Empowering Students with Predictive Intelligence: A Career Guidance System for Sri Lanka

Ahamed A L I
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
imthadh.ahamed.iahs@gmail.com

Ahmed M A A
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
azaamahmed555@gmail.com

Bandara R M M K T
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
kavindutheekshana2000@gmail.com

Areeb Aflah N
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
nafeesareebaflah@gmail.com

Jenny Krishara
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
jenny.k@sliit.lk

Poorna Panduwawala
Faculty of Computing
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka.
poorna.p@sliit.lk

***Abstract*—In Sri Lanka, students at key transition points in the education system lack access to comprehensive, data-driven systems of career assistance based on local academic and labor market conditions. In this paper, we introduce *AspireAI*, an AI-based career advice tool that supports the learner from the level of stream selection at the Ordinary Level to the world of work. The system is composed of four basic modules, which are stream recommendation with XGBoost and Retrieval-Augmented Generation (RAG) validation, university course prediction with ARIMA-Prophet ensemble for Z-score prediction, career pathway generation for non-traditional learners, and soft skill evaluation with Automatic Speech Recognition (ASR) and Natural Language Processing (NLP). In a longitudinal evaluation of 450 learners, researchers reported increases in program enrollment by 23%, increases in soft skills scores by 18.7%, and a user satisfaction rate of 92%. AspireAI is a scalable context-aware AI solution that democratizes personalized career guidance across the Sri Lankan education system..**

***Keywords*—Career Guidance, Artificial Intelligence, XGBoost, Retrieval-Augmented Generation, Time Series Forecasting, Soft Skill Assessment**

I. Introduction

In the education system in Sri Lanka, students are given several critical decision points which have a huge impact on their academic and professional careers. After the completion of General Certificate of Education Ordinary Level (G.C.E. O/L) examination, students have to select one of the five Advanced Level (A/L) streams namely, Mathematics, Bio Science, Commerce, Arts and Technology. Only 15-20% of around 300,000 A/L candidates per year can enter state universities later, while most of them have to find their ways in fragmented alternatives without systematic guidance [1], [2]. These transitions are often high stakes decisions with limited information, subjective counseling and large information gaps between urban and rural populations. [3].

Consistent evidence in the literature points to misaligned educational pathway selection as a driver of stream switching, academic underperformance, long time-to-graduation and ultimately, skills mismatch in the labor market [4]. Manual counseling limited by counselor-to-student ratios, subjective evaluations and a lack of connection to real-time labour market information characterize traditional career guidance methods. Further, the examination-oriented curriculam lacks appropriate structure for the development of soft skills necessary for employability [5].

Recent advances in artificial intelligence offer opportunities for transformative decision support in education. Machine learning can analyze historical academic data to identify patterns and predict the best paths forward, and Large Language Models (LLMs) can provide personalized explanations and create content that aligns with the curriculum. However, existing AI-powered career platforms are largely designed for developed market environments and fail to account for the unique characteristics of education systems in developing countries: Z-score driven admissions, district quota systems, resource constraints, and multi-lingual requirements. [6], [7].

This paper introduces an integrated AI-based career guidance ecosystem for Sri Lankan students in four essential areas. The primary contributions of this study include the development of a hybrid stream recommendation system that combines the XGBoost classification with the RAG-based curriculum-aligned quiz generation for readiness validation, a Z-score forecasting and course recommendation framework based on a combination of ARIMA and Prophet, a career pathway generator for non-traditional learners based on collaborative filtering and visualization powered by LLM, and a soft skill development module that combines ASR-based speech assessment, NLP-based communication scoring, and adaptive learning resource recommendation.

II. Literature Review

Educational pathway recommendation has been explored through various machine learning approaches. A Random Forest-based stream recommendation system [8] achieving 89.5% accuracy on Sri Lankan O/L data, An ensemble approach [9] combining Random Forest and XGBoost with 91.3% accuracy. However, these systems operated as static predictors without interactive knowledge validation or curriculum-aligned assessment mechanisms. Tree-based ensemble methods [10] outperformed traditional algorithms for educational classification tasks, yet did not incorporate readiness verification beyond grade-based prediction.

Time series forecasting for university admission has received limited attention in developing country contexts. One of the past research [11] analyzed Z-score cutoffs descriptively but did not develop predictive models. Another one [12] applied Bayesian analysis to eligibility patterns, revealing geographic disparities without providing prospective guidance tools. An AI-driven advisory platform [13] for Sri Lanka but focused on post-admission planning rather than admission prediction.

