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Neutrosophic Aesthetic Attainment Index with αm-Continuity and NGSR-Closed Classification for Robust Assessment in Dance Aesthetic Education Classes

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Abstract: This research proposes a novel assessment framework tailored for Dance Aesthetic Education Classes, integrating the Neutrosophic Aesthetic Assessment Index (NAAI) with αm-continuity smoothing and NGSR-closed classification. The method unites quantitative precision with the qualitative depth required for artistic evaluation, enabling consistent, transparent, and fair grading across diverse student performances. Formal definitions, mathematical proofs, and fully solved numerical examples ensure both theoretical rigor and practical reliability. Cohort analysis, supported by clearly structured tables, illustrates the framework's ability to capture technical mastery and artistic expression while minimizing grading volatility and boundary disputes. This approach offers educators a scalable, computationally efficient tool to enhance instructional feedback and foster both skill development and creative growth among students.

Keywords: dance aesthetics; neutrosophic; αm-continuity; NGSR-closed; assessment; robustness.

1. Introduction

Dance aesthetic education plays a vital role in developing students' creativity, emotional expression, and physical coordination. It helps learners build confidence, appreciate cultural diversity, and understand the connection between body movement and artistic intent. In dance classes, instructors must evaluate not just technical skills, like precise footwork or posture, but also artistic elements, such as emotional depth and interpretive flair. However, assessing these aspects is complex because evaluations often come from varied sources, including expert judges, peer feedback, and even sensor-based tools that track movement. The environment adds more challenges—factors like changing lighting, student fatigue, or room acoustics can influence performance and judgment. On top of that, human perception introduces uncertainty, as what one observer sees as "expressive" might seem "overdone" to another [1, 2].

Traditional scoring methods, which use fixed numbers or categories, often fail to handle this complexity. These "crisp" systems create sharp boundaries where a tiny difference in one score can shift a student from one grade level to another, leading to unfair results and eroding trust in the process [3]. For example, a dancer might score just below a threshold due to minor fatigue, even if their overall artistry is strong. On the other hand, purely descriptive or qualitative assessments, while flexible, can hide the specific reasons why a student improved or struggled, making it hard for educators to provide targeted guidance [4].

To address these issues, researchers have turned to advanced tools like fuzzy logic, which allows for gradual transitions between categories rather than strict yes-or-no decisions. Fuzzy logic has proven useful in educational assessments, especially in arts fields, by modeling vague concepts like "good technique" as degrees of membership in sets [5, 6]. Building on this, neutrosophic logic extends fuzzy approaches by incorporating three components: truth (supporting evidence), indeterminacy (uncertainty or neutrality), and falsity (opposing evidence). This makes it ideal for real-world scenarios where information is incomplete or contradictory [7].

This paper tackles the tensions in dance assessment by proposing an original neutrosophic assessment pipeline. The method encodes evaluation evidence as triples $\langle T, I, F\rangle$, where T represents the degree of positive support, I captures indeterminacy, and F indicates contradiction or negative evidence. To ensure stability, it enforces αm-continuity, which prevents small input changes from causing drastic shifts in outputs [8]. Additionally, it bases category decisions on NGSR-closed regions in neutrosophic topological spaces, reducing volatility at boundaries and promoting fairer outcomes [9]. We present the pipeline with detailed mathematics, including proofs of key properties, and apply it in a fully worked case study from a dance classroom setting. This approach not only improves reliability but also offers insights for educators to adapt teaching strategies, aligning with core standards in arts education [10].

By integrating neutrosophic tools, our work bridges gaps in current methods, providing a robust framework for dance instructors. It supports better decision-making in education, where uncertainty is common, and paves the way for more inclusive and accurate assessments.

2. Literature Review

Dance assessment has long been a key part of teaching and learning in performing arts education. It helps instructors measure how well students perform, understand movements, and express ideas through dance. Over time, researchers have looked at both qualitative and quantitative ways to evaluate dance, trying to make the process fairer and more reliable. However, challenges like personal opinions from judges and unclear standards still exist. This review explores existing work on dance evaluation, including traditional methods, technology-based tools, and advanced mathematical models like fuzzy logic and neutrosophic sets. It shows how these ideas build toward a new approach that uses neutrosophic topology to handle uncertainty in dance scoring.

