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Methodology to Develop A Generative AI Driven Model for Optimized Higher Education Course Selection.

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ABSTRACT:

The Kenya University Central Placement service (KUCCPS) is responsible for placing students expected to join various Kenyan public higher education institutions under the government sponsorship scheme. The students are expected to select at least three courses they are eligible of, depending on the prescribed subject and mean grade. A student is placed to one of the selected courses. Due to this, students are forced to select courses for their placement. Most of the time, students are even not aware of the courses pursued in higher education. This makes students to be placed in any course provided they meet the requirements. At times, students may not be able to pursue the course to completion. This paper explores the development of a course recommendation model as a critical determinant of a suitable course selected for a student, depending on the academic performance and student's interest. Traditional models for course selection often rely on rule-based decision-making, limiting their adaptability to dynamic student needs. This research proposes a Generative AI-Driven Meta-Learning Model designed to optimize course selection by providing adaptive learning mechanisms that evolve based on student performance and KUCCPS dynamics. The model integrates generative AI with meta-learning techniques, enabling continuous effectiveness of predictive capabilities through iterative learning, for improved accuracy. Multi-Objective Optimization (MOO) techniques, specifically Particle Swarm Optimization (PSO), will perform optimization of course recommendations to ensure both personalization and institutional compliance.

Keywords: Generative AI, Meta-Learning, Course Selection Model, Higher Education.

Introduction

Examining the effectiveness of a course recommendation model integrating Generating Artificial Intelligence (AI) technology in educational settings is a crucial part of a critical analysis of AI tools in education. This research explores how automated course recommendation models with individualized learning algorithms can highly personalize reliable course selection to students. AI in education holds the promise of improving student results, streamlining the educational process, and customizing the learning process for each student.

Higher education institutions play a pivotal role in preparing students with the knowledge and skills needed to thrive in increasingly competitive and technology-driven economies. One of the foundational pillars for student success is selecting the right combination of courses and academic pathways (Romero & Ventura, 2020). In an era characterized by big data and AI, education systems have a unique opportunity to transform traditional, generalized advising into intelligent, data-driven recommendations tailored to each student's unique profile (Al-Shabandar et al., 2017).

By leveraging vast amounts of historical academic data, student preferences, generative AI models can produce highly personalized and adaptive course recommendations. This research proposes the development of a Generative AI-Driven Model aimed at enhancing the accuracy, relevance, and effectiveness of higher education course selection.

In the competence-based curriculum, the identity of learners' professions may be shaped by adequate career exposure and commitment in their junior secondary life. Therefore, it is necessary for junior secondary schools to provide relevant career choices to students by guidance from the course recommendation model. This is because in senior secondary schools, students strictly learn on their specified areas of study. Moreover, it is evident that it may be difficult for students to clearly determine their choice of course at their age, hence ending up pursuing courses that they are incapable of doing their best resulting in poor performance.

Literature review

Recommendation systems have been widely applied in domains such as e-commerce, businesses, security, entertainment, and education. These systems aim to deliver personalized suggestions based on user preferences or behaviors. In education, recommendation systems support decision-making in course selection, learning resources, and career pathways. Key techniques include collaborative filtering, content-based filtering, and hybrid models (Ricci et al., 2015). With the rise of data availability in education, recommender systems have become crucial for improving learning experiences and institutional outcomes (Drachsler & Greller, 2016).

Higher Education is the education beyond the secondary level (tertiary education) is commonly the undergraduate and post graduate studies. This education takes place in the Universities, Vocational training institutions. These institutions are expected not only to impart knowledge but also to equip students with the capacity for critical thinking, innovation, skills to handle job markets and adaptability.However, many institutions continue to grapple with challenges such as high student dropout rates, extended study durations, and graduate unemployment, lack of valuable skills from graduates partly due to misaligned course choices and poor academic advising systems (Sclater, 2017).

The growth of machine learning has significantly advanced course recommendation models by enabling systems to learn from complex, multidimensional data (Chen et al., 2020). Techniques such as support vector machines (SVM), decision trees, logistic regression, and neural networks have been applied to forecast student course selection and higher education placement. (Kabakchieva, 2013; Pandey & Sharma, 2013).

