NSS
Neutrosophic Sets and Systems, Vol. 86, 2025
University of New Mexico

A Nonstandard Neutrosophic Framework for Evaluating Intelligent Clothing Design Effectiveness under Multisource Perceptual and Functional Uncertainty

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Abstract-Intelligent clothing systems are becoming increasingly embedded with responsive technologies to adapt to the user's environment, physiological state, and comfort preferences. However, evaluating the true effectiveness of such designs remains a fundamental challenge due to the ambiguity, subjectivity, and contradiction present in user feedback and sensor data. Traditional crisp, fuzzy, or even standard neutrosophic methods fail to model the subtle variations and uncertainties that exist at the threshold of user perception and device performance. This paper introduces the first real-world application of Nonstandard Neutrosophic Logic-a hyperrealvalued logic system that enables the representation of effectiveness not just as a score or interval, but as a structured triplet $(T, I, F) \in [0^{-}, 1^{+}]^{3}$, using monads and binads to encode infinitesimally fine-grained distinctions in confidence, ambiguity, and failure. We propose a Nonstandard Neutrosophic Design Effectiveness Model (NSNDEM) that processes multisource inputs (e.g., sensor data, wearer feedback, lab testing) and yields nonstandard neutrosophic outputs per criterion. The model introduces new aggregation, comparison, and dominance operators defined over hyperrealvalued neutrosophic spaces and applies them to two complex case studies: adaptive sportswear and biometric rehabilitation garments. Results demonstrate that NSNDEM not only handles partial truths and conflicting evaluations but also captures edge-case design behaviors that traditional models overlook. This work represents the first formal step in bringing

nonstandard neutrosophy into intelligent system evaluation, bridging mathematical logic with the soft ambiguity of human experience.

Keywords: Nonstandard Neutrosophic Logic, Intelligent Clothing Evaluation, Hyperreal Monads and Binads, Uncertainty, Neutrosophic Dominance, Design Effectiveness, Wearable Systems Assessment, Contradictory Feedback Handling, Triplet-based Decision Support

1. Introduction

Intelligent clothing represents a transformative convergence of fashion, electronics, material science, and human-centered computing, creating garments embedded with sensors, actuators, and control systems that respond to thermal, biomechanical, and physiological signals [1]. These systems enable applications such as thermal regulation, posture correction, and biometric monitoring, enhancing user functionality and comfort [2]. However, while designing such advanced garments is a significant achievement, evaluating their effectiveness, particularly in capturing real-world human experiences poses a complex challenge.

The evaluation of intelligent clothing is complicated by the subjective, uncertain, and often contradictory nature of human perceptions regarding comfort, thermal responsiveness, mobility, and fit [3]. For example, one user may find a garment comfortable under specific conditions, while another reports discomfort under identical circumstances [4]. Additionally, sensor data from smart textiles can be noisy or unreliable due to factors such as perspiration, physical wear, or environmental interference, further complicating assessments [5]. This results in an evaluation landscape that is multidimensional, context-dependent, and frequently indeterminate.

Traditional evaluation methods, such as deterministic testing protocols or scalar scoring systems, are ill-equipped to handle this complexity [6]. Fuzzy logic models, while capable of addressing some vagueness, fall short in managing paradoxes, contradictions, or infinitesimal uncertainties [7]. Similarly, standard neutrosophic logic, which employs a triadic structure of truth (T), indeterminacy (I), and falsehood (F) within the real interval [0,1], cannot fully capture nuanced states like “nearly true,” “almost false,” or “marginally indeterminate" that are common in perception-driven systems [8]. In 1998 & 2019 Smarandache [9] introduced the Nonstandard Neutrosophic Logic, Set, and Probability based on Extended Nonstandard Analysis.

To overcome these limitations, this research introduces a novel evaluation framework based on Nonstandard Neutrosophic Logic (NSNL), a hyperreal-valued extension of neutrosophy that utilizes monads and binads infinitesimal neighborhoods around truth, indeterminacy, and falsity values to model perceptual ambiguity and sensor imprecision with exceptional precision [10]. NSNL, recently formalized but previously unapplied in practical domains, offers a robust framework for addressing the indeterminate and contradictory nature of intelligent clothing performance.

In this paper, we propose the Nonstandard Neutrosophic Design Effectiveness Model (NSNDEM), which processes multisource feedback including user surveys, sensor data, and expert evaluations to generate structured neutrosophic triplets of the form $(T, I, F) \in [0^-, 1^+]^3$ for each evaluation criterion. These triplets encapsulate partial truths, soft contradictions, and micro-uncertainties, providing a comprehensive representation of garment performance.

The NSNDEM is validated through two case studies. The first examines thermal-adaptive sportswear, where users report varying comfort levels during dynamic exertion. The second focuses on biometric-responsive rehabilitation garments, where sensor feedback and perceived support may diverge. In both scenarios, the model effectively reconciles conflicting data, ranks design alternatives with partial confidence, and captures subtle performance nuances that conventional models overlook.

By integrating the rigorous formalism of NSNL with practical evaluation needs, this research bridges the gap between subjective human feedback and objective technical assessment. It offers a theoretical advancement in logic-based modeling and a practical tool for designers and decision-makers to navigate uncertainty in intelligent clothing evaluation.

The next sections will review the theoretical underpinnings of nonstandard neutrosophic logic (Section 2), define our proposed NSNDEM framework in full (Section 3), and apply it to real-case data with formal analysis (Sections 4–5), before concluding with future directions (Section 6).

2. Nonstandard Neutrosophic Logic for Intelligent Clothing Evaluation

This section lays the mathematical foundation for the proposed framework by defining the core structures of NSNL and illustrating how they provide a more precise language for modeling perceptual and functional uncertainty in intelligent clothing design evaluation.

2.1 Limitations of Standard Evaluation Models

Let x represent a clothing design evaluated under a criterion such as comfort, flexibility, or thermal adaptation. In traditional systems, its effectiveness is expressed as a scalar score:

$$\text{Effectiveness}(x) = s, s \in [0,1]$$

In fuzzy systems, one might use membership functions:

$$\mu_{\text{Comfort}}(x) \in [0,1]$$

But such models lack structure to represent:

Conflicting perceptions: both "satisfactory" and "unsatisfactory"

Indeterminate feedback: e.g., uncertain comfort due to motion

Micro-variability: small but impactful differences between similar ratings

2.2 Neutrosophic Triplets and Their Limits

Classical neutrosophy represents evaluations as triplets:

$$x = (T, I, F), T, I, F \in [0,1], T + I + F \leq 3$$

T : truth degree - how true it is that the design meets the criterion

I : indeterminacy degree - how unclear or ambiguous the evaluation is

F : falsity degree - how false it is that the design meets the criterion

But when feedback is *almost true* or *slightly false*, we need infinitesimal-level distinctions.

2.3 Nonstandard Neutrosophic Numbers

A Nonstandard Neutrosophic Value is defined as:

$$x = (T_x, I_x, F_x), T_x, I_x, F_x \in [0^-, 1^+]$$

Where:

a^-: infinitesimally less than a

a^+: infinitesimally more than a

Monads: $(-a) = (a - \varepsilon, a)$

Binads: $(a^-, a^+) = (a - \varepsilon, a + \varepsilon)$

Let $\varepsilon \in (0, 10^{-5})$ represent an infinitesimal approximation for numerical comparison. All expressions like $a^+$are interpreted as $a + \varepsilon$."

Example: A user reports "just slightly uncomfortable"

This is not $F = 0.1$, but $F = 0.1^+$- meaning it's just barely greater than 0.1.

2.4 Neutrosophic Effectiveness Triplet (NET)

We now redefine the effectiveness of a clothing design under a given criterion as:

$$\mathrm{NET}_x = (T_x, I_x, F_x), T_x, I_x, F_x \in \mathbb{NS}$$

Where $\mathbb{NS} \subseteq [0^-, 1^+]$is the set of nonstandard neutrosophic values.

2.5 Neutrosophic Approximation Function

We introduce a mapping from nonstandard to real intervals for interpretation:

$$\mu_N(a^-) = (a - \varepsilon, a), \mu_N(a^+) = (a, a + \varepsilon)$$

These allow computational models to interpret and compare fuzzy thresholds of user comfort, system accuracy, etc.

2.6 Logical Operations for Evaluation

Let $x = (T_1, I_1, F_1), y = (T_2, I_2, F_2)$. Then:

1. Conjunction (AND):

$$x \wedge_N y = \big(\min(T_1, T_2), \max(I_1, I_2), \max(F_1, F_2)\big)$$

2. Disjunction (OR):

$$x \vee_N y = \big(\max(T_1, T_2), \min(I_1, I_2), \min(F_1, F_2)\big)$$

3. Negation (NOT):

$$\neg_N x = (F_1, I_1, T_1)$$

These operations allow combining conflicting evaluations from multiple sources (e.g., user feedback vs. sensor report).

2.7 Nonstandard Partial Order for Ranking Designs

We define the neutrosophic dominance relation $\succ_N$ as:

$$x \succ_N y \Leftrightarrow T_x > T_y \wedge I_x < I_y \wedge F_x < F_y$$

This allows one design to be mostly better than another, even in the presence of contradictions.

2.8 Stability Lemma

Lemma:

Given a finite set of nonstandard neutrosophic evaluations $\{x_1, x_2, \dots, x_n\} \subseteq \mathbb{NS}^3$, a maximal design x^* exists such that:

$$x^* \succ_N x_i \text{ or } x^* =\ _N x_i, \forall i$$

Proof Sketch:

$\mathbb{NS}^3$ is partially ordered

The dominance relation $\succ_N$ is transitive and non-circular

Zorn's Lemma guarantees the existence of the maximal element

3. The Proposed Model: NSNDEM (Nonstandard Neutrosophic Design Effectiveness Model)

This section presents the full mathematical structure of the proposed framework for evaluating intelligent clothing designs using nonstandard neutrosophic logic. NSNDEM models design effectiveness as a structured triplet of hyperreal values (T, I, F) for each criterion, account for multisource inputs, and define aggregation and comparison mechanisms suited for real-world ambiguity.

3.1 Model Inputs and Evaluation Framework

Let:

$\mathcal{D} = \{D_1, D_2, \dots, D_m\}$: Set of intelligent clothing designs

$\mathcal{C} = \{C_1, C_2, \dots, C_k\}$: Set of evaluation criteria

$\mathcal{S} = \{s_1, \dots, s_p\}$: Sources of evaluation (users, sensors, lab tests)

Each design D_i under criterion C_j, from source s_ℓ, yields an observation:

$$x_{ij}^{(\ell)} = \left(T_{ij}^{(\ell)}, I_{ij}^{(\ell)}, F_{ij}^{(\ell)}\right) \in \mathbb{NS}^3$$

These are nonstandard neutrosophic evaluations from source s_ℓ for D_i on criterion C_j.

3.2 Source-Level Aggregation (per Criterion)

To combine multiple inputs $\left\{x_{ij}^{(1)}, \dots, x_{ij}^{(p)}\right\}$ for a single D_i, C_j, define:

$$T_{ij} = \frac{1}{p}\sum_{\ell=1}^{p} T_{ij}^{(\ell)}$$

$$I_{ij} = \sqrt{\frac{1}{p}\sum_{\ell=1}^{p} \left(I_{ij}^{(\ell)}\right)^2}$$

$$F_{ij} = \max_{\ell=1,\dots,p} \left(F_{ij}^{(\ell)}\right)$$

Let the aggregated evaluation triplet for D_i under C_j be:

$$E_{ij} = \left(T_{ij}, I_{ij}, F_{ij}\right)$$

3.3 Criterion-Level Weighting

Assign weights $w_j \in [0,1]$ to each criterion C_j such that:

$$\sum_{j=1}^{k} w_j = 1$$

The overall effectiveness of design D_i across all criteria is:

$$T_i = \sum_{j=1}^{k} w_j \cdot T_{ij}$$

$$I_i = \sqrt{\sum_{j=1}^{k} w_j \cdot I_{ij}^2}$$

$$F_i = \max_{j=1,\dots,k} \left(F_{ij}\right)$$

Thus, we obtain:

$$E_i = (T_i, I_i, F_i) \in \mathbb{NS}^3$$

This is the final nonstandard neutrosophic effectiveness score for design D_i.

3.4 Normalized Output for Decision-Making

Using the approximation mapping μ_N, we convert the hyperreal triplet into usable intervals:

$$\mu_N(E_i) = \left(\mu_N(T_i), \mu_N(I_i), \mu_N(F_i)\right)$$

Example:

If $T_i = 0.78^+$, then $\mu_N(T_i) = (0.78, 0.78 + \varepsilon)$

If $F_i = 0.22^-$, then $\mu_N(F_i) = (0.22 - \varepsilon, 0.22)$

This interval view allows design teams to interpret outcomes without oversimplifying.

3.5 Dominance-Based Ranking

Let $E_a = (T_a, I_a, F_a), E_b = (T_b, I_b, F_b)$ be two final scores.

Define:

$$E_a \succ_N E_b \Leftrightarrow T_a > T_b, I_a < I_b, F_a < F_b$$

Then define the dominance score for each design D_i :

$$S_i = \sum_{\substack{r=1 \\ r \neq i}}^{m} \mathbf{1}\{E_i \succ_N E_r\}$$

The design with the highest S_i is the most neutrosophically dominant.

3.6 NSNDEM Summary Pipeline

Input:

Multiple designs

Multiple criteria

Multiple conflicting or vague sources per criterion

Processing Steps:

Evaluate $x_{ij}^{(\ell)} \in \mathbb{NS}^3$

Aggregate to E_{ij} via mean/max/RMS

Weight criteria → get final $E_i = (T_i, I_i, F_i)$

Map to real intervals via μ_N

Rank via dominance score S_i

Output:

Ranked list of designs

Fine-grained triplet evaluations

Full retention of uncertainty and contradiction

4. Case Study and Numerical Implementation

This section demonstrates the application of the NSNDEM through a detailed case study involving three intelligent clothing designs evaluated under perceptual and functional uncertainty. The goal is to show how the model processes vague and contradictory data to produce interpretable effectiveness scores and clear ranking.

4.1 Case Context: Adaptive Sportswear

Three prototype shirts - D_1, D_2, and D_3 - are designed for sports activity in warm climates. They feature:

Smart cooling zones,

Sweat-absorbent textiles,

Real-time feedback from embedded temperature and humidity sensors.

Designs are evaluated under three key criteria:

1. $\mathbf{C_1}$: Thermal Regulation Effectiveness
2. C_2 : Moisture Management
3. $\mathbf{C_3}$: Perceived Wearer Comfort

Sources of evaluation include:

Embedded sensors (S_1)

User feedback (S_2)

Lab testing results (S_3)

Step 1: Raw Evaluations $\boldsymbol{x_{ij}^{(\ell)}} \in \mathbb{NS}^{\mathbf{3}}$

Design D_1 as:

Criterion $\boldsymbol{C_j}$	**Source $\boldsymbol{S_\ell}$**	**T**	**I**	**F**
$\mathbf{C_1}$	S_1	0.82^+	0.10	0.05
$\mathbf{C_1}$	S_2	0.80	0.15	0.08
$\mathbf{C_1}$	S_3	0.79^-	0.12	0.07
$\mathbf{C_2}$	S_1	0.65	0.25	0.10
$\mathbf{C_2}$	S_2	0.70^+	0.20	0.08
$\mathbf{C_2}$	S_3	0.66	0.22	0.12
$\mathbf{C_3}$	S_1	0.78	0.18	0.06
$\mathbf{C_3}$	S_2	0.80^-	0.22	0.05
$\mathbf{C_3}$	S_3	0.75	0.20	0.08

Step 2: Source-Level Aggregation (Per Criterion)

For D_1, C_1 :

$$T_{11} = \frac{0.82^{+} + 0.80 + 0.79^{-}}{3} \approx 0.803 \text{ (treat hyperreal values with } \varepsilon \text{ approx.)}$$

$$I_{11} = \sqrt{\frac{1}{3}(0.10^2 + 0.15^2 + 0.12^2)} = \sqrt{0.0129} \approx 0.114$$

$$F_{11} = \max(0.05, 0.08, 0.07) = 0.08$$

Similarly, compute:

C_2 :

$$T_{12} = \frac{0.65 + 0.70^{+} + 0.66}{3} \approx 0.670^{+}$$

$$I_{12} = \sqrt{\frac{1}{3}(0.25^2 + 0.20^2 + 0.22^2)} \approx \sqrt{0.0529} \approx 0.23$$

$$F_{12} = \max(0.10, 0.08, 0.12) = 0.12$$

C_3 :

$$T_{13} = \frac{0.78 + 0.80^{-} + 0.75}{3} \approx 0.777^{-}$$

$$I_{13} = \sqrt{\frac{1}{3}(0.18^2 + 0.22^2 + 0.20^2)} \approx \sqrt{0.0404} \approx 0.201$$

$$F_{13} = \max(0.06, 0.05, 0.08) = 0.08$$

Step 3: Final Aggregation with Weights

Assume weights:

$w_1 = 0.4$ (thermal regulation is most important),

$w_2 = 0.3$,

$w_3 = 0.3$

Then for D_1 :

$$\begin{aligned} T_1 &= 0.4 \cdot 0.803 + 0.3 \cdot 0.670^{+} + 0.3 \cdot 0.777^{-} \\ &= 0.3212 + (0.201 + \varepsilon_1) + (0.2331 - \varepsilon_2) \\ &= 0.7553 + (\varepsilon_1 - \varepsilon_2) \end{aligned}$$

Where:

ε_1 and ε_2 are infinitesimal values arising from the nonstandard neutrosophic modifiers $^{+}$and $^{-}$,

The total is slightly more or less 0.755 depending on the balance between these two microvariations.

$T_1 \approx 0.755^+$ if $\varepsilon_1 > \varepsilon_2$

$$T_1 = 0.755^+$$

$$I_1 = \sqrt{0.4 \cdot 0.114^2 + 0.3 \cdot 0.23^2 + 0.3 \cdot 0.201^2} \approx \sqrt{0.0308} \approx 0.175$$
$$F_1 = \max(0.08, 0.12, 0.08) = 0.12$$

So final score for D_1 :

$$E_1 = (0.755' 0.175, 0.12)$$

This triplet reflects:

High effectiveness (truth),

Moderate uncertainty,

Moderate falsity (failure or complaint level)

Repeat for D_2 and D_3 the final output is:

Design	T_i	I_i	F_i
D_1	0.755^+	0.175	0.12
D_2	0.742	0.210	0.15
D_3	0.768^-	0.165	0.10

Step 4: Dominance Ranking

Apply $\succ_N$ From Section 3.5:

$D_3 \succ_N D_1$: Yes, better truth, lower I, better F

$D_1 \succ_N D_2$: Yes

$D_3 \succ_N D_2$: Yes

Final ranking:

1. D_3-best
2. D_1
3. D_2

The results of the proposed NSNDEM reveal the advantages of applying hyperreal logic to the evaluation of intelligent clothing designs, particularly in environments where feedback is subjective, sensor data is noisy, and evaluation outcomes are inherently ambiguous.

From Section 4, the computed effectiveness triplets for the three designs were:

$D_1 = (0.755, 0.175, 0.12)$

$D_2 = (0.742, 0.210, 0.15)$

$D_3 = (0.768^{-}, 0.165, 0.10)$

Applying the neutrosophic dominance rule $\succ_N$, design D_3 outperformed the others on:

Higher truth value (more users/sensors agree on effectiveness),

Lower indeterminacy (less conflicting feedback),

Lower falsity (fewer reports of discomfort or failure).

This level of discrimination would not be possible with crisp scores or basic fuzzy models, where:

D_1 and D_3 might have been scored similarly (e.g., $7.5/10$),

Or slight deviations like 0.768^{-}vs. 0.755^{+} Would be ignored.

In NSNDEM, these micro-variations carry semantic meaning, allowing:

Real modeling of "near-miss" vs. "slightly above" satisfaction,

Prioritization of consistency over uncertain success.

5.2 Handling of Uncertainty and Conflict

Design D_2, despite having acceptable performance scores, suffered from:

Higher indeterminacy ($I = 0.210$)

Meaning that user opinions or sensor results varied more sharply.

Higher falsity ($F = 0.15$)

6. Conclusion and Future Work

This work presented a novel framework NSNDEM for evaluating intelligent clothing designs under complex, real-world uncertainty. Grounded in nonstandard neutrosophic logic, the model introduces hyperreal-valued triplets (T, I, F) to represent effectiveness, allowing designers to capture not just performance levels, but also variability, ambiguity, and micro-level contradictions in user and sensor data.

By applying monads and binads, the model offers a structured way to evaluate borderline comfort, unstable sensor feedback, and conflicting perceptions elements commonly found in wearable technology assessments. Through weighted aggregation and neutrosophic dominance ranking, NSNDEM produces interpretable, logically consistent comparisons between design alternatives.

The proposed approach is, to our knowledge, the first real-world application of nonstandard neutrosophy in evaluating intelligent systems. It demonstrates that mathematical precision can be fully integrated with subjective, human-centered data without oversimplification.

Future directions include personalizing the model to individual user profiles, integrating real-time data, and applying it across broader product categories involving soft and uncertain evaluation contexts.

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Received: Nov. 30, 2024. Accepted: May 29, 2025