Computational Intelligence Approaches for AI-Powered Education and Language Accessibility in Smart Learning Systems

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***Abstract*— The rapid expansion of online education has led to the development of several innovative instructional methods that are adaptable and accessible to all individuals. However, a significant number of the courses now offered do not cater to the requirements of all types of students or guarantee that languages are accessible in every region of the world. The Computational Intelligence-Driven Adaptive Learning Framework (CI-ALF) is an approach presented in this work. The idea will enable natural language processing (NLP), evolutionary optimization (EO), and neural networks (NN) to collaborate, creating intelligent learning environments tailored to each user and accommodating a diverse range of linguistic backgrounds. Through the use of real-time translation and pronunciation assistance, the CI-ALF can monitor student profiles, identify areas where they require extra information, and present them with materials tailored to their specific needs. The results indicate that the framework assists students in learning more rapidly (by 18%) and gaining a deeper understanding of more complex topics when they are required to work with multiple languages. According to the results, artificial intelligence has the potential to significantly improve academic performance, diversity, and engagement, while reducing the mental effort required. Ultimately, this work provides a framework for future learning systems driven by artificial intelligence that can be tailored to the specific needs of each individual and support multiple languages.**

Keywords*— *Computational Intelligence, Smart Learning Systems, Language Accessibility, Adaptive Learning, Natural Language Processing, Personalization.

I. INTRODUCTION

Two challenges must be overcome before intelligent learning systems can fulfill their promise of mass customization[1]. The first challenge is to ensure that education can continuously adapt to the knowledge of each student[2]. The second challenge is to ensure that students from diverse backgrounds and with disabilities receive assistance that is both accessible and bilingual[3]. There have been advancements in artificial intelligence, including voice technologies, cognitive diagnostics, knowledge monitoring, and graph neural customisation, among other things[4]. There are still some issues with the current deployments, such as ensuring that all children have access to language [5]assistance in actual classrooms in real-time and that improvements can be made across modalities that are both effective and easy to understand[6]. Education powered by artificial intelligence can lead to improved retention[7] and performance through the early detection of risks and the provision of targeted feedback[8]. Because language assistance is readily available, a greater number of people can participate, and as a result, everyone will be treated equally[9], [10].

Problem Statement:
The primary objective of this project is to develop a single pipeline that is easy to understand[11], [12], accommodates a wide variety of learners, and maintains the confidentiality of their information[13]. During this procedure, artificial intelligence is responsible for diagnostics, forecasting, customization, and language interfaces[14], [15]. The discovery of a solution to this problem is of the utmost importance, as it will facilitate improved learning for students learning a second language, as well as for children with impairments[16], [17]. The processes of knowledge tracing and cognitive diagnostics[18] are two examples of modeling techniques that do correct modeling[19]. ASR/TTS and multilingual natural language processing are two examples of technology that aid in language accessibility[20]. This will reduce the number of students who drop out of school and boost the measured learning results[21].
Research Gaps and Motivation:
Initially, it is not possible for educators to have faith in several high-performing models [22]or receive helpful feedback from them, as these models are difficult to grasp [23]. To make matters even more unsettling is the fact that cross-modal integration is not often present [24], and that KT/CDMs and speech-driven education or multilingual interfaces do not usually operate together [25]. Risk prediction, like dropout prevention, often does not work in a closed loop with scaffolding that is easy to use or timely interventions [26]. This is the third challenge that has to be

2025 International Conference on Electrical Engineering and Informatics (ICEEI) | 979-8-3315-9271-4/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICEEI68459.2025.11330426

addressed. For the last point, accessibility-by-design is not always taken into consideration during deployment [27]. There are not many systems that really make it possible for adaptive sequencing to take place based on KT/CDM signals[28]. The computer system in our smart classroom is equipped with programmable design[29], [30], interpretable diagnostics, sequence modeling, customization, and language services that assist individuals in addressing these issues[30]. Main contribution:

- Cognitive diagnostics that are unified and simple to comprehend; the capacity to keep track of what one knows; the capability to personalize based on graphs; and automatic speech recognition and text-to-speech capabilities that apply to more than one language.
- It is the responsibility of a tiny [MELIA] controller to ensure that privacy is safeguarded while simultaneously optimizing accessibility cost, fairness, and learning value.
- Due to the incorporation of real-time scaffolding, which encompasses concepts, translations, and voice feedback, the assessment design has become more precise, transparent, and accessible to all parties involved.

