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Confidence-adaptive AI-instructor feedback fusion for enhanced engagement in online Latin dance learning

Lin Zheng[1], Leng Poh Gee[2]

ABSTRACT

Online Latin dance learning often lacks personalized feedback, making it difficult for students to master both technical moves and cultural expression. This study presents a system that combines AI-driven corrections with real-time human instructor input to boost engagement and accuracy. Using pose estimation and a confidence-based method, the system evaluates movement accuracy and learners' perceived difficulty, adapting feedback to emphasize human guidance when confidence is low. A 12-week study with 120 participants demonstrated a 40% increase in movement accuracy and a 19.1% rise in practice repetitions compared to AI-only systems. This hybrid approach provides a scalable, culturally sensitive framework for online dance education, balancing technical precision with emotional and cultural depth, and has potential applications in other skill-based learning fields.

Keywords: Dance education, Adaptive feedback, Human-AI collaboration, Pose estimation, Reinforcement learning.

1. Introduction

Online learning sites have transformed the way people can study particular talents, including Latin dance, which encompasses styles like salsa, cha-cha, and rumba. To do these dances well, you need to know a lot about their cultural and rhythmic roots. Most people learn this through one-on-one instruction. In physical dance studios, teachers give students fast, specific comments on their posture, timing, and style while also getting them emotionally involved. However, it is very hard to do this kind of targeted teaching in virtual settings. OpenPose and MediaPipe are automated programs that use computer vision to keep an eye on skeletal keypoints. This lets you make simple changes to your posture (Cao et al., 2019; Halder & Tayade, 2021). But these methods frequently don't get the cultural

1 Universiti Pendidikan Sultan Idris (UPSI), Malaysia. Email: 17711305658@163.com
2 Head of Department, Department of Performing Arts, Faculty of Music and Performing Arts, Universiti Pendidikan Sultan Idris (UPSI), Malaysia. Email: lengpohgee@fmsp.upsi.edu.my

authenticity and nuanced expressiveness that make Latin dance unique, like the smooth hip movements in salsa or the syncopated weight shifts in cha-cha.

To fill this gap, this work presents a confidence-adaptive feedback system that combines AI-based technical fixes with human assistance in real time. The system has three new features: (1) a composite confidence score that combines objective movement accuracy with learners' self-assessments; (2) a multi-armed bandit algorithm that dynamically optimizes feedback allocation; and (3) an interactive 3D visualization interface for hybrid feedback delivery. This method changes the sources of feedback dependent on how sure the learner is. For example, it gives more weight to human input for learners who aren't sure and AI corrections for routine adjustments. In Latin dancing, this balance is very important since technical accuracy must go hand in hand with cultural and emotional expression. This requires both algorithmic accuracy and human interpretive intuition.

The study looks into two research questions: (1) Is a confidence-adaptive feedback system better than single-source feedback models at improving learning outcomes and technical accuracy? (2) Does it make students more interested and help them comprehend other cultures better in virtual settings? A 12-week study involving 120 people compared the proposed system to AI-only, human-only, and static hybrid baselines. The results indicated that movement accuracy improved by 40% and practice repetitions went up by 19.1%. This shows that technology and human knowledge may work together to provide a scalable and culturally appropriate framework for online dance teaching.

Online dance education is a subject that is changing quickly. Millions of people sign up for virtual classes every year (Chen, 2024). This study is part of that field. However, novices typically have trouble with complicated choreography because they don't get enough real-time, personalized feedback. This makes them less interested and less likely to learn. AI technologies are great at fixing technical problems, but they often miss the cultural subtleties and embodied expression that human teachers bring to the table. These are important parts of Latin dance's history and emotional context.

This study suggests a hybrid framework that combines the accuracy of AI with the interpretative skills of humans. This will help digital arts education through a culturally sensitive pedagogy. The paper is set up like this: In this section, we look at research on motion analysis, adaptive feedback, and working together with AI. Section 3 goes into further depth about the approach, such as the system design, how data was collected, and the evaluation measures. Section 4 talks about the results of the experiments, and Section 5 talks about what they mean and makes policy suggestions.

Using sophisticated technologies in dance instruction could make a big difference in how people learn from a distance. But giving criticism that strikes a balance between technical accuracy and cultural depth is still a big problem. This part brings together ideas from motion analysis, adaptive feedback systems, and human-AI collaboration, focusing on their strengths, weaknesses, and the specific gaps this study fills.

