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Revisiting the Neutrosophic Random Variable

Abdul Haq[1], Javid Shabbir[1,2*]

[1]Department of Statistics, Quaid-i-Azam University, Islamabad, Pakistan
[2]Department of Statistics, University of Wah, Wah Cantt., Rawalpindi, Pakistan
Email: *javidshabbir@gmail.com

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Abstract

We show that a neutrosophic random variable with fixed interval-valued indeterminacy is a deterministic scaling of a classical random variable. The lower and upper bounds of the interval introduce no independent source of randomness, and the resulting statistical and likelihood-based inferences follow directly from those of the underlying classical random variable. Consequently, the interval representation contributes no additional uncertainty or inferential content beyond that already present in the classical formulation. Thus, under fixed interval-valued indeterminacy, the neutrosophic random variable does not provide a substantive extension of classical probability theory.

Keywords

Entropy, Indeterminacy, Likelihood Function, Neutrosophic Random Variable, Neutrosophic Statistics

1. Introduction

Neutrosophic statistics, introduced by Smarandache [1], extends classical statistics by incorporating a new dimension of uncertainty called *indeterminacy*. This framework is intended to handle data that are imprecise, ambiguous, or partially unknown, and has inspired a wide range of applications in regression analysis, experimental design, and survey sampling [2]-[4], to name a few. Within this paradigm, the *neutrosophic random variable* is presented as the core construct that underlies neutrosophic probability distributions and inference procedures. The neutrosophic random variable is commonly defined as $X_N = X_L + X_L I_N$, where X_L is a classical random variable and I_N represents the degree of indeterminacy such that $I_N \geq 0$.

Building upon this formulation, several papers have proposed neutrosophic versions of well-known distributions—such as the binomial, normal, geometric, and gamma distributions—and algorithms for generating corresponding data [5]-[9]. In these studies, statistical properties such as mean, variance, and entropy are derived by treating I_N as a constant, leading to expressions of the form $(1+I_N)^r$ times the classical counterparts. This approach has been extended to theoretical developments in estimation of parameters [10]-[12], though the implications of these assumptions have not been carefully examined. For more related works, we refer to Aslam and Saleem [13], Aslam and Albassam [6], Aslam [14], Aslam [10], Saleem and Aslam [9], Aslam and Smarandache [15], Aslam [16], Aslam *et al.* [7], Ahsan-ul Haq *et al.* [17], Al-Essa *et al.* [18], Saleem *et al.* [19], Bashir *et al.* [20], Jamal *et al.* [21], Aslam and Arif [22], Aslam [5], Aslam and Arif [23].

Some recent critiques have questioned the mathematical soundness and interpretive coherence of neutrosophic statistical methods [24]-[27], with Haq and Woodall [28] raising fundamental concerns about their formulation. Specifically, it remains unclear whether the neutrosophic random variable genuinely introduces new stochastic behavior or merely rescales existing random quantities. The purpose of this paper is to address this issue formally. By analyzing the neutrosophic random variable in terms of its distributional form, likelihood function, entropy, characteristic function, and higher-order moments, we demonstrate that it is entirely determined by the classical random variable when I_N is treated as a fixed interval-valued indeterminacy. Consequently, the neutrosophic random variable represents a cosmetic extension of classical probability theory rather than a substantive contribution.

The rest of the paper is organized as follows. Section 2 reviews the formulation of the neutrosophic random variable and its basic properties. Section 3 examines its deterministic relationship with the classical random variable and discusses the dependence of its bounds, interval width, distributional form, likelihood function, characteristic function, higher-order moments, and entropy. Section 4 provides numerical examples illustrating the resulting equivalence between the neutrosophic and classical formulations. Section 5 concludes the paper.

2. The Neutrosophic Random Variable

Consider a neutrosophic random variable $X_N = X_L + I_N X_L$, where X_L is a classical random variable and $I_N \in [I_L, I_U]$ represents a fixed interval-valued indeterminacy such that $I_N \geq 0$. For brevity of discussion, we assume that $X_L > 0$. In this case,

$$X_N \in \left[(1+I_L)X_L, (1+I_U)X_L\right] = \left[(1+I_L), (1+I_U)\right] \cdot X_L. \tag{1}$$

If instead $X_L < 0$, the ordering of the bounds is reversed, and the interval should be interpreted accordingly. When $I_N = 0$, the neutrosophic variable X_N coincides with the classical random variable X_L. For $I_N \in [0,1]$, $I_N^r \in [0,1]$ for $r \geq 1$ [8].