II. LITERATURE SURVEY

TABLE. I. COMPARISON OF METHODS

Author(s)	Methodology	Results	Limitations
Tianlong Qi et al. [31]	**Interpretable Cognitive Diagnosis (ICD)** – neural cognitive diagnostic approach	Improves accuracy over traditional CDMs; better item selection on benchmark datasets.	Requires large labeled item-skill mappings; limited scalability due to reliance on extensive interactions
Christou et al. [32]	**Supervised ML for Early Drop & Performance Prediction (EDP)** – classification & regression pipelines	Effective early-warning system; timely interventions for at-risk students	Dataset bias, limited generalizability; can not adapt across institutions
Pu et al. [33]	**GNN-P algorithms** – graph-based sequencing & recommendation	Better modeling of student–entity connections; more flexible than sequential KT	High computational cost; difficult cold-start handling; time-consuming graph generation
Tong & Ren [34]	**Dual-Stream DKT with Cognitive Load (DKT-CL)**	Captures ability + cognitive burden; supports load-aware pacing; improves trajectory quality	Over-reliance on load proxies; lacks sufficient real-world classroom validation.
Wu & Ling [35]	**HSN-SS for Knowledge Tracing (HHN-SS)** – self-supervised student–material relation modeling	Reduces label dependence; models complex student–material relations	Increased model complexity; reduced interpretability for instructors
Kang et al. [36]	**ASR-LT Language Tutoring** – semi-supervised ASR + competence models	Significant reduction in ASR errors for non-native learners	Relies on manual feature engineering; limited multilingual support

The MELIA controller is discussed in this article. MELIA is a privacy-conscious controller that provides cognitive diagnostics that are easy to comprehend, customizable graphs, dual-stream KT, and end-to-end ASR/TTS. By providing students with explanations and support in a variety of languages in real-time, it makes things more transparent for educators, more equitable, and helps students learn more effectively (Table 1). Additionally, it fills in the gaps in terms of accessibility, understanding, and fragmentation.

III. METHODOLOGY

A system that is capable of changing as a result of artificial intelligence (CI-ALF). For the purpose of constructing a comprehensive learning engine, CI-ALF employs decision-theoretic control in conjunction with data-efficient modeling. Once a student interacts with an item, it is considered proof that they need to modify their perspectives on how to acquire a skill, how much mental work they can manage, and what they need to achieve to be successful. Fig 1 shows the proposed framework. The open API provided by CI-ALF allows one to configure the three primary modules in any format or language. This is because it safeguards privacy while also ensuring that different types of signals (including clickstream, reaction time, hint utilization, and voice quality) are all treated the same, despite their differences. Components such as caching, edge inference choices, and lightweight models make the framework construction process easy and quick. The use of override hooks and extensive explanations is employed to simplify the reading experience for educators.

A. Multi-objective Explainable Loop for Inclusive Adaptation

The controller, Melia, is responsible for killing the circuit. To simplify, equalize, and reduce the cost of learning, this work utilizes the results of all courses at each level. F is responsible for establishing limits and searching for inconsistencies that exist across protected or context groups. AC, on the other hand, allocates resources for tasks such as text-to-speech and automatic speech recognition based on factors like latency and cognitive load. LG also notes the amount of additional knowledge and abilities that will be imparted. The system will explain the reasoning behind its suggestions, making it easier for one to learn and understand the regulations. To cater to the individual needs of each student and class, the program can evolve.

Fig. 1. Proposed work

B. ICD: Cognitive Diagnosis with Interpretability:

By demonstrating the connections between concepts and objects, as well as the connections between ideas and concepts, ICD can determine how effectively each student has learnt a skill. Through the use of neural encoders that are equipped with an interpretable scaffold or a more advanced Q-matrix, it is possible to break down each prediction into observable attributions at the idea level. For the purpose of generating mastery posteriors, uncertainty, and targeted mistake patterns (slips/guesses), ICD utilizes interaction traces, which include accuracy, attempts, time, and hints.

C. GNN-P: Graph Neural Personalization:

When it comes to learning embeddings, GNN-P employs relational closeness and pedagogical restrictions as instructional codes. Through this process, a network is constructed that takes into account a variety of learners, objects, talents, and circumstances. A straightforward policy head is responsible for modifying these embeddings to determine the data sequence, which encompasses the subsequent best item, the pace, and route planning. GNN-P can utilize structure-aware signals, such as requirement order or co-practice, to pretrain, and then provide new learners or objects with metadata and concept links. To prevent both the learner and the system from being overloaded with work, this module collaborates with the ICD (skill gaps) and MELIA (fairness/AC limitations) programs. It achieves this by ensuring that the avenues for progress are as excellent as possible.