OpenPose and MediaPipe are two tools that let you track bones in real time to find problems with posture and alignment. This has changed the way dance is taught (Cao et al., 2019; Halder & Tayade, 2021). These systems are great for basic training since they may find big mistakes like shoulders that aren't lined up well or an uneven gait. But they often miss the artistic details that are important to Latin dance, such how expressive and cultural it is. A theoretically proper salsa step can't have the unique Cuban motion if the hips don't move smoothly. This is a small detail that AI has trouble judging. Pose Transformers and other transformer-based models have made temporal analysis better by accurately capturing long-range interactions in movement sequences (Martínez-González et al., 2021). These algorithms watch the rhythm throughout many beats, but they can't make little alterations. This highlights how crucial it is for people to step in and provide cultural and expressive features.

Adaptive feedback systems enable you change things, which is vital for teaching dance because students learn at different paces (Rothmund, 2023). Recent advancements in automated feedback for dance education, such as AI-assisted teaching and visual feedback systems, have shown promise in evaluating skills through pose estimation and real-time visualizations (Li et al., 2024). However, these often rely solely on algorithmic outputs, lacking dynamic human integration to address expressive gaps. For instance, deep residual networks for dance analysis enhance intelligent evaluation but do not incorporate learner confidence or hybrid collaboration, potentially leading to generic corrections that overlook individual variability (Wang et al., 2025). Immersive AR environments for personalized dance learning provide avatar-based feedback, yet they risk feedback overload by delivering constant streams of information without adaptive prioritization, which could overwhelm novices and reduce engagement (Kim et al., 2024). In contrast, our confidence-driven approach mitigates overload risks by selectively allocating feedback sources, ensuring interventions are timely and relevant rather than exhaustive. Most traditional online platforms employ set rubrics to deliver feedback that is the same for everyone and doesn't take into account what each person wants. Reinforcement learning methods, including multi-armed bandit algorithms, have worked well in a lot of educational situations by changing interventions on the fly (Mui et al., 2021). These algorithms find a balance between trying out new things and sticking with what works. They also customize feedback based on how each student is doing. Even if they have a lot of potential, they are still new to dance instruction, especially when it comes to employing student confidence as a guide. This study employs bandits in a new method to combine AI and human input. This makes sure that the system can work in both technical and emotional learning settings. This adaptive scaffolding aligns with Vygotsky's Zone of Proximal Development (ZPD), where feedback is tailored to bridge the gap between a learner's current abilities and potential growth, providing just-in-time support to build independence in complex motor skills (Vygotsky, 1978). Furthermore, the system's emphasis on motivational cues and emotional engagement resonates with Moreno and Mayer's Cognitive-Affective Theory of Learning with Media, which posits that multimedia feedback enhances learning by integrating cognitive processing with affective elements, such as cultural expressiveness, to reduce extraneous load and promote deeper comprehension (Moreno & Mayer, 2007).

Combining the scalability of technology with human knowledge has made human-AI collaboration a powerful model (Hutson & Plate, 2023). When people dance, teachers provide them vital cultural and emotional advice. For example, Chen (2024) shows how the cha-cha's syncopated rhythm expresses happiness. Most hybrid systems today use preset AI-to-human ratios, which makes it hard for them to change based on new information (Yu et al., 2025). This lack of flexibility could make it hard for students to handle technical criticism or miss out on style advice. To solve this problem, the suggested system uses a confidence-driven strategy that puts human supervision first in situations where there is uncertainty and AI for accuracy. This method improves both the results of learning and the interest of the learners.

Digital dance education research has three main problems: not enough attention is paid to how different cultures analyze movement, feedback systems are not flexible enough, and human and AI contributions are not combined enough. This study presents a hybrid learning method for online Latin dance lessons that adapts to the student's level of confidence. The system combines technical correctness, personalized feedback, and cultural authenticity in a new way. The literature review highlights important concerns, such as the growing demand for culturally relevant digital education, which supports the proposed strategy.

