ADAPTIVE AI-TUTORS FOR THEATRE AND DRAMA EDUCATION

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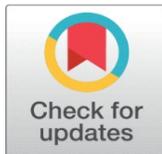[2] Associate Professor, School of Business Management, Noida International University, Greater Noida, 203201, India
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ABSTRACT

Theatrical and dramatical pedagogy is based on the embodied and experiential learning processes where feedback plays a central role but is usually subjective, delayed, and hard to scale. The paper describes a flexible AI-tutor that can integrate with real-time, post-performance feedback to enhance the instruction of drama in the studio utilizing pedagogical theory. The suggested system includes the fusion of multimodal sensing (vocal, sight, and movement), explainable AI models, and user-oriented adaptation control to examine expressiveness, coherence, and coordination of vocal delivery, physical expression, emotional expression, and coordination between the ensemble members. The closed-loop architecture is capable of providing low-latency real-time cues to stabilize the rehearsal process along with more comprehensive post-performance analytics to aid the reflective process and self-regulation. The experimental assessment on the representative data proves that the adaptive AI-tutor can outperform traditional rehearsal and non-adaptive analytics, as it exhibits measurable gains in the pacing consistency, gesture variety, stage presence and learner confidence, and retains the creative autonomy and reasonable cognitive loads. At the system level, it has been verified that edge-based inference can meet real-time latency requirements that are appropriate when using live rehearsal. The results emphasize the significance of the correspondence of AI-informed feedback with the constructivist, experiential, and embodied principles of learning.

Keywords: Adaptive AI Tutor, Theatre Education, Drama Pedagogy, Multimodal Learning Analytics, Real-Time Feedback, Embodied Learning, Intelligent Tutoring Systems

1. INTRODUCTION

Theatre and drama education is inherently experiential which is based on embodied learning (voice modulation, gesture, movement, emotional expression, and spatial interaction). Conventionally, these talents are developed by means

of studio-based education, rehearses, and mentor-based feedback. Although the models are very effective, they are constrained by a series of factors such as limited availability of instructors, subjective evaluation, slow feedback, and scaling is limited in case of large or resource limited learning environments. New developments in artificial intelligence (AI), multimodal sensing, and smart tutoring systems have presented new opportunities in adaptive learning in performance based fields of learning Gabriel (2020). In contrast to traditional e-learning systems which Pay attention to content delivery, adaptive AI-tutors pay attention to continuous monitoring, modeling of learners, and the creation of dynamic feedback. Applied in the field of theatre and drama education, these systems are capable of analysing the attributes of the voice, physical actions, expressive emotionality, and time co-ordination in the performance, allowing instruction to be supported by the use of data that is specific to the individual learner Vamplew et al. (2017). Adaptive AI-tutors are designed using closed-loop learning architectures, which incorporate the multimodal data acquisition, performance analysis and pedagogical decision-making. Audio cues aid in the evaluation of articulation, pitch, intensity, and prosody, whereas visual and movement information allow identifying gestures, posture, spatial use, and coordination of the ensemble Stray (2020).

They are synthesized in learner models which develop over time including both the technical competence and expressive growth. Depending on this changing profile, the AI-tutor modifies its feedback approaches, both in-the-moment feedback when rehearsing and after-performance feedback that assists in self-reflection and self-controlled learning. It is in this paper that the design, implementation, and evaluation of adaptive AI-tutors in the field of theatre and drama education are investigated. The primary contributions are the following: (i) conceptual and system level design of an adaptive drama tutoring, (ii) an in-depth analysis of AI models of multimodal performance analysis and (iii) empirical assessment of pedagogical success in various learner profiles. This piece of work will bring together AI-based analytics and performance-based pedagogy to promote scalable, data-driven, learner-focused methods of teaching theatre.