At King Saud University, the information technology department in their case study, used the J48 decision tree classification algorithm and utilized classification to assist recommending learners' final aggregate points based on their performance of courses (Mashael A. Al-Barrak and Muna Al-Razgan, 2016). Zhang et al. (2019) developed a deep-learning model incorporating temporal patterns to predict student preferences.

In education, researchers have begun exploring the potential of generative AI to synthesize realistic student profiles, predict performance under various scenarios, and create adaptive, personalized course pathways (Zhang et al., 2021).

The integration of generative AI into course recommendation allows for adaptive content generation and tailored learning materials. For example, GANs have been applied to generate synthetic academic data to enhance training datasets, improving model robustness where real data is limited (Chen et al., 2020).

This research addresses these gaps by proposing a dynamic, generative AI course selection model that continuously learns and integrates diverse student data, uses meta-learning for improved adaptability, and employs multi-objective optimization to balance various student and institutional goals., ensuring better alignment with student needs and institutional objectives. This will greatly enhance the accuracy, relevance, and effectiveness of higher education course selection.

Methodology

The course recommendation research adopts an experimental design of research to develop, implement, and asses a Generative AI-Driven Meta-Learning Model for course selection. The research involves collecting and analyzing secondary data (historical academic (KCSE) data) for around 2500 students in the year 2021- 2024. The dataset will be used to train and validate the proposed model. The study targets students joining higher education institutions. The study follows a structured approach that includes data preprocessing, model development, meta learning, optimization, and performance evaluation. This study will be conducted on a research center where historical data required is stored.

The focus is on understanding how Generative Artificial Intelligence (GenAI) tool can improve on course selection in the coast region in Kenya. Studies were selected based on relevance to personalized learning, adaptive assessments, and course selection enhancements, ensuring alignment with educational challenges such as course and education constraints and advance technological needs necessary for the model development. This qualitative review of generative artificial intelligence in improving course recommendation amongst students is based on secondary data emanating from the literature.

The GAI-CSRM Model: Effective Course Recommendation through Generative AI meta learning integration in Higher Education

The integration of generative AI into course recommendation allows for adaptive content generation and tailored learning materials. Despite its promise, the practical application of generative AI in higher education course selection remains underexplored, particularly in integrating generative capabilities with real-time course recommendation trends and multi-objective optimization.

The proposed model incorporates three core components: (1) a Generative AI engine to synthesize student profiles and simulate course fit scenarios Transformers, specifically BERT-based model, is applied to process unstructured textual data such as course descriptions and student feedback for generative AI personalization, (2) a meta-learning framework (Model-Agnostic Meta-Learning - MAML) for rapid adaptation to varying student cohorts, and (3) multi-objective optimization using PSO to optimize for accuracy and satisfaction. The dataset includes historical course constraints, standardized subject results, mean grade, personal interest and cluster points.

Problem Formulation

The development of the GAI-CSRM model aims to address the limitations of traditional course selection systems that struggle to identify relevant courses to students and require student's input or decisions to select courses for them. The GAI_CSRM integrates Generative AI features to model subject grades_ mean grade_ cluster points_ persona interest relationships and intervening factors, thus enabling effective automated course recommendation. The seven subjects used are: English, Kiswahili, Mathematics, two sciences subjects, one humanity subject, one technical subject and the subject left over or the best subject chosen from one humanity or the third science subject for student took more than seven subjects.

Transformer Model (BERT Integration).

The Transformer architecture is a deep learning algorithm based on neural networks, introduced by Vaswani et al. (2017) that uses self-attention instead of recurrence or convolution to process sequences.

BERT, GPT, and many modern large language models are based on the Transformer architecture. BERT, has demonstrated remarkable performance in capturing semantic meaning from textual data (Devlin et al., 2019). In the context of this research, BERT can be applied to encode students' personal interests (Pi), course descriptions, and program requirements into dense semantic embeddings. These embeddings can then be fused with structured academic features to build a comprehensive representation of each student–course pair. The significance of BERT in this study lies in its ability to understand refined student preferences and contextual course information, thereby enhancing the personalization and accuracy of the recommendation model. Through BERT implementation, the system can move beyond numeric predictors and incorporate unstructured data, resulting in a more holistic, student-centered, and intelligent course selection process (Brown et al., 2020; Zawacki-Richter et al., 2019).

