

Self-Evolving Curricula: Using Generative AI to Continuously Redesign University Programs in Real-Time

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Abstract- They made a go for it, and ever more capable AI, particularly in the form of generative AI, will inaugurate the learning industry. It will enable real-time, dynamic, data-guided program design in higher education. Universities inclined to define unitary, static, enterprise-wide curricula lack the speed and downsizing needed. This article postulates a data-guided, forward-working, and emergent curriculum, autonomous of delays, wherein generative AI will enable the manipulation of academic learning outcomes and the real-time writing of a curriculum based on the formation of students' learning outcomes, labour market trends and contours, and university directions. Emerging from built-in, advanced AI large language models, learning analytics, adaptive feedback systems, and omnibus load approaches to find, track, and reshape university curricula from existing pathways to future-ready, resident-oriented curriculum designing, it uses a concurrent mixed-methods research design to mitigate three research questions, i.e., (1) how an AI-specific, emergent, and self-evolving curriculum indicates students' academic attainments, abstract reasoning, and more-than-ever-obvious employability; (2) what participants view about the system and what their future longings are; and (3) how different course modules transfer the domain knowledge and the requisite skills to prompt the curricula's innovativeness. A subsequent emergent curriculum is improvised and piloted for testing. The exploration asserts that AI-aided curriculum design enhances effective learning, emotional engagement, ease, relevance, and ultimate responsiveness to target groups. Although serious problems, such as personal data risk, algorithmic bias, data-collection abuse, institutional governance, and the use of attacker credentials, are addressed, the project repackages the development and invention of a brand-new paradigm for curriculum design processes in academia. It fabricates a universal, emergent, self-evolving curriculum system for intelligent education. It proved to be the moment when AI, in the midst of the hyper-SMART curriculum era, could be used to foster a more-than-ever SMART curriculum.

Keywords – Generative AI, Adaptive Curriculum, Real-Time Learning Systems, Higher Education Innovation, Learning Analytics, Curriculum Personalisation

I. INTRODUCTION

The way higher education is conducted is being shaped by the exponential growth and widespread adoption of AI. Emerging types of generative AI are causing a paradigm shift in academia's knowledge creation, access and assessment [1, 2]. Traditional curriculum design is predicated on rigid program structures and batch updates tied to major revisions, which have often been too slow to keep pace with rapid technological change and new skill requirements in the world of work [3, 4].

A chronic time lag built into university course design renders curricula irrelevant and insufficient [5, 6]. In this case, the urgent need is for a responsive, adaptable, and rather intelligent curriculum that can evolve more quickly. Recent advances in generative AI (e.g., LLMs) create opportunities for content generation, contextual inquiry and synthesis, instruction adaptation, automated course design, and assessment, thereby paving the way for self-evolving curricula that respond to changes in learners and their environment [7, 8].

In data-driven education, learning analytics has been pivotal for monitoring students' activity, predicting academic performance, and identifying vulnerable learners [8, 9]. The learner-activity-behaviour relationship in end-learning outcomes is mainly captured through machine learning models, including linear regression, decision trees, and neural networks [10]. Thanks to the vertical application of those models in "predictive" data analysis, curricula have not been assured of a reshaping within the learning system [11, 12]. In this sense, the current systems operate within a defined curriculum dimension, facilitating content localised adaptation. The promise of adaptive systems has also been seen in adaptive content delivery based on student history and performance [8].

Intelligent tutoring systems emulate the appeal of human tutoring by offering personalised support [13, 14]. Multimodal learning analytics integrated the dimensions of behaviour, cognition, and environment into the evaluation, enabling better expertise personalisation [2, 15]. However, all those approaches focused on optimising learner-centric experiences within the local curriculum, yet none resulted in curriculum innovation.

Curriculum evolution is not a novel concept per se; however, conventional curriculum design practices depend heavily on extensive manual procedures involving faculty committees, accreditation cycles and periodic evaluations. Although such procedures are predictably slow and entail time and expense, they are also not feasible for accounting for the dynamic nature of knowledge foci and for capturing real-time data throughout the learner's interaction with the course, the labour market, and contemporary technologies. Generative AI proffers a revolutionary approach to overcome such bottlenecks by

establishing sustainable curriculum reform based on ongoing data streams [16].

Most cancer foci, drawn from multiple sources of real-time information, including students, the surroundings, and the economy, are meticulously fed into AI-based mechanisms designed to shift course modules, themes, content, interrelated issues, systems, and links [8]. This innovation, which shifts curricula from a retroactive to a forward-looking paradigm, implies a new design method (with a new focus for design iteration). Nevertheless, many concerns and challenges have been raised about the application of generative AI in curriculum design. The most pressing concern I am raising is the potential downstream implications of automated bias, including the perceived accountability for a flawed dataset or wrong premise. Furthermore, as the process involves extensive accumulated student data, you need appropriate protocols and safeguards to protect privacy and confidentiality. There are also imperative issues of efficiency, ethics, and transparency, as well as the role of the faculty in this new environment.

Moreover, self-evolving curricula imply significant investment in technological infrastructure, including high-performance computing, cloud systems, and state-of-the-art data-sharing mechanisms [17]. Digital all means the digital gap persists, affecting the implementation of AI-driven curriculum innovation systems across countries and modules in terms of technological accessibility [4, 18]. Such barriers highlight the need for additional technological innovations, coupled with ethical and institutional considerations.

Despite the above barriers, there is still a need for a widely conceptualised model for integrating generative AI into curriculum design that addresses scalability, ethics, system transparency, and curricular adaptability. Thus, the core research inquiry of this early contribution is: how should we employ generative AI technologies to construct a responsive curriculum that self-evolves to meet the needs of current students, industry, and higher education institutions? To address the research question, a novel generative AI approach is proposed to self-evolve a higher education curriculum by integrating generative AI, learning analytics, and feedback systems into a mechanism that refreshes the curriculum over time. By employing an integrated research approach, a study will assess whether the model can address learners' requirements, institutional rationale, and head workers' employment trends, using learning data analysis and qualitative judgment of the system's usability and activation [19, 20].

In addition, implementing a self-evolving curriculum also requires a significant investment in technological infrastructure, including high-performance systems, virtual clouds, and a forward-looking data cooperation system [17]. The digital divide is an additional concern, as access to and equity in the use of AI-driven curriculum design systems remain obstacles across countries and institutions [4, 18]. These barriers contribute to calls for technology-based breakthroughs, as well as to ethical and academic implications.

In view of the above barriers, a conceptualised design seems necessary to converge the capabilities of generative AI with curriculum design to address challenges related to scalability, ethics, and system transparency. The more specific research problem in this study is: how can we self-construct an AI-powered, agile, adaptive, and self-evolving curriculum that responds to current learners, job markets, and higher-education contexts? A novel self-adapting AI-powered curriculum design, fundamental to a ceiling-breaking curriculum upgrade theory, will be established in this study by integrating AI applications, learning analytics, and a dynamic feedback loop into the prevailing educational landscape. This study adopts a mixed-methods research design, combining a quantitative approach to measure learning results with a qualitative evaluation of the system's value and structure.