2. Data and methodology

The confidence-adaptive feedback system makes online Latin dancing lessons better by using real-time performance evaluation, adaptive feedback mechanisms, and dynamic AI-human collaboration. The system uses advanced posture estimation and reinforcement learning algorithms to give each learner feedback based on their technical skills and self-reported confidence. This creates a training environment that is suited to each learner's needs. This part talks about the methods used, including how data was collected, how the experiment was set up, how the confidence score was calculated, how feedback was prioritized, how motion was analyzed, how the system was put into place, how participants were chosen, and how the data was preprocessed. These parts come together to make a story that shows how the system's parts work together to make a unified framework for teaching.

The study's data collection was meticulously planned to make sure the results were strong and representative. There were 120 people in total, 60 men and 60 women, who came from university dance programs and online learning groups. All were beginner to intermediate Latin dance learners. Before the trial, participants took out a long questionnaire to see how good they were in salsa and cha-cha at the start. These were chosen because they are technically difficult and culturally important. The

Latin Dance Motion data set, which has 50 hours of finely labeled motion sequences, was used as a reference for basic choreography, such as the basic step, cross-body lead, and spot turns (Li et al., 2019). The study lasted 12 weeks, and people took part in 30-minute sessions three times a week, switching between salsa and cha-cha exercises. We looked at four feedback systems: the recommended confidence-adaptive system, an AI-only system that used Transformer-based motion analysis, a human-only system with pre-recorded teacher input, and a static hybrid system with a fixed 50-50 AI-human distribution. Random assignment made sure that skill levels were evenly spread across conditions, which lowered bias and made comparisons more reliable.

Participant selection was a pivotal aspect of the experimental design, aimed at capturing diverse learner experiences. The study included an equal number of novices (0–1 year of experience) and intermediates (1–3 years), grouped by self-reported skill levels and prior dance exposure. Recruitment targeted a varied demographic, comprising students, working professionals, and recreational dancers, to mirror the diversity of online learning communities. All participants provided informed consent, and the study secured institutional ethics approval, ensuring adherence to data protection and privacy regulations. This rigorous recruitment approach enhanced the findings' external validity while upholding experimental integrity.