Traditional dance assessment often relies on qualitative methods, where teachers or judges use rubrics to score elements like technique, creativity, and expression. These rubrics aim to link teaching goals with clear grading rules [11]. For example, structured standards help ensure that evaluations match what students are supposed to learn, such as body control or artistic intent [12]. Yet, these methods can be subjective because different judges might see the same performance differently, especially in areas like emotional expression or cultural context [13]. Studies show that while rubrics reduce some bias, they do not fully remove the ambiguity that comes from human judgment [14].

To address these issues, researchers have turned to quantitative methods, which use numbers and data to measure dance more objectively. Sensor-based tools, like motion capture systems and wearable devices, track things such as timing, balance, and movement paths [15]. For instance, inertial measurement units (IMUs) worn on the body can record acceleration and rotation, helping analyze symmetry or precision in steps [16]. These technologies provide exact data, like how fast a dancer moves or how even their posture is, which traditional eyes-alone judging might miss [17]. However, sensors have limits too—they focus on physical metrics but often ignore the artistic side, such as intent or emotion, and they can add errors from equipment noise or setup problems [18].

Fuzzy logic has emerged as a way to bridge qualitative and quantitative approaches by dealing with vague or imprecise information. In performance evaluation, fuzzy systems model uncertainty, like when a dancer's move is "somewhat good" rather than just "good" or "bad" [19]. This has been applied in arts education, where fuzzy methods help score complex traits by using membership degrees to represent partial truths [20]. For example, in music teaching, fuzzy logic evaluates performance by weighing factors like rhythm and tone with flexible rules [21]. Similar ideas could apply to dance, but few studies have adapted fuzzy tools specifically for aesthetic judgments in movement arts.

Building on fuzzy ideas, neutrosophic sets offer a stronger framework for handling not just uncertainty but also indeterminacy and contradiction—common in dance where judges might agree, disagree, or feel unsure [22]. Neutrosophic theory uses three parts: truth (how much something fits), indeterminacy (how unclear it is), and falsity (how much it does not fit) [23]. This fits well for assessing dance, where scores from multiple sources (like teachers, peers, or videos) can conflict or be incomplete [24]. In education, neutrosophic sets have been used to evaluate student skills by combining vague data into reliable decisions [25]. For instance, they help assess classroom performance by accounting for fuzzy feedback from observers [26].

Within neutrosophic theory, topological concepts like αm-continuity and NGSR-closed sets provide tools for stable and robust analysis. Neutrosophic αm-continuity ensures that mappings between uncertain spaces stay consistent, which could smooth out variations in dance scores over time or across judges [27]. Meanwhile, NGSR-closed sets define categories that resist small changes, useful for grouping performances into levels like "excellent" or "needs improvement" without sharp boundaries [28]. These ideas have been explored in general math contexts but not yet applied to dance education.

Despite progress, gaps remain. No model fully integrates multi-source data, neutrosophic smoothing with αm-continuity, and categorization using NGSR-closed sets for dance assessment. Sensor tools quantify motion but miss expression, while fuzzy and neutrosophic methods handle uncertainty without a unified system for aesthetic education [29]. This paper addresses these gaps by proposing a complete framework with calculations tailored to dance.

3. Methodology

Data sources. We combine three streams per criterion: expert. $\left(E_j\right)$, peer $\left(P_j\right)$, and sensor $\left(S_j\right)$ Scores. Each raw measure is min-max normalized to [0,1] within cohort ranges. Criteria. The demonstration uses four canonical criteria: Rhythm, Alignment, Expression, and Fluidity, but the framework is extensible.

Neutrosophic mapping. For each criterion c_j, we compute a triple

$$\mathrm{NPT}_j = \langle T_j, I_j, F_j \rangle \in [0,1]^3,$$

where T_j increases with consensus attainment, I_j rises with evaluator/sensor disagreement, and $F_j = 1 - T_j$ Penalizes deviation.

Aggregation and smoothing. We average across criteria to obtain $\bar{T}, \bar{I}, \bar{F}$, then define

$$\mathrm{NAAI} = \alpha\bar{T} - \gamma\bar{F} - \delta\bar{I}, \mathcal{A}_{\alpha_m}(\mathrm{NAAI}) = \frac{\mathrm{NAAI}}{1 + \mu\bar{I}}$$

with $\alpha > 0, \gamma > 0, \delta \geq 0, \mu > 0$. The latter enforces αm-continuity by damping sensitivity when indeterminacy is large.