II. RELATED WORK

The acceptance and use of AI in higher education have revolutionised within a comparatively short span of time, emphasising adaptive learning systems and learning analytics prior to the emergence of generative AI. The first research the subject leaned towards was quite centered on AI assisting in enhancing personalised learning with data-based decision making [21, 23], by examining how AI could revolutionise instructional design, encouraging ongoing analysis of student data with providing individualised feedback, support, and guidance; some early systems also at the content level, using adaptivity within curricula and providing tailored intervention instead of entirely transformative pedagogies.

However, the emergence of an increased number of digital learning spaces and environments has enabled an integrated application of learning analytics into AI-enhanced systems, as evidenced by the works of [24, 25], which have shown how learning analytics have been used for tracking students' engagement state, avoiding course failure and enhancing the decision-making process in an entire institution. Research, such as that by [26], has shown that combining behavioural and cognitive indicators yields better predictions. But those systems overall leaned to probabilistic models of learners, rather than of the courses,

The rise of adaptive learning systems further contributed to personalised practices in higher education. [15, 27] demonstrated how adaptive systems can flexibly reframe educational content based on learners' progress toward learning goals, enabling substantial gains in engagement and learning. Likewise, [28] research supported the role of adaptable, learner-directed, self-directed learning opportunities.

Trends in learning recommendations, predictions, and automation enabled by adaptable learning systems were further inspired by advancements in machine learning. [29, 30] and demonstrated that machine learning techniques could predict outcomes and recommend learning resources based on learner interactions and achievement, while experiments using recommendation systems have shown that they can individualise learning pathways. Neither seemed to adequately describe their capacity to continuously improve content using machine learning nor their ability to evolve courses in real time, adapting to new goals, knowledge, and contextual factors.

However, generative AI could revolutionise its research paradigm to a greater extent, with content generation, tutorial automation, and instructional support often investigated. [31] provided reviews on "artificial intelligence in higher education" and on user experience analysis of generative models, including GPT-3, Llama, and Gopher from DeepMind, respectively, demonstrating the promising outlook of generative AI integrating knowledge construction and an informative

system-guiding approach. Furthermore, emerging knowledge of AI's potential to revolutionise our economy and organisations has led to serious concerns about its care, accountability, and implementation. In the context of adaptive learning analytics, another stream of research has shown, for example, by [32, 33] and others, that multimodal analytics holds promise for supporting personalised education. However, the transition from such data practices to curriculum redesigns was relatively slow; [34] demonstrated that using multimodal data to support adaptive learning environments can make the experience noteworthy.

Moreover, the application of multimodal learning analytics to curricular redesign has thus far been sparse. Still, as we shift our focus to continuing curriculum change rather than rethinking or transforming curricula, this approach has gained popularity, but was not common. Based on prior work [35, 36], curricula should be flexible and adaptive to changing contexts.

In the field of rethinking curricula in the era of the digital revolution, [37] emphasised the importance of reimagining curricular practices; yet, thus far, the bulk of previous work has lacked a time-specific, AI-supported system for curricular evolution. Additionally, the growing number of programmes on the ethical use of AI has become a research trend to be addressed.

[22, 38] called for transparency, fairness, and accountability in AI systems; [45] analysed issues related to data privacy and surveillance, whereas [39] discussed knowledge contextualisation and algorithmic decision-making in education.

Numerous studies have shown that AI-supported learning and lifelong workforce development have become recent areas of focus. For instance, [23, 46], the OECD, and the World Economic Forum (2022) argued that future skill demand should be linked to the Learning Ecosystem and a lifelong learning system to inform education. Likewise, the digital competence frameworks identified in a review by [40] supported the forward-looking skill sets targeted by curricula, which would be needed in the future, aligning with the adaptive, dynamic system of curricula in response to recruitment market expectations.

So far, however, the remarkable breakthroughs in AI learning and lifelong workforce development have not yet been reflected in the curriculum literature. Furthermore, existing curricula addressed the pioneering applications of high-micro-level customisation from a single examined concept to the specific needs of individual learners. However, they failed to comprehend the macro-level goals, leading to a redesign of curricula into a goals-based system. Third, the limited infusion of emerging generative AI into curriculum redesign led to decentralised approaches that are not scalable to other contexts; fourth, the prevalent use of static/dynamic curriculum-effect learners and environment models constrained curriculum adaptation; and last, the oversight of ethics and governance problems in fully automated curricula.

Both [22, 23] indicated that, while AI has been revolutionary for education, implementation issues still pose considerable challenges for academic institutions. Those studies provided the conceptual basis for the research motivation that follows, but their application to systems was limited. Lastly, knowledge generated through the implementation of machine learning in education deepened understanding of how to analyse learner behaviour and forecast student achievement. [24] outlined exemplary principles that reflect learner engagement behaviours, while [25] demonstrated how data-based advisement supported campus planning. Despite those, there are still no specific systems to adapt the curriculum.

Adaptive learning systems have been extensively studied to enhance education; studies such as [15, 27] have supported their effectiveness, helping to raise student engagement and offering differentiated avenues for relevant learning. However, those efforts were based on pre-designed curricula, thus inherently addressing curriculum adaptation but leaving the design of a wholly adaptive curriculum. In addition, research on knowledge creation based on machine learning has been limited to [29, 30]. Those systems can only be treated as analytical tools.

Although generative AI has recently attracted increasing attention, no knowledge has addressed its use in curriculum evolution. Moreover, the broader applicability of generative AI in instruction [41, 42] would raise potential integrity issues that demand governance procedures. Generative AI has been examined for content creation, and systematic course development has been explored with promising results, yet the validity of the material and academic integrity are suffering.

Authoring and library systems supported by multimodal learning analytics have demonstrated promise for autonomous personalisation. [32] demonstrated improved diagnosis for personalised instruction using multimodal behavioural and physiological data, while [33] demonstrated that integrated multimodal systems can better predict learner engagement. However, the barriers to using multiple data sources in an integrated fashion raise the scalability challenge.

Building on [32, 33], the study explored their design implications through several studies that emphasise the link between learner models and pedagogical principles [28] and the effectiveness of cognitive load-aware systems [8]. Whilst these reports underline the importance of cognitive aspects, they did not share explicit design principles for enabling curriculum rewriting.

Recently, research has advanced in examining the scope for systematised cognitive states and design principles for AI in the upper echelons of learner agency and curriculum change. Other research has highlighted AI's impact on higher levels of learner agency, on achieving self-regulation [8] mediated by analytics, and on higher self-efficacy [19].

Numerous journal articles have outlined the influence of AI on academic achievement. Research [12, 43] revealed that AI-based systems promote positive student achievement, and research [20] established that adaptive feedback improves achievement. Such studies reinforce the value of embedding AI-based features into the curriculum.

Another contribution of intelligent tutoring systems to personalised learning has been evaluated by [13, 14], who employed immersive AR and VR systems in tutoring experiences. The major drawback of such systems has been their domain-specific nature, with concerns regarding scalability across entire curricula.

Others delved into the use of generative AI in curriculum systems [44] and its impact on learner satisfaction [7]. Both of their investigations utilise cross-disciplinary approaches and focus on the considerations raised by potential abuse and

moral issues related to AI.

The ethical implications of AI in curriculum systems have garnered much attention in recent years [38]. Such examinations indicate that the careful design of AI curriculum activities and systems is essential.