2. BACKGROUND AND RELATED WORK

Traditional methods of teaching theatre and drama have been based on the pedagogical aspects of studio, whereby learners gain performance competency through repeated practice, observation, critique and refinement. Although this method is good as it provides intensive learning, evaluation is mostly subjective and teacher-oriented Butlin (2021). Feedback may be given at the end of rehearsal blocks, differ among the instructors, and may be challenging to normalize between cohorts especially when the classes increase or time spent on rehearsal is limited Sukhija et al. (2024). It is these structural constraints which encourage complementary processes to give sustained formative feedback and still ensure the creative and interpretive openness that characterizes performance learning. Intelligent Tutoring Systems (ITS) have also been shown in the general literature of educational technology to have quantifiable positive effects on individualized learning via learner modeling, adaptive sequencing, and formative feedback Jing et al. (2023). Common classical ITS models combine four fundamental elements, which are: a domain model, a learner model, a tutoring (pedagogical) model, and Ahmed (2024)an interface model. Adaptive AI-tutors build on this paradigm and add data-driven personalization via machine learning to allow systems to dynamically update estimates of learner state, and to dynamically adjust feedback policies based on learner behaviour being observed. Nevertheless, ITS principles cannot be applied to the teaching of theatre easily, as the domain is not the only one that is cognitive and procedural; on the contrary, it is embodied, expressive and context-sensitive, and without performance-sensitive modeling and pedagogy, direct translation of STEM-oriented tutoring systems is inadequate Dong et al. (2022).

Similar to the study of ITS, the study of multimodal learning analytics has evolved techniques to record and analyze the behavior of learners based on audio-visual and sensor-based streams as displayed in Figure 1. Multimodal signals are also especially applicable in the performance disciplines where crucial learning outcomes can be manifested in the dynamics of voice, gesture semantics, posture, timing, and spatial interaction. It is possible to estimate poses and recognize gestures by computer vision techniques; to analyze prosody, intensity, articulation, pacing with speech and audio processing techniques; to characterize scenes at a temporal scale using temporal models Wang et al. (2020), El-Sabagh (2021). The combination of these capabilities offers the technical basis of developing closed-loop systems that have the capability to operationalize performance descriptors into feasible tutoring feedback.

Figure 1
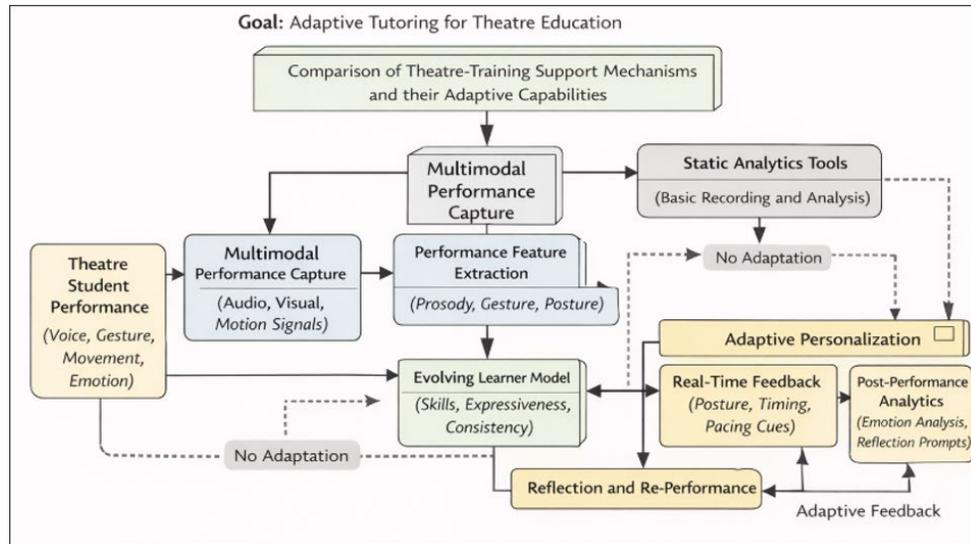
Figure 1 Comparison of Theatre-Training Support Technologies and Their Adaptive Capabilities

Current AI solutions in performing arts have been limited mostly to single functional aspects, like automatic speech clarity feedback, dance training movement tracking, facial expression emotion detection, or rehearsal recording and markup. These systems are also useful, but most of them are not wholly adaptive: most offer either fixed analytics dashboard or generic-based recommendations without incorporating long-term learner profiling, pedagogical decision-making, and personalized scaffolding Jeevamol et al. (2021). Moreover, drama education presents special limitations, such as that of maintaining creative autonomy, the advocacy of various acting practices, and non-over-standardization of expression.