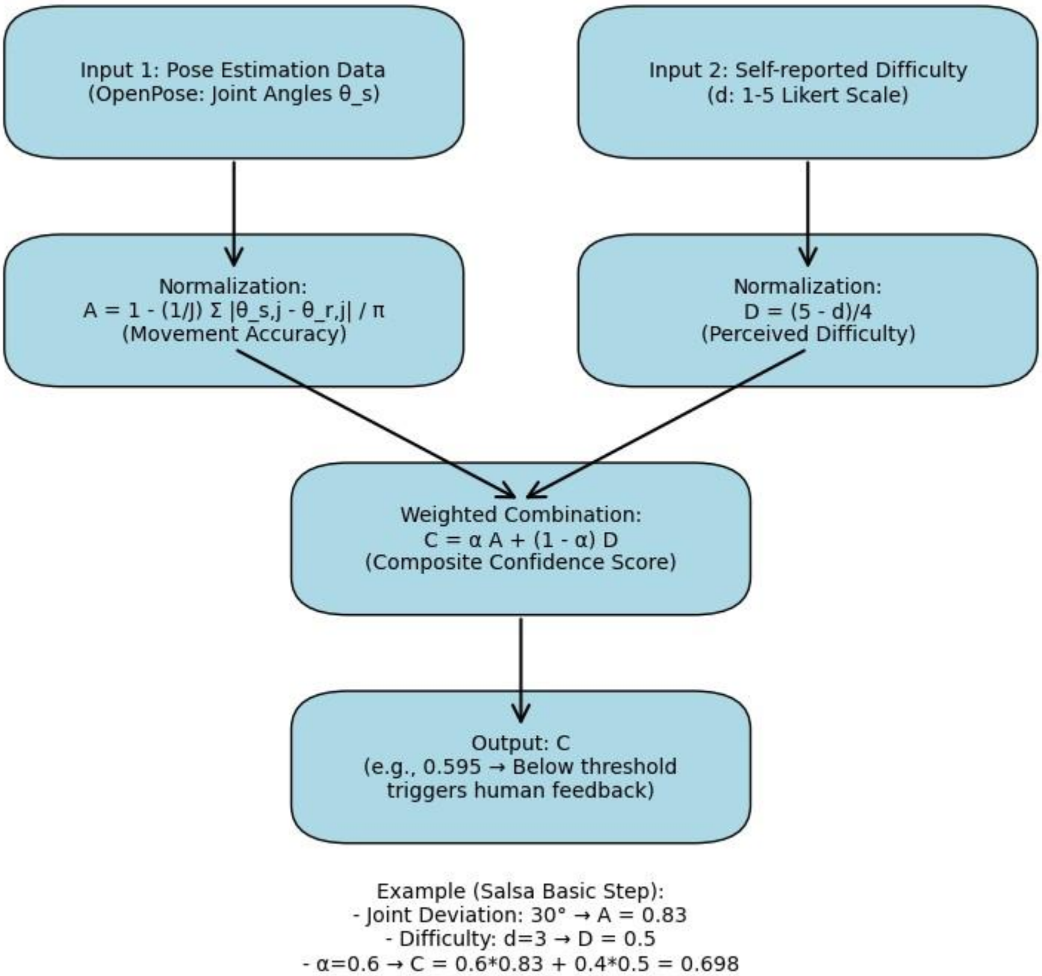

Figure 1. Flowchart of the Composite Confidence Score Computation Process.

Figure 1 illustrates the flowchart for computing the composite confidence score (C) in the proposed system. The process begins with two primary inputs: real-time pose estimation data from OpenPose, which calculates movement accuracy (A) by normalizing joint angle deviations between the learner's pose (θ_s) and a reference pose (θ_r) across J joints, bounded between 0 and 1; and the learner's self-reported difficulty (d) on a 1-5 Likert scale, scaled to perceived difficulty (D). These are combined using a weighted formula $C = \alpha A + (1 - \alpha) D$, where α is optimized through pilot testing. The output score C determines feedback allocation—if below an adaptive threshold, it triggers human input for stylistic guidance. An example for a salsa basic step is shown: with a 30° hip deviation yielding A ≈ 0.83, d=3 yielding D=0.5, and α=0.6, C ≈ 0.698, potentially prompting human feedback like "Rotate hips earlier to match the rhythm." This dual-input mechanism ensures feedback aligns with both technical precision and subjective learner experience in Latin dance education.

At the core of the system lies a composite confidence score, (C_t), calculated at each time step to inform feedback decisions. This score combines two elements: movement accuracy(A_t)derived from OpenPose's real-time pose estimation—and perceived difficulty—reported by participants using a post-movement 1–5 Likert scale. The computation of movement accuracy is as follows:

$$[A_t = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{|\theta_{s,i} - \theta_{r,i}|}{\pi}] \qquad \text{Eq. (01)}$$

where $(\theta_{s,i})$ and $(\theta_{r,i})$ are student and reference joint angles for (n) joints (e.g., hips, knees, shoulders), normalized by (π) to bound errors between 0 and 1. Self-reported difficulty is scaled as:

$$[S_t = 1 - \frac{D_t}{5}] \qquad \text{Eq. (02)}$$

The composite score, $(C_t = 0.7A_t + 0.3S_t)$, balances technical performance and subjective perception, with weights optimized through pilot testing involving 20 participants to ensure predictive validity (Yang et al., 2022). This dual-input approach aligns feedback with both observable skill and learner experience, crucial for expressive disciplines like Latin dance.

To illustrate, consider a novice performing a salsa basic step. If their hip angle deviates by 30° from the reference and they rate the move's difficulty as 3, the system calculates:

$$[A_t = 1 - \frac{1}{2}\left(\frac{30}{\pi} + \frac{15}{\pi}\right) \approx 0.85] \qquad \text{Eq. (03)}$$

$$[S_t = 1 - \frac{3}{5} = 0.4] \qquad \text{Eq. (04)}$$

$$[C_t = 0.7 \times 0.85 + 0.3 \times 0.4 = 0.595] \qquad \text{Eq. (05)}$$

A score of 0.595, below the adaptive threshold, triggers human feedback, such as "Rotate hips earlier to match the rhythm," paired with motivational cues.