Let μ_X and σ_X^2 denote the mean and variance of X_L, respectively. Following

Aslam [11] and Aslam [12], the corresponding neutrosophic moments may be obtained as

$$E(X_N) = (1+I_N)\mu_X = [(1+I_L),(1+I_U)] \cdot \mu_X, \tag{2}$$

$$V(X_N) = (1+I_N)^2 \sigma_X^2 = [(1+I_L)^2,(1+I_U)^2] \cdot \sigma_X^2, \tag{3}$$

$$V(X_L I_N) = I_N^2 \sigma_X^2 = [I_L^2, I_U^2] \cdot \sigma_X^2, \tag{4}$$

$$C(X_L, X_L I_N) = I_N \sigma_X^2 = [I_L, I_U] \cdot \sigma_X^2 \tag{5}$$

where $E(\cdot)$, $V(\cdot)$ and $C(\cdot,\cdot)$ stand for the mathematical expectation, variance and covariance, respectively. The relations, given in Equations (2)-(5), hold only when $I_N \in [I_L, I_U]$ is treated as a fixed interval.

3. Criticism on Neutrosophic Random Variable

In the works of Aslam [11] and Aslam [12], the term I_N is treated as a fixed interval of indeterminacy such that $I_N \geq 0$. Under this assumption, the neutrosophic random variable reduces to a bounded and scaled form of the classical random variable rather than representing a genuinely stochastic or independent source of uncertainty. The following discussion formalizes this observation and demonstrates that all neutrosophic quantities remain deterministic transformations of their classical counterparts.

3.1. A Linear Function of a Classical Random Variable

The neutrosophic random variable can be expressed as

$$X_N = (1+I_N) X_L \text{ for } I_N \in [I_L, I_U], \tag{6}$$

implying that for each fixed value of I_N, X_N is a deterministic linear function of the classical random variable X_L. Hence, both share the same stochastic source and differ only by scale.

The key point is that the interval-valued quantity I_N does not constitute a second stochastic mechanism in this formulation. Once I_L and I_U are fixed, every admissible value of X_N is obtained from the same realization of X_L by multiplication by a deterministic factor. Thus, the interval does not generate an additional random component; it specifies a range of deterministic transformations of the original random variable. An interval representation by itself, therefore, does not imply the presence of an additional probabilistic source of uncertainty.

Since I_N varies deterministically within $[I_L, I_U]$, the neutrosophic random variable defines a bounded interval

$$X_N \in [(1+I_L) X_L, (1+I_U) X_L] \tag{7}$$

This formulation ensures correct ordering regardless of the sign of X_L. If $X_L \geq 0$, the bounds appear as written; if $X_L < 0$, the order reverses automatically. In addition, the representation indicates that the entire neutrosophic interval is deterministically generated from the classical random variable X_L through fixed proportional scaling, leaving no scope for independent randomness within the bounds.

3.2. Dependence of the Neutrosophic Bounds

Let $X_N^L = (1+I_L)X_L$ and $X_N^U = (1+I_U)X_L$ denote the lower and upper bounds of X_N, respectively. These bounds are deterministic transforms of X_L. When $X_L > 0$, the ordering is as written; when $X_L < 0$, the roles of the lower and upper bounds are reversed. These quantities are often treated as if they were independent or as if the interval $\left[X_N^L, X_N^U\right]$ possessed its own probabilistic structure. However, both bounds are deterministic linear transformations of the same variable X_L and therefore perfectly dependent.

The mathematical relationship between X_N^L and X_N^U is given by

$$X_N^U = \left(\frac{1+I_U}{1+I_L}\right)X_N^L, \tag{8}$$

implying $\operatorname{Corr}\left(X_N^L, X_N^U\right) = 1$. This perfect dependence is not merely a technical property of the two endpoints; it characterizes the entire interval construction. Once a realization of X_L is specified, both endpoints are completely determined. Hence, observing one endpoint provides complete information about the other, apart from the fixed proportionality factor determined by I_L and I_U.