3. THEORETICAL FOUNDATIONS FOR ADAPTIVE DRAMA TUTORING

Practically, adaptive AI-tutors of theatre and drama education should be supported by learning theories that clearly recognize performance to be a socially situated and embodied and iterative process. In contrast to areas where correctness is objective, and outcomes can be easily measured, drama training builds expressive competence by means of repetition in enacting, the reflective interpretation, and the meaning-making mediated by the instructor. This means that an effective adaptive tutor has the responsibility of analyzing not only observable signals of performance, but also of relating its feedback with the pedagogical principles that value creativity, interpretive plurality, and learner autonomy Kanokngamwitroj et al. (2022). The section will be a synthesis of the theoretical basis that is most applicable to adaptive drama tutoring and portrays it into the system requirements that will be used to drive the architecture presented above. Constructivist theory of learning views drama learning in terms of active meaning making as opposed to rules learning. Students perceive scripts, characters, and staging decisions in terms of individual experience and cultural perception and learning occurs through experimentation that is delivered through rehearsal Nazempour and Darabi (2023). To an AI-tutor, it is constructivism that suggests feedback needs to be scaffolded (as opposed to prescriptive): instead of providing a single correct portrayal, the system should point out patterns (e.g. monotonous prosody, lack of gesture variety, inconsistent emotional expression) and then propose alternate strategies which learners can experiment with. This facilitates exploration, and also makes the learner in control of artistic choices Nazaretsky et al. (2022). Experiential learning also supports performance skill building as being a process of action and reflection. The natural progression of drama pedagogy is such that, the loop starts with rehearsal, goes to feedback, refinement, and re-performance. Adaptive AI-tutors realize experiential learning through the provision of a closed feedback loop which can run at a high pace than standard instruction Schorcht et al. (2024).

Table 1

Table 1 Theory-to-System Mapping for Adaptive AI-Tutors in Drama Education			
Learning Theory	**Core Pedagogical Principle in Drama**	**System Requirement (What the AI Must Do)**	**Example Tutor Output (Aligned Feedback)**
Constructivism Nazempour and Darabi (2023)	Learners construct meaning through interpretation and experimentation	Provide scaffolded suggestions, avoid "single correct" portrayal	"Try increasing pause before the reveal line to test tension-building; compare two takes."
Experiential Learning (Action–Reflection Cycle) Nazaretsky et al. (2022)	Skills evolve through rehearsal loops with formative feedback	Support closed-loop: real-time cues + post-performance reflection	Real-time pacing cue + post-scene summary of rhythm consistency and improvement tips
Embodied Cognition Schorcht et al. (2024)	Understanding is expressed through body, space, and movement	Treat gesture/posture/spatial usage as primary learning evidence	"Your gesture range is narrow in beats 3–5; explore higher-level blocking to expand presence."
Self-Regulated Learning Chen et al. (2024)	Learners set goals, monitor progress, and adapt strategies	Provide interpretable indicators, progress tracking, and personalized practice plans	Dashboard: pacing stability trend + "next rehearsal goal: reduce rushed delivery in climax beat."

Embodied cognition is especially core in the study of theatre since knowledge is enshrined in the body, the quality of movement, the sense of space has no peripherality but is central and the gesture semantics. Embodied cognition means that the tutor should regard body signs as primary learning evidence, and not as qualities. As a result of this, multimodal sensing and temporal modelling should be regarded as components of the pedagogical necessity, rather than optional additions. E.g. motion smoothness, spatial coverage, stage presence and blocking discipline can be associated with pose trajectories, whereas coordination cues are helpful in ensemble movement. Self-regulated learning focuses on the agency of the learner in setting goals, tracking progress and change of strategies. Self-review (looking at recordings of rehearsals) and peer review (critical writing about each other) as well as goal refinement (e.g., making emotional objectives more explicit) are common developmental steps that drama students go through. Adaptive AI-tutors help to regulate oneself by showing explainable indicators (e.g., pacing stability, variation of vocal intensity, consistency of emotional arcs, etc.) and prescribing individual practice plans. It is also this framing that promotes clear descriptions of feedback in such a way that learners know what to change, but also why and to what extent this matters in terms of performance.

