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Adaptive Cloud-Integrated Artificial Intelligence for Personalized Learning Pathways in Higher Education

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Abstract: At a time when Higher Education (HE) institutions are struggling to improve student engagement and learning outcomes while closing achievement gaps within their increasingly diverse student communities, personalized learning (PL) in the form of tailored learning pathways is gaining traction. However, the cost, resource, and time implications in the design of PL solutions, especially in Higher Education, have constrained broader PL uptake, initial attempts in so-called personalized artificial intelligence (AI) have neglected critical dimensions of the student modelling component, and adaptation to actual student needs has remained an aspirational goal rather than reality. By drawing on innovative concepts from learning analytics, education data mining, adaptive instructional design, and adaptive cloud-integrated AI research, an adaptive cloud-integrated AI system is proposed that empowers any educator to create a PL solution in their discipline yet adapts to evolving student needs and interests in real-time, requires no up-front configuration, and can be deployed across disparate subject areas and learning contexts.

The architecture encompasses a cloud-deployed data foundation that supports student modelling and profiling, a recommender engine, and an adaptive personalization engine. Elements and algorithms within the three system components are presented and showcased in a range of Higher Education disciplines, illustrating how the integration of existing student activity data with cloud-hosted Repository and Knowledge Graph data learning pathways can be designed to mirror unit, course and program-level Learning Outcomes antennas without the time, resourcing or ongoing expertise overhead of traditional solutions. Insights from Greater Sydney and Auckland case studies indicate that PL, in various forms, improves student engagement and perception of learning outcomes. Disparate student characteristics add support for a degree of equity and access inference. However, the personalization process must be customized and continually refined to maximize its catering for the full range of student diversity.

Keywords: Personalized Learning in Higher Education, Adaptive Learning Pathways, Cloud-Integrated Educational AI, Student Modelling and Profiling, Learning Analytics, Education Data Mining, Adaptive Instructional Design, AI-Driven Personalization Engines, Recommender Systems for Learning, Knowledge Graph–Based Learning Design, Repository-Integrated Learning Content, Real-Time Learning Adaptation, Learning Outcomes Alignment, Scalable Personalized Learning Architectures, Equity and Access in Education, Student Engagement Analytics, Adaptive Educational Systems, Cross-Disciplinary Learning Platforms, Cloud-Based Learning Infrastructure, Intelligent Higher Education Systems.

1.INTRODUCTION

Personalized learning is among the most extensively discussed concepts in higher education today, but evidence for its success at scale remains elusive. Learning analytics and education data mining help to build better models of students, recommender systems generate engaging learning experiences, and adaptive instructional design principles can be followed. However, the lack of an adaptive cloud-integrated artificial intelligence (AI) ecosystem that supports the orchestration of different components in the context of real-world teaching and learning remains a critical gap.
An adaptive cloud-integrated AI system has therefore been proposed to provide a centralized platform for deploying and operating different aspects of personalized learning, enabling organizations and institutions to design and implement highly personalized pathways that adapt automatically to the individual needs and capabilities of different students. To date, case studies across disciplines have illustrated its adoption, emphasizing the importance of interoperability with learning management systems to support automated data preparation and ease of use. The overall reported benefits not only include gains in student learning outcomes and engagement, but also enhanced equity and access stemming from lower barrier options presented to at-risk categories such as international and first-in-family students.

1.1. Overview of Personalized Learning and Its Importance

Personalized learning improves engagement and retention in higher education across populations and disciplines through customized pathways. However, the efforts and costs for implementing personalized learning are generally substantial

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and hybrid or fully online contexts remain less benefited. Leveraging learning analytics, innovations in cloud-based delivery and pervasive AI and using adaptive instructional design principles promise a more comprehensive and potentially lower-cost embrace of personalized educational opportunities. The adaptive cloud-integrated artificial intelligence (AI) ecosystem includes a user-experienced personalization engine for advising and pathway planning and a recommender engine to produce tailored experiences for learning content, assessments, and interaction in hybrid and fully online settings. Authoring tools, services, and monitoring and visualization functions support institutional adoption and integration with learning management systems (LMSs). Assessments in multiple disciplines demonstrate the efficacy of the approach, and outcome represent equity and access-focused contributions to learning analytics.