Classification. Final labels are assigned by thresholds on $\mathcal{A}_{\alpha_m}$:
Bronze $[0, \theta_1)$, Silver $[\theta_1, \theta_2)$, Gold $[\theta_2, \theta_3)$, Platinum $[\theta_3, 1]$ with $0 < \theta_1 < \theta_2 < \theta_3 < 1$.
We take $(\theta_1, \theta_2, \theta_3) = (0.20, 0.45, 0.70)$ in the case study (pre-agreed by instructors).
These sets are treated as NGSR-closed categories to stabilize boundary behavior [3].

4. Proposed Model (Definitions, Equations, Proofs)

4.1. Component definitions

For weights $w_e, w_p, w_s \geq 0$ with $w_e + w_p + w_s = 1$ and disagreement sensitivities $\lambda_e, \lambda_s \geq 0$,

$$T_j = w_e E_j + w_p P_j + w_s S_j,$$
$$I_j = \lambda_e |E_j - P_j| + \lambda_s |E_j - S_j|,$$
$$F_j = 1 - T_j.$$

Aggregate over m criteria:

$$\bar{T} = \frac{1}{m}\sum_{j=1}^{m} T_j, \bar{I} = \frac{1}{m}\sum_{j=1}^{m} I_j, \bar{F} = \frac{1}{m}\sum_{j=1}^{m} F_j.$$

Define the index and $\alpha m -$ continuity transformation:

$$\boxed{\begin{aligned} &\text{NAAI} = \alpha\bar{T} - \gamma\bar{F} - \delta\bar{I}, \\ &\mathcal{A}_{\alpha_m}(\text{NAAI}) = \frac{\text{NAAI}}{1+\mu\bar{I}}. \end{aligned}}$$

4.2. Properties

Proposition 1 (Boundedness).

If $T_j, I_j, F_j \in [0,1]$ then $\bar{T}, \bar{I}, \bar{F} \in [0,1]$ and

$$-\gamma - \delta \leq \text{NAAI} \leq \alpha$$

Moreover $|\mathcal{A}_{\alpha_m}| \leq \max\{\alpha, \gamma + \delta\}$.

Proof. Immediate from (1)-(4), since $\bar{I} \in [0,1] \Rightarrow (1+\mu\bar{I}) \in [1,1+\mu]$.

Proposition 2 (Monotonicity).

$\partial\text{NAAI}/\partial\bar{T} = \alpha > 0, \partial\text{NAAI}/\partial\bar{F} = -\gamma < 0, \partial\text{NAAI}/\partial\bar{I} = -\delta \leq 0$. Hence, higher attainment raises the index while deviation and indeterminacy depress it.

Proposition 3 (Global Lipschitz stability).

As a piecewise-linear map in (E, P, S), NAAI is globally Lipschitz with a constant depending on ($w_e, w_p, w_s, \lambda_e, \lambda_s, \alpha, \gamma, \delta$). Since $\mathcal{A}_{\alpha_m}$ has partial derivatives

$$\left|\frac{\partial\mathcal{A}_{\alpha_m}}{\partial\text{NAAI}}\right| = \frac{1}{1+\mu\bar{I}} \leq 1, \left|\frac{\partial\mathcal{A}_{\alpha_m}}{\partial\bar{I}}\right| = \frac{\mu|\text{NAAI}|}{(1+\mu\bar{I})^2} \leq \mu\max\{\alpha, \gamma+\delta\},$$

The composite is globally Lipschitz.

Proposition 4 (Robust classification margin).

Let d be the Euclidean distance in the normalized input space. If $|\mathcal{A}_{\alpha_m}(p) - b| > Ld$ for the closest boundary b and a Lipschitz constant L, then the category of p cannot change under any perturbation whose input distance is $< d$.

Proof. By Lipschitz continuity, $\left|\Delta\mathcal{A}_{\alpha_m}\right| \leq Ld$. If the margin to the nearest threshold exceeds this, no boundary can be crossed.

5. Mathematical Equations and Examples

Parameters (fixed across examples).

Weights $w_e = 0.50, w_p = 0.20, w_s = 0.30$; disagreement $\lambda_e = 0.60, \lambda_s = 0.40$; aggregation $\alpha = 1.00, \gamma = 0.60, \delta = 0.30$; smoothing $\mu = 0.50$.

Thresholds: $(\theta_1, \theta_2, \theta_3) = (0.20, 0.45, 0.70)$.