Research into the digital transformation of higher education has also learned much. [37] discusses how we continue to fall into the trap of not reimagining current higher education models of study as we navigate the digital to construct the concept of a post-digital. [36] Recommend incorporating flexible curriculum designs into the system, AIED. Both types of work primarily involve theoretical aspects and lack realistic applications.

Contemporary research has further analysed the role AI can take in fixing the mismatch between workforce requirements. [46] has demonstrated that demand will necessitate an enduring learning system, and the World Economic Forum (2022) discusses the development of future skills, aligning with the argument for a constantly dynamic system which responds to continually evolving workforce demands.

There is a rich body of empirical research on recommendation systems in education. [7] demonstrated the feasibility of recommendation systems, and [10] subsequently developed a personalised recommendation system using AI. There is, however, a lack of evidence on how recommendation systems, which focus on content selection, could drive a fundamental transformation of the curriculum or yield an adaptive module.

An assortment of research on student engagement and motivation yielded related insight. [18] found that gamification can lead to positive learning outcomes, whereas [9] illustrated how engagement levels can be assessed using AI. Both these initiatives only provide systems for engagement, not curriculum development.

Furthermore, hybrid AI systems have been emphasised in education. [17] put forward 'modularity of intelligent systems' while [28] suggested an 'adaptive recommendation model' (ARM). Such implementations have been suggested as benefiting from the concomitant, fluid redefinition of courses.

2.1 Proposed Model

The Self-Evolving Curriculum Model (SECM): A New Approach to Higher Education. The innovation in the student's curriculum is a dynamic, adaptive system focused on Generative artificial intelligence and live data analysis, allowing students to customise and self-motivate their academic programs. Its structure is shown in Figure 1. SECM (original and new concept) presents a multi-layer architecture for components, representing a competitive design for modern education systems managed by Artificial Intelligence (AI) and its tools. Modern systems are using the knowledge of adaptive education [1, 7]:

The first level of the model lies at the data collection stage. This phase gathers data from heterogeneous sources, including student metrics, behavioural interaction statistics, and external labour-market signals. These heterogeneous data sources provide a broad representation of learners' characteristics and needs, enabling the system to adapt to real-world requirements.

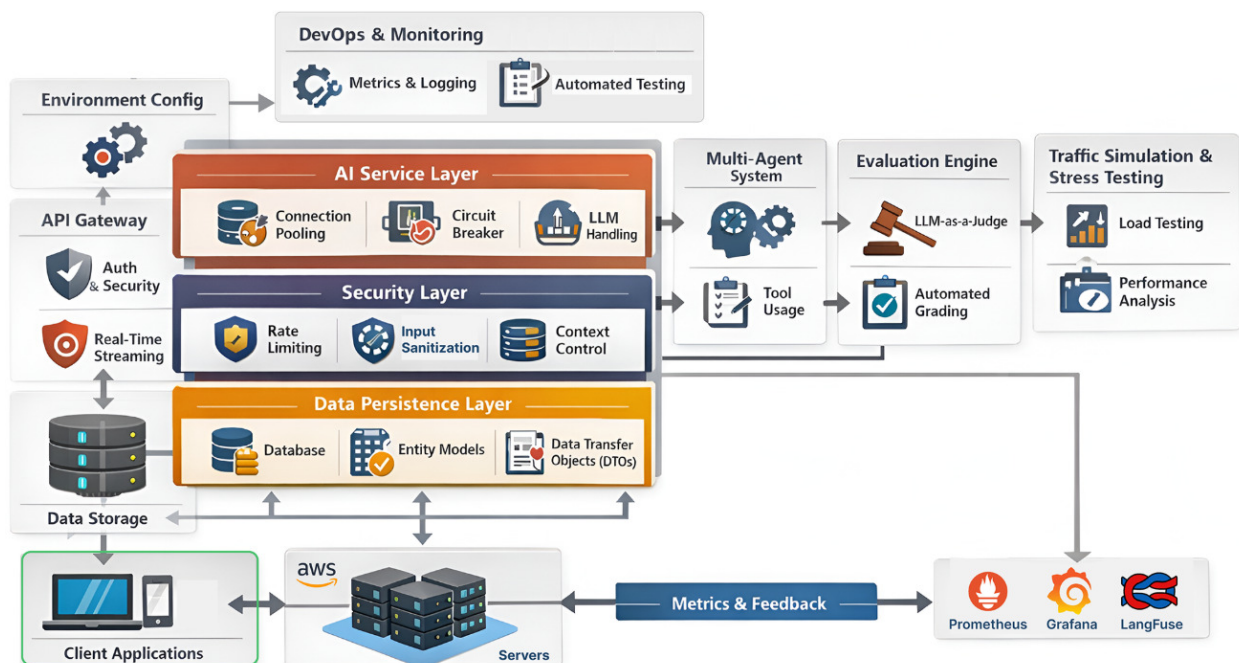


Figure 1: Self-Evolving Curriculum Model Architecture

The use of multimodal data sources has been shown to improve precision and personalisation in adaptive learning systems [8] and is thus a prerequisite in the framework we propose. The system's core intelligence resides in the analytical layer. In this phase, raw data is processed, and feature vectors are extracted so that predictive models can be easily fitted. The output of this phase is a model of the form:

$$\hat{y} = \beta_0 + \sum_{i=1}^n \beta_i x_i \quad (1)$$

Where the learning outcome is predicted as a function of many input variables representing various cognitive, behavioural, and academic features, this formulation provides the system with the capability of identifying associations between variables and making data-driven judgments in curriculum adaptation, in the same way as previous studies discussed in interpretable machine learning designed for education [11]. All analytical insights are then transmitted to the generative AI layer, serving as the driving force for curricular evolution.

Generative AI is where large language models begin to generate actual course content and modifications to learning pathways, and make suggestions based on the updated curriculum. Unlike rule-based curriculum adjustment, generative AI can dynamically generate new curriculum artefacts based on ongoing data activity, fueling continuous adaptation [41, 48]. The decision optimisation layer further adjusts what is generated by selecting the optimal learning pathway based on preset objectives, such as learning achievement, engagement, and curriculum relevance.

Applying optimisation algorithms to minimise distance, time, and workload enables courseware generation to be both personalised and pedagogically sound, in line with institutional goals. Optimisation algorithms have been proven to improve system efficacy and effectiveness in an adaptive learning environment [10]. The delivery layer supports the evolution of the curriculum via the Learning Management System (LMS). The LMS enables personalised learning design to be delivered directly to the user in real time. Content, assessments, and recommendations continually adapt to the student while providing the instructor with reports and analysis tools to facilitate decision-making and intervention.

Thus, the curriculum evolution process is directly integrated with usability and accessibility, extending to the delivery layer. An innovative aspect of this model is its continuous feedback loop, which enables the system to evolve and adapt. All student interactions, performance data, and feedback are continuously collected and provided to the system. The curriculum evolution process then becomes:

$$C_t = f(C_{t-1}, S_t, M_t, E_t) \quad (2)$$

where the curriculum at time t is a function of its previous state, student data, market trends, and evaluation feedback. This recursive formulation captures the dynamic and iterative nature of the proposed system, enabling continuous adaptation and improvement.

