning AI as a key enabler of lifelong learning and professional growth.

2 Agentic Artificial Intelligence Implementation in Higher Education Practice

Learning analytics at our institution, Nanyang Technological University, Singapore, is performed as a data service through cleaning, engineering, modeling, analysis, visualization, and deployment. This is done by integrating and leveraging leading data science and machine learning technologies, including Denodo, Dataiku, Qliksense, Snowflake, and Sreamlit. These data services cater for the learning needs of 25,000 undergraduate students, pulling information from five key data hubs:

1. The Curriculum Hub contains curricular and co-curricular activity data, offering structured academic content and additional learning experiences beyond the classroom. This information might be used to recommend academic courses, workshops, or extracurricular engagements that align with the user's educational goals.
2. The Education Hub includes diverse continuous learning activities such as student engagement with online interactive exercises, assignments, and announcements, as well as course-specific resources such as videos, textbooks, and PowerPoint slides that would enhance students' understanding of the course.
3. The Career Hub aggregates career preparation opportunities, including internships, mentorship programs, and industry-specific training. This information might help students align their academic experiences with career aspirations and gain exposure to professional environments.
4. The Library/Resource Hub provides access to digital libraries and online learning resources, including books, research articles, and multimedia materials. These resources might support self-directed learning and provide additional context to academic coursework.
5. The Student Academic Hub serves as a personalized knowledge repository that is the foundation of a student profile, which includes information such as their academic background, performance, course registration history, program, and academic requirements. These historical data are essential for refining future recommendations and adapting learning pathways to ensure continuous student growth.

2.1 Existing Work 1: Early Alert for Learning Intervention

This project aims to proactively identify students who may require academic support before the commencement of a new semester. By leveraging machine and deep learning models—specifically SVM, logistic regression, LSTM, and Short-term gated LSTM—our predictive learning analytics model analyzes historical performance data from the aforementioned student academic hub to predict students at risk of failing and pinpoint specific courses where intervention might be necessary [14,15] (See data pipeline Fig. 1). The implementation involves generating a list of students at risk of academic warning. This list is provided to student care managers through a dedicated dashboard. These managers may contact the identified students to offer academic, financial, psychological, or social support. Its primary aim is to analyze student engagement and learning behaviors using data-driven insights, ultimately improving teaching effectiveness and student outcomes by:

– Understanding Student Learning Patterns: By analyzing data such as time spent on course materials, participation in online discussions, and frequency of resource access, the system identifies trends, such as both long-term academic trajectories and short-term performance fluctuations, in how students engage with their studies.

- Providing Timely Interventions: Leveraging predictive data analytics, the system identifies students who may struggle academically before their performance declines significantly. The model detects patterns associated with academic risk by analyzing historical academic records and engagement metrics.

Trialed across six cohorts in five schools (nearly 14,000 students), it achieved over 70% true-positive rates. Reports from student care managers indicate that early intervention has improved academic outcomes, with some students showing significant GPA improvements following personalized support.

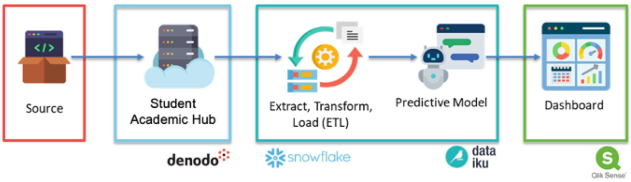

Fig. 1. The automated model pipeline for grade prediction to highlight potential at-risk students. Can be augmented with, and replicated for other forms of academic prediction.