Conceptual Framework

The conceptual model variables were mapped between independent and intervening variables. Subject grades were mapped with course eligibility, cluster points were mapped with course cluster group, mean grade was mapped with course level and personal interest generally was mapped with generative AI and meta learning features. The relationship between these variables were encoded within a transformer (BERT) algorithm, which mathematically models nonlinear dependencies between independent variables (subject grades, mean grade, cluster points and personal interest) and intervening variables (course eligibility, course cluster group, course level and metal earning features). This algorithm drives the behavior of both the particle swarm optimization and meta learning adaptation in the GAI-CSRM.

The Optimization mechanism optimizes the performance of the model while the meta learning mechanism learns from subsequent training. The combined approach enables the model to gather/cluster points, subject grades and mean grade with automatic recommendation accuracy being the primary output.

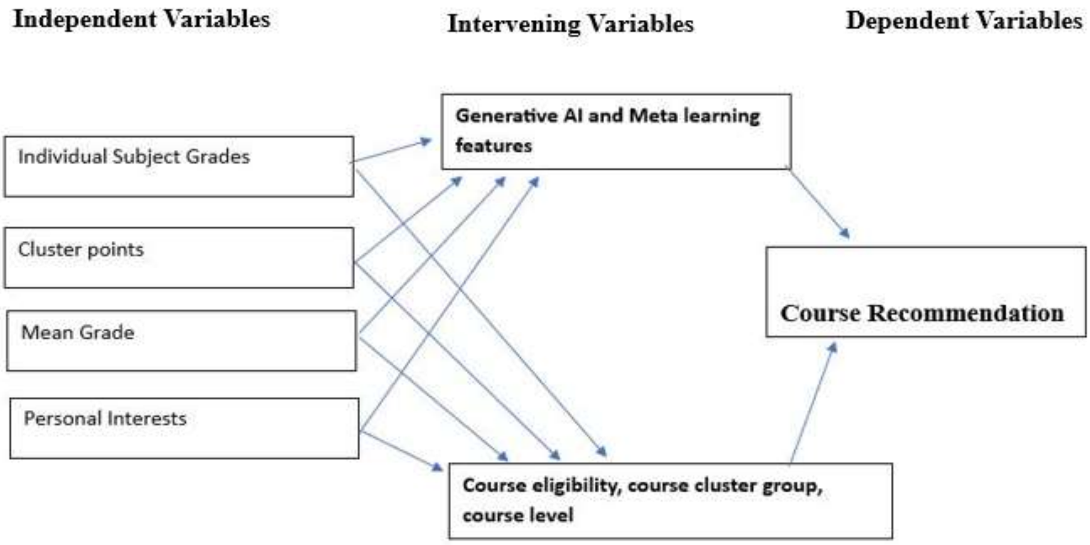

Figure 2: Conceptual Model Diagram for GAI-CSRM.

Variables

Independent variables: Students' academic scores, per subject and final grade, cluster points and Personal Interests. Intervening variables: meta-learning features, course eligibility, course level, course cluster group. Dependent variables: Course recommendations.

This equation describes how your course recommendation model uses BERT to process a mix of academic and personal variables, contextualize them, and produce personalized course recommendations in higher education.

Let S denote subject grades, final grade (Fg), cluster points (Cp), Personal Interests (Pi) as input variables. Intervening variables such as meta-learning features, course eligibility, course level, course cluster group are denoted by X and the output variable representing the recommendations is denoted by Y.

Mathematical expressions

1. Input Representation

Concatenate and embed all input variables for each student:

$$Z_{ij} = \text{Embedding}(S, Fg, Cp, Pi, X)$$

Where {Embedding} denotes the process of converting all features (numerical/categorical/text) into a unified vector representation suitable for BERT input.