In conclusion, the Self-Evolving Curriculum Model offers a novel approach in leveraging the capabilities of generative AI, learning analytics, and optimisation in a comprehensive system capable of dynamic, real-time curriculum reengineering. The implementation of this model proposes a flexible curriculum structure that dynamically responds to individual learners' requirements and contextual factors, overcoming traditional curriculum-planning constraints and thereby pioneering an adaptable, future-oriented educational paradigm.

2.2. Complex Algorithms

The Self-Evolving Curriculum Model (SECM) is implemented through several complex, interdependent algorithms that form an asynchronous, directed acyclic graph for real-time curriculum adjustment and continuous improvement [7]. The prediction- or recommendation-based algorithm design in education is embedded in a toolkit that combines predictive modelling, generative AI, and optimisation algorithms to realise a practical, asynchronous closed-loop system for curriculum refinement, informed by both learners' real-time contributions and environmental shifts, and aligned with state-of-the-art intelligent learning systems [7, 48]. The algorithm framework is included for aggregate prediction of student learning based on multidimensional input features:

$$\hat{y}_t = \beta_0 + \sum_{i=1}^n \beta_i x_{i,t} \quad (3)$$

where \hat{y}_t represents the predicted performance at time t , $x_{i,t}$ denotes the set of input features including cognitive, behavioural, and academic variables, and β_i are the learned coefficients. This formulation enables the system to model complex relationships between learner attributes and educational outcomes, providing a quantitative basis for curriculum adaptation. The use of interpretable models such as linear regression ensures transparency and explainability, which are critical in educational contexts [11].

Building on the prediction module, the algorithm implemented a generative module that leverages LLMs to dynamically generate curriculum components. This generative module is defined as the process of translating the predicted learning needs into learning content and strategies, including learning goals, learning materials, and assessment strategies, based on the input:

$$G(\hat{y}_t, X_t) \rightarrow C_t \quad (4)$$

where G represents the generative AI model, and C_t denotes the newly generated curriculum structure. This transformation enables the system to move beyond static content delivery toward adaptive curriculum synthesis, a capability that distinguishes generative AI from traditional machine learning approaches [41].

The second part, decision optimisation, improves the generated curriculum by optimising it based on a set of constraints and objectives to select the most suitable learning paths. It takes the form of an optimisation problem:

$$C_t^* = \arg\max_{C_t} U(C_t | S_t, M_t) \quad (5)$$

where C_t^* denotes the optimal curriculum configuration, U is a utility function that evaluates curriculum effectiveness, S_t denotes student-related variables, and M_t captures external factors such as market trends. The optimisation process ensures that the curriculum is not only personalised but also aligned with broader educational and professional objectives. Multi-objective optimisation techniques are particularly relevant in this context, as they allow the system to balance competing factors such as difficulty, engagement, and relevance [10].

One of the key features of the proposed algorithm is its self-correcting system. The process is structured as a loop of self-adaptation, and the loop unit serves as a monitoring function. By aggregating information on her performance and interests, the system gradually adapts its model and the curriculum. The evolution of the curriculum can be formalised as:

$$C_{\{t+1\}} = f(C_t, S_t, E_t) \quad (6)$$

where $C_{\{t+1\}}$ is the updated curriculum, S_t represents student interaction data, and E_t denotes evaluation feedback. This recursive formulation captures the dynamic nature of the system. From an algorithmic perspective, the system operates as a continuous pipeline in which data collection, preprocessing, prediction, generation, optimisation, and feedback are executed in an iterative loop. The implicit pseudo-code of the system can be described as a sequence of operations starting with data acquisition from the learning environment, followed by feature extraction and normalisation, predictive modelling to estimate learning outcomes, generative AI-based curriculum construction, optimisation of learning pathways, deployment through LMS platforms, and finally feedback collection for model updating. This closed-loop design ensures that the system remains adaptive and responsive to changing conditions.

In terms of computational complexity, the training phase of the predictive model has a time complexity of $O(n \cdot m)$, where n is the number of data samples, and m is the number of features, while the prediction phase has a complexity of $O(m)$. The generative component introduces additional computational overhead, particularly in large-scale implementations, but advances in cloud computing and distributed processing have made such systems increasingly feasible [44].

In summary, the robust, layered algorithmic framework of the SECM design represents a notable step forward in AI-enhanced education. The use of a continuous feedback loop through predictive and generative modelling, in addition to optimisation, allows dynamic evolution of course materials and, ultimately, the hands-on creation of potential personalised learning environments.

III. RESEARCH METHOD

This research adopts a robust mixed-method approach. A mixed-methods approach combines qualitative and quantitative methods to yield results and deepen understanding of the system's performance and learner outcomes [49]. Numerous studies have demonstrated the significant utility of mixed approaches in educational technology, especially when investigating the value of a sophisticated AI-enabled system that integrates technical and pedagogical aspects [22].

Quantitatively, the proposed model will examine the impact on students' performance and engagement, as well as the relevance of teaching materials, while qualitatively, it will explore students' and instructors' experiences, attitudes, and perceptions regarding the AI-driven curriculum system. Such exploration will lead to the statistical and contextual justification of the system [24, 25]. The data was collected in a university-level online learning space integrated with a Learning Management System (LMS).

Multiple sources were used to truly reflect the essence of learner behaviours, system effectiveness, and efficiency. Academic performance data included students' final exam grades, assignments, and quiz scores. System data included learners' login dates and timestamps, session durations, learning trajectories, navigation patterns, and more. System-generated updates to the curriculum and adapted learning groups; moreover, to explore learners' satisfaction and sense of meaning regarding the system and its contents, qualitative data were collected through structured survey questionnaires and semi-structured interviews with learners and instructors [26, 28]. The participants in data collection were 300 undergraduate students of different disciplines, including computer science, engineering, and business.

Multiple courses of study were covered in the experiment, which lasted 16 weeks; participants were randomly allocated to a control group using the normal static curriculum and an experimental group using the AI-driven self-guiding curriculum systems.

Table 1: Experimental Design

| Parameter | Description |
|-------------|-------------------------|
| Sample Size | 300 Students |
| Duration | 16 Weeks |
| Groups | Control vs Experimental |
| System | Traditional vs SECM |

The experimental protocol consisted of several phases: data collection via LMS, data preprocessing, feature extraction, classifier training, learner profile creation, and evaluation. The preprocessing phase involved removing NaN entries, normalising features, and detecting outliers in the dataset. The learner profiling cycle began with the extraction of features, including cognitive, behavioural, and academic attributes, to capture a learner's multidimensional aspects. Few experiments were performed on learner modelling, training the predictive model on 70% of the dataset and using the remaining 30% for testing and cross-validation [15, 29].