2.2 Existing Work 2: Career Preparation with Skills Profile

Additionally, we have implemented an AI-enabled career preparation platform to enhance university students' awareness of their career readiness and skill development (Fig. 2) based on a needs analysis from a previous study [8]. It acts as an intervention that allows students to self-assess their current competencies and identify gaps in relation to industry requirements. The platform aims to provide students with tailored insights into their suitability for specific roles and to identify skill gaps based on their skill profile and career aspirations. Its key goal is to empower students to map their career goals, develop essential skills, and discover suitable internships, bridging the gap between their current skill set and future aspirations. The platform is a prototype of the career hub and assists students in identifying their skills and skills gaps through:

- AI-powered Skill Profiling: The platform automatically generates a skills profile by analyzing uploaded resumes, showcasing the student's relevant competencies based on AI methods and tagging.
- Comparison with Role Requirements: When students explore internship opportunities, the platform displays the skills required for each role and highlights the skills they already possess. This visual comparison helps students understand which skills they have and which are needed for their desired roles.

– Identification of Skills for Development: The platform automatically shows skills for development. This feature directly addresses the students' skill gaps in relation to their career aspirations.

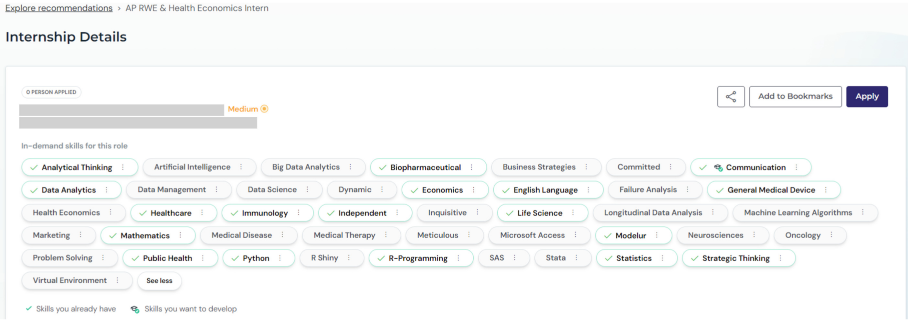

Fig. 2. Skills in demand for a specific internship, skills possessed by the user are identified from their resume by AI and highlighted in green. This allows the user to identify skill gaps and work on them. (Color figure online)

From our existing works, we know that learning analytics can help inform through predictive means in a student's academic and career-preparation journey. However, they currently operate in silos, answering to specific needs.

We now outline our proposed transformation into an agentic system. By embedding AI-powered learning analytics within student-facing platforms, learners can receive personalized recommendations on course selection, skill development, and career planning based on their learning goals. This shift from an institutional-centric approach to a student-centered model aligns with the vision of agentic AI, empowering students to take ownership of their learning pathways. This expansion will require robust AI-powered interfaces that translate complex learning analytics insights into actionable recommendations tailored to each student. The AI Orchestrator performs this task while handing the agency of goal-setting and learning pathways to the student.

As illustrated in Fig. 3, the agentic AI framework operates as an intelligent intermediary between the user and multiple academic and career-related information hubs. This AI-powered system synthesizes data from various sources to provide highly personalized learning recommendations based on a user's needs, preferences, and academic or career aspirations. At the core of this framework is the AI Orchestrator, which functions as the central intelligence responsible for dynamically processing and generating personalized learning pathways. Students interact with this system via a front-end interface. They are encouraged to select areas they would like to learn and the cadence (such as weekly, fortnightly, or monthly) they want AI recommendations to be delivered to them. In response, the AI Orchestrator will communicate with specialized AI agents

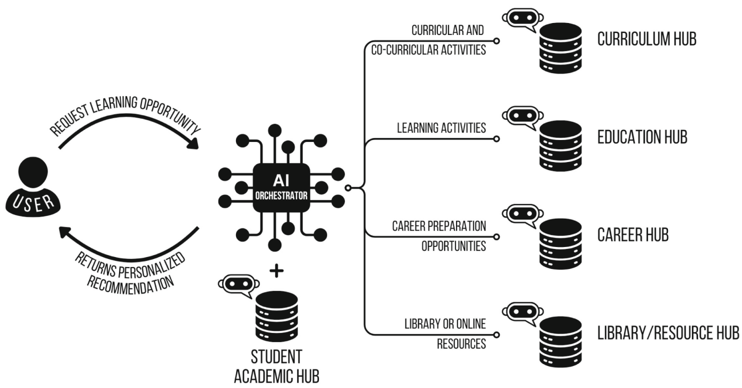

Fig. 3. Agentic AI Framework for Personalized Learning – The AI Orchestrator integrates data from multiple hubs to provide tailored learning recommendations based on user requests.