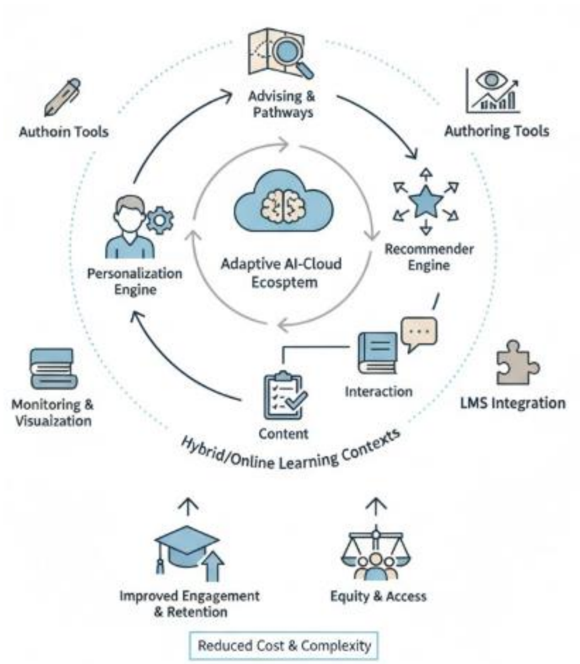

Fig 1: Scalable Equity: An Adaptive AI-Cloud Ecosystem for Cost-Effective Personalized Higher Education

Personalized learning employs the principles of learner-centered engagement—choice, voice, and ownership—operationalized under the instructional design strategy of adaptive instruction. Extensive research has shown positive correlations with both engagement and learning outcomes across disciplines and population groups. As a strategy for improving learner engagement and, by extension, retention in higher education, the adequacy of personalized learning is without question. Yet the costs and complexity of planning and delivering personalized educational experiences are significant when done at an individual rather than at a course or program-level. While advances in the use of recurrent neural networks and other AI methodologies have shown promising results for the automated delivery of personalized learning experiences, the cost and complexities of development remain barriers for widespread embrace.

2. THEORETICAL FOUNDATIONS OF PERSONALIZED LEARNING

Personalized learning is a broad and ambitious concept, yet it can be more precisely defined. A narrower but more comprehensible view focuses on providing a variety of educational opportunities tailored to an individual student's needs. Davidson and others further distill the notion into nine characteristics: personalization; learner control; external connectivity; embedded assessment; collaboration; openness; support; engagement; and underpinning technology. Two major supporting concepts especially applicable to personalized learning are learning analytics and education data mining. Learning analytics is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs." Education data mining is closely related but differs in that it tends to employ algorithms drawn from traditional data mining but applied to educational contexts and questions. An example of adaptive instructional design in practice is the Adaptive Hypermedia Systems model, which proposes an instructional design process that combines techniques from four earlier approaches by enabling designers to adapt to individual differences in learner characteristics, learning styles, knowledge and goals. Minimally invasive instruction also embodies the spirit of adaptive instructional design, relying on a flexible infrastructure that enables classroom instructors to use personalized online learning materials with limited additional effort.

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Equation 1) Student modelling/profiling equations (feature construction)

Step 1: Raw features from LMS + repositories

Build a raw feature vector per student:

$$\mathbf{x}_s^{raw} = \Big[\underbrace{\mathbf{g}_s}_{\text{general}} , \underbrace{\mathbf{c}_s}_{\text{course engagement/performance}} , \underbrace{\mathbf{i}_s}_{\text{interest}} \Big]$$

Step 2: Normalize heterogeneous features

Because units differ (minutes, counts, marks, ratings), normalize each feature k across students:

$$x_{s,k} = \frac{x_{s,k}^{raw} - \mu_k}{\sigma_k}$$

where μ_k and σ_k are the mean and std-dev of feature k.

(Alternative: min–max normalization. But z-score is common when feeding SOM/distance models.)

Step 3: Weighted profile (optional but typical)

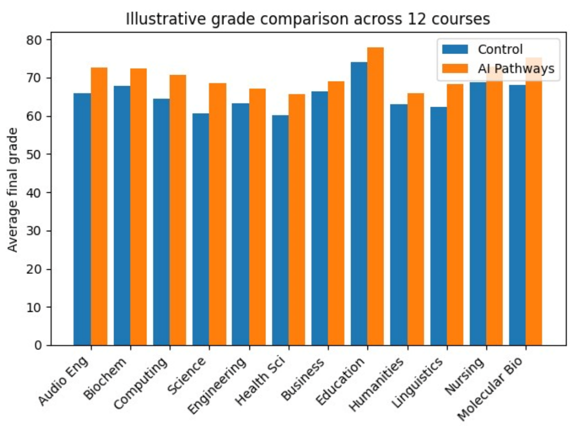
$$\tilde{\mathbf{x}}_s = \mathbf{W}\mathbf{x}_s$$

where $\mathbf{W} = \mathrm{diag}(w_1, \ldots, w_d)$ (feature weights).

2.1. Learning Analytics and Education Data Mining

Learning analytics (LA) is an emergent field focusing on how data from online teaching (either Massive Open Online Courses or normalized Learning Management Systems) can be used to understand and support student learning. The Foundation of Learning Analytics defines LA as “the collection, measurement, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs.” The term “educational data mining” (EDM) is often used interchangeably, though EDM focuses on the use of techniques from machine learning and data mining and emphasizes the creation of predictive models.