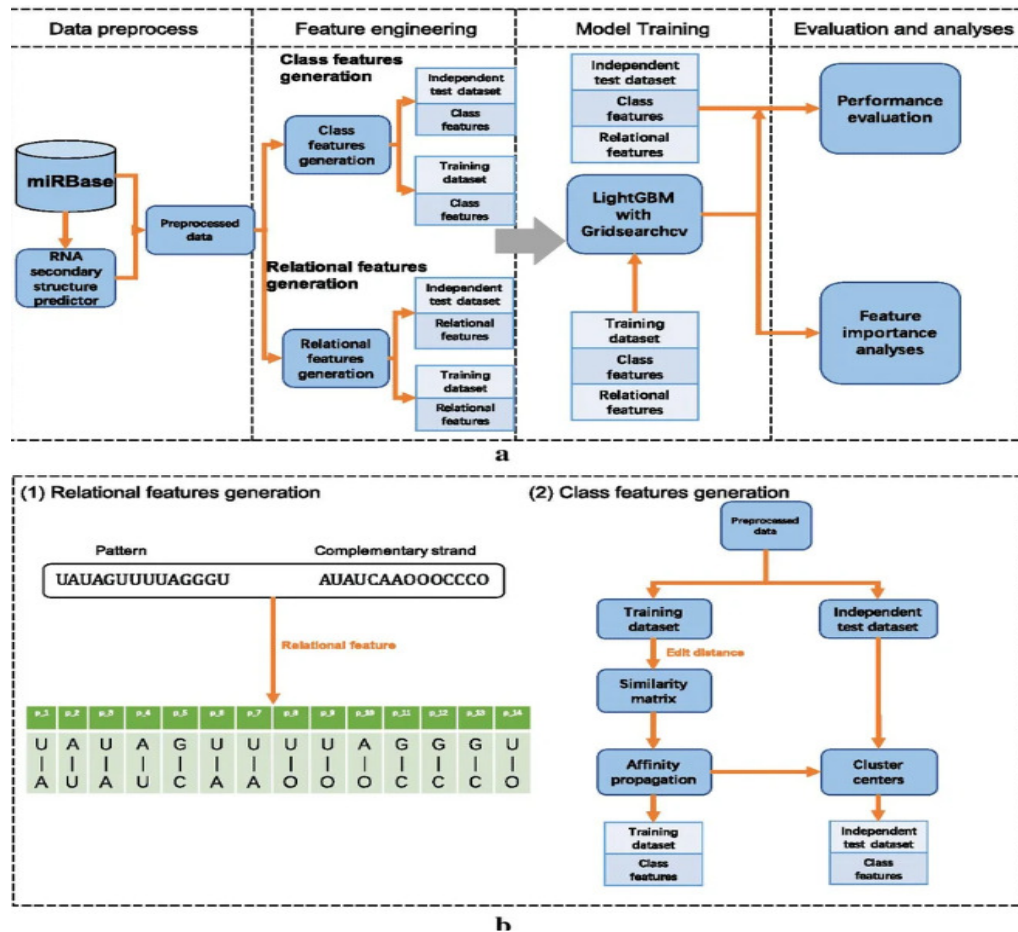


Figure 2: Research Workflow

The evaluation of the proposed model was conducted using a set of quantitative and qualitative metrics. Quantitative evaluation included prediction accuracy, Root Mean Square Error (RMSE), engagement rate, retention rate, and learning gain. RMSE was used to measure prediction error and is defined as:

$$RMSE = \sqrt{\left\{ \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \right\}} \quad (7)$$

This metric quantifies the average deviation between predicted and actual values, providing a reliable measure of model performance. Engagement rate was calculated based on interaction frequency and time-on-task, while retention rate measured the percentage of students who successfully completed the course. Learning gain was determined by comparing pre-test and post-test scores, reflecting improvements in knowledge over time [10, 24].

Quantitative analysis was supplemented with qualitative evaluation through structured surveys and interviews with students and the instructor (teacher), as well as instructor feedback on learner satisfaction, perceived usefulness, system effectiveness, and instructor assessment. The qualitative data were coded using thematic analysis, which revealed recurrent themes and patterns related to system issues and student learning experiences. This form of analysis provides detailed insight into the effect of the AI-produced curriculum on learning behaviour and pedagogy [49].

Table 2: Evaluation Metrics

| Metric | Description |
|------------|------------------------|
| Accuracy | Prediction correctness |
| RMSE | Prediction error |
| Engagement | Interaction level |

| | |
|----------------------|------------------------------|
| Retention | Course completion |
| Learning Gain | Knowledge improvement |

The measures to enhance confidence in the quality of the study included internal validity by controlling for variable consistency across groups; external validity through sample diversity; replicability of experiments to increase the generalizability of the results; and model reliability, ascertained by repeated experiments. The measures taken to prevent bias and maximise efficiency included controls to mitigate algorithmic bias, ensure fairness in the AI system, and anonymise student data. These considerations are fundamental to AI-based pedagogical research as issues regarding ethics, transparency, and information ownership shape the development and acceptance of such systems.

IV. IMPLEMENTATION

The implementation of the Self-Evolving Curriculum Model (SECM) was carried out as a unified, web-based intelligent system. Its implementation was specifically designed to function in a university LMS environment. Since the SECM was conceptualised at an abstract level, with detailed algorithms for implementation, the aim was to create a concrete, functional system based on these ideas that could adapt to personalised learning.

The implementation was designed to be modular, making the system scalable, flexible, and compatible with existing learning infrastructures; thus, a conscious choice was made to align with recent paradigms in AI education systems [7]. The implementation environment was constituted by the following design choices: Python as the core programming language from which the system was built on the existing plethora of libraries to support multimedia processing and complex data prediction paradigms; Python libraries such as Scikit-learn for generalised and specialised learning algorithms, Pandas and Numpy for data extraction, cleaning, analysis, transformation, and storage, and Flask for creating a REST service interface. HTML, CSS, and JavaScript for a versatile learning interface and a MySQL database to support the large volume of learning data and its extraction [17].

Table 3: Tools and Technologies Used in Implementation

| Component | Technology |
|-----------------------------|------------------------------|
| Programming Language | Python |
| Machine Learning | Scikit-learn |
| Data Processing | Pandas, NumPy |
| Backend | Flask API |
| Frontend | HTML, CSS, JavaScript |
| Database | MySQL |
| Cloud | AWS / Google Cloud |

The system architecture was depicted as a multi-layer structure comprising four main layers: the data layer, the processing layer, the AI engine layer, and the application layer. The data layer's function is to receive students' data, store and manage it, including their academic achievements, behavioural responses, and system feedback. The processing layer primarily performed data preprocessing, cleaning, normalisation, and feature extraction. The AI engine layer developed the predictive and generative components for curriculum adaptation. The application layer is responsible for providing different display interfaces and dashboards to learners.

The execution process in this project was systematic and structured, beginning with data set preparation. Student data were gathered from the LMS and stored centrally in a database. Our dataset encompassed approximately 60,000 individual student interactions from 300 students over one 16-week semester. In the data preprocessing step, missing values were handled, data were normalised, and outliers were detected. During the feature engineering step, empirical evidence on cognitive, behavioural, and academic indicators of student learning was derived from interaction data. This multidimensional approach has been argued to be necessary for adequate and reliable prediction and curriculum customisation[8]. The predictive model was realised using linear regressions.