attached to each hub to fulfill the request. In our proposed architecture, generative AI models embedded within individual hubs enable localized knowledge generation, while the agentic orchestrator synthesizes their outputs to achieve a higher-order, adaptive decision-making capability.

For example, students set learning goals ("I want to be in data science") and when they want recommendations (such as "I want recommendations every fortnight") to be pushed to them. Based on this information and their academic history from the student academic hub, the AI Orchestrator would be activated and seek inputs from the specialized AI agents responsible for each hub. If the request is near the course registration period, the AI agent for the curriculum hub might return information about elective courses that the student can choose to support their learning goals. If the request is during the term, the AI agent curriculum hub could return the available co-curricular activities related to the learning goals instead. Similarly, the AI agent for the education hub may return some practice questions for the courses if the request is near the examination period. If there are some groundbreaking papers on data science, the library hub agent may also return a summary of the latest study in this area. Before the term break, the AI agent of the career hub may alert students of internship opportunities. Taking in all the responses from each hub, the AI Orchestrator collates the responses from each AI agent and then packages the recommendations to the students.

3 Reflection on Challenges and Opportunities Associated with Implementation

Implementing agentic AI in education has several challenges that must be addressed to realize its full potential. One of the most significant hurdles is the labor-intensive process of gathering and integrating data from various sources. Educational institutions collect vast amounts of data from academic records, student engagement metrics, career aspirations, and extracurricular activities. However, this data is often scattered across different systems, managed by various departments, and stored in inconsistent formats. Bringing these disparate data sources into a centralized and structured data warehouse requires extensive collaboration with multiple data owners, which can be time-consuming and complex. Once the data is collected, the next challenge is building systems that can effectively integrate and communicate with an AI Orchestrator. Many institutions rely on legacy systems not designed for interoperability with AI-powered platforms. Developing a seamless integration between learning management systems, student information databases, and career guidance tools demands significant technical investment and careful planning. Ensuring that these systems work together efficiently is critical for AI-powered recommendations to be accurate and relevant.

Beyond technical challenges, ethical considerations and data privacy concerns must be carefully managed. AI-powered education systems depend on vast amounts of student data, raising critical questions about security, confidentiality, and responsible AI use. Institutions must implement strict data governance and use of AI policies to protect student information while ensuring compliance with privacy regulations. Furthermore, trust remains a significant barrier to AI adoption. Some students may be hesitant to rely on AI-generated recommendations due to concerns about bias or a lack of understanding of how the system operates. Henceforth, we need to educate students that they have control over their learning decisions and can give feedback to the system should they find the AI recommendations not helpful.

Despite these challenges, the successful implementation of agentic AI presents significant opportunities for transforming education. Once the data integration and system interoperability issues are resolved, AI can provide a truly personalized learning experience. By analyzing a student's academic history, engagement patterns, and career aspirations, AI can tailor educational content to fit their unique needs. Unlike traditional learning analytics that primarily focus on identifying struggling students for intervention, agentic AI actively supports all learners by dynamically adapting content and learning pathways. Another significant opportunity is the scalability of AI-powered education [16]. Due to resource constraints, personalization has traditionally been challenging to implement at large institutions. However, AI enables scalable, tailored learning experiences, ensuring every student receives support that aligns with their goals [11]. Ultimately, harnessing AI-powered insights allows institutions to create a more equitable and effective learning environment, ensuring that students from all backgrounds have access to high-quality education and support.

