A MultiAlist Framework for Learning Quality Assessment in the Digital Media Technology Major under the Big Data Paradigm

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Abstract- The rise of digital media education necessitates novel evaluation strategies that are adaptable to diverse cognitive systems and educational data sources. This study proposes a comprehensive method for teaching quality evaluation in the Digital Media Technology major, employing big data analytics enriched by the MultiAlist system of thought. Through integrating multi-dimensional educational indicators and processing them with neutrosophic logic and plithogenic set theory, this research develops a multi-valent evaluation framework. A case study at a Chinese university is conducted to demonstrate the approach, incorporating behavioral, academic, and engagement metrics. The results provide a transparent, scalable model for education stakeholders, supported by big data tools and multi-systemic logic for increased precision and inclusivity.

Keywords: Teaching Quality Evaluation; Digital Media Technology; Big Data; MultiAlist System; Neutrosophy; Education Analytics; Multi-Valent Models

1. Introduction

With the proliferation of digital media technologies and their integration into higher education curricula, particularly in fields like animation, game design, and digital storytelling, traditional models for teaching quality assessment face challenges in accuracy and adaptability. Existing methods often depend on static surveys or simplistic grading rubrics, failing to accommodate the complexity of real-time data generated through learning management systems, interaction platforms, and student performance metrics.

In this context, big data offers an unprecedented opportunity to capture multifaceted information about teaching effectiveness. However, the complexity of data interpretation calls for a theoretical and methodological framework that accounts for contradictions, uncertainties, and multiple perspectives. Inspired by Florentin Smarandache's MultiAlist system which integrates opposites, neutralities, and indeterminacies across systems this paper introduces a novel approach to evaluate teaching quality in the Digital Media Technology major using a multi-systemic, data-driven lens.

1.1. Key Theoretical Terms from the MultiAlist System

1) Neutrosophy: A logic that incorporates three values T, I, and F for each proposition, allowing for nuanced interpretation beyond binary logic.
2) Plithogeny: A generalization of fuzzy logic where attributes may have contradictory tendencies and can be combined using flexible aggregation functions.
3) MultiPolar System: An open system of thought accepting multiple elements from multiple systems, including opposites, neutralities, and contradictions.
4) PluriPolar System: A closed system with multiple perspectives or values, but without incorporating neutralities or indeterminacies.
5) MultiAlism: A comprehensive philosophical framework that integrates elements from various systems (monism, dualism, trialism, pluralism) into one open and inclusive structure.

2.1 PluriPolar vs MultiPolar Systems

A key distinction in the MultiAlist framework is between PluriPolar and MultiPolar systems. A PluriPolar system allows multiple viewpoints or elements to coexist but does not include the neutral or indeterminate states between them. In contrast, a MultiPolar system as conceptualized by Smarandache embraces complexity by incorporating not only opposites but also the spectrum of neutrality and contradictions that exist between them. This makes MultiPolar systems more suitable for evaluating educational quality in environments characterized by ambiguity, diverse feedback, and multiple data sources.

2. Literature Review

The integration of big data in education has led to the emergence of Learning Analytics and Educational Data Mining, both of which emphasize the use of student interaction logs, performance data, and participation metrics to improve educational outcomes [1]. While many studies utilize machine learning models for prediction and clustering, fewer embed a philosophical or systemic approach to handle contradictions and uncertainties in educational data [2].

Smarandache's MultiAlist thought offers a new paradigm where teaching evaluation is not a fixed polarity between "effective" and "ineffective," but a dynamic assessment inclusive of indeterminate states [3]. This extends traditional models like Likert scales or binary rubrics, by enabling triadic and plithogenic evaluations thus creating room for partial truths, neutral perceptions, and context-specific contradictions.

Previous educational evaluation systems have attempted to integrate fuzzy logic [4], analytic hierarchy process (AHP) [5], and multi-criteria decision-making (MCDM) tools, but without the capability to interpret contradictions as integral components of truth. This paper proposes a

MultiAlist-based evaluation framework that surpasses those limitations by accounting for multi-source indicators and their neutrosophic interrelations.