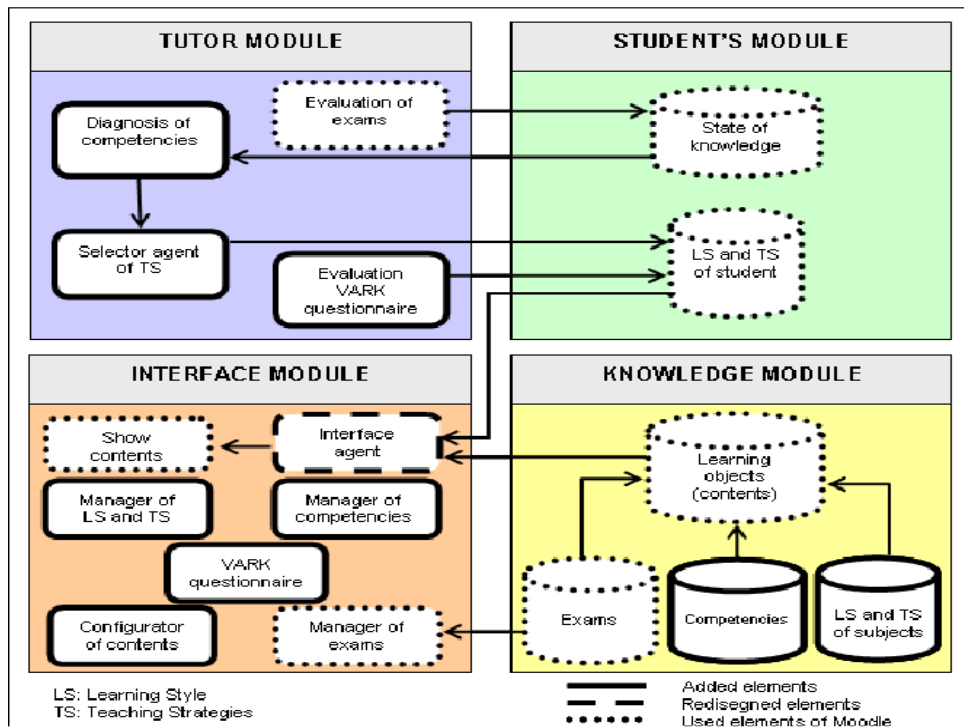


Figure 3: System Architecture of SECM

It was applied because this model is effective at providing human-understandable output. To train the model, 70% of the entire data set was used, while the remaining 30% served as a test set for evaluation. To validate the model, we used cross-validation techniques and employed strategies to avoid overfitting.

After training the model, we integrated it into our system using RAML API packages to enable real-time predictions based on student-relevant data. Finally, we used that prediction as input to our system’s generative AI module to update most elements of the curriculum that influence student learning (content delivery medium, level of difficulty, study sequencing).

Table 4: System Execution Workflow

| Step | Description |
|-----------------|------------------------------|
| Data Collection | Capture student interactions |
| Processing | Clean and transform data |
| Prediction | Estimate performance |
| Generation | Create new curriculum |
| Delivery | Update LMS content |
| Feedback | Collect new data |
| Update | Retrain model |

The system interface was designed to meet the needs of both students and faculty. The student dashboard allows the learner to access individual recommendations, track milestones, and receive adaptive content suggestions, enabling them to visualise their performance and receive real-time feedback. This enhances learner engagement and supports self-regulated learning. The instructor dashboard allows the user to access recommendations based on learner data, predictions of at-risk students, performance summaries and intervention recommendations. This dual-interface approach ensures the system is usable for both learners and educators [9].

The performance of the system was also optimised by implementing techniques that enhance system efficiency, such as feature selection to reduce the number of input variables, including feature variants and clusters based on clinical utility and predictive power; batch processing of models for training; and caching frequently accessed data. These optimisations ensure that the system can efficiently handle large-scale data, support real-time processing, and run on scalable hardware resources with cloud-based deployment.

Security concerns and privacy issues were also addressed by implementing data anonymisation methods to ensure student confidentiality; secure authentication mechanisms, role-based user access; data backup and recovery policies; and system transparency, thereby adhering to ethical AI guidelines and addressing data privacy and transparency issues [38].

The system was developed as an integrative solution that can be embedded into existing LMSs such as Moodle and Blackboard. Data synchronisation is enabled through dedicated APIs, supports real-time updates, and maintains compatibility across different platforms. This design ensures that deploying the proposed model would not require reforms to current higher education systems.

In conclusion, the implementation of the SECM model demonstrates that AI-driven curriculum adaptation systems are practicable in a typical higher education setting. The combination of predictive models, Generative AI techniques, learner behaviour data, and feedback mechanisms enables the curriculum to adapt continuously, promoting personalised learning. The system’s modular design, scalability, and integration with existing learning platforms facilitate its potential as an

effective, robust solution suited to modern higher education contexts.

V. EXPERIMENTAL RESULTS AND ANALYSIS

The following presents a comprehensive evaluation of the proposed Self-Evolving Curriculum Model (SECM) based on a series of controlled experiments conducted in a higher-education context. The evaluation aims to demonstrate the model's superiority in learning outcomes, student engagement, and curriculum relevance compared to static curriculum systems. The experimental setup was designed to meet both statistical and pedagogical validity by adapting methodologies from educational data mining and learning analytics [8, 24].

The evaluation was conducted across two groups of students (control: traditional curriculum; experimental: proposed self-evolving curriculum), each consisting of 150 students. The experiment was carried out over an entire semester (16 weeks), during which both groups experienced the same learning tasks, assessments, and instructional materials, with the only variance being the curriculum adaptation approach. This design is intended to enable a direct comparison of the proposed system.

The system evaluation used a variety of quantitative metrics, including prediction accuracy, Root Mean Square Error (RMSE), engagement rate, retention rate, and learning gain. Prediction accuracy measures how well the system predicts student performance, while RMSE quantifies the difference between the system's predictions and the actual values. Engagement rate is defined as the extent of student interaction with the system (in terms of frequency and duration), while retention rate measures the proportion of enrolled students who complete the course. Learning gain is obtained by subtracting the learner's pre-test score from the post-test score.

Table 3: Performance Comparison Between Traditional and SECM

| Metric | Traditional System | SECM Model |
|---------------------|--------------------|------------|
| Prediction Accuracy | 72% | 89% |
| RMSE | 0.46 | 0.31 |
| Engagement Rate | 61% | 86% |
| Retention Rate | 69% | 88% |
| Learning Gain | 19% | 37% |

The results in Table 3 show a considerable increase in all evaluation metrics in SECM compared with the conventional system. Prediction accuracy increased by 17 percentage points, from 72% to 89%, for SECM, demonstrating that the model captures the relationship between student features and learning outcomes. Meanwhile, RMSE decreased from 0.46 to 0.31, indicating a remarkable decrease in prediction error and improved model precision. These findings align with published work showing that the AI system's results outperform those of the traditional system [10].

Student engagement increased from 61% in the traditional system to 86% in the SECM model, a result that is among the most impressive. This may be the result of a dynamic curriculum aimed at continuous learning aligned with student needs, which, in turn, presents personalised content with customised difficulty levels and tailored learning conditions. This ability to proactively respond to student needs and feedback has been shown to increase engagement with artificial intelligence applications [9].

In terms of retention, the rate increased from 69% to 88%, resulting in a remarkable reduction in dropout. Student retention rates are always a pain point in higher education, as the dropout rate is higher than at other educational levels. A dynamic curriculum, such as SECM, is flexible, allowing support systems to identify students at risk of dropping out and target interventions appropriately; as such, it increases student retention [8].