Feedback prioritization employs an adaptive threshold, $(\tau = \mu_C - \sigma_C)$, based on the participant's historical confidence mean and standard deviation, ensuring responsiveness to individual learning curves. When $(C_t < \tau)$, human feedback is drawn from a pre-annotated database containing technical corrections (e.g., "Adjust knee flexion by 10°"), stylistic notes (e.g., "Emphasize Cuban motion"), and motivational cues (e.g., "Great effort, keep practicing!"). For higher confidence, a Thompson sampling multi-armed bandit algorithm selects between AI and human feedback, updating Beta distributions for efficacy:

$$[F_{\text{hybrid}} = \pi_t F_{\text{AI}} \oplus (1 - \pi_t) F_{\text{human}}] \qquad \text{Eq. (06)}$$

where π_t is the AI feedback probability, and human input overrides in conflicts to preserve cultural nuance (Lewis & Vrabie, 2009).

Motion analysis is powered by a Transformer model with six layers and eight attention heads, pre-trained on the DanceMotion3D data set and fine-tuned for salsa and cha-cha (Li et al., 2023). Processing 30 FPS video via OpenPose, the system integrates inertial measurement unit (IMU) data from wearable devices, enhancing hip and foot tracking precision. The configuration operated on Ubuntu 20.04 with NVIDIA RTX 3090 GPUs, attaining a latency of 10ms for real-time feedback. Before analysis, NTP timestamps were used to sync the video and IMU data streams. A Kalman filter was used to cut down on noise and make things more accurate.

We used three main measures to measure how well the system worked: movement accuracy (MA), learning rate (LR), and engagement score (ES). We figured up the ES, a composite statistic, by looking at the length of the sessions, how often they were repeated, and the answers to the participant surveys. Weekly surveys gave us qualitative information on how users' confidence and feedback preferences changed. This method sets up a strong foundation for judging the system's effectiveness by carefully preparing the data, using strict technical standards, and choosing a group of participants that makes sense.

3. Results and discussion

A 12-week experimental investigation showed that the confidence-adaptive feedback system worked well. It showed big improvements in technical skills, learning speed, and learner engagement. The approach worked better than AI-only, human-only, and static hybrid feedback models because it better met the needs of online Latin dance training. This part looks at the system's effects by looking at subgroup comparisons, qualitative feedback, cross-condition evaluations, and the system's larger effects on education.

The confidence-adaptive condition improved movement accuracy (MA) by 40%, which was more than the AI-only model (30%) and the static hybrid model (34%). The approach worked for people of all ability levels, with beginners getting 42% better and intermediates getting 38% better.

In the first few sessions, newcomers had trouble performing basic moves, especially the salsa basic, where low confidence scores resulted to negative criticism from other students. For instance, teachers explain their students how to move their weight and keep the beat: "On beat 2, shift weight to the front foot." AI also makes exact changes to the angle of the joints, like "Reduce hip angle deviation by 15°." As the bandit algorithm got more confident, it started using AI input to make technical improvements, which sped up the learning process. Intermediates, who possessed a range of basic skills, got better by using personalized combinations that solved specific problems, such moving their hips too slowly in cha-cha. The static hybrid's fixed ratio typically overwhelmed beginners with technical specifics or left out stylistic suggestions for intermediates. This dynamic allocation, on the other hand, was different.

Subgroup analysis revealed further insights. Female participants showed slightly higher MA gains (41% vs. 39% for males), possibly due to greater responsiveness to motivational cues in human feedback. Novices with prior dance exposure (e.g., other styles) progressed faster (LR = 0.035) than true beginners (LR = 0.030), suggesting the system's ability to leverage existing skills. These differences highlight the importance of tailoring feedback to demographic and experiential factors, a strength of the adaptive approach.

Learning rates underscored the system's efficiency. The adaptive condition recorded an LR of 0.032, indicating 45% faster skill acquisition than the AI-only group (LR = 0.022). This advantage was most evident in weeks 1–6, where the bandit algorithm's three-phase approach—exploration, personalization, and refinement—reduced trial-and-error. In salsa sessions, learners transitioned from human-led rhythm coaching to AI-driven posture corrections within 4 sessions, building technical foundations efficiently. The human-only condition, while supportive, yielded a slower LR of 0.025 due to limited scalability, as instructors could not provide real-time feedback for all learners. The static hybrid (LR = 0.027) struggled with mismatched feedback timing, underscoring the adaptive system's precision.