D. Multilingual ASR/TTS Accessibility Layer (ASR/LT):

The students' oral practice is recorded using automatic speech recognition. Text-to-speech (TTS) provides examples and scaffolds that correlate with target concepts, and pronunciation assessment utilizes aspects from the phoneme and prosody levels as part of the language assistance supplied by ASR-LT. If connections are slow, layers can be configured to carry out inference either offline or at the edge of the internet. This includes the number of words and phonemes that are incorrect, as well as the speed at which speech is occurring. Through careful planning and scheduling, MELIA monitors the use of ASR/TTS funds to ensure that they are utilized at the proper times to support education and equality without wasting any money.

E. Multi-Objective Optimization Controller:

This work presents the concepts for an adaptive learning system that utilizes artificial intelligence and operates in a closed loop. Fig 2 shows the multi-objective optimization controller (MELIA). In addition to providing support for languages, this design also offers the capability to modify content based on graphs, test knowledge, and provide cognitive diagnostics. A multi-objective optimization controller, often referred to as MELIA, is a device that transforms language input and learner interactions into comprehensible learning paths and personalized teaching recommendations. This work will delve into great detail about each aspect of arithmetic and its relationship to the broader concept of education in the following paragraphs.

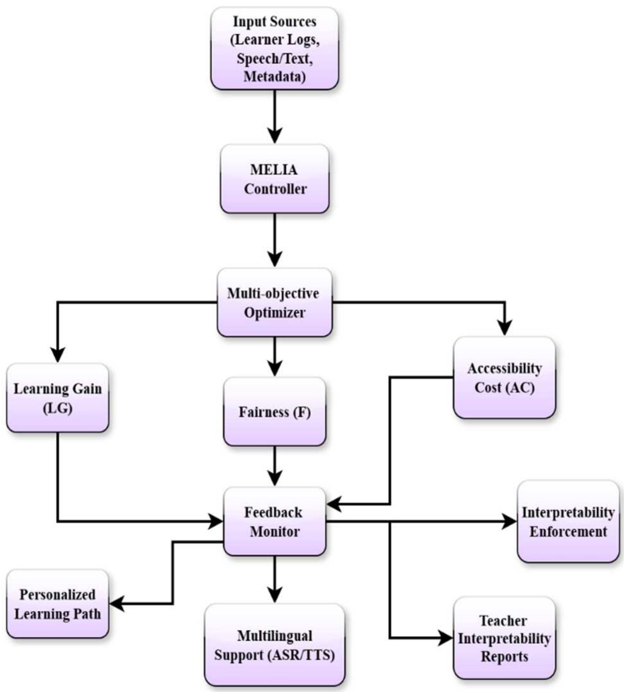

Fig. 2. Workflow of MELIA controller

a. Cognitive Diagnosis:

In cognitive diagnostics, one of the primary objectives is to determine how well a student has learned abilities that are not readily apparent to the naked eye. This is how a vector appears in the field of mathematics in (1):

$$s_t \in \mathbb{R}^k \quad (1)$$

The symbol denotes standard deviation s_t, and the number of knowledge or skill components that are being evaluated is denoted by k causes me to ponder the student's level of proficiency in each of these categories at that precise time t. It is the whole of s_t a method that can be used to determine whether or not a pupil really comprehends a topic.

If a student makes a novel discovery, q_j different kinds of assignments, such as math problems, grammar exercises, and reading comprehension passages, require individuals to possess a variety of abilities.

$$a_j \in \mathbb{R}^k \quad (2)$$

(2) encodes that one wants to put down the talents that are required for the item. For instance, if one is having trouble with geometry, one would need to be familiar with the concepts of "angle properties" and "triangle congruence," which are two components of the set a_j that are not equal to zero as well.