Token embeddings for Zij and course text:

Zij= $[E_{CLS}, E_{t1}, \ldots, E_{tn}]$,

Cj = $[E_{CLS}, E_{u1}, \ldots, E_{um'}]$,

passed through L encoder layers (multi-head self-attention + FFN).

where E_{CLS} is a special classification embedding, and t1, …….tn are tokens in Zij.

2. BERT Encoding

Process the embedded input with a BERT Transformer:

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)V$$

with

$Q=P_i W_Q$, $K=P_i W_K$, V= $V=P_i W_V$ H=BERT(E)

Where (H) is the output sequence of hidden states from BERT.

The Transformer encoder stacks multiple such layers:

$H^{(l)}=\text{LayerNorm}\,(H^{(l-1)} + \text{Attention}(H^{(l-1)})$

$H^{(l)}=\text{LayerNorm}(H^{(l)}+\text{FFN}\,(H^{(l)})$

where FFN = Feed-Forward Network

3. Pooling/Selection for Recommendation

Obtain a pooled representation (e.g., using [CLS] token or mean pooling):

Z=Pooling(H)

CLS pooling: $p_i=\text{Enc}\,(Z_{ij})[_{CLS}]$, $e_j= \text{Enc}\,(C_j)[_{CLS}]$.

Fusion with tabular inputs (including X):

Z_{ij}= [S_i,Fgi, Cpi,Xij,pi,ej]

4. Prediction Layer

Use a feedforward layer to generate course recommendations: Y=Softmax (WZ +b)

Softmax feed-forwarding: Score $S_{ij} = f_\theta\,(z_{ij})$

Probability eligibility masking and probability over feasible courses $C_i=\{j:M_{ij}=1\}$:

$$s_{ij} = w^\top \phi\big(W_2\,\phi(W_1\tilde{\mathbf{z}}_{ij} + b_1) + b_2\big) + b, \qquad P_\theta(j \mid i) = \frac{\exp(s_{ij})}{\sum_{j'\in C_i}\exp(s_{ij'})}.$$

Where (W) and (b) are learnable parameters, and (\text {Softmax}(\cdot)) outputs probabilities over available courses. A feedforward layer with softmax produces probabilities for each possible course recommendation.

5) Generative AI training objectives

(A) Masked Language Modeling (BERT-style) for contextual embeddings

$$\mathcal{L}_{\text{BERT}}(\theta) = -\sum_{t\in M_i}\log P_\theta(w_t \mid \mathbf{P}_i \setminus M_i, S_i, Fg_i, Cp_i, X_{ij}) \; -\sum_{t\in M_j}\log P_\theta(u_t \mid \mathbf{C}(\S) M_j, S_i, Fg_i, Cp_i, X_i$$

(B) (Optional) Causal LM for generative personalization

$$\mathcal{L}_{\text{GenAI}}(\theta) = -\sum_{t=1}^{T} \log P_\theta(w_t \mid w_{<t}, S_i, Fg_i, Cp_i, X_{ij}).$$

(C) Recommendation loss (listwise or pointwise)

Listwise softmax (per student):

$$\mathcal{L}_{\text{Rec}}(\theta) = \sum_i -\log \frac{\exp(s_{ij_i^*})}{\sum_{j \in \mathcal{C}_i} \exp(s_{ij})},$$

or NDCG-weighted:

$$\mathcal{L}_{\text{NDCG}}(\theta) = \sum_i \sum_{j \in \mathcal{C}_i} w_{ij}\left(-\log P_\theta(j \mid i)\right), \quad w_{ij} = \frac{2^{rel_{ij}} - 1}{\log_2(rank_{ij} + 1)}.$$

(D) Composite Generative-Recommendation objective

$$\mathcal{L}_{\text{Joint}}(\theta) = \lambda_1 \mathcal{L}_{\text{BERT}}(\theta) + \lambda_2 \mathcal{L}_{\text{GenAI}}(\theta) + \lambda_3 \mathcal{L}_{\text{Rec/NDCG}}(\theta) + \lambda_4 \|\theta\|_2^2.$$

6. Meta-learning (task adaptation) + PSO

We view each program as a task *T*. Let θ be model weights; α be hyperparameters (learning rate, regularization,) optimized by PSO.