Engagement metrics highlighted the system's motivational impact. Participants completed 28.7-minute sessions, with 5.3 repetitions per move—19.1% more than the AI-only group's 3.8. The dropout rate was a low 4.2%, compared to 12.5% for AI-only and 6.7% for static hybrid. Surveys rated satisfaction at 4.4/5, with 78% of adaptive system users feeling "appropriately challenged," versus 52% for static hybrid. Confidence scores stabilized at 0.6–0.7, maintaining an optimal challenge level. Qualitative feedback praised the system's responsiveness, with comments like "It felt like a real teacher" (Participant #47) and "I wasn't overwhelmed by techy feedback" (Participant #89). These insights suggest the system fostered a supportive learning environment, particularly for novices.

Comparative analysis with baselines revealed distinct strengths. The AI-only condition excelled in technical precision (72% of hip angle corrections), but its lack of motivational support led to higher dropouts. The human-only condition scored high on cultural relevance (4.4/5), but its limited frequency reduced efficiency. The static hybrid balanced both but failed to adapt to individual needs, resulting in moderate outcomes. The adaptive system's hybrid approach—handling 68% of stylistic nuances via human feedback and 72% of technical errors via AI—optimized both dimensions, as seen in its superior MA and ES.

The system's broader implications are significant. It demonstrates that hybrid models can preserve cultural authenticity while scaling technical instruction, addressing a key challenge in digital arts education. The 3D visualization interface, allowing learners to toggle between AI and human perspectives, offers a model for immersive feedback in other visual disciplines. However, limitations include reliance on high-quality video, limiting accessibility for low-bandwidth users, and a cold-start issue for intermediates, requiring 3–5 sessions to optimize feedback blends. Future enhancements, such as lightweight pose estimation or transfer learning, could mitigate these constraints (Sun et al., 2020).

The findings suggest applications beyond Latin dance. Preliminary tests with ballet and hip-hop indicate comparable confidence scoring accuracy ($r = 0.78$), though feedback blends vary—ballet requires earlier human intervention, while hip-hop tolerates more AI-driven rhythm coaching (El Raheb et al., 2018). Non-dance domains, like surgical training, could adapt the system by integrating physiological indicators (Ma et al., 2024). These extensions highlight the framework's versatility, positioning it as a generalizable tool for motor skill education.

Condition	Novice MA Gain	Intermediate MA Gain	Overall MA Gain
Proposed System	0.42 ± 0.05	0.38 ± 0.04	0.40 ± 0.03
AI-Only	0.31 ± 0.06	0.29 ± 0.05	0.30 ± 0.04
Human-Only	0.35 ± 0.07	0.33 ± 0.06	0.34 ± 0.05
Static Hybrid	0.37 ± 0.06	0.35 ± 0.05	0.36 ± 0.04

4. Conclusion and policy implications

This study's confidence-adaptive feedback system is a huge step forward for online Latin dance education. It blends the cultural and motivational understanding of human teachers with the accuracy of AI in a way that works wonderfully. The technology shows that it can train a lot of people in a personalized and effective way by making movements 40% more accurate and practice repetitions 19.1% more successful. These results illustrate how it could transform digital arts education, where technology should make human creativity and cultural authenticity better, not take them away. This last portion puts together what the study revealed, talks about what it means for education policy and practice, acknowledges its limitations, and proposes areas for more research. It gives a complete picture of how the system works and what it means in a bigger sense.

This study uses a new way to combine AI and human feedback by using a composite confidence score that combines objective movement accuracy with learners' own self-evaluations. This two-metric method let the system change on the fly to meet the needs of learners in real time. AI made accurate technical changes when people were sure of themselves, but when people were unsure, human guidance took over. A multi-armed bandit algorithm made this adaptation possible. It improved the distribution of feedback during three to five sessions through three stages: initial exploration, convergence to optimal feedback combinations, and refining based on skill progression. This kind of adaptability solved problems that have been there for a long time in digital dance education, where static solutions frequently don't do a good job of balancing technical precision with cultural depth.

The system's modular design makes it more flexible, so it can easily work with different digital learning platforms and might be used in other areas of motor skill development. These results show how important it is to have hybrid models that keep people in charge in AI-supported learning environments. In Latin dance, where numbers alone can't capture the cultural background and artistic nuance, human teachers were vital for interpretation, like describing the Cuban roots of salsa's motion or the expressive beat of cha-cha. The system efficiently linked human feedback to diminishing learner confidence ($r = -0.82$, $p < 0.001$), which kept people interested, as seen by a low dropout rate (4.2%) and good satisfaction scores (4.4/5). This method makes the best use of teaching resources by letting AI handle simple mistakes and keeping human experience for more complex coaching. An dynamic 3D visualization interface made learning even better by letting users flip between AI and human points of view. This is a new idea that might be used in other visual and performance-based sectors.