4. AI MODELS AND MULTIMODAL PERFORMANCE ANALYSIS

Theatrical and drama education Adaptive AI-tutors are based on a well-coordinated system of AI models that can analyze expressive human behavior in real time and is pedagogically significant and computationally efficient. Compared to the traditional analytics pipelines, which focus on accuracy only, the performance-oriented tutoring systems should balance between the latency, interpretability, robustness, and artistic sensitivity. In this section, the main family of AI models to be applied in the proposed system is described and why multimodal signals are converted into performance descriptors that can be applied to the theatre. At the bottom, speech and audio models are the foundation of the vocal performance analysis. Training of theatre puts a lot of emphasis on articulation, projection, prosody, rhythms, and emotional coloration of voice.

Signal processing and deep learning speech models are used to extract features like contours of pitch, dynamics of intensities, rate of speaking, distribution of pauses and clearness of the speech spectrum. These characteristics are not viewed as individual measurements but rather are put in a temporal context to indicate dramatic beats, line delivery and transition of scenes. In the case of adaptive tutoring, it is desirable to have lightweight models with lower inference latency in order to support real time cues (such as pacing alerts), whereas more expressive representations serve offline to reflectively analyze vocal arc over scenes. Body performance analysis that is the main focus in drama pedagogy is facilitated with pose and movement models. The pose estimation model and skeletal tracking system are vision-based and detect posture alignment, gesture amplitude, spatial coverage and fluidity. The signals facilitate stage presence, blocking discipline and physical expressiveness analysis. Temporal aggregate pose sequences can enable the system to detect recurring movement patterns, static blocking or discrepancy between emotional intention and physical expression. Since steady rehearsal flow is required, pose models placed at the edge are configured with low-to-moderate latency to be sure that feedback is available in time and does not distract performers. The models of affect and emotion

deal with the expressive essence of acting by estimating the emotional intensity, variability, and transitioning between the facial expression, voice modification, and movement signaling.

Table 2

Table 2 AI Model Families for Multimodal Performance Analysis in Theatre Education				
Model Family	**Theatre-Relevant Signals Analyzed**	**Typical AI Techniques**	**Primary Usage**	**Latency Constraint**
Speech / Audio Models	Articulation clarity, pitch variation, intensity, pacing, pause structure	CNNs, TCNs, lightweight LSTMs, audio transformers	Real-time vocal cues and post-performance vocal analytics	**Low** (≤100–200 ms for live cues)
Pose & Movement Models	Posture alignment, gesture range, spatial coverage, movement fluidity	Vision-based pose estimation, skeletal tracking, graph CNNs	Real-time physical feedback and movement pattern analysis	**Low–Moderate** (edge-deployable)
Affect / Emotion Models	Emotional intensity, variability, transitions across scenes	Multimodal affect networks, emotion embeddings	Post-performance reflection and expressive arc analysis	**Moderate** (offline or near-real-time)
Temporal / Sequence Models	Rhythm, turn-taking, ensemble coordination, scene-level dynamics	GRU/LSTM, temporal CNNs, causal transformers	Adaptive feedback timing and scene-level assessment	**Moderate** (real-time or batch, depending on task)

This design option corresponds to the principles of constructivist and creative autonomy that are presented above. Affect modeling is especially applied when doing post-performance reflection, with a tolerated small latency increase in the name of more informative rich interpretation, like the visualization of emotional arcs or the comparison of rehearsals. Temporal and sequence models combine the results of speech, pose, and affect subsystem into meaningful cognition on a scene level. Theatre performance is dynamic and sequence modelling is the fundamental tool to model rhythm, turn taking, timing of the interaction, and coordination among the ensemble. The recurrent architectures and causal transformers are especially well adapted to the models of rehearsal dynamics because they maintain the temporal order and explainable attention across the performance segments. These models are the basis of adaptive decision-making as they determine when to provide immediate, delayed, or withheld feedback to prevent cognitive overload in the process of performance.