Inner (task) adaptation (MAML-style)

Given support data $D_\mathcal{T}^{tr}$ and query/validation $D_\mathcal{T}^{val}$:

$$\theta'(\alpha) = \theta - \eta(\alpha)\, \nabla_\theta \mathcal{L}_{tr}\left(\theta; D_\mathcal{T}^{tr}\right),$$

$$\mathcal{L}_{tr}(\theta; D) = \sum_{(i,j) \in D} \ell\left(y_{ij}, P_\theta(j \mid i)\right).$$

Outer (meta) objective

$$\min_{\theta, \alpha} \ \mathcal{L}_{meta}(\theta, \alpha) = \sum_\mathcal{T} \mathcal{L}_{val}\left(\theta'(\alpha); D_\mathcal{T}^{val}\right) + \lambda \|\theta\|_2^2 + \beta\, \mathcal{R},$$

where $\mathcal{R}$ may include fairness/diversity penalties (examples below).

PSO over hyperparameters α

Particles $k = 1, \ldots, K$ with position α_k and velocity v_k:

$$v_k^{t+1} = \omega v_k^t + c_1 r_1\left(pbest_k - \alpha_k^t\right) + c_2 r_2\left(gbest - \alpha_k^t\right), \quad \alpha_k^{t+1} = \alpha_k^t + v_k^{t+1},$$

with fitness $J(\alpha_k) = \mathcal{L}_{meta}(\theta, \alpha_k)$ (after inner adaptation).

7. Full Model Equation

Y=Softmax (W· Pooling (BERT (Embedding (S, Fg, Cp, Pi, X))) +b)

Given learned θ and PSO-selected α:

$$P_{\hat{\theta}}(j \mid i) = \frac{\exp(s_{ij})\, M_{ij}}{\sum_{j' \in C_i} \exp(s_{ij'})}, \qquad Y_i = \arg\underset{j \in C_i}{\mathrm{topK}}\, s_{ij}.$$

The Course Recommendation Process

The student's academic performance, that is the individual subject grade, generates the mean grade of the scored performance. The student aggregate score is calculated from seven subjects that is mathematics, English, Kiswahili, biology and chemist, one humanity, one technical subject and one of the best performed subject from humanity or sciences for those who did three sciences two humanities. The personal interest variable, allow student to input the possible ideas of the field of study they are passionate about or dream to study. The Gen AI course recommendation model then comes in, introducing recommendation capabilities based on the algorithms, embedded meta learning adaptations, particle swarm optimization techniques and the course dataset trained into the model with the possible courses with subject pre requisites to mirror from the student's input and offer a realistic and effective course. The entire Performance _Gen AI recommendation_ recommended course loop is refined by embedding three intervening variables - course eligibility, course levels, course cluster groups which indicate easier flow of the recommendation process as they improve on the high performance of the recommendation process in terms of speed and efficient output. The real time recommendation output evolves by continuous learning from student's input hence capable of making better recommendations with time.