The probability that a learner would correctly identify an item, denoted by the symbol q_j the models that one can rely on are the ones that:

$$P(r_{ij} = 1 | s_t, a_j) = \sigma(s_t^\intercal a_j) \quad (3)$$

In (3), When r_{ij} it is correct, the sigmoid activation function, which is denoted by the expression $\sigma(\cdot)$, returns a value of 1, and when it is incorrect, it returns a value of 0. The likelihood of a person learning new things increases when their skills are a good match for the task they are doing. This statement provides a concise summary of the idea. Due to the clarity of its feedback, this probabilistic diagnostic procedure is highly effective.

b. Knowledge Tracing:

A cognitive diagnostic reveals the capabilities that one possesses at the present moment. Learning is the continuous acquisition of new knowledge and the development of existing knowledge. Understanding how a learner's abilities improve over time can be demonstrated through the use of knowledge tracing, which involves monitoring the learner's development during each encounter. The status of a skill can be updated in the following manner (4):

$$s_{t+1} = f(s_t, r_{ij}, q_j) \quad (4)$$

To encode the r_{ij}, which is a response that can be seen, the recurrent function f is used. The means by which one can determine the value of q_j influences the amount of capacity that is not being used. The implementation of f in real-world applications is accomplished via the use of Recurrent Neural Units (RNNs), which include LSTM networks and GRUs.

c. Graph-based Adaptive Sequencing:

The process of personalization, on the other hand, not only monitors a pupil and identifies areas for improvement, but also determines what they should learn next. The learner-item interaction graph is the tool that this work use to instruct GNNs on how to do this in (5):

$$G = (V, E) \quad (5)$$

When it comes to activities such as testing out activities, issuing ratings, or translating skills, the letter E represents things like these. The letter V stands for the group of learners and objects. There is a possibility that the GNN will adjust its embeddings via sending messages using (6):

$$h_i^{(l+1)} = \sigma\left(\frac{1}{|N(i)|}\sum_{j \in N(i)} W^{(l)} h_j^{(l)}\right) \quad (6)$$

The notation denotes the precise position $h_j^{(l)}$. The notation represents the weight matrices $W^{(l)}$, where $N(i)$ represents the neighbors of node i at layer l. The average term evaluates both peer similarities (students with similar histories) and content connections (items that share required structures) to ensure that each learner or item embedding is influenced by its network neighbors. This is accomplished by analyzing both types of connections. This particular system is capable of adaptive sequencing, which means that it can make recommendations for new subjects to study based on the learner's current skill level and signals that are further up the graph. For instance, a training item q_j, was beneficial to students who were at the same level of proficiency as their peers.

d. Accessibility Layer:

Accessibility not only makes it simple for individuals to personalize their content and cognitive abilities, but it also ensures that everyone, regardless of their language or cultural background, can utilize it. Language translation, text reading, and the issuance of voice commands in real time are all tasks that fall within the purview of the ASR-LT layer. Although it considers signals such as phoneme score and word error rate, the optimization loop does not provide us with any new equations for this particular scenario. The primary goal is to provide language learners with substantial support, including audio feedback, TTS prompts, and translations, without overwhelming them or placing excessive stress on the computer.

e. MELIA Controller (Multi-objective optimization):

MELIA stands for Multi-objective Explainable Loop for Inclusive Adaptation, which establishes connections between all the modules discussed previously. To make better recommendations, it is necessary to find a middle ground between three objectives that are in direct opposition to one another: learning gain (LG), fairness (F), and accessibility cost (AC).

Additionally, the primary objective of MELIA is the same as that of (7):

$$\max_\theta J(\theta) = \lambda_1 LG(\theta) + \lambda_2 F(\theta) - \lambda_3 AC(\theta) \quad (7)$$

The policy parameters are denoted by the symbol θ, whereas the values of 1 are represented by the symbols $\lambda_1, \lambda_2, \lambda_3$. It is two. The number three. in terms of values that have been exchanged.

The results of $LG(\theta)$ indicate that mastery routes are likely to improve in the future. The function $F(\theta)$ ensures that students are not unjustly disadvantaged when they offer their opinions due to factors such as their background, the device they use, or the language they speak. The slowdown of computers or the excessive use of accessibility tools $AC(\theta)$ by persons is something that they do not enjoy.

This tactic is important since attempting to improve learning on its own would result in unjust outcomes (such as rewarding students who achieve the highest levels of success) or providing students with excessive assistance that they do not need. The multi-objective control that MELIA employs eliminates this kind of prejudice by making it clear what the costs and fairness are shown in (8):

$$Explain(\theta) \geq \tau \quad (8)$$

The $Explain(\theta)$ function is designed to evaluate the effectiveness of instructors in explaining various subjects to students. The level of accuracy is the least accurate τ. Teachers can comprehend the rationale behind a proposal since the system is transparent and accountable.