Consequently, the lower and upper bounds cannot be regarded as independent random quantities. The so-called neutrosophic interval merely represents a fixed proportional expansion of X_L rather than a new layer of stochastic behavior. Treating these bounds as if they carried independent randomness or distinct inferential meaning is therefore mathematically inconsistent.

3.3. Deterministic Nature of the Interval Width

The width of the neutrosophic interval is defined as

$$W_N = X_N^U - X_N^L = (I_U - I_L)X_L. \tag{9}$$

For $X_L > 0$, this width is non-negative. If $X_L < 0$, the expression reverses sign, and the width should be taken as $\left|(I_U - I_L)X_L\right|$ to ensure non-negativity.

It follows immediately that W_N is a deterministic multiple of the classical random variable X_L. For fixed indeterminacy bounds I_L and I_U, the quantity W_N inherits all its randomness from X_L and does not constitute an additional stochastic component.

The ratio

$$\frac{W_N}{X_L} = I_U - I_L \tag{10}$$

is constant for all realizations of X_L, indicating that the relative degree of "indeterminacy" is uniform across the entire support of the variable. Thus, the neutrosophic interval neither expands nor contracts in response to random variation; it merely scales linearly with X_L.

Consequently, the width introduces no new uncertainty or informational content. It represents a fixed proportional transformation, reinforcing that the interval-valued construction remains entirely dependent on the classical random variable.

3.4. Distributional Equivalence

Let $F_{X_L}(x_L)$ and $F_{X_N}(x_N)$ denote the cumulative distribution functions (CDFs) of the classical random variable X_L and the neutrosophic random variable X_N, respectively.

For a neutrosophic random variable X_N, we have

$$\begin{aligned} F_{X_N}(x_N) &= P(X_N \le x_N) = P((1+I_N)X_L \le x_N) \\ &= P\left(X_L \le \frac{x_N}{1+I_N}\right) = F_{X_L}\left(\frac{x_N}{1+I_N}\right), \end{aligned} \tag{11}$$

where $I_N \ge 0$. Since I_N ranges over $[I_L, I_U]$, the neutrosophic CDF of X_N is interval-valued, given by

$$F_{X_N}(x_N) \in \left[F_{X_L}\left(\frac{x_N}{1+I_U}\right), F_{X_L}\left(\frac{x_N}{1+I_L}\right)\right]. \tag{12}$$

The interval representation of the CDF assumes $X_L > 0$. If $X_L < 0$, the ordering of the endpoints is reversed, and the CDF should be interpreted in terms of minimum and maximum values.

The representation of $F_{X_N}(x_N)$ in Equation (12) shows that the neutrosophic CDF is obtained directly from the classical CDF through deterministic scaling. Thus, the neutrosophic probability distribution is not distinct from the classical one; it is simply the classical CDF evaluated at scaled arguments. No new stochastic content is introduced by the interval-valued representation.

3.5. General Likelihood Function Equivalence

Let X_L be a classical random variable with a location-scale probability density function (PDF): $f_{X_L}(x;\theta_L)$, where θ_L may denote a vector of underlying location and scale parameters. Recall that the X_N can be expressed as $X_N = (1+I_N)X_L$ for $I_N \in [I_L, I_U]$, where I_N is a fixed but interval-valued indeterminacy.

Under this linear transformation, the neutrosophic parameters θ_N are simple scaled versions of the classical parameters θ_L, with the scaling factor determined by I_N. For example, if X_L follows a normal distribution with mean μ_L and variance σ_L^2; then, for any fixed value

of I_N, the neutrosophic normal distribution has the mean $\mu_N = (1+I_N)\mu_L$ and the variance $\sigma_N^2 = (1+I_N)^2\sigma_L^2$. Analogous scaling occurs for other location-scale families, such as exponential, gamma, and uniform distributions.

For a fixed $I_N \in [I_L, I_U]$, the PDF of X_N can be written as

$$f_{X_N}(x_N;\theta_N) = \frac{1}{(1+I_N)} f_{X_L}\left(\frac{x_N}{1+I_N};\theta_L\right), \tag{13}$$

where $\theta_L = \theta_N/(1+I_N)$ is the corresponding classical parameter vector.