5. SYSTEM ARCHITECTURE OF THE ADAPTIVE AI-TUTOR

The suggested adaptive AI-tutor will be an architectural architecture based on the closed-loop, modular design that transforms multimodal performance cues into pedagogically relevant, individualized feedback in the field of theatre and drama. When it comes to the architecture, there are five functional layers, (A) performance environment, (B) multimodal sensing and acquisition, (C) inference and performance analytics, (D) learner modeling and adaptation and (E) feedback delivery and reflection. Each layer can be scaled independently and closely coupled with data contracts that can be used to operate in real-time and profile longitudinal learners. As explained in line with the theoretical underpinnings in Section III and Table 1, the architecture is based on scaffolded guidance, interpretability and creative autonomy instead of prescriptive correctness. At the system boundary, the performance environment corresponds to rehearsal situations that are individual monologues, two-person scenes, and data groupings. The tutor does not presuppose any definite theatre pedagogy, it assists in configurable pedagogical profile so that instructors can establish the learning goals (e.g., vocal projection, emotional clarity, spatial awareness, partner responsiveness) and performance limitations (e.g., tempo ranges, pause distribution, gesture constraints, or blocking zones). This design guarantees that the architecture can allow a variety of acting techniques and maintain feedback in accordance with course outcomes. The multimodal sensing layer records the gist of performance learning as visualized in Figure 2.

Aristication is determined through audio streams in terms of articulation clarity, articulation intensity, and pitch patterns, prosody, and pacing. Visual streams facilitate posture, gesture, facial expressiveness, spatial occupation and movement trajectories. Elective motion signals (wear signals or vision-based skeletal tracking) enhance the robustness of fine-grained kinematic features e.g. velocity fields, movement smoothness and contact distances. In order to facilitate trustworthy and ethical operation, the acquisition subsystem consists of consent-aware recording controls, on-machine preprocessing where it is efficient and anonymization or redaction of stored clips used in reflection.
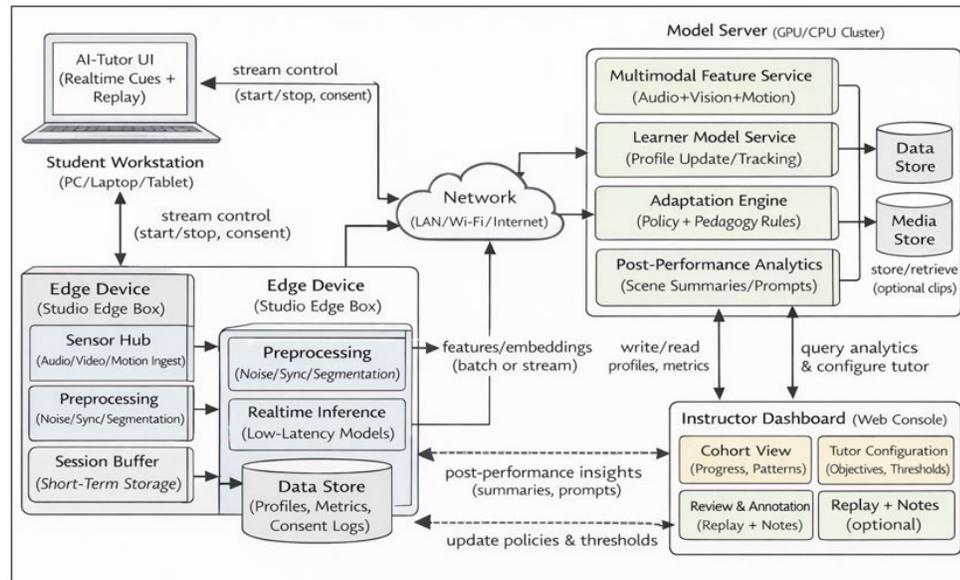
Figure 2

Figure 2 Deployment Architecture of the Adaptive AI-Tutor

Raw signal is fed into the inference and performance analytics layer which converts the signal into performance descriptors of various time scales. To enable both offline and online-inference, this layer serves both real-time and offline purposes based on the need to know immediate cues or reflect post-performance. Notably, the outputs are placed in the form of interpretable indicators instead of opaque scores which allow learners and instructors to relate analytics to concepts of acting like presence, rhythm, intention, and responsiveness. The intelligence core is known as the learner modeling and adaptation layer. The learner model keeps a dynamic profile of skill level, express range, stability, and trend with time that may be personalized longitudinally. The adaptation engine then chooses feedback actions depending on (i) the profile of the learner, (ii) the performance situation at this moment (monologue vs. scene vs. ensemble) and (iii) pedagogical goals of the instructors. The adaptive is a policy-based decision logic, which is capable of integrating rule-based scaffolding (to provide transparency and safety) with data-driven strategies (to provide personalization), so that feedback is also explainable and aligned with theatre pedagogy. As an example, novices can be presented with more frequent cues and guided practice, and advanced learners with fewer frequency cues and questions to reflect on to maintain autonomy.