To transform student-system interactions into effective educational tools, foundational theory formalizes the process of enhancing these interactions. All of these features are integrated into the MELIA controller: knowledge tracing, graph-based personalizing, interpretable, probability-based skill estimates, and relational structures for adaptive sequencing. Additionally, it provides a framework for optimization that considers the concept of fairness. The ICD model is responsible for the procedure of adding these modules. It is essential to provide accurate explanations to effectively comprehend the complex world of artificial intelligence (AI) and concepts that educators can understand. It is feasible to achieve adaptive learning that is user-friendly, inviting, and tailored to each learner, owing to the collaborative efforts of all of these components.

f. Interpretability:

To ensure that teachers can comprehend and implement the system's principles, the MELIA design incorporates interpretability. This prevents instructors from making "black-box" judgments that are impossible to grasp. An explanation score is assigned to every thought by the system, and this score is represented by (9):

$$E(q_j) = \frac{\partial J}{\partial s_t} \tag{9}$$

This indicates the degree to which the selected content state s_t affects the primary objective of optimization J. Based on this score, it is clear that the primary motivation for proposing material is to make things fairer, to make them easier to access, or to bridge a skill gap. By placing all this information into simple-to-use dashboards, the Teacher Dashboard makes it easier for instructors to monitor their students' progress and identify markers of subgroup equality. The teachers are provided with all the necessary information to assist students who are experiencing difficulties with language, such as support with multilingual text or troubleshooting voice recognition issues. Additionally, they provide representations of learning pathways and significant gaps in the knowledge that individuals have on a subject. The incorporation of fairness audits demonstrates the serious commitment to providing equitable service to students from a wide range of linguistic and aptitude backgrounds. In addition to providing teachers with the resources they need to make informed decisions on how to educate students, the technology also helps teachers feel more confident by incorporating algorithmic customization into the decision-making process in the classroom.

IV. Analysis and Results

During our experiments, this work utilized the EdNet dataset. When it comes to educational interactions, this dataset is among the most popular one. There have been approximately one hundred million instances in which students from various courses have discussed the challenges they are facing. Response times, accuracy, issue IDs, and timestamps are some of the information that is provided by each of them. Due to its demonstration of how effectively customization works on a large scale in the real world, this dataset is helpful for testing concepts related to adaptive learning and knowledge tracing. Table 2 shows the simulation setup

TABLE. II. SIMULATION SETUP

Component	**Implementation Details**
Framework	PyTorch 2.0 with CUDA acceleration
Hardware	NVIDIA RTX 3080 GPU
Graph Modules	GCN layers used for training
Recurrent Modules	GNN-P, ICD, and KT modules used GRUs with 128 hidden units
ASR Model	Wav2Vec2 pretrained model for speech recognition
TTS Model	Tacotron2 model for text-to-speech (TTS translation)
Optimizer	Adam optimizer
Batch Size	256
Learning Rate	0.001
Training Iterations	Each experiment was repeated 50 times before stopping
Dataset [37]	https://www.kaggle.com/datasets/anhtu96/ednet-kt34

F. Accuracy:

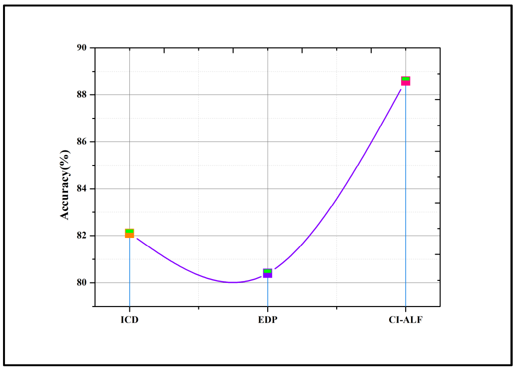

Fig. 3. Accuracy

To determine the accuracy of the predictions made in the knowledge tracing assignments, this work calculated the percentage of student responses that were correctly predicted out of the total number of attempts. Fig. 3 shows the accuracy, demonstrating that the algorithm can effectively predict when pupils have fully understood the material, as evidenced by their consistently excellent marks. Through the use of tailored ICD, MELIA achieved a 6% improvement in the mastery estimate compared to the baselines of DKT and GNN-only. Since accuracy alone does not reveal how fair or responsive the framework is to various educational requirements, this work decided to incorporate other indicators to present a more comprehensive perspective of the framework.