3. Proposed Method

To address the challenges of teaching quality evaluation in the Digital Media Technology domain, this study introduces a MultiAlist (MMVES). The MMVES is grounded in the MultiAlist system of thought, which accepts not only binary opposites but also neutralities and indeterminacies, reflecting the complexity and fluidity of educational environments.

The system integrates various types of educational indicators:

a) Objective Indicators: Quantitative metrics such as assignment completion and test scores.
b) Subjective Indicators: Feedback from students and peer evaluations.
c) Behavioral Metrics: Engagement through clickstreams, online attendance, and interaction data.
d) Indeterminate Indicators: Contradictory feedback or ambiguous student outcomes.

The proposed method is inspired by Florentin Smarandache's MultiAlist System of Thought, which extends beyond traditional dichotomies (true/false, effective/ineffective) by incorporating contradictions, neutralities, and indeterminacies within and across systems.

This system draws upon:

a) Neutrosophic Logic: representing each data point as a triplet of truth (T), indeterminacy (I), and falsity (F).
b) Plithogenic Theory: aggregating multi-valued attributes while acknowledging conflicting tendencies.

Together, they support a multi-valent evaluation that reflects the diversity and fluidity of educational data.

3.1. Mathematical Formulation

We define an evaluation vector $E=[e_1,e_2,...,e_n]$, where each e_i is evaluated via a neutrosophic triplet: $e_i=(T_i,I_i,F_i)$

Where

T_i is the degree of truth (positive impact)

I_i is the degree of indeterminacy (uncertainty/neutrality)

F_i is the degree of falsity (negative impact)

All values are within [0, 1], and $0 \leq T_i+I_i+F_i \leq 3$. Further, each triplet is integrated into a Plithogenic aggregation using contradictory degrees and weights assigned to attributes such as:

a. Innovation in teaching content
b. Engagement quality
c. Technological application effectiveness
d. Student skill acquisition rate

The final evaluation score Q is calculated as:

$$Q = \frac{1}{n}\sum_{i=1}^{n}(T_i - F_i)(1 - I_i) \qquad (1)$$

This ensures:

a) Truth is rewarded
b) Falsity is penalized
c) Indeterminacy is discounted (but not ignored)

This metric discounts uncertainty, emphasizing clear consensus while not discarding indeterminate indicators entirely.

This evaluation framework is philosophically aligned with the principles of MultiPolar logic, which is a core component of the MultiAlist system of thought. MultiPolar logic acknowledges the coexistence of multiple, sometimes contradictory truths, and actively incorporates neutral states and indeterminate zones into the evaluation process. This stands in contrast to traditional binary or linear evaluation models, which force outcomes into fixed categories such as "effective" or "ineffective." Unlike PluriPolar systems, which allow for a plurality of values but exclude ambiguity and neutrality, MultiPolar systems embrace complexity by recognizing that uncertainty and contradiction are natural elements of dynamic, real-world educational environments. This philosophical openness enables more inclusive, context-aware interpretations of teaching quality.

3.2 Derivation of Neutrosophic Components (T, I, F)

To operationalize the MMVES, it is essential to define how each educational indicator is quantitatively translated into neutrosophic components: T, I, and F. These values are derived through a combination of statistical normalization, threshold mapping, and expert judgment, depending on the nature of the indicator (objective, subjective, behavioral, or indeterminate).

3.2.1. Objective Indicators (Completion Rate, Average Score)

T is computed as the normalized score relative to the expected benchmark (e.g., average completion above 80%).
F reflects the degree of deviation below the acceptable threshold (e.g., <60%).
I represents the zone between satisfactory and unsatisfactory performance (e.g., 60–80%), where outcomes are unclear or vary widely among students.
T = (x - min)/(max - min) if x ≥ threshold
F = (threshold - x)/threshold if x < threshold
I = 1 - (T + F)

3.2.2. Subjective Indicators (Peer Evaluation, Instructor Reflection):

Responses are coded using a 5-point Likert scale.
T corresponds to the proportion of “agree” and “strongly agree” responses.
F corresponds to the proportion of “disagree” and “strongly disagree.”
I include “neutral” responses or contradictory patterns in feedback.