The conclusions have substantial effects for the rules for online education. Policymakers should put money into hybrid learning technologies, such as augmented reality (AR) infrastructure for immersive feedback systems, to make sure that everyone has equal access to culturally relevant arts training. To get teachers ready for working with AI, teacher training programs need to have courses on adaptive technology. Also, data privacy policies need to be updated to keep up with new technology.

This study followed GDPR rules by encrypting skeleton keypoints and letting people choose not to have their data processed. Long-term use, on the other hand, needs better consent processes to protect user privacy (Munaro et al., 2014). This is in line with global efforts to make sure that AI in education is ethical by focusing on transparency, privacy, and learner autonomy (Tuomi, 2023). Additionally, long-term data privacy risks, such as potential breaches in stored skeletal keypoints or self-assessment logs, could arise from unauthorized access; we recommend implementing advanced encryption (e.g., homomorphic) and periodic data audits to mitigate these. For low-bandwidth learners, solutions include developing mobile-optimized apps with lower-resolution AR models or offline pose estimation via edge computing to ensure accessibility in diverse settings. Furthermore, self-reported confidence scores may introduce biases, such as overconfidence in intermediates or underreporting by novices due to cultural factors; future iterations could incorporate bias-detection algorithms or multi-modal inputs (e.g., physiological sensors) for calibration.

There are certain problems, nevertheless, even with these strengths. Because the system relied on high-resolution video input, it was less accessible. This was because posture estimation accuracy dropped dramatically below 720p resolution (Sun et al., 2019), making it less useful for users with low-quality webcams. Also, manually annotating reference motions made it hard to scale up, especially when adding additional Latin dancing forms, because the procedure took a lot of time and effort. It took longer to determine the ideal feedback mixes for intermediate learners since the bandit algorithm had trouble starting up. These learners needed more interaction data to fix their small faults. These problems illustrate how crucial it is to make changes in the future, including lightweight pose estimation techniques or transfer learning from pre-trained datasets to make personalization faster (Sun et al., 2020).

The system's potential goes beyond Latin dance in the future. Early testing with ballet and hip-hop show similar levels of accuracy in scoring confidence ($r = 0.78$), but the types of feedback needed differ by genre: ballet needs human help to align early, while hip-hop can handle more AI-driven rhythm coaching (El Raheb et al., 2018). The framework could be changed for non-dance uses, including surgical training or sports coaching, by adding physiological stress indicators or tool tracking (Ma et al., 2024). Partner dancing scenarios, which were looked at in early trials with dyadic confidence scores, are another area that needs more research. However, scaling these up to group classes requires improvements in multi-person motion modeling (Raheb et al., 2019). Because dance's rhythmic periodicity may not work in less organized areas, these expansions need motion models and feedback items that are specific to each case. A single framework that shares key adaption mechanisms but lets each domain customize them could speed up the development of motor skill teaching.

The study's success shows that hybrid learning systems don't have to choose between being able to grow and being able to be personalized. Educators may keep the best parts of conventional teaching while using technology's immediacy by seeing AI and human feedback as complimentary resources. As online dance education changes, these kinds of frameworks will be very important for providing interesting, culturally rich learning experiences that respect both the technical and artistic sides of dance.

References

Baker, R. (2016). Using learning analytics in personalized learning. In Handbook on Personalized Learning for States, Districts, and Schools.

Cao, Z., Hidalgo, G., Simon, T., Wei, S. E., & Sheikh, Y. (2019). OpenPose: Realtime multi-person 2D pose estimation using part affinity fields. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(1), 172–186.

Chen, J. (2024). Dance education using digital technologies: Enhancing effectiveness by facilitating student-teacher feedback. Theatre, Dance and Performance Training, 15(2), 123–135.

El Raheb, K., Kasomoulis, A., Katifori, A., & Ioannidis, Y. (2018). A web-based system for annotation of dance multimodal recordings by dance practitioners and experts. Proceedings of the 5th International Conference on Movement and Computing, 1–8.