4 Future Steps

The next phase of this project will focus on structuring data to enhance the intelligence, adaptability, and privacy of the agentic AI system. Instead of simply integrating and storing data in a centralized warehouse, the emphasis will shift toward organizing information using knowledge graphs within distributed hubs. Each hub will be accessed only by a specialized AI agent, ensuring that data owners maintain control over their respective datasets. This separation of responsibilities enhances data protection and aligns with governance best practices by preventing any single entity from holding comprehensive user profiles. The AI system can better understand relationships between different learning components by structuring academic records, student engagement metrics, career aspirations, and extracurricular activities into localized semantic networks. The orchestrator model will not store or directly manage this data but synthesize insights from multiple agents, each responsible for its domain-specific hub. This approach ensures that data privacy is maintained while allowing for highly contextualized and dynamic recommendations. The system can provide personalized learning journeys without compromising data sovereignty by mapping connections between coursework, skills, career pathways, and real-world job requirements.

We will refine AI models that leverage graph neural networks (GNNs), natural language to SQL generation, and semantic reasoning to make these dynamic recommendations more adaptive and explainable. GNNs are a class of neural models designed to operate on graph-structured data, making them suitable for reasoning over interconnected concepts or relationships [9]. Instead of treating student progress as a linear sequence of courses and grades, the AI will interpret learning as a network of interrelated concepts, competencies, and experiences about their learning goals. This will improve the granularity of goal-oriented recommendations and the system's ability to explain why a particular suggestion is relevant. Enhancing explainability will be a key priority, helping students understand how and why AI-generated guidance is tailored to them while maintaining trust in the system's governance framework. We intend to pilot this with at least one of the hubs and one of the university's colleges in the coming year.

5 Conclusion

Implementing agentic AI represents a transformative shift in higher education, moving beyond traditional learning analytics to offer proactive and personalized student support. By integrating AI-powered learning analytics with career and skill-building recommendations, this system optimizes student engagement and ensures that education remains adaptive to evolving career pathways. While challenges exist, including ethical considerations and the need for institutional integration, ongoing research, and strategic partnerships will be essential to refining the AI framework and expanding its implementation.

Agentic AI has the potential to revolutionize education by empowering students with personalized learning trajectories that evolve in real time. By shifting from reactive intervention models to proactive guidance, AI-powered systems foster a more inclusive, adaptable, relevant, and student-centered approach to learning. As educational institutions embrace this technology, continued research and collaboration will ensure its long-term success and sustainability. By advancing the integration of agentic AI in education, which leverages and agglomerates data and resources uniquely available within the universities, we prepare students for lifelong success and ensure the relevance of university education in an ever-changing world.

Disclosure of Interests. The authors declare that they have no conflict of interest.