RAG has demonstrated effectiveness in grounding LLM outputs in authoritative sources, minimizing hallucination in educational contexts [14]. A Second-Classroom Personalized Learning Path Recommendation System [15] showed that LLM-based recommendation can overcome cold-start limitations by analyzing natural language descriptions, achieving 89% accuracy for Chinese university students. However, no existing work addresses fragmented educational landscapes in developing countries where learners must choose between formal degrees, vocational certificates, and short courses without clear equivalencies.

Soft skill assessment has evolved from subjective rubrics to computational approaches. Sun [16] demonstrated that ASR-enabled interventions improve speaking performance through automated feedback loops. Soft skill Module [17] proposed for mining soft skills from text, demonstrating NLP's capacity to operationalize soft-skill constructs. Educational recommender systems have been surveyed extensively [18], revealing persistent challenges including cold-start problems, limited transparency, and dependence on external content sources [19].

However, existing literature does not consider an integrated context-aware platform that integrates predictive stream selection and curriculum aligned validation, Z-score forecasting and personalized course ranking, Career pathway visualization for non-traditional learners and And soft skill assessment and adaptive resource recommendation. This gap drives the need for an integrated ecosystem aimed at Sri Lankan students at all critical transition points in education.

III. Methodology

A. System Architecture

We propose a system based on a modular microservices architecture with four integrated components that interact through a single web interface. For O/L to A/L transitions, the Stream Recommendation Module uses XGBoost based classification, along with RAG powered quiz generation. The University Course Prediction Module employs hybrid time series forecasting (ARIMA-Prophet) and weighted multi-criteria ranking for A/L to university admissions. The Career Pathway Generator leverages collaborative filtering and LLM based visualization to assist non-traditional learners. The Soft Skill Assessment Module combines ASR transcription, NLP-based scoring and adaptive recommendation.

Each component is independent but has a common user profiling layer, datastores in MongoDB and a React-based front-end interface.

B. Data Collection and Preprocessing

Data were collected using stratified sampling for various learner categories. Historical O/L and A/L examination results from 2015-2024 were gathered from 15 schools in Western, Central and Southern provinces, yielding 7,094 student records. The UGC admission data including 3,847 course-district-year combinations with Z-score cutoffs were collected from the official publications through automated web scraping and the datas from the Exam Department . Non-traditional learners ($n = 3,247$) participated in structured surveys to gather information on their demographics, educational background, work experience, and career preferences. The soft skills assessment dataset comprises over 200 speech recordings with proficiency labels provided by the experts and 1200 historical aptitude examination questions digitized from official UGC papers.

Missing values were handled by median substitution for numerical features and mode substitution for categorical variables. For the continuous variables, the Z-score normalization was applied and the categorical features were transformed using the one-hot encoding. To tackle the class imbalance in the stream distributions, we applied Synthetic Minority Oversampling Technique (SMOTE) on the minority classes like Technology and Arts.

Composite aptitude scores were derived by feature engineering, including STEM aptitude as a weighted average of Mathematics, Science and ICT, Humanities aptitude as a weighted average of History, Geography and Language related subjects and Commerce aptitude as a weighted combination of commerce related subjects.

The soft skill module used NLP preprocessing of speech transcripts, such as tokenization, lemmatization, and sentence segmentation, to prepare textual data for downstream analysis.

C. Integrated Model Design

1) Stream Recommendation: The stream recommendation component is designed as a two phase intelligent advisory system that combines RAG with supervised machine learning.

In Phase 1, an XGBoost multi-class classifier is trained to predict the most suitable A/L stream based on students' O/L academic performance. The model is trained on structured tabular data with subject wise scores (Mathematics, Science, English, ICT etc) with target labels of the five A/L streams (Biological Science, Physical Science, Commerce, Arts and Technology). Hyperparameters were tuned with 5-fold cross-validation, with learning rate $\eta = 0.05$, max depth $= 6$, and $n\_estimators = 200$. The model will produce probability distributions over all classes . You can recommend based on confidence

We propose an adaptive assessment mechanism based on RAG to validate the recommendation in Phase 2. Official A/L syllabus documents are parsed and split into overlapping chunks (roughly 450 words with 75 words overlap) These chunks are then embedded with the *all-MiniLM-L6-v2* model and stored in a vector database called ChromaDB.

At inference time the relevant syllabus content is retrieved using the predicted stream. A LLM creates structured MCQs based on the content retrieved. Students conduct a comparative performance analysis of recommended-stream and preferred-stream quizzes with data-driven validation.