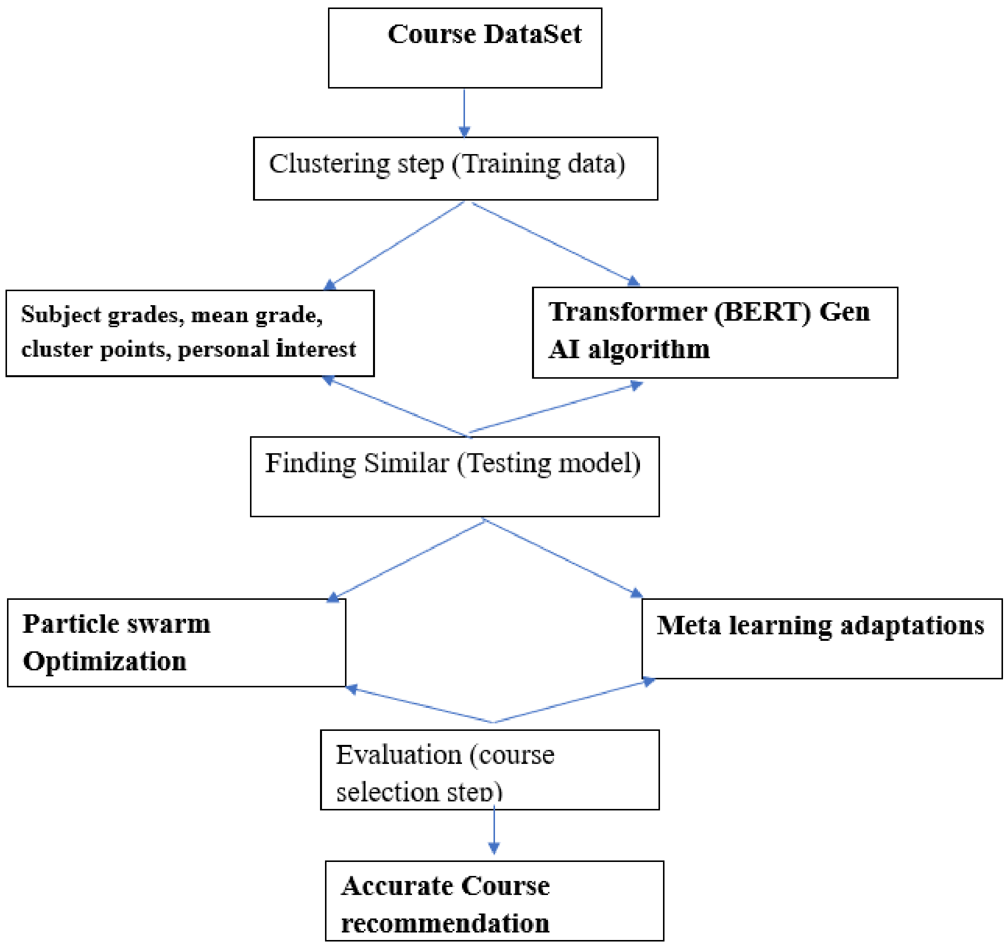

Figure 1: Conceptual Modelling Diagram for GAI-CSRM integrating theoretical foundations into a python framework.

Conclusion

This study demonstrates the potential of integrating Generative AI, meta-learning, and multi-objective optimization for higher education course selection. The generative AI model offers a significant advancement in course recommendation optimization over traditional machine learning algorithms by integrating a structured transformer algorithm to enhance reliable course recommendations. Future work will focus on large-scale deployment, real-time adaptation, and integration with institutional advising systems as well as using hybrid generative algorithms for enhance performance.

However, combining Generative AI with adaptive optimization techniques can transform academic advising from a static, one-size-fits-all approach into a dynamic, personalized guidance process. By responding quickly to evolving student profiles and academic trends, the system can address the limitations of existing recommendation models and better support diverse learners.

Looking ahead, incorporating real-time labor market analytics, internship availability, and industry skills forecasts could further refine recommendations and ensure their relevance to current workforce demands. Such enhancements would not only guide students toward academically suitable courses but also improve their preparedness for post-graduate opportunities, ultimately bridging the gap between education and employability.

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References

Al-Shabandar, R., Hussain, A. J., Liatsis, P., & Keight, R. (2017). An ensemble approach to predict student performance. International Journal of Innovative Computing and Applications, 8(4–5), 181–193.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., … Amodei, D. (2020). *Language models are few-shot learners.* Advances in Neural Information Processing Systems, 33, 1877–1901.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). *BERT: Pre-training of deep bidirectional transformers for language understanding.* Proceedings of NAACL-HLT, 4171–4186.

Finn, C., et al. (2017). Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks. International Conference on Machine Learning.

Nguyen, T., & Do, M. (2022). Personalized Learning Pathways through AI Course Recommendations. Journal of AI in Education.

Sinha, S., & Dutt, A. (2020). Student course selection prediction using hybrid machine learning models. Education and Information Technologies, 25(6), 5311–5326.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1–27.