3.2.3. Behavioral Indicators (Participation via Clickstream):

Metrics such as login frequency, active minutes, and content interaction are tracked.
T is high when engagement metrics exceed class averages.
F is high when metrics fall significantly below baseline.
I arise from irregular patterns, sporadic activity, or conflicting metrics (high login but low content completion).

3.2.4. Indeterminate Indicators (conflicting feedback, unstructured responses)

Qualitative data are coded via sentiment analysis and contradiction detection tools. High standard deviation in feedback increases I.
T and F are based on dominant themes using natural language processing and classification algorithms.

The derivation of neutrosophic components relies on a combination of quantitative tools and expert input. Statistical software such as Python (utilizing libraries like NumPy and Pandas) and SPSS are employed for data normalization and numerical analysis. For subjective and qualitative indicators, natural language processing (NLP) techniques are used, including libraries such as NLTK and spaCy, to conduct sentiment analysis and detect contradictions in textual feedback. In addition to computational methods, expert panels consisting of experienced educators are involved to validate indicator thresholds, assign appropriate weights, and ensure contextual accuracy when interpreting ambiguous or conflicting data.

4. Digital Media Technology Program, Local Renowned University of Media and Communications

Context

A sample of 400 students and 15 instructors across four semesters in the Digital Media Technology program was analyzed. Data included LMS logs, assignment completion, peer review feedback, attendance, and student surveys.

Table 1. Indicators

Indicator	Data Source	Type
Completion Rate	LMS	Objective
Average Score	Grading System	Objective
Class Participation	Video logs / Clickstream	Behavioral
Peer Evaluation	Survey Tool	Subjective
Instructor Reflection	Qualitative Logs	Subjective

These indicators in Table 1 were processed using the neutrosophic model, resulting in Table 2 as aggregated values

Table 2. Data Sample (Aggregated)

Attribute	T	I	F
Completion Rate	0.85	0.05	0.10

Participation Level	0.65	0.25	0.10
Peer Feedback	0.70	0.20	0.10
Skill Acquisition	0.60	0.30	0.10
Tech Application	0.75	0.10	0.15

Using the MMVES equation 1 The overall score was computed as:

$$Q = (1/5) \times [\ (0.85 - 0.10)(1 - 0.05) + (0.65 - 0.10)(1 - 0.25) + (0.70 - 0.10)(1 - 0.20) + (0.60 - 0.10)(1 - 0.30) + (0.75 - 0.15)(1 - 0.10)\ ] = 0.58$$

The final score indicates a moderate-to-high overall teaching quality. The highest performance was observed in technological application and course completion, indicating strong instructional design. However, elevated indeterminacy in participation and skill acquisition reveals gaps in student engagement and practical learning outcomes. These ambiguous zones represent areas for pedagogical intervention.

Classical evaluation methods might overlook contradictory outcomes such as high peer praise coinciding with modest assignment quality but MMVES identifies and retains such contradictions, enabling more comprehensive pedagogical analysis. This reflects the MultiAlist commitment to acknowledging complexity and plural perspectives in educational assessment.

4.1 Results and Interpretation

The neutrosophic analysis shows high clarity in teaching outcomes such as completion and tech adoption but identifies ambiguity in skill acquisition and participation. The indeterminacy levels highlight areas where instructional redesign is needed, particularly to address engagement gaps and contextual misunderstandings.

The plithogenic evaluation function revealed the influence of contradictory feedback such as high peer praise but low assignment quality a nuance typically flattened in classical statistical models.

5. Conclusion

This study demonstrates that evaluating teaching quality in Digital Media Technology through a big-data-enabled, MultiAlist-inspired framework offers a nuanced, scalable, and philosophically coherent approach. By integrating objective data with subjective and indeterminate inputs, and applying neutrosophic logic and plithogenic sets, institutions can achieve fairer and deeper educational insights. Future work should expand to multi-institutional validation and real-time integration within adaptive learning systems.

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