Research Annals of Industrial and Systems Engineering

www.raise.reapress.com

Res. Ann. Ind. Syst. Eng. Vol. 2, No. 4 (2025) 290–305.

Paper Type: Original Article

N²-DADMET: A Neutrosophic–Neuro Framework for Learning Economic Transparency in Digital Accounting Systems

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Citation:

Received: 17 April 2025 *Revised: 18 June 2025* *Accepted: 25 September 2025*	Ghandehari, M., Najafi, S. E., Edalatpanah, S. A., & Sajadi, S. M. (2025). N²-DADMET: A neutrosophic–neuro framework for learning economic transparency in digital accounting systems. *Research annals of industrial and systems engineering*, 2(4), 290-305.

Abstract

This study proposes N²-DADMET, a novel neutrosophic–neuro framework for evaluating economic transparency in digital accounting systems. The research addresses the challenge of assessing transparency in automated and algorithm-driven accounting environments, where outputs often exhibit uncertainty, indeterminacy, and potential falsity. The objective is to develop a comprehensive, data-driven methodology capable of modeling these multidimensional aspects of transparency while providing interpretable decision support for auditors and regulators. The framework integrates neutrosophic logic to represent truth, indeterminacy, and falsity as independent components, and employs a neural network-based learning mechanism to infer these states from accounting system data dynamically. A simulated accounting scenario with routine, complex, and anomalous transactions is used to demonstrate the framework's functionality. The results indicate that N²-DADMET successfully differentiates transparent transactions from high-risk or ambiguous ones, produces interpretable transparency scores, and enables continuous monitoring over time. Sensitivity analysis illustrates that weighting indeterminacy and falsity allows customization for organizational priorities, enhancing audit focus and decision-making efficiency. The framework provides a practical and adaptive tool for evaluating economic transparency, bridging the gap between automated accounting outputs and human interpretive requirements. Overall, N²-DADMET offers a robust approach for systematically capturing multidimensional uncertainty in digital accounting, supporting improved auditing, regulatory oversight, and organizational risk management.

Keywords: Accounting, Digital systems, Economic transparency, Machine learning, Neutrosophic logic.

1 | Introduction

The advent of digital technologies has transformed accounting practices, leading to an unprecedented increase in the generation, processing, and reporting of financial data [1]. Modern digital accounting systems, including