2) University Course Prediction: The university course prediction module employs a hybrid forecasting and ranking framework. The ranking score for each course c is computed as:

$$R(c) = 0.5S_Z(c) + 0.3S_S(c) + 0.2S_I(c) \tag{1}$$

where $w_{ARIMA} = 0.6$ and $w_{Prophet} = 0.4$.

ARIMA captures linear temporal dependencies and Prophet captures seasonality and trend variations. Further improvements to these outputs are obtained by using gradient boosting models like LightGBM, XGBoost, and CatBoost.linguistic features like vocabulary richness

a) Course Recommendation Engine: The ranking score for each course c is computed as:

$$R(c) = 0.5S_Z(c) + 0.3S_S(c) + 0.2S_I(c) \tag{2}$$

where $S_Z(c)$ represents Z-score compatibility, $S_S(c)$ denotes subject alignment, and $S_I(c)$ captures interest matching.

Additional features include district-level trends, course demand, and employment statistics.

b) Career Interest and Aptitude Assessment: The module integrates a RIASEC-based career interest model and an AI-driven aptitude test generation system using BERT and RAG techniques. Semantic validation is performed using Sentence-BERT.

3) Career Pathway Guidance for Non-Traditional Learners: This component provides a multi-agent AI-driven recommendation and planning system.

a) RAG-Based Recommendation: User profiles are converted into natural language queries and embedded using *nomic-embed-text-v1.5*. These embeddings are matched against a ChromaDB vector store containing course data. The retrieved results are further refined through a multi-factor scoring pipeline that considers semantic similarity between the query and course content, career domain alignment with the user's stated goals, language compatibility based on preferred study language, study method preference (online, onsite, or hybrid), and financial feasibility with respect to the learner's economic constraints.

b) Skill Gap Analysis: A multi-agent pipeline is employed to perform skill analysis and alignment. The CurriculumAgent extracts relevant skills and attributes from course curricula, the CareerPathAgent defines required industry skills and competency expectations for the selected career goal, and the SkillGapAgent compares the extracted curriculum skills with the required competencies to identify existing gaps and areas for improvement.

Gap severity is categorized as low ($< 30\%$), medium (30–60%), or high ($> 60\%$).

c) Six-Stage Roadmap Generation: A personalized career roadmap is generated comprising six progressive stages: Foundation, Skill Development, Practical Application, Performance Optimization, Knowledge Expansion, and Job Readiness. Each stage is designed to guide the learner through a structured learning pathway and includes clearly defined goals, recommended duration, actionable tasks, relevant learning resources, and measurable success criteria to ensure effective skill development and career readiness.

4) Soft Skill Assessment: The soft skill module evaluates communication skills using speech processing and NLP.

a) Feature Extraction: The soft skill module evaluates communication skills using speech processing and NLP. Audio inputs are first standardized into a uniform 16 kHz WAV format and transcribed using ASR. From the processed audio, multiple feature types are extracted, including acoustic features such as speech rate, pause frequency, and pitch variation, linguistic features such as vocabulary richness, grammatical accuracy, and coherence, and semantic features derived from contextual embeddings to capture deeper meaning and expression.

b) Model Design: The extracted features are combined into a unified feature vector and fed into a multi-output regression model. The model predicts multiple communication dimensions, including fluency, clarity, confidence, and structural coherence, enabling a comprehensive assessment of the learner's communication abilities.

c) Adaptive Feedback: Based on the predicted outputs, the system provides targeted feedback, example responses, and guided practice activities. The difficulty and focus of subsequent tasks are dynamically adjusted according to learner performance, forming a continuous adaptive learning loop. Additionally, a pre- and post-assessment framework is employed to track improvement over time while maintaining user privacy through session-based processing without permanent data storage.

D. Adaptive Recommendation Algorithm

The adaptive recommendation mechanism is designed as a hybrid multi-agent and rule-based system that dynamically personalizes learning pathways and resources. For each learner interaction, the system performs multi-dimensional skill evaluation using inputs from quizzes, aptitude assessments, and soft skill analysis. Based on these evaluations, skill gaps are identified through threshold-based analysis. The system then retrieves context-aware learning resources using a Retrieval-Augmented Generation (RAG) pipeline, followed by a multi-factor ranking process that prioritizes relevant learning materials. Additionally, user interactions and performance metrics are continuously logged to support system refinement and long-term personalization.

The ranking function is defined as:

$$R(r) = \lambda \cdot GapMatch(r) + (1 - \lambda) \cdot LevelFit(r) \quad (3)$$

where $GapMatch(r)$ measures the alignment between identified skill gaps and resource content, and $LevelFit(r)$ evaluates the suitability of resources based on the learner's proficiency level.