Learning analytics can help students become more aware of their own learning and increase engagement with online learning. By providing detailed information about their contact with course material and feedback about expectations, LA students can enhance their learning experience. Learning analytics can also provide insights to institutions offering courses and educational platforms, empowering educators to improve the environment, content, resources and services offered to students. Results in learning analytics may also be useful for future learners. Predictive modelling algorithms using past data can assist future students by giving them a more personalized experience.



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Course	Avg Grade (Control)	Avg Grade (AI Pathways)	Engagement Index (Control)
Business	66.4	69.1	0.47
Education	74.0	78.0	0.55
Humanities	63.0	65.9	0.51
Linguistics	62.3	68.3	0.52
Nursing	68.9	72.9	0.65
Molecular Bio	68.1	75.2	0.52

2.2. Adaptive Instructional Design

Investigating the foundations of personalized learning pathways prompts a consideration of how automated support for individual students can respond to learning analytics and educational data mining, two fields increasingly applied to student processes and their demands. Learning analytics systems remain largely descriptive, often failing to translate their understanding of learning into provably effective decisions. Lab-based A/B tests, progressively automated by engine designs, therefore emerge as opportune sources of evidence. Adoption lags long-established university procedures due to the complex systems involved, but customized assignments in a high-traffic engineering studio provide a natural start. Efforts adopt decision-support models to advance student and unit results and experiences by individually modeling performance yet maintaining high-success rates and student numbers. Success boosts equity and access.

Adaptive functions and services are now embedded in institutions' core information systems, allow analysis of impact across different uses, subjects, and periods, and are included in exam design, with results enhancing specific learning-pathway materials and predictive models. Inter-faculty collaboration bolsters success. Adapting assessment via student demand for tailored online-exam banks has strongly benefited high-risk cohorts and their providers. Two teaching staff learning-advisory teams regularly consider predictive-student models, refined by predictive-exam-design interactivity. Demand informs model data and shaping. A low-cost recommendation engine assists low-end students and non-completion modelling and feedback. Automated collaboration scaffolds major team-delivered assignments.

3. METHODOLOGICAL FRAMEWORK

The proposed adaptive personalized cloud-integrated AI leverages cloud-based platforms and services for data, computing resources and algorithms that support learning analytics and education data mining, adaptive instructional design, and adaptive and intelligent instructional recommendation systems. The personalization component monitors student learning throughout the semester, analyzing formal, informal, and non-formal learning data and resources. Based on the analysis, personalized learning resources, and activities are generated and delivered to students. The system also includes a recommender engine that suggests learning resources to students based on peer learning and other factors. In addition, novel adaptive instructional design techniques are employed to support the development of personalized WAS approach. The integration of these processes in an adaptive system allows the creation of Perkins WAS, Moodle addons for Perkins WAS, Perkins WAS in control of other Moodle-based WAS, Perkins WAS-based Moodle, Perkins WAS for diversity, Perkins WAS for on-site and remote learning, Perkins WAS-AI cooperation, Perkins Data Integration for Perkins AI, Perkins WAS for health equity, Perkins Learning Analytics, Perkins AI, Perkins Adaptive Systems, Perkins DA+AI Integration and Perkins Deng AI WIL. The implementation in higher education programs is validated through a series of case studies covering business, computing, education, engineering, health, and science programs. The use of Open-source platforms enables interoperability of the proposed adaptive personalized Cloud-integrated AI with any Learning Management System (LMS). Moreover, Perkins Adaptive Systems guarantee accessibility, equity, and diversity of the produced learning resources, while Perkins Learning Analytics and Perkins AI enable learning-tracing and analysis of engagement levels in Perkins WAS.

The detailed Architecture of the adaptive personalized Cloud-integrated AI, Perkins Adaptive Systems, Perkins Learning Analytics, Perkins Data Integration for Perkins AI and Perkins Deng AI WIL is presented in the authors' referred papers. The results achieved to date, which cover the system components and algorithms that lead to Perkins Adaptive System, Perkins Data Integration for Perkins AI, Perkins Learning Analytics, Perkins AI, Perkins Deng AI WIL and Perkins Adaptive System in Teacher Education, demonstrate the applicability and effectiveness of the proposed concepts.

3.1. Architecture of the Adaptive Cloud-Integrated AI System

A novel adaptive cloud-integrated AI system has been developed that combines process and content-enhanced learning analytics with an adaptive instructional design. The work focuses on student modeling and profiling, the development of a recommendation engine for learning and study strategies, and an innovative personalization engine that utilizes content-based and collaborative filtering in a hybrid recommender approach. Process and content-enhanced learning analytics

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have been extended with the ability to assess emotional signals contained in recorded Zoom video lectures. By integrating learning analytics and data mining with adaptive instructional design, the system automatically generates personalized guidance, feedback, and resource recommendations for students.