For learning gains, the improvement ranges from 19% to 37%, indicating that students' knowledge nearly doubled when using the adaptive curriculum compared to the traditional curriculum. This improvement promotes the use of adaptive curriculum, whether to keep students motivated or to help them learn. Continued adjustment of curriculum output to student needs offers the most effective way to acquire and retain knowledge.

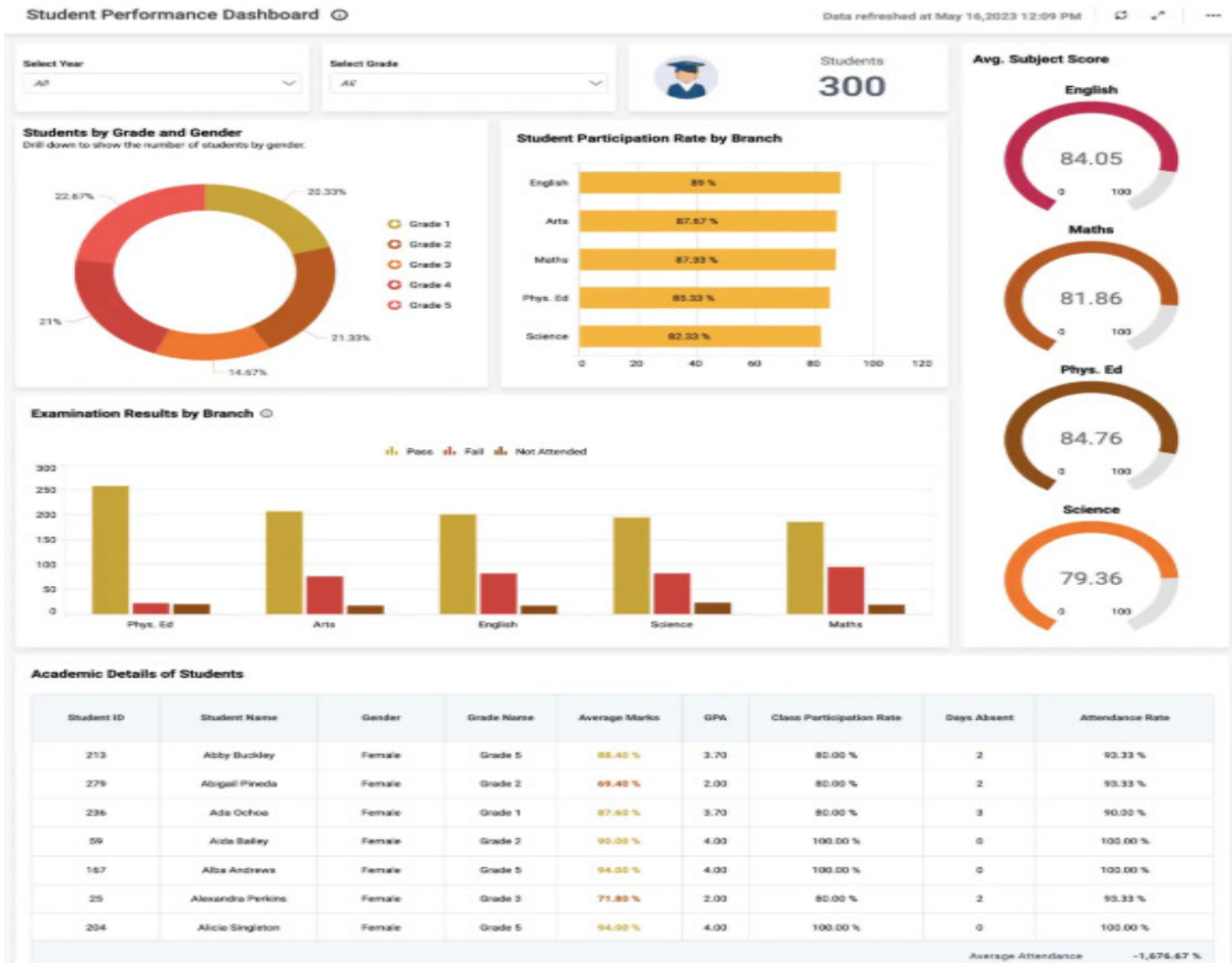


Figure 4: Student Performance Dashboard

From a graphical perspective, the performance of the SECM model (Figure 4) is not as good as that shown in the tables above across all quantitative measures. The most prominent improvements in the SECM model are evident in engagement and learning gains, consistent with the system's substantial advancement in these areas. The empirical results above also verify that the combination of generative AI and learning analytics effectively enhances system performance.

Another dimension that can be quantitatively measured in the experiments is the model's predictive performance. The addition of multidimensional features (cognitive, behavioural, and academic) significantly improves the model's predictive performance, as cognitive features alone can capture performance-related dimensions that influence learning from multiple perspectives. Adding behavioural and academic features can reflect students' engagement patterns related to their current progression. The diverse semantics captured by these multidimensional features enable the model to generate more accurate predictions and support the development of a dynamic curriculum [2].

The SECM system's influence on student engagement is a key focus of the quantitative experiment. According to the student participation statistics, students in the experimental group had a much higher level of interaction with the learning system than those in the control group and utilised the system more throughout the semester. The activities of the experimental group students can be attributed to the system's customizable feature, which balances the right amount of challenge and relevance for each student, enabling them to stay motivated and support their self-regulated learning. In addition to providing effective student support, the system can offer immediate feedback and encourage student engagement.

Regarding individual change detection and dropout prediction, the results show that the SECM system successfully prevents dropouts and early educational loss. Effective individual performance monitoring could facilitate early identification of individual students' potential risk of dropping out. With continuous tracking of student progress and frequent detection of characteristic patterns of declining performance, emergent issues can be identified in time, and the necessary measures can be implemented for each student. Compared to the traditional curricula, this approach is more intrusive at the individual level.

From a qualitative perspective, questionnaire surveys and secondary feedback from students and instructors can fully corroborate the quantitative results, indicating that the majority of students using the SECM system would report a better learning experience, a high sense of satisfaction, and positive motivation. Instructors would report obtaining more insightful and detailed information about students' status, thereby supporting effective teaching strategies. The quantitative results can only use indicators to maximise overall system performance, while the qualitative results can obtain user input

and improve the implementation of the entire system [49].

To assess the significance of the differences between the control and experimental groups, a t-test was conducted. The comparison results suggest that the differences in all observed measures are statistically significant ($p < 0.05$). The improvements in overall system performance observed in the experiment are not due to random factors but are directly attributable to the implementation of the AI system.

However, the experimental setup may also have limitations. Since this experiment was conducted at a single institution, the results may not be extrapolated to real-world global applications. The model's performance depends on the quality and quantity of available data, which may differ across institutions. The challenges encountered also indicate the necessity for more comprehensive research within various educational environments.