References

1. Acharya, D.B., Kuppan, K., Divya, B.: Agentic AI: autonomous intelligence for complex goals–a comprehensive survey. IEEE Access **13**, 18912–18936 (2025). https://doi.org/10.1109/access.2025.3532853
2. Bobula, M.: Generative artificial intelligence (AI) in higher education: a comprehensive review of challenges, opportunities, and implications. J. Learn. Dev. High. Educ. **30** (2024). https://doi.org/10.47408/jldhe.vi30.1137
3. Collie, R.J., Martin, A.J.: Teachers' motivation and engagement to harness generative AI for teaching and learning: the role of contextual, occupational, and background factors. Comput. Educ. Artif. Intell. **6**, 100224 (2024). https://doi.org/10.1016/j.caeai.2024.100224
4. Giannakos, M., et al.: The promise and challenges of generative AI in education. Behav. Inf. Technol. 1–27 (2024). https://doi.org/10.1080/0144929x.2024.2394886
5. Guo, J., Ma, Y., Li, T., Noetel, M., Liao, K., Greiff, S.: Harnessing artificial intelligence in generative content for enhancing motivation in learning. Learn. Individ. Differ. **116**, 102547 (2024). https://doi.org/10.1016/j.lindif.2024.102547
6. Hmoud, M., Swaity, H., Hamad, N., Karram, O., Daher, W.: Higher education students' task motivation in the generative artificial intelligence context: the case of chatgpt. Information **15**(1), 33 (2024). https://doi.org/10.3390/info15010033
7. Lai, J.W., Zhang, L., Chan, Y.S., Sze, C.C., Lim, F.S.: Compelling educational offerings: a study on the efficacy of skills identification platforms with course descriptions. In: INTED2024 Proceedings. INTED2024, vol. 1, pp. 2553–2561. IATED (2024). https://doi.org/10.21125/inted.2024.0709
8. Lai, J.W., Zhang, L., Sze, C.C., Lim, F.S.: Learning analytics for bridging the skills gap: a data-driven study of undergraduate aspirations and skills awareness for career preparedness. Educ. Sci. **15**(1), 40 (2025). https://doi.org/10.3390/educsci15010040
9. Li, X., Tian, Y., Ji, S.: Semantic- and relation-based graph neural network for knowledge graph completion. Appl. Intell. **54**(8), 6085–6107 (2024). https://doi.org/10.1007/s10489-024-05482-2
10. Morze, N., Varchenko-Trotsenko, L., Terletska, T., Smyrnova-Trybulska, E.: Implementation of adaptive learning at higher education institutions by means of Moodle LMS. J. Phys. Conf. Ser. **1840**(1), 012062 (2021). https://doi.org/10.1088/1742-6596/1840/1/012062
11. Ng, S.H.S., Lai, J.W.: AI-augmented heutagogy for higher education (2025). https://doi.org/10.31219/osf.io/nxgau_v1
12. Pei, B., Xing, W., Wang, M.: Academic development of multimodal learning analytics: a bibliometric analysis. Interact. Learn. Environ. **31**(6), 3543–3561 (2021). https://doi.org/10.1080/10494820.2021.1936075

13. Popli, N.K., Singh, R.P.: Enhancing academic outcomes through industry collaboration: our experience with integrating real-world projects into engineering courses. Discov. Educ. **3**(1) (2024). https://doi.org/10.1007/s44217-024-00300-w
14. Qiu, W., Khong, A., Supraja, S., Tang, W.: A dual-mode grade prediction architecture for identifying at-risk students. IEEE Trans. Learn. Technol. **17**, 803–814 (2024). https://doi.org/10.1109/tlt.2023.3333029
15. Qiu, W., Supraja, S., Khong, A.W.H.: Toward better grade prediction via A2GP - an academic achievement inspired predictive model. In: Mitrovic, A., Bosch, N. (eds.) Proceedings of the 15th International Conference on Educational Data Mining, pp. 195–205. International Educational Data Mining Society, Durham, United Kingdom (2022). https://doi.org/10.5281/zenodo.6852984
16. Saragih, R.I.E.: AI-powered education: Transforming learning through personalized and scalable solutions. Int. J. Inf. Syst. Innov. Technol. **3**(2), 1–9 (2024). https://doi.org/10.63322/qm9dk118
17. Sehgal, G.: AI & agentic AI in education: shaping the future of learning (2024). https://www.meratutor.ai/blog/agentic-ai-in-education/. Accessed 12 Feb 2025
18. Sghir, N., Adadi, A., Lahmer, M.: Recent advances in predictive learning analytics: a decade systematic review (2012–2022). Educ. Inf. Technol. **28**(7), 8299–8333 (2022). https://doi.org/10.1007/s10639-022-11536-0
19. Spanjaard, D., Hall, T., Stegemann, N.: Experiential learning: helping students to become 'career-ready'. Australas. Mark. J. **26**(2), 163–171 (2018). https://doi.org/10.1016/j.ausmj.2018.04.003
20. Ye, D.: The history and development of learning analytics in learning, design, & technology field. TechTrends **66**(4), 607–615 (2022). https://doi.org/10.1007/s11528-022-00720-1