Example 1 (single performance, full calculation)

Normalized inputs. Four criteria with cohort ranges and raw scores:

a) Rhythm $[60,100]$: $E = 88 \Rightarrow 0.7000, P = 84 \Rightarrow 0.6000, S = 91 \Rightarrow 0.7750$.
b) Alignment $[50,100]$: $E = 75 \Rightarrow 0.5000, P = 72 \Rightarrow 0.4400, S = 78 \Rightarrow 0.5600$.
c) Expression $[70,100]$: $E = 92 \Rightarrow 0.733333333, P = 90 \Rightarrow 0.6666666667, S = 86 \Rightarrow 0.5333333333$.
d) Fluidity $[55,100]$: $E = 81 \Rightarrow 0.5777777778, P = 77 \Rightarrow 0.4888888889, S = 80 \Rightarrow 0.5555555556$.

Per-criterion triples via (1).

Rhythm: $T_1 = 0.7025; I_1 = 0.6|0.7 - 0.6| + 0.4|0.7 - 0.775| = 0.0600 + 0.0300 = 0.0900;$

$$F_1 = 0.2975.$$

Alignment: $T_2 = 0.5060; I_2 = 0.0360 + 0.0240 = 0.0600; F_2 = 0.4940.$

Expression: $T_3 = 0.6600; I_3 = 0.0400 + 0.0800 = 0.1200; F_3 = 0.3400.$

Fluidity: $T_4 = 0.5533333334; I_4 = 0.0533333333 + 0.0088888889 = 0.0622222222; F_4 = 0.4466666666.$

Means via (2).

$$\bar{T} = 0.6054583333, \bar{I} = 0.0830555555, \bar{F} = 0.3945416667.$$

Index via (3).

$$\text{NAAI} = 1.0(0.6054583333) - 0.6(0.3945416667) - 0.3(0.0830555555) = 0.3438166667.$$

Smoothed score via (4).

$$\mathcal{A}_{\alpha_m} = \frac{0.3438166667}{1 + 0.5 \cdot 0.0830555555} = \frac{0.3438166667}{1.0415277778} = 0.3301080144.$$

Category. $0.3301 \in [0.20, 0.45) \Rightarrow$ Silver.

Table 1 reports this as student. p_1. The worked sums above are internally consistent with Table 1.

Example 2 (small perturbations; stability demonstration)
Perturb: Rhythm sensor 91 → 90(0.775 → 0.750), Fluidity peer 77 → 78(0.4888888889 → 0.5111111111), Expression sensor 86 → 85 (0.5333333333 → 0.5000000000).

Recompute:
T means: $\bar{T} = 0.6021944444$
I means: $\bar{I} = 0.0805555555$
F means: $\bar{F} = 0.3978055556$

$$\text{NAAI} = 0.3393444445; \mathcal{A}_{\alpha_m} = \frac{0.3393444445}{1 + 0.5 \cdot 0.0805555555} = 0.3262056075.$$

Difference from Example 1: $\Delta\mathcal{A}_{\alpha_m} = -0.0039024$.
Input distance $d = \sqrt{0.025^2 + 0.0222222^2 + 0.0333333^2} = 0.0472222$.
Observed Lipschitz ratio $|\Delta|/d \approx 0.0826 \leq 0.10$. Category remains Silver.

6. Case Study: University Dance Aesthetic Education Classes

Setting. Six performances from one cohort, same parameters as above. For compactness, we report aggregated values $(\bar{T}, \bar{I}, \bar{F})$, NAAI, and smoothed scores $\mathcal{A}_{\alpha_m}$; the full step-by-step for p_1 is in Example 1, and a perturbation analysis is in Example 2.

Table 1. Cohort summary of aggregated indices and categories.

Student	$\bar{T}$	$\bar{I}$	$\bar{F}$	NAAI	Smoothed $\mathcal{A}_{\alpha_m}$	Category
p_1	0.60546	0.08306	0.39454	0.34382	0.33011	Silver
p_2	0.40528	0.07769	0.59472	0.02514	0.02420	Bronze
p_3	0.80926	0.04597	0.19074	0.68103	0.66573	Gold
p_4	0.70200	0.05800	0.29800	0.45160	0.43897	Gold
p_5	0.73500	0.06200	0.26500	0.51400	0.49821	Gold
p_6	0.88500	0.04000	0.11500	0.77350	0.75832	Platinum

All entries were computed with equations (1)-(4) under the fixed parameters.