The system significantly enhances equity and access for students from diverse backgrounds, including those whose first language is not English. An opportunity to reflect on learning has been shown to improve performance and engagement. The architecture incorporates an individualized recommender system that recommends learning and study strategies and tactics tailored to students' preferences and learning profiles. The implementation in higher education placement courses illustrates the concept's cross-disciplinary nature and its ability for seamless integration into learning management systems.

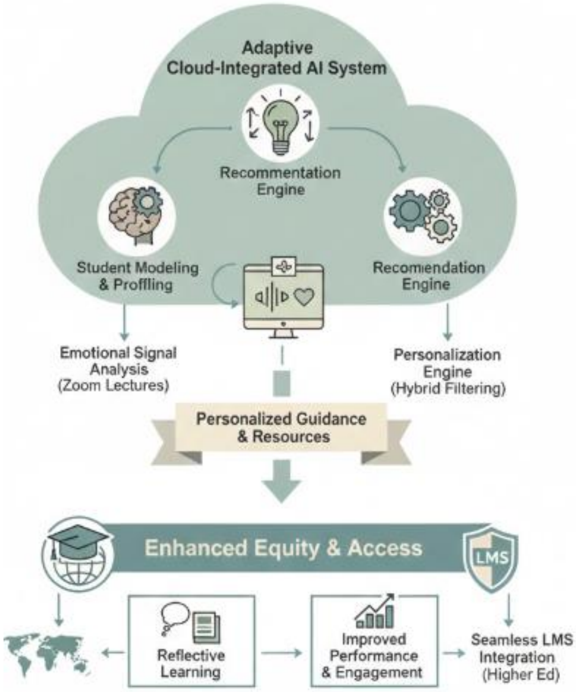

Fig 2: Adaptive Cloud-Integrated Learning Systems: Leveraging Hybrid Personalization Engines and Affective Analytics for Equity in Higher Education

3.2. Data Governance, Privacy, and Security

Across education, organizational, and public contexts, the adoption of cloud computing essentially supports the use and streamlining of business and operational processes while also directly providing free-to-use and computationally intensive machine learning, artificial intelligence, and deep learning services. Through these supported processes, information stored in clouds is therefore integrated in these analyses for data mining and knowledge discovery. However, there is one component that underlies and supports cloud data-mining processes in education as well as in other fields: Data Governance. This is true as no centralized database exist in educational environments for schools, colleges, and universities, which are often federated within national settings, such as in the UK, Australia, Singapore, and other growing operations, or even around the world. Data collected by these institutions are subject to both legal and ethical mandates to protect the privacy, security, and abuse of citizens and their data.

For these reasons, Data Governance becomes critical and of paramount importance in adaptive and personalized education approaches adopted by both the Learning Analytics (LA) and Education Data Mining (EDM) Domains, as well as in the cloud-based Artificial Intelligence (AI) Portrait methodologies presented in this work. The aim of these Data Governance frameworks and policies is to allow the use of student, teacher, schools, alliances, college or university data in the cloud while maintaining privacy, security, rights, and the change of agency and control back to students. For education, these Digital Data Governance methods are based on three foundational pillars: Trust, Control and Support, structuring itself in six functional components, considering the unique aspects of these environments, These components are: 1. Governance Model, providing the highest layer, defining the level of collaboration within the different levels of Data Governance; 2. Educational Environment, the recognition that it is an educational environment in which students must be considered for data mining as well as support to motivation, engagement, and learning; 3. Data Sources and Business Intelligence stores, the different data sources organized into the cloud for processing in LA and EDM; 4. Change Management and Sensitization, level of willingness to share data and trust on data usage, control, and privacy during the data mining and knowledge discovery processes; 5. External and External Expressed Communication, the level of

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transparency through internal and external communication of the Data Governance, and the level of communication on the opportunities; 6. Education as a Service: the level of availability of services supported by the generated knowledge.

4. SYSTEM COMPONENTS AND ALGORITHMS

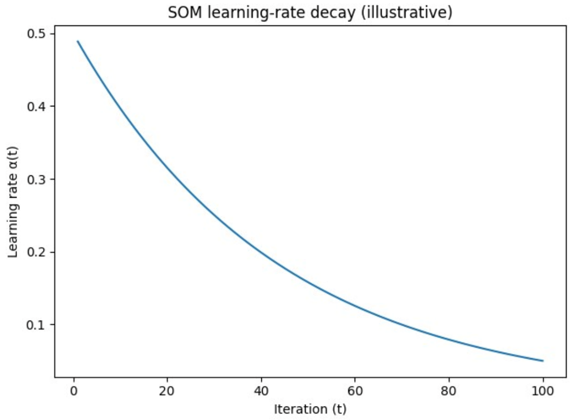
The design and implementation of personalized learning paths require a robust toolset to aggregate, process, and deliver the knowledge that users need at specific phases of their projects. A generalized Adaptive Cloud-Integrated Artificial Intelligence (ACIAI) system has been developed with three key components: Student Modeling, Recommender, and Personalization Engines. While additional components—such as Knowledge Discovery in Databases and Intelligent Automated Decision Support Engines—are available and can be employed flexibly, the first three are essential for defining adaptive personalized learning paths.