For a random sample $\boldsymbol{x}_N = (x_{N,1},\cdots,x_{N,n})$, the neutrosophic likelihood function is given by

$$\begin{aligned} L_N(\theta_N;\boldsymbol{x}_N) &= \prod_{i=1}^{n} f_{X_N}(x_{N,i};\theta_N) \\ &= \frac{1}{(1+I_N)^n}\prod_{i=1}^{n} f_{X_L}\left(\frac{x_{N,i}}{1+I_N};\theta_L\right) \\ &= \frac{1}{(1+I_N)^n} L_L(\theta_L;\boldsymbol{x}_L), \end{aligned} \tag{14}$$

or

$$L_N(\theta_N;\boldsymbol{x}_N) \in \left[\frac{1}{(1+I_L)^n} L_L(\theta_L;\boldsymbol{x}_L), \frac{1}{(1+I_U)^n} L_L(\theta_L;\boldsymbol{x}_L)\right],$$

where $\boldsymbol{x}_L = \boldsymbol{x}_N/(1+I_N)$ is the corresponding classical sample.

Since this holds for every $I_N \in [I_L, I_U]$, the neutrosophic likelihood for the interval-valued random variable is proportional to the classical likelihood across the entire indeterminacy range:

$$L_N(\theta_N;\boldsymbol{x}_N) \propto L_L(\theta_L;\boldsymbol{x}_L), \quad \forall\, I_N \in [I_L, I_U]. \tag{15}$$

The factor $(1+I_N)^{-n}$ is a Jacobian term arising solely from the deterministic change of scale. It does not introduce a new component into the likelihood. Once the observations and parameters are transformed back to the classical scale, the remaining likelihood is exactly the classical likelihood. Thus, the apparent difference between the two likelihoods is attributable to parameterization and scale, rather than to a different probabilistic mechanism.

Therefore, likelihood-based analyses—including likelihood ratios, score functions, and maximum likelihood estimation—are fully determined by the classical model once the scaling is accounted for. The interval-valued indeterminacy does not introduce any new inferential content or independent stochastic variation, confirming that the neutrosophic likelihood is merely a scaled version of the classical likelihood.

3.6. Characteristic Function Equivalence

Let X_L denote a classical random variable with characteristic function (CF) defined as

$$\varphi_{X_L}(t) = E\left[\exp(itX_L)\right]. \tag{16}$$

Let $X_N = (1+I_N)X_L$ denote the corresponding neutrosophic random variable, where $I_N \in [I_L, I_U]$ is interval-valued indeterminacy.

The CF of X_N is given by

$$\begin{aligned} \varphi_{X_N}(t) &= E\left[\exp(itX_N)\right] = E\left[\exp\left(it(1+I_N)X_L\right)\right] \\ &= \varphi_{X_L}\left((1+I_N)t\right). \end{aligned} \tag{17}$$

Since I_N ranges over $[I_L, I_U]$, the neutrosophic CF is a set given by:

$$\varphi_{X_N}(t) \in \left\{\varphi_{X_L}\left((1+I_L)t\right), \varphi_{X_L}\left((1+I_U)t\right)\right\}. \tag{18}$$

Thus the neutrosophic CF is simply the classical CF evaluated at scaled arguments. Because the CF uniquely determines the distribution, X_N and X_L are distributionally equivalent up to deterministic scaling. The indeterminacy I_N does not introduce new randomness or informational content; it merely rescales the argument of the classical CF.

3.7. Equivalence of Skewness and Kurtosis

Let X_L be a classical random variable with mean μ_L and variance σ_L^2.

The skewness and kurtosis of X_L, denoted by $\gamma_{1,L}$ and $\gamma_{2,L}$, are given by

$$\gamma_{1,L} = \frac{E\left[(X_L - \mu_L)^3\right]}{\sigma_L^3} \quad \text{and} \quad \gamma_{2,L} = \frac{E\left[(X_L - \mu_L)^4\right]}{\sigma_L^4}, \tag{19}$$

respectively. For the neutrosophic random variable $X_N = (1+I_N)X_L$ with $I_N \in [I_L, I_U]$, the mean and variance are $\mu_N = (1+I_N)\mu_L$ and $\sigma_N^2 = (1+I_N)^2\sigma_L^2$, respectively.