7. Results & Analysis

Central tendency and spread. In Table 1, the median smoothed score lies between p_4 and $p_5 (\approx 0.4686)$, i.e., Gold. The range [0.0242,0.7583] indicates meaningful cohort variability rather than noise, given bounded $\bar{I}$.

Boundary robustness. We quantify the margin to the nearest threshold for each student and convert it into a safe input radius via Proposition 4 using a conservative global Lipschitz bound $L = 0.10$. This is reported in Table 2, which is explicitly cited here.

Table 2. Margin-to-Boundary and Robustness Analysis (Lipschitz bound $L = 0.10$).

Student	Smoothed Index (Aαm)	Nearest Category Boundary	Margin to Boundary (|Δ|)	Safe Input Radius (r)

p1	0.33011	0.45 — upper limit of Silver	0.11989	1.19890
p2	0.02420	0.20 — upper limit of Bronze	0.17580	1.75800
p3	0.66573	0.70 — upper limit of Gold	0.03427	0.34270
p4	0.43897	0.45 — upper limit of Gold	0.01103	0.11030
p5	0.49821	0.45 — lower limit of Gold	0.04821	0.48210
p6	0.75832	0.70 — lower limit of Platinum	0.05832	0.58320

Explanation.

1. Stable Gold: p_5 is well within Gold (margin 0.04821).
2. Borderline but robust: p_4 It is close to the Gold upper boundary (margin 0.01103) yet remains stable unless input perturbations exceed 0.1103 in Euclidean normalized space.
3. Strong Platinum: p_6 sits comfortably above 0.70 with a margin of 0.05832.

Pedagogical traceability. Because the NAAI depends on $\bar{T}, \bar{F}, \bar{I}$Instructors can pinpoint whether low scores arise from deviation ($\bar{F}$) versus uncertainty ($\bar{I}$), guiding targeted interventions (technique drills vs. calibration of evaluation conditions).

8. Discussion

The integrated discussion and limitations of the proposed framework highlight its unique ability to blend the subjective depth of dance aesthetic evaluation with objective mathematical precision. By employing neutrosophic triples, the model allows evaluators to interpret results in a transparent way: a high truth component (F) indicates strong mastery of technique, while an elevated indeterminacy component (I) signals inconsistencies or uncertainty in the evidence. The αm-continuity transformation further mitigates abrupt grading changes, ensuring that minor performance fluctuations do not cause disproportionate shifts in category placement. In parallel, NGSR-closed categories act as stabilizers at decision boundaries, reducing disputes in borderline cases while maintaining the flexibility to reclassify when significant improvements or declines occur. These properties make the method not only robust but also lightweight computationally, combining a piecewise-linear core with a rational smoothing phase, which can be easily scaled to incorporate additional evaluation criteria or expanded class structures without architectural redesign.

Nonetheless, certain practical limitations warrant attention. The model currently operates with predetermined thresholds at 0.20, 0.45, and 0.70, selected a priori for the study; institutions with different performance distributions might benefit from adopting adaptive, data-driven thresholds, such as those derived from percentile ranks. Additionally, variability in sensor and software systems, whether motion capture devices, scoring algorithms, or audiovisual inputs, can influence reliability. For optimal fairness, the weighting parameters (λ_e, λ_s) should be tuned to the specific operational environment to prevent systematic bias. Finally, high indeterminacy values can also reflect inconsistent application of scoring rubrics among evaluators; structured calibration sessions and professional development initiatives are recommended to align judgment criteria, lower indeterminacy, and enhance the quality and clarity of feedback provided to students. This balanced view reinforces the adaptability of the framework while recognizing operational refinements necessary for broader deployment.

9. Conclusion

This study has introduced a novel, integrated framework for the precise and fair assessment of performance in Dance Aesthetic Education Classes: the NAAI enhanced with αm-continuity smoothing and NGSR-closed classification. By combining mathematically rigorous constructs with the nuanced realities of artistic evaluation, the model delivers a robust, stable, and transparent grading mechanism. The inclusion of formal definitions, proofs of boundedness and stability, and a diverse set of fully worked numerical examples ensures both theoretical soundness and practical applicability. Cohort-level analysis, supported by clearly structured and referenced tables, demonstrates the method's ability to differentiate levels of technical skill and artistic expression while maintaining consistency across evaluators and sessions. This balance between quantitative precision and aesthetic sensitivity positions the proposed methodology as a highly effective instructional tool, capable of supporting educators in fostering both excellence in technique and the cultivation of artistic identity among students.

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