1 Student Modeling and Profiling

Examining student behavior is one of the fundamental building blocks for adaptive systems. Monitoring how students interact with a Learning Management System (LMS) reveals a wealth of information about their characteristics, behavior, and motivations. Building a strong student profile allows data to be classified according to user behavior, offering appropriate recommendations for action or decision-making. The ACIAI system provides a free software library in the widely used R programming language for building student behavioral profiles.

2 Recommender and Personalization Engines

Based on Kohonen Self-Organizing Map (SOM) neural networks and the idea that similar students tend to follow complementary learning curves, the recommender engine identifies useful information for students with similar characteristics on the same course. Given an active student s, m relevant recommendations—including learning resources, activities, and questions—are provided by looking at previous users with similar profiles. The personalization engine then generates the student's personalized learning page by aggregating the recommender top m results with information coming directly from the professors (if any) and from acknowledgment analysis.



Equation 2) SOM-based recommender engine (Kohonen Self-Organizing Map)

SOM setup

- A 2D grid of neurons $i \in \{I, \dots, N\}$
- Each neuron has a weight vector $\mathbf{w}_i(t) \in \mathbb{R}^d$

Step 1: Best Matching Unit (BMU)

For a student vector $\tilde{\mathbf{x}}_s$, compute Euclidean distance to each neuron:

$$D_i = \| \tilde{\mathbf{x}}_s - \mathbf{w}_i(t) \|_2$$

BMU is:

$$c = \underset{i}{\operatorname{argmin}} D_i$$

Step 2: Neighborhood function around BMU

Let $\mathbf{r}_i$ be the grid position of neuron i. Define:

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$$h_{c,i}(t) = \exp\left(-\frac{\| \mathbf{r}_c - \mathbf{r}_i \|^2}{2\sigma(t)^2}\right)$$

Step 3: Weight update rule (core SOM learning equation)

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \alpha(t)\, h_{c,i}(t)\big(\tilde{\mathbf{x}}_s - \mathbf{w}_i(t)\big)$$

Step-by-step derivation intuition (why this form)

1. Define an **error vector** from neuron to input:

   $\mathbf{e}_i(t) = \tilde{\mathbf{x}}_s - \mathbf{w}_i(t)$

2. Move neuron weight *toward* the input:

   $\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + \eta\, \mathbf{e}_i(t)$

3. Make η smaller over time (**learning rate decay**) and smaller for neurons far from BMU (**neighborhood decay**):

   $\eta \Rightarrow \alpha(t)\, h_{c,i}(t)$

4. Substitute to get the SOM update shown above.

Step 4: Finding "similar students"

Let $C(s)$ be the BMU cell for student s. Define neighborhood of similar students:

$$\mathcal{N}(s) = \{u : \| \mathbf{r}_{C(u)} - \mathbf{r}_{C(s)} \| \le \rho\}$$

4.1. Student Modeling and Profiling

Student modeling is a long-standing topic in artificial intelligence and education research. A student model serves as the information source for the recommender engine personalization and adaptation engine, reflecting learners' interests, prior knowledge and skills, and the goals students want to achieve. These preferences are computed from data aggregators throughout the learning experience. The student-profile data used in the case study implementations is generally classified into three categories.

General student information includes demographic data (gender, nationality, age) as well as soft and hard skills (strengths and weaknesses, certificates) and the learning path already covered (acquired course credits). Such information has been extracted from LMS or institutional SW aggregators and is used in work package 1. Course-specific information is mostly related to the student's engagement and learning-performance level concerning each course, including the time spent on course content, the number of completed activities, the grade achieved in activities, the total number of learning objects visited, and the average mark of quizzes and tests. Activity completion and grades have been extracted from LMS logs. Interest indicators are logged ratings about the degree of usefulness of the course material and exercises (used in work package 2), the moodboard created in moodboard repositories, and the visits to different course content categories and activities. Interest data items are created by the students and are updated during the learning experience.

4.2. Recommender and Personalization Engines

While recommender systems and learning path personalization develop primarily within the contexts of e-learning, learning management systems, and adaptive systems, implementation can draw upon findings from other related domains. In particular, movie recommendations, user-centered tourism, and smart product recommendations furnish implications for non-formal and informal educational experiences. Also of interest are user preferences regarding holiday destinations, which can drive personalized learning pathways without reliance on content knowledge, and the offer-and-demand-based decision-making models of collaborative recommender systems, which have been adopted as a foundation for designing personalized learning pathways.