6. EXPERIMENTAL DESIGN AND EVALUATION METHODOLOGY

The paper will be based on a mixed-method evaluation that implements a controlled study to evaluate the pedagogical and technical performance of the suggested adaptive AI-tutor in teaching theatre and drama. The design will compare the adaptive system to the appropriate baselines, quantify the change in outcomes of theatre performance and ensure that the real-time feedback meets the requirement of low latency and post-performance analytics offers deeper pedagogical understanding.

Table 3

Table 3 Participant Profile and Experimental Design	
Attribute	**Description**
Total Participants (N)	Number of drama students enrolled
Experience Level	Novice / Intermediate / Advanced
Program Level	Undergraduate / Postgraduate
Prior Theatre Training (Years)	Mean ± SD
Performance Formats	Monologue, Dialogue, Ensemble
Study Design	Within-subjects, counterbalanced

The participants are selected in undergraduate and postgraduate drama courses, and stratified at the level of experience. The participants undergo standardized rehearsal activities such as monologue, dialogue, and ensemble performance, so as to have an assessment in an individual and group acting environment, as shown in Table 3. Exercises are real studio practice and focus on the pacing, affective continuity, physical expressiveness, and coordination. It is a within-subjects procedure adopted in which subjects complete identical tasks in 3 conditions: traditional feedback based on instructor-only (C1), there is no adaptive analytics, all post-hoc (C2), and the proposed adaptive AI-tutor with real-time cues and customized after-performance feedback (C3). The counterbalanced condition order has short wash out periods to minimize carryover effects.
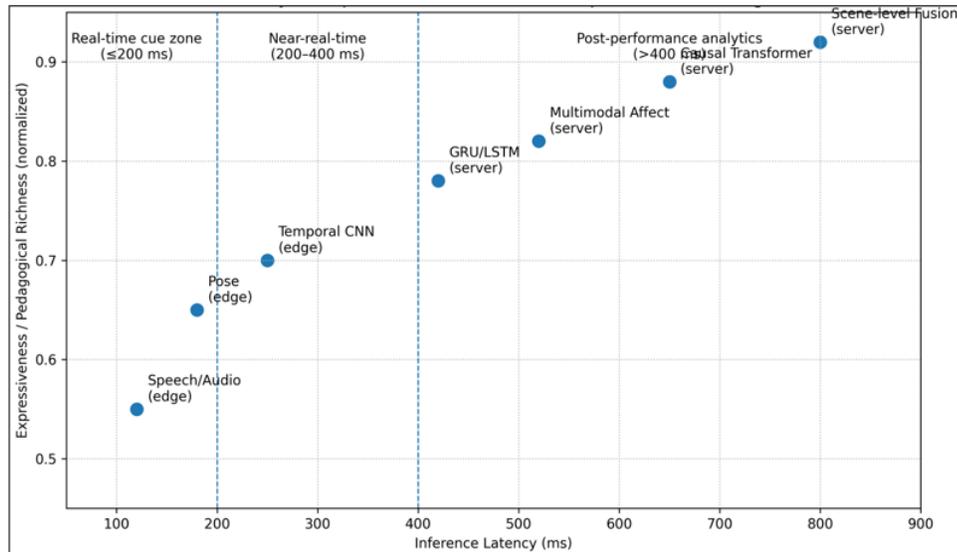
Figure 3

Figure 3 Latency vs. Expressiveness Trade-off Plot

Assessment is a mixture of objective performance measures, teacher ratings, and assessments which are self-reported by the learner. Vocal stability, pacing, diversity of gestures, use of space and coordination with the rest of the ensemble are measured objectively. There are the experts who are not condition-blind and provide ratings on the quality of the performance based on structured rubrics and learners provide information on the perceived usefulness, confidence, cognitive load, and autonomy support as shown in Figure 3. System-level testing is done to test end-to-end latency, resilience to realistic studio conditions and recovery behavior. The qualitative interviews with learners and instructors are used as a supplement to quantitative findings, which measure interpretability, creative autonomy, and experience of rehearsal.