The ranked outputs are subsequently integrated into the six-stage personalized roadmap, enabling structured, adaptive, and goal-oriented learning progression.

E. Implementation Details

The system is built on a scalable microservices architecture to allow modularity, flexibility and efficient deployment of multiple components.

a) A. Backend and AI Stack: The backend is built with FastAPI, with asynchronous processing to allow for efficient processing of concurrent requests. The machine learning and artificial intelligence components are implemented using a combination of libraries: scikit-learn for preprocessing and baseline modeling, XGBoost, LightGBM and CatBoost for prediction and ranking tasks, statsmodels for ARIMA-based forecasting, Prophet for trend and seasonality modeling, and Transformers for natural language processing and embedding generation. RAG pipelines store vectors in ChromaDB and produce content with LLM APIs.

b) B. Multi-Agent Integration: The system is intended to follow a multi-agent architecture in order to make decision making modular and intelligent. The CurriculumAgent retrieves relevant course-level skills and attributes, the CareerPathAgent defines industry-matched competency requirements, the SkillGapAgent highlights gaps between learner skills and required competencies, and the RoadmapPlanningAgent creates structured learning pathways.

c) C. Frontend: The frontend is built using Next.js for a responsive and user friendly interface. We use Material-UI for component design and styling, and D3.js for interactive data visualization (career roadmaps, analytical dashboards).

d) D. Data Storage and System Performance: The system adopts a hybrid data storage approach, utilizing MongoDB for structured and semi-structured data, ChromaDB for vector embeddings and semantic retrieval, and Redis for caching frequently accessed data to improve performance. The platform is designed to support more than 100 concurrent users, achieving a response latency of less than 2.3 seconds at the 95th percentile.

e) E. Privacy and Security: Session-based processing to ensure privacy and security and no permanent storage of sensitive data such as audio inputs. Furthermore, robust authentication protocols and encrypted data management are implemented to ensure user data security and system integrity.

IV. Results and Discussion

A. Experimental Setup

Evaluation used a multi-phase methodology that was comprehensive. We performed offline testing on historical data with 70/15/15 train/validation/test splits and 5-fold stratified cross-validation. Usability testing involved 85 participants completing structured tasks and the System Usability Scale (SUS) survey. We conducted a longitudinal deployment with 450 learners over 6 months, tracking enrollment rates, confidence in setting goals, and skill gains. An integrated system was compared to baseline approaches, such as rule-based eligibility checking, standalone collaborative filtering, and non-personalized recommendation systems.

B. Component Performance

Table I comprehensive performance comparison of all system components and baseline methods. The stream recommendation model with XGBoost achieved an accuracy of 94.2% with precision, recall, and F1-scores ¿0.93 for critical streams such as Mathematics and Bio Science. The hybrid Z-score forecasting model yielded a MAPE of 3.2% which is better than the stand-alone ARIMA (4.7%) and Prophet (3.9%) models.

The course recommendation module achieved 89.4% top-10 accuracy and 87.2% precision and 91.3% recall, significantly outperforming traditional rule-based methods. The career guidance module for non-traditional learners had an accuracy of 87.3% which increased to 89.1% with the inclusion of RAG-based retrieval and LLM-generated explanations. The soft skill assessment module achieved an ASR Word Error Rate (WER) of 13.2% with three proficiency levels and 86% classification accuracy.

Additionally, the RAG retrieval component achieved 91.5% top-5 relevance accuracy, providing high quality content grounding for recommendations and quiz generation. The aptitude assessment module achieved a prediction accuracy of 88.6% for career interest categories while the roadmap generation system received an 84.7% user satisfaction score based on structured feedback evaluation.

C. Longitudinal Impact Assessment

Longitudinal evaluation over six months involving 450 learners showed significant gains in multiple dimensions. Program enrollment rates increased by 23% relative to the control group (68% vs. 45%, $p < 0.001$). Self-reported confidence in establishing career goals improved by 18% (4.96/7 vs. baseline 4.2/7). The personalized intervention group improved by 18.7% in soft skill composite scores, compared to a

TABLE I
SYSTEM PERFORMANCE COMPARISON

Component	Metric	Prop.	Base.
Stream Rec.	Acc.	94.2%	89.5%
	F1	0.930	0.879
Z-Score	MAPE	3.2%	8.1%
	R^2	0.921	0.743
Course Rec.	Top-10 Acc.	89.4%	68.4%
	Prec.	87.2%	62.1%
	Recall	91.3%	65.7%
Career Path	Acc.	89.1%	82.4%
	w/o LLM	87.3%	—
RAG	Top-5 Rel.	91.5%	78.2%
	Sem. Score	0.89	0.71
Aptitude	Acc.	88.6%	73.4%
Roadmap	Satisfaction	84.7	69.5
SUS	Score	82.4	68.2
Soft Skills	Acc.	86%	—
	WER	13.2%	—

9.4% improvement in the non-personalized baseline. When we looked at pathway completion metrics, we found that 79% of those in the intervention group hit at least one milestone within three months, compared to 62% of those in the control group.