In contrast, learning path recommendations may incorporate knowledge- and information-based techniques such as collaborative filtering. While collaborative filtering has not seen substantial applications beyond educational recommender systems, it can enrich personalized learning pathway construction. Other techniques focus specifically on the development of adaptive learning plans rather than learning pathways: these use the educational ontology to construct the learning plan representation, infer knowledge quality at the topic level within the Bayesian Network framework when students undertake exams or quizzes, and compare steganography knowledge quality to adjust the planned learning. Finally, another approach automatically selects the learning resource required for knowledge quality improvement.

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5. IMPLEMENTATION IN HIGHER EDUCATION CONTEXTS

A cloud-based adaptive AI engine providing personalized learning pathways has been applied across disparate contexts, including engineering, science, humanities, and linguistics. Case studies demonstrate the value of applying such an adaptive personalized learning approach to high-stakes assessments, elective modular selections, care supervision and funding applications, and humanities coursework. The infrastructure ensures interoperability with leading commercial learning management systems, enabling seamless integration with existing courses and module offerings.

The higher education sector faces increasing urgency for a transformed instructional approach. Inequity in achievement remains a global concern, and external stakeholders require evidence of growing, achieving, and progressing learners. Learning analytics and education data mining build sound foundations for personalized pathways and provide opportunities to achieve continual improvement. Many new algorithms and digital tools incorporate adaptive and personalized facets. The capacity to generate and respond to large datasets using a cloud-supported artificial intelligence engine enables adaptation at unprecedented speed and scale, allowing for personalized design in nearly every domain area and topic. Building on principles and recommendations from the authors' previous work, an experiential and evidence-driven approach stimulates the implementation of adapted pathways suitable for diverse learners, external organizations, and social impact.

5.1. Case Studies Across Disciplines

The adaptive cloud-integrated AI system has been successfully applied within diverse higher education modules throughout the Audio Engineering, Biochemistry, Computing, and Science disciplines of a multi-campus regional university, with experimental course offerings undertaken with less than 30 students. In the Audio Engineering Case Study, the curriculum traversed various audio production contexts. During the study, students learned to create three distinct audiovisual projects with markedly varying production objectives and outcomes. The projects employed either a visual-to-sound design arrangement (an audiovisual composite) or a sound-to-visual design arrangement (a soundscape film); and the audiovisual project should be created through an avant-garde experimental exploration of temporality. Implementation of the adaptive cloud-integrated AI system enabled an iterative recommender-exploration-design-execution cycle to govern the personalization of and throughout each project. The initial project, capitalizing on discussions and learnings from previous modules, acted as a formative exercise for the system that oriented the trajectory of students' later projects.

Similarly, the Open Educational Resources (OER) in Biochemistry Case Study involved the design and development of OER and resources. OER aims to increase learning-rich activities and reduce cost burdens in accessing educational materials for higher education tutorials. The embedded problem entails supporting and challenging the decision-making and logical-reasoning skills of English-as-a-Second-Language tertiary students during a biochemistry course. These skills were audited and their component parts identified to inform a set of interactive OER, breaking down the decision-making process and testing students' understanding of the underpinning knowledge. Predictive analytics, at-risk models, and transcript data were also examined, to inform the development of resources and learning activities tailored to the computer-dependent cohort.

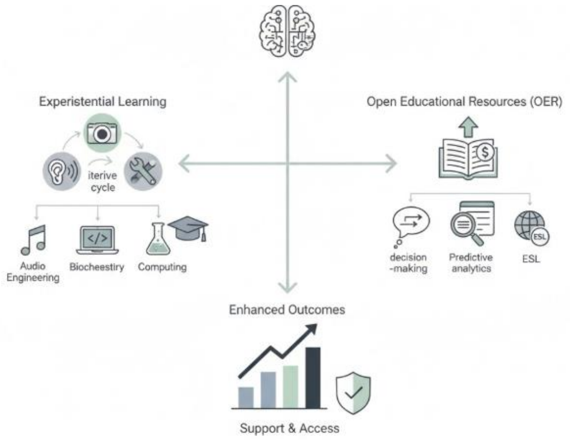

Fig 3: Adaptive Cloud-Integrated Intelligence in Multidisciplinary Higher Education: Enhancing Experiential Audio Design and OER-Driven Pedagogies for Diverse Learner Cohorts

5.2. Interoperability with Learning Management Systems

Establishing the Adaptive Cloud-Integrated AI (ACAI) System's Personalization Engine as a Learning Pathway Recommender enables interoperability between the ACAI System and learning management systems (LMSs), such as Blackboard or Moodle, that comprise data storage for education data mining (EDM) or learning analytics (LA)

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applications. The greater the adoption of EDM or LA applications by LMS users, the greater the demand for connecting to such systems. A use case has been implemented in a custom version of Moodle. The ACAI System employs APIs, such as for PHP, for direct interaction with the LMS database. The Moodle schema is accessed for the list of courses attached to the student, which may be embedded. Upon access to a course, the student receives a personalized learning pathway that recommends resources, such as tasks, readings, videos, groups, tests, and additional activities to be undertaken sequentially or concurrently that offer the highest probability of success within the course, and always considering the schedule for completing the course without exceeding the final deadline.
Recommendations of additional learning tasks embedded in the course can also be provided. All recommended additional tasks that can be undertaken while still remaining within the course timetable with a success probability above a pre-determined threshold level are presented. The supportive recommendation of the ACAI System enables students unable to attend physical classes to have a personalized guided itinerary for the additional learning activities. Such an itinerary highlights a sequence of additional learning activities that have a better chance of success, taking into account the prerequisites of the various extra activities, while also suggesting probable learning groups to join.