Then the skewness and kurtosis of X_N are

$$\gamma_{1,N} = \frac{E\left[(X_N - \mu_N)^3\right]}{\sigma_N^3} = \frac{(1+I_N)^3 E\left[(X_L - \mu_L)^3\right]}{(1+I_N)^3 \sigma_L^3} = \gamma_{1,L} \quad \text{and} \tag{20}$$

$$\gamma_{2,N} = \frac{E\left[(X_N - \mu_N)^4\right]}{\sigma_N^4} = \frac{(1+I_N)^4 E\left[(X_L - \mu_L)^4\right]}{(1+I_N)^4 \sigma_L^4} = \gamma_{2,L}, \tag{21}$$

respectively. Since these equalities hold for all $I_N \in [I_L, I_U]$, we conclude

$$\gamma_{1,N} = \gamma_{1,L}, \quad \gamma_{2,N} = \gamma_{2,L}. \tag{22}$$

Therefore, the skewness and kurtosis of the neutrosophic random variable are identical to those of the classical random variable across the entire indeterminacy interval. This confirms that neutrosophic scaling does not modify distributional shape, further reinforcing the complete dependence of X_N on X_L.

3.8. Entropy Equivalence

3.8.1. Discrete Random Variable

Let X_L be a discrete (classical) random variable with the PMF $P_L(X_L = x_L)$. The Shannon entropy of X_L is given by

$$H(X_L) = -\sum_{x_L} P_L(x_L)\log\left(P_L(x_L)\right). \tag{23}$$

For the neutrosophic random variable $X_N = (1+I_N)X_L$ with $I_N \in [I_L, I_U]$, the PMF satisfies

$$P_N(X_N = x_N) = P_L\left(X_L = \frac{x_N}{1+I_N}\right). \tag{24}$$

Since each x_N corresponds uniquely to $x_L = x_N/(1+I_N)$, the set of probabilities $\{P_L(x_L)\}$ is preserved. Therefore,

$$H(X_N) = H(X_L), \tag{25}$$

for all $I_N \in [I_L, I_U]$. Thus, the Shannon entropy of the neutrosophic random variable is identical to that of the classical random variable, confirming that interval-valued indeterminacy introduces no additional uncertainty in the discrete case.

3.8.2. Continuous Random Variable

Let X_L be a continuous (classical) random variable with the PDF $f_{X_L}(x_L)$.

Its differential Shannon entropy is

$$H(X_L) = -\int_{-\infty}^{\infty} f_{X_L}(x_L)\log\left(f_{X_L}(x_L)\right)\mathrm{d}x_L. \tag{26}$$

For the neutrosophic random variable $X_N = (1+I_N)X_L$ with $I_N \in [I_L, I_U]$, the PDF is given by

$$f_{X_N}(x_N) = \frac{1}{(1+I_N)} f_{X_L}\left(\frac{x_N}{1+I_N}\right). \tag{27}$$

The entropy of X_N becomes

$$\begin{aligned} H(X_N) &= -\int_{-\infty}^{\infty} f_{X_N}(x_N)\log\left(f_{X_N}(x_N)\right)\mathrm{d}x_N \\ &= H(X_L) + \log(1+I_N). \end{aligned} \tag{28}$$

Since $I_N \in [I_L, I_U]$, the neutrosophic entropy is interval-valued:

$$H(X_N) \in \left[H(X_L) + \log(1+I_L), H(X_L) + \log(1+I_U)\right]. \tag{29}$$

The additive constant $\log(1+I_N)$ arises solely from deterministic scaling and does not represent new uncertainty. Hence, neutrosophic entropy is merely a shifted version of the classical entropy, confirming redundancy in the continuous case as well.

4. Numerical Examples

4.1. Normal Distribution

To illustrate the redundancy of interval-valued indeterminacy, consider

$$X_L \sim N\left(\mu_L = 10, \sigma_L^2 = 4\right) \text{ with } I_N \in [0.1, 0.3].$$

- Mean: $E[X_N] \in [11, 13]$, obtained by scaling $E[X_L] = 10$.
- Variance: $V(X_N) \in [4.84, 6.76]$, obtained by scaling $V(X_L) = 4$.
- CDF: $F_{X_N}(15) \in \left[F_{X_L}(11.54), F_{X_L}(13.64)\right]$, illustrating that the neutrosophic CDF is obtained from the classical CDF through deterministic scaling.
- Entropy: $H(X_N) \in \left[H(X_L) + \log(1.1), H(X_L) + \log(1.3)\right]$, a deterministic shift of the classical entropy.
- Skewness/Kurtosis: identical to classical values (0 and 3).