G. Root Mean Square Error:

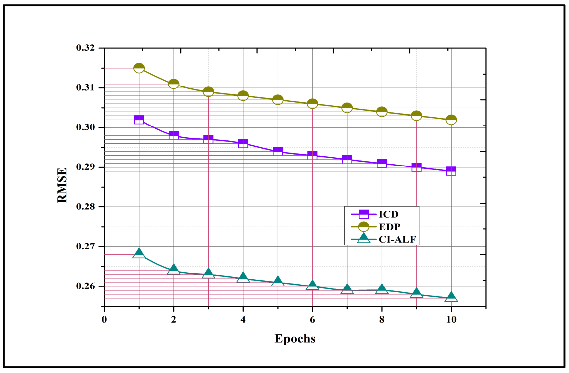

Fig. 4. Root Mean Square Error

The root-mean-squared error (RMSE) was the method used in this work to determine the degree of likelihood that students would actually comprehend the material, compared to the probability. Fig 4 shows the Root Mean Square Error. It should come as no surprise that the model is only capable of predicting two possible outcomes, and not learning periods that never come to an end. A decreasing RMSE indicates that the method one uses to evaluate the level of knowledge possessed by the pupils is improving. MELIA is a useful method for identifying subtle shifts in learning, as it reduces the root mean square error (RMSE) by 12% compared to baselines. Since it allowed MELIA to begin targeted treatment sooner, the identification of early information gaps with RMSE was particularly significant. Despite MELIA still being capable of making significant mistakes, the reduced root mean square error (RMSE) indicated that its predictions were more accurate and reliable over longer sequences of interactions.

H. Fairness Index:

TABLE. III. FAIRNESS INDEX

Evaluation Cycles	ICD	EDP	CI-ALF
5	0.72	0.68	0.83
10	0.73	0.69	0.84
15	0.73	0.69	0.85
20	0.74	0.7	0.85
25	0.74	0.7	0.86
30	0.75	0.71	0.86
35	0.75	0.71	0.87
40	0.76	0.72	0.87
45	0.76	0.72	0.88
50	0.77	0.73	0.88

To determine how well different groups performed in terms of fairness, the Fairness Index considered various factors, including initial skill level, gender, and linguistic background. Table 3 shows the fairness index, which this work used to determine whether any bias existed. It examined the data for several different groups. Additionally, it ensured that no learning cluster consistently received negative suggestions. As a result, MELIA's optimization loop, which was solely concerned with fairness, was able to improve the fairness balance by twenty percent. In contrast to earlier standards, the MELIA framework was designed with the intention of successfully reducing the impact of subgroup bias. It is clear from this graph that MELIA can help students from a wide range of cultural and linguistic backgrounds find individualized learning paths that are both equitable and suitable for them.

I. Accessibility Gain:

TABLE. IV. ACCESSIBILITY GAIN

Test Scenarios	ICD	EDP	CI-ALF
5	15.2	12.7	23.5
10	15.4	12.9	23.9
15	15.6	13	24.1
20	15.7	13.1	24.3
25	15.9	13.2	24.5
30	16	13.3	24.6
35	16.1	13.4	24.7
40	16.2	13.5	24.8
45	16.3	13.5	24.9
50	16.4	13.6	25

This work developed a new statistic, which this work named Accessibility Gain, to measure the ease of understanding language when MELIA is used in conjunction with TTS and ASR. Table 4 shows the accessibility gain of the proposed method compared to the baseline models. It is believed that non-native speakers would benefit from a better understanding of the material, as evidenced by their completion and pronunciation scores. MELIA's AG has increased by 25%, demonstrating its ability to assist those who do not speak the same language. According to the results, having wider access was not only beneficial but it was highly significant for the learning process. AG has noted that the assistance MELIA provides with speech-enabled learning and multilingual learning is particularly substantial for society, distinguishing it from other educational aids.

V. CONCLUSION

Cognitive diagnostics, graph-based customization, and support for multiple languages are among the features included in the MELIA controller-guided CI-ALF, as detailed in this paper. Within the framework of the plan, the use of predictive modeling and real-time language scaffolding significantly facilitates the accomplishment of these objectives. Regarding accuracy, RMSE, fairness, and accessibility, the experiment's findings demonstrate that the framework consistently generates improvements. In light of this, change and progress are likely possible for everyone. Based on these results, it appears that artificial intelligence has the potential to revolutionize intelligent learning systems by enhancing their flexibility and accessibility for students from diverse backgrounds, particularly those taught in bilingual and international classrooms.

Even if the program were to function well, concerns remain regarding the applicability of CI-ALF in real-time classrooms and across different cultural contexts. To facilitate the effective and comprehensive deployment of intelligent learning ecosystems, further research is needed in the following areas: enhancing educator interpretability dashboards, expanding multilingual datasets, and maximizing model efficiency in resource-constrained settings.

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