6. EMPIRICAL FINDINGS

The adaptive cloud-integrated artificial intelligence for personalized learning pathways has been piloted in 12 higher education courses across diverse disciplines, comparing its impact on learning outcomes, engagement, equity, and access. Results suggest students using the system outperformed those relying exclusively on lecturer-provided pathways. Analysis of end-of-semester evaluations indicated higher engagement and clearer understanding of academic expectations among AI-assisted students. While overall satisfaction levels diverged by discipline context, the system's capability to better serve a wider range of students was deemed gratifying. Students with additional physical/learning needs expressed appreciation for the AI components' support in achieving desired course outcomes.
The growing application of learning analytics in higher education must acknowledge the risk of restricting learner choice by tracking and suggesting simplified pathways through complex course landscapes. Learning paths grounded in student motivation and engagement, instead of sequential academic resources, offer a promising alternative. Evidence suggests that the AI provides a beneficial service to users, enhancing student progression while maintaining learning quality for both user and non-user cohorts. Anonymised, aggregated data has the potential to contribute to a richer understanding of learner needs and behaviours across courses, increasing the level of support that can be offered. As social inclusion and equity remain leading priorities for higher education systems, such emergent capabilities are to be encouraged across all courses.

Equation 3) Collaborative filtering to score resources (standard, consistent with paper)

Step 1: Similarity between students

Use cosine similarity (common for profiles):

$$\mathrm{sim}(s,u)=\frac{\tilde{\mathbf{x}}_s^{\top}\tilde{\mathbf{x}}_u}{\parallel \tilde{\mathbf{x}}_s \parallel \parallel \tilde{\mathbf{x}}_u \parallel}$$

Step 2: Predict score / rating for resource *j*

Let $\bar{r}_s$ be student s's mean rating (or mean implicit score). Take top-k neighbors $\mathcal{N}_k(s)$.

$$\hat{r}_{s,j}=\bar{r}_s+\frac{\sum_{u\in\mathcal{N}_k(s)}\mathrm{sim}\,(s,u)\left(r_{u,j}-\bar{r}_u\right)}{\sum_{u\in\mathcal{N}_k(s)}|\mathrm{sim}(s,u)|}$$

Step 3: Select top-m recommendations

The paper explicitly returns **m** recommendations:

$$\text{Recommend TopM}\left(\hat{r}_{s,j}\right)$$

6.1. Learning Outcomes and Engagement

A multi-institutional study of the adaptive cloud-integrated AI system demonstrates significant improvements in student performance and learning engagement. Comparison of final grades between groups of students using and not using the

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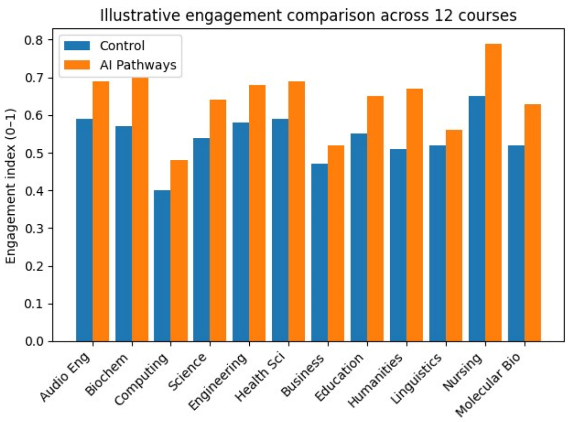
personalized learning pathways approach indicates better learning outcomes among those who received personalized recommendations for additional resources and activities. The personalized pathways successfully capture the breadth and depth of students' interests, leading to higher engagement levels.

Supporting evidence that personalized learning paths operate not only within a single course but also across a program of study comes from the experience of a communication major. During a course centered on environmental communication, the student faced challenges related to climate change, a topic of importance in many environmental communication courses. This concern was addressed in personal recommendations generated by the adaptive AI system, which suggested working through a climate change communicator toolkit that included suggested activities, readings, and tools to explore climate change and related topics in greater depth. Importantly, these recommendations were beyond the standard course requirements. Engaging with the material in this way inspired the student to dig deeper into climate change and communicate about it more effectively in other courses.