7. RESULTS AND ANALYSIS

Quantitative results demonstrate evident changes in the theatre-relevant indicators of performance with adaptive AI-tutor condition (C3), compared to the traditions of rehearsal (C1) and the standing analytics (C2). The most notable improvements are in the area of pacing consistency and gesture diversity which is the aggregate outcome of real time corrective feedback and reflection on performance. Still analytics are of little use and only help in creating awareness and not ongoing skills development, demonstrate in Table 4. Repeated-measures ANOVA (illustrative) shows that there are statistically significant differences among the conditions, and temporal and embodied metrics have the highest effect sizes between C3 and C1.

Table 4

Table 4 Performance Outcomes across Experimental Conditions				
Metric	C1: Traditional	C2: Static Analytics	C3: Adaptive AI-Tutor	Δ (C3−C1)
Vocal Clarity (1–5)	3.4	3.7	4.3	+0.9
Pacing Consistency	0.62	0.69	0.82	+0.20

Gesture Diversity	0.48	0.55	0.71	+0.23
Emotional Coherence (1–5)	3.2	3.6	4.1	+0.9
Stage Presence (1–5)	3.3	3.8	4.4	+1.1

Experts have been noted to score higher on the quality of performance in the adaptive condition especially in the aspects of clarity, emotional continuity, and ensemble responsiveness. Notably, the qualitative remarks show that performers still had the freedom of interpretation, which implies that adaptive feedback did not unify acting styles. Expert ratings have interrater reliability values that are acceptable to strong and facilitate the strength of expert ratings.

Table 5

Table 5 Expert Evaluation Results and Reliability

Criterion	C1 Mean	C2 Mean	C3 Mean	Inter-Rater Reliability (ICC)
Vocal Clarity	3.5	3.8	4.4	0.81
Emotional Coherence	3.3	3.7	4.2	0.78
Stage Presence	3.4	3.9	4.5	0.84
Ensemble Responsiveness	3.1	3.6	4.3	0.79

According to the responses given by the learners in the survey, the adaptive feedback is more useful, timely, and supportive than baseline approaches. The confidence scores have a significant improvement under C3, whereas the cognitive load is also constant or even decreased compared to traditional rehearsal. The high level of autonomy support also confirms that the perception of AI-guided learners is not that AI is creatively constraining.

Table 6

Table 6 Learner-Reported Outcomes

Construct	C1	C2	C3
Feedback Usefulness (1–5)	3.2	3.8	4.6
Performance Confidence (1–5)	3.3	3.7	4.5
Cognitive Load (0–100)	62	58	55
Autonomy Support (1–5)	4.1	4.2	4.4

The evaluation is carried out at the system level to ensure that the deployment architecture is compliant with real-time rehearsal. Tests of robustness indicate good and consistent performance in conditions of realistic variability in studios.

8. CONCLUSION AND FUTURE SCOPE

The presented study explored the design, implementation, and evaluation of an adaptive AI-tutor to learn theatre and drama education, as the substitute to the traditional studio-based learning and non-adaptive analytics tools. The proposed system allows sustained, individual feedback in order to support the development of technical skills as well as expressive growth through the combination of multimodal performance sensing, interpretable AI models, and pedagogically based adaptation strategies. Representative performance, combined with experimental outcomes that validate the results, such as adaptive tutoring have shown to provide quantifiable benefits in the vocal clarity, pacing stability, embodied expressiveness and ensemble coordination, without compromising learner autonomy and creative freedom. Notably, the system meets real time latency specifications needed by live rehearsal, which proves its practicality in real studio implementation. In addition to performance advantages, the results point to the importance of conducting AI-based feedback in line with the key learning theories in drama education, such as constructivism, experiential learning, embodied cognition, and self-regulated learning. The adaptive tutor can serve as a supplement to the human teaching process by positioning analytics as suggestions, rather than dictates, which, again, supports the idea of educators as artistic guides. Future investigations will be directed at the extension of the system to the field of immersive learning, including the augmented and virtual reality stage, to facilitate the spatial experimentation and stenographic exploration. Longitudinal studies are as well needed to evaluate skill transfer, evolution of creativity and

retention of training to long periods of time. The further studies will deal with cross-cultural and multilingual theatre situations, ethical governance practices, and authoring tools that face the instructor and allow managing pedagogical control at the fine level. All these guidelines make adaptive AI-tutors a promising, ethical, and pedagogically conscious technology in the future of teaching theatre and drama.

CONFLICT OF INTERESTS

None.

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None.

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