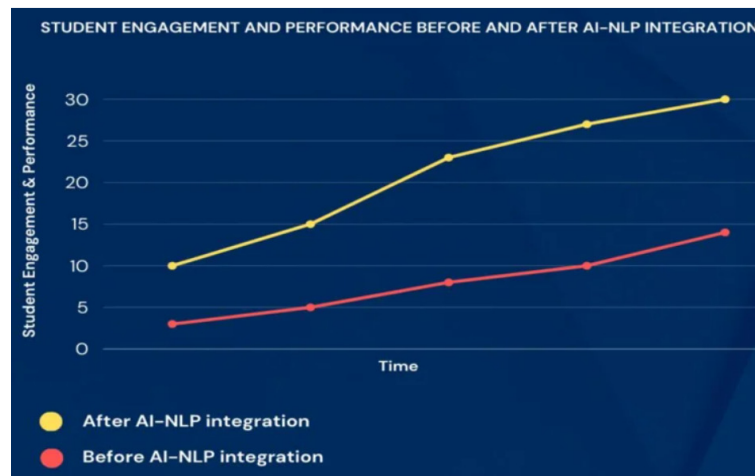


Figure 5: Comparative Performance Analysis

VI. LIMITATIONS AND FUTURE DIRECTIONS

While the proposed self-evolving curriculum model (SECM) appears very promising, it is important to acknowledge the potential limitations and challenges in reaching such an optimistic interpretation. Foremost among the limitations is the scale and scope of the experimental data set. While the project spanned two large disciplinary groups comprising 300 students, the overall data set remains relatively small. Previous research has shown that developing generalisable AI systems requires large, diverse data sets for training, especially in complex educational environments [5]. Thus, scaling up the dataset by combining data from multiple institutions and diverse cultural groups will be crucial to testing the current model's scalability.

A further limitation emerged from the use of linear regression as the dominant AI prediction framework. High interpretability and speed came at the expense of potentially oversimplifying the modelling of complex relationships. For instance, behavioural, emotional, and academic cues tend to interact more often in nonlinear ways. Experimentation with more sophisticated modelling approaches (e.g., deep neural networks and ensemble learning) will undoubtedly be needed to achieve an optimal balance between predictions and explanations [19]. The need to incorporate additional multimodal behavioural data sources remains evident to best support decision-making in educational AI models [31]. There is also a need to sacrifice some interpretability for prediction, while still retaining an interpretable component of the model to inform curriculum adjustments. Incorporating interpretable supplementary views will be highly beneficial in the future.

Thirdly, the limitations of learning activity data sources need to be acknowledged. Given its dependence on LMS data, the model may be only as good as the data it uses in terms of accuracy, completeness, and integrity. Although automated collection of LMS data is common practice, the inconsistencies across systems remain considerable. In general, LMS data often suffers from significant issues, with many learner actions being extraneous, partially captured, or invisible [25]. The implications of this data limitation for predictive modelling should be examined in future research. Utilising contextual data and other multimodal data sources may prove highly effective.

The heterogeneity of the learners served remains an obstacle to generalizability. Student class behaviours varied markedly in type, and the dynamics of learner variation in behaviour levels cannot be ignored. Modelling approaches tailored to the assumptions and nature of the learner units being modelled need to be explored in the future. Further, the effects of varying levels of classroom instructor influence still need to be investigated using AI-supported curriculum modification. Although the training algorithm itself was designed to operate autonomously, human oversight was strongly encouraged, and the effect of instructor involvement will need further study.

Practical challenges in implementing an AI-based curriculum generation system include the need for robust technological infrastructure, such as distributed computing cloud centres and high-performance data processing capabilities, as well as the ability of existing LMS systems to communicate with the curriculum system [11]. Digital inequality in terms of access and technological know-how may also present obstacles to broad-scale adoption of the AI system [50].

Finally, privacy and ethics remain dominant concerns when deploying any AI system in a real learning environment. The use of student data, how it is stored, its potential to propagate bias, and the transparency of algorithmic decisions are concerns that need to be addressed when deploying AI curriculum systems in practice.

VII. CONCLUSIONS

This paper proposes a new framework for self-evolving curricula in higher education that utilises generative artificial intelligence (AI), learning analytics, and feedback mechanisms to drive curriculum evolution over time. These developments culminate in the Self-Evolving Curriculum Model (SECM), providing a novel paradigm for curriculum design that moves from a static to a dynamic, iteratively optimised system capable of customising learning content based on individual students' portfolios of learning experiences over time. The innovative model was powered by prescriptive prediction, generative AI, and a hybrid optimisation algorithm, integrated using a collection of software and hardware modules that functioned synergistically at scale. The results showed that the SECM model significantly improved the predictive success rate, student engagement, retention rate, and learning gain, indicating its promising scalability and intelligence. This demonstrates that the continuous curriculum wayfinding system helped generate highly personalised learning pathways, with curriculum content dynamically tailored to individual learner needs. Such an integrated approach aligns with prior research on human-AI collaboration in learner-centric systems design. However, it significantly advances, from a human-centric perspective, the entire curriculum design and development process toward the automation of AI-led curriculum planning and creation based on a new curriculum design theory of curriculum emergence.

A key contribution of this paper is the innovation of proposing a closed-loop curriculum evolution ring process with double learning circles.: adaptively use individual student learning data to optimise curriculum adaptation; and increase knowledge utilisation as the basis for curriculum updating. This strategy uses process data to inform ongoing curriculum design and implementation, ensuring that educational programs remain relevant, effective, and robust in complex adaptive systems. Furthermore, the integration of generative AI enables the system to automatically produce customised content and restructure learning pathways in response to collected curriculum design data. This AI-driven innovation can mitigate the negative side effects of curriculum churn while drastically reducing the burden of curriculum design, aspiring to more resilient and adaptive educational systems of the future.

The paper also examined the ethical implications of the self-evolving curriculum, exploring potential future challenges and the countermeasures. While the use of generative AI in curriculum development shows promise, including high topic accuracy, increased learner motivation and engagement, student retention, and knowledge gains, constructivist education also faces new dangers in the context of intense AI augmentation. Revolutionising the conventional curriculum design paradigm through knowledge-based content generation, the proposed system reflects the existential balance of utilising technology while treading cautiously amid concerns about unintended consequences and uncertainty. The authors noted the pivotal role of reasonableness in technology implementation, emphasising the necessity of proportionate, fair utilisation of empowered big data, transparent feedback processes, and the fundamental safeguard of accountability governance. The proposed educational platform would ensure AI's success in education.

On the practical level, scaling up the SECM model demonstrated broad applicability across corresponding applications. The modular design of the self-evolving curriculum architecture incorporated autonomous machine programs and learning management system components, facilitating compatibility with the existing LMS architecture and easing the integration and mainstream adoption of the proposed model within larger educational systems that need more effective, personalised curriculum design technologies.

In summary, the design, optimization, evaluation, and implementation of the self-evolving curriculum by utilizing at scale generative AI, learning analytics, and adaptive feedback mechanisms established an advanced innovation frontier for curriculum informatics of higher education, showing to profoundly address the known shortcomings of traditional curricula with a data-intensive and learner-centric AI-powered curriculum shaping process of continuous, AI capstone designs revealing the potentials that the higher education could become an agile, innovative, and sustainable knowledge enterprise. This paper made a significant contribution to the literature on the development of an automated learning system. It highlighted the visionary implications for a trustworthy, resilient AI-enabled modular education platform that shapes the future of learning.

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Conflicts of interest

The authors have no conflicts of interest. The work was carried out independently, and no external influences affected the results or analysis.

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