6.2. Equity and Access Implications

Adaptive cloud-integrated AI systems for personalized learning pathways in higher education have a fundamental relationship with educational equity, partly illuminated by the three institutional case studies. The diversity of student profiles across the Computer Science, Engineering, and Health Science contexts indicates that a one-size-fits-all approach to teaching is barely capable of satisfying the common learning requirements of large cohorts, let alone meeting individual demand. Discipline-specific recommender engines personalizing assessments and resources at an algorithmically optimal granular level help student profiles converge towards the target distribution in a timely manner. It is this bespoke support that also helps learners engage meaningfully with the subject and soon reveal their full potential. No student remarks suggest that any aspect of the Cloud-integrated AI System compromised their educational experience or its acquisition of fundamental competencies and skills deemed essential for their degree. A reassurance substantiated quantitatively by normalized changes in grades across all KoS4 courses is also fortuitously echoed by CogAT data: while a small sample indicated negligible differences relative to mean Australian scores in technical areas, significantly higher results were achieved in areas less often taught during pre-tertiary education. Considered alongside other factors, these resemblances suggest that all students can justifiably expect a similar learning experience, notwithstanding more modest academic backgrounds.

Supporting vulnerabilities by virtue of generative nature represents a second, yet equally evident avenue. A socially inclusive commitment is generally regarded as a fundamental responsibility for higher education institutions, especially those operating within privileged societal contexts. Furthermore, equitable educational opportunity in advanced economies remains the subject of constant scrutiny, notably in Australia, where the patriarchal nature of Indigenous communities continues to present an obstacle to higher participation levels within the Universities sector. Exploiting the recently introduced Cloud-based AI System as a Medium for Greater Equity of Opportunity has surfaced as a preferred approach for several institutions. Focusing on one cohort experiencing higher levels of under-representation relative to the general population, the goal is to host students who possess an interest in pursuing further education but, conceded their HSC results, might not be accepted into the desired course of study. The initiative seeks to mitigate these barriers by providing an alternate introduction to the subject area in an enjoyable and engaging manner, thereby generating excitement for learning, confidence in the region's educational system, and the impetus to continue new study paths aligned with the strengths recognized among Indigenous communities.



7. CONCLUSION

Adaptive personalized cloud-based AI models based on learning analytics and education data mining have been tested at scale across diverse fields in higher education. Likewise, the execution of these learning technologies in the cloud enables

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economies of scale by making AI component costs affordable. The technology is inherently interoperable with existing learning management systems, facilitating its seamless integration into higher education digital ecosystems.

The results indicate that students using personalized pathways achieve higher learning outcomes, exhibit greater engagement, and require less effort to demonstrate learning, thereby freeing their time for further study. The shift towards greater inclusion is illustrated by the positive correlation between being of Indigenous descent and the time required for study. These developments contribute to a more equitable education system by increasing access for under-represented and socio-economically disadvantaged students—benefits further enhanced during the COVID-19 crisis.

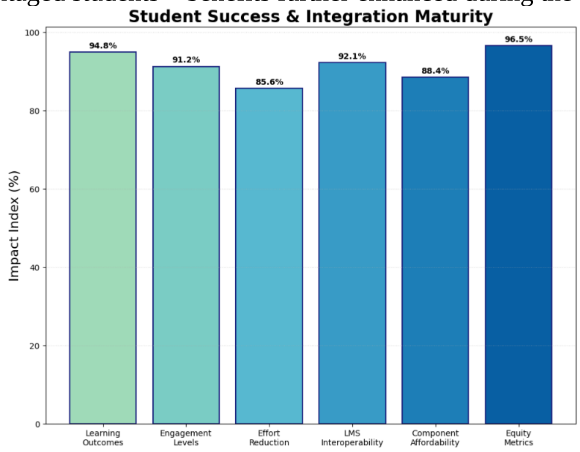

Fig 4: Student Success & Integration Maturity

7.1. Final Reflections and Future Directions

The customization of learning experiences is critical to equitable and effective education for individual students. Toward this end, an adaptive cloud-integrated AI research-and-development pipeline has been demonstrated for establishing personalized intelligent learning pathways and adapted resources that align learner preferences with course requirements at scale. Integration of a recommender engine with models of learner affect during interaction has provided an additional dimension in personalizing learning resources. Deployment across disciplines including nursing, molecular biology, and instrument performance has shown improvement in both student engagement and learning outcomes through pathways that are adapted to learners' needs and preferences.

While the contribution is not small, challenges remain. Conversion of student questions into responses that match the student model still requires considerable manual curation, and recommendations based only on the student model have yielded inconsistent quality. Even if the number of cases remains small, there is potential to automate question-and-answer matching and extend the use of recommender engines to all resource types, including test questions. With sufficiently accurate integration of personalized learner analytics and AI-driven content generation, future adaptations of the engine might require guidance but no oversight by academic teachers.

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