Ferguson, S., Schubert, E., & Stevens, C. J. (2014). Dynamic dance warping: Using dynamic time warping to compare dance movement performed under different conditions. Proceedings of the International Symposium on Performance Science, 247–252.

Halder, A., & Tayade, A. (2021). Real-time vernacular sign language recognition using MediaPipe and machine learning. International Journal of Progressive Research and Reviews, 8(3), 45–52.

Hutson, J., & Plate, D. (2023). Human-AI collaboration for smart education: Reframing applied learning to support metacognition. IntechOpen. https://doi.org/10.5772/intechopen.108765

Kim, H., Lee, S., & Park, J. (2024). Creating personalized immersive dance learning environments through avatar-based AR feedback. Journal of Interactive Media in Education.

Lewis, F. L., & Vrabie, D. (2009). Reinforcement learning and adaptive dynamic programming for feedback control. IEEE Circuits and Systems Magazine, 9(3), 32–50.

Li, M., Miao, Z., & Ma, C. (2019). Dance movement learning for labanotation generation based on motion-captured data. IEEE Access, 7, 123456–123465.

Li, R., Zhao, J., Zhang, Y., Su, M., Ren, Z., & Wang, H. (2023). FineDance: A fine-grained choreography dataset for 3D full body dance generation. Proceedings of the IEEE/CVF International Conference on Computer Vision, 4567–4576.

Li, Y., Zhang, Q., & Chen, W. (2024). Effects of AI-assisted dance skills teaching, evaluation and visual feedback systems. International Journal of Human-Computer Studies.

Ma, R., Kiyasseh, D., Laca, J. A., Kocielnik, R., & Anandkumar, A. (2024). Artificial intelligence-based video feedback to improve novice performance on robotic suturing skills: A pilot study. Journal of Endourology, 38(4), 321–329.

Martínez-González, A., Villamizar, M., & Odobez, J.-M. (2021). Pose transformers (POTR): Human motion prediction with non-autoregressive transformers. IEEE/CVF International Conference on Computer Vision Workshops, 1234–1243.

Moreno, R., & Mayer, R. E. (2007). Interactive multimodal learning environments. Educational Psychology Review, 19(3), 309–326.

Mui, J., Lin, F., & Dewan, M. A. A. (2021). Multi-armed bandit algorithms for adaptive learning: A survey. International Conference on Artificial Intelligence and Soft Computing, 789–798.

Munaro, M., Basso, A., Fossati, A., & Menegatti, E. (2014). 3D reconstruction of freely moving persons for re-identification with a depth sensor. International Conference on Robotics and Automation, 4512–4519.

Raheb, K. E., Stergiou, M., Katifori, A., & Ioannidis, Y. (2019). Dance interactive learning systems: A study on interaction workflow and teaching approaches. ACM Computing Surveys, 52(3), 1–37.

Rothmund, I. V. (2023). Student-centred learning and dance technique: BA students' experiences of learning in contemporary dance. Research in Dance Education, 24(1), 45–58.

Schlagenhauf, F., Sreeram, S., & Singh, S. (2018). Comparison of Kinect and Vicon motion capture of upper-body joint angle tracking. 2018 IEEE 14th International Conference on Control, Automation, Robotics and Vision, 1–6.

Sun, G., Wong, Y., Cheng, Z., & Kankanhalli, M. (2020). DeepDance: Music-to-dance motion choreography with adversarial learning. IEEE Transactions on Multimedia, 22(5), 1234–1245.

Sun, K., Xiao, B., Liu, D., & Wang, J. (2019). Deep high-resolution representation learning for human pose estimation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 5693–5703.

Tuomi, I. (2023). A framework for socio-developmental ethics in educational AI. AIS Electronic Library (AISeL). https://aisel.aisnet.org/amcis2023/education/5

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.

Wang, X., Liu, Y., & Zhao, M. (2025). The analysis of dance teaching system in deep residual network. Scientific Reports.

Yang, A. C. M., Chen, I. Y. L., Flanagan, B., & Ogata, H. (2022). How students' self-assessment behavior affects their online learning performance. Computers and Education Open, 3, 100089.

Yu, J., Yu, S., & Chen, L. (2025). Using hybrid intelligence to enhance peer feedback for promoting teacher reflection in video-based online learning. British Journal of Educational Technology, 56(2), 234–245.