The average SUS score of 82.4 demonstrated excellent usability and user satisfaction . Qualitative feedback indicated high satisfaction with pathway visualization (4.3/5) and LLM-generated explanations (4.2/5).

D. Discussion and Key Findings

The results demonstrate that AI applications in context can make a meaningful difference in education to employment transitions in developing countries. Key factors were: hybrid approaches that combine data-driven algorithms with LLM-based natural language understanding, addressing both quantitative constraints and qualitative aspirations; visual pathway representations translating abstract career guidance into actionable and structured roadmaps; and the integration of localized labor market data, ensuring that recommendations are credible, relevant and context-aware.

At national scale, this 23% increase in enrollment is estimated to mean 45,000-60,000 additional non-traditional learners accessing appropriate training annually .

Mathematics O/L grades contributed (28.7%) to stream prediction followed by Science (21.4%) and composite STEM Aptitude scores (12.8%). ROI prediction accuracy varied by program category, with IT/Software Development exhibiting the highest accuracy (10.3% MAE, R2=0.82) and Hospitality showing more variation (16.8% MAE) due to seasonal demand shifts and entrepreneurial dynamics. Improvements were largest for students initially identified as low proficiency which is consistent with threshold based escalation to foundational practice modules for communication skills.

E. Limitations

There are several limitations to note. First, the geography-limited datasets were largely limited to Western and Central provinces and may limit generalizability to Northern and Eastern regions. Second, ROI forecasts were off by 12.8% on average, with large differences between volatile sectors. Third, long-term employment outcomes must be tracked for several years beyond the six-month evaluation window. Fourth, Language support is still under development and not yet comprehensive for all languages. Fifth, ASR-based speech scoring, despite normalization techniques, propagated transcription errors (13.2% Word Error Rate) into downstream NLP features. And the curated resource catalog. Good for recommendation stability, but limited discovery outside of curated content.

V. CONCLUSION

The study presented a holistic AI-enabled career guidance ecosystem that filled critical gaps in Sri Lanka's education-to-employment pipeline. The system provides comprehensive and adaptive support at all major student transition points using XGBoost-based stream recommendation, RAG-based knowledge validation, hybrid ARIMA–Prophet Z-score forecasting with gradient boosting optimization, a multi-agent RAG-driven career guidance framework for non-traditional learners and an ASR with NLP-based soft skill assessment module.

The proposed framework employs a multi-agent architecture with CurriculumAgent, CareerPathAgent, SkillGapAgent and RoadmapPlanningAgent for personalized career planning, which is different from the conventional system. Including RAG-based retrieval means that all recommendations and evaluations are based on domain-specific knowledge sources, increasing accuracy and contextual relevance. The system also includes a six-stage personalized career roadmap and skill-gap analysis, allowing for structured and progressive learning paths tailored to the individual learner.

Empirical validation showed that the proposed approach outperforms baseline approaches with 94.2% stream prediction accuracy, 3.2% Z-score MAPE, 89.4% top-k course recommendation accuracy, 89.1% career pathway recommendation accuracy with LLM enhancement, and 86% soft skill classification accuracy. Additionally, the high semantic relevance of the RAG retrieval module and the improved accuracy of the career alignment module of the aptitude assessment module further improved the overall effectiveness of the system.

Beyond the technical performance, the importance of the system is in its contribution to educational equity and accessibility. The platform supports career development for over 300,000 students annually in Sri Lanka, providing scalable, data-driven and personalized advice irrespective of geographical location or socioeconomic background. The real-world effects of the proposed system are validated by the observed 23% increase in program enrollment, 18.7% improvement in soft skill performance, and SUS score of 82.4.

Future work will involve extending the system to include full multilingual support including Tamil and Sinhala languages, real-time labour market intelligence and employer driven datasets and further personalization using reinforcement learning based adaptive pathways. Other enhancements include mobile first interface design for rural access, further integration of aptitude and behavioral analytics, and longitudinal studies to assess long-term career outcomes.

The long-term vision is to build a sustainable, scalable and globally applicable AI-based framework that will eventually lead to decreasing youth unemployment, solving skill mismatch problems, and promoting inclusive economic growth in developing countries.

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