These calculations confirm that neutrosophic measures are merely interval-scaled versions of classical measures, introducing no new stochastic content.

4.2. Sampling from a Normal Distribution

To illustrate the interval-valued nature of the neutrosophic random variable, consider a classical sample drawn from $X_L \sim N\left(\mu_L = 10, \sigma_L^2 = 1\right)$:

$$X_L = \{9.50, 10.13, 9.92, 10.89, 10.12\}.$$

Let the indeterminacy vary over $I_N \in [0.1, 0.3]$. Then the parameters of the neutrosophic normal distribution are $\mu_N \in [11, 13]$ and $\sigma_N^2 \in [1.21, 1.69]$.

For each observation $x_{L,i}$, for $i = 1, 2, \cdots, 5$, the neutrosophic random variable is

$$X_{N,i} \in \left[(1+0.1)X_{L,i}, (1+0.3)X_{L,i}\right].$$

Explicitly, the neutrosophic sample is given by

$$\begin{aligned} X_{N,1} &\in [10.45, 12.35], \\ X_{N,2} &\in [11.14, 13.17], \\ X_{N,3} &\in [10.91, 12.90], \\ X_{N,4} &\in [11.98, 14.16], \\ X_{N,5} &\in [11.13, 13.16]. \end{aligned}$$

The classical MLEs are

$$\hat{\mu}_L = 10.11 \text{ and } \hat{\sigma}_L^2 = 0.20.$$

The neutrosophic MLEs are interval-scaled versions:

$$\hat{\mu}_N \in [11.12, 13.14] \text{ and } \hat{\sigma}_N^2 \in [0.24, 0.34].$$

These MLEs can be verified as

$$\hat{\mu}_N \in \left[(1.1)\cdot(10.11), (1.3)\cdot(10.11)\right] = [11.12, 13.14] \text{ and}$$

$$\hat{\sigma}_N^2 \in \left[(1.1)^2\cdot(0.20), (1.3)^2\cdot(0.20)\right] = [0.24, 0.34].$$

This example confirms that each neutrosophic observation is simply a deterministic interval scaling of the classical sample, and that neutrosophic estimators are scaled versions of their classical counterparts. Moreover, the transformation is reversible: since the indeterminacy bounds are fixed and known, each original classical observation can be recovered exactly from either endpoint as $X_i = X_{L,i}/(1+I_L) = X_{U,i}/(1+I_U)$. Thus, the neutrosophic sample contains the same underlying information as the classical sample, expressed in interval form. No new randomness or inferential content is introduced by the interval-valued indeterminacy. Similar numerical examples can be found in Aslam [11] and Aslam [12].

More importantly, the example illustrates a general relationship rather than merely a numerical coincidence. Once the classical observations are given, every endpoint of every neutrosophic observation is determined. Conversely, when the fixed indeterminacy interval is known, the original classical observations can be recovered exactly from either endpoint. Thus, the mapping between the classical and neutrosophic observations is one-to-one and involves only deterministic scaling. Consequently, the neutrosophic representation does not provide a different statistical analysis; it merely expresses the same classical analysis in interval form.

5. Conclusions

This paper establishes that the neutrosophic random variable X_N is not a genuinely new construct but an interval-valued deterministic scaling of the classical random variable X_L. When I_N is treated as a fixed but interval-valued indeterminacy, the neutrosophic formulation yields ranges of classical measures rather than independent stochastic behavior. Distributional forms, likelihoods, entropy, and higher-order moments retain their classical structure, with differences arising only through deterministic rescaling or, in the case of continuous entropy, an additive shift. Numerical examples confirm that neutrosophic observations and estimators are interval-valued representations of their classical counterparts.

Thus, the interval-valued indeterminacy introduces no new stochastic or inferential content. The neutrosophic random variable is mathematically equivalent to a deterministic transformation of a classical random variable and, under the fixed interval-valued formulation considered here, does not constitute a substantive extension of classical probability theory.

Author Contributions

AH conceptualized the study and prepared the original manuscript. JS reviewed the manuscript and contributed to its improvement and refinement. Both authors read and approved the final version of the manuscript.

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No potential conflict of interest was reported by the authors.

Data Availability Statement

The work presented in this paper is theoretical/methodological in nature and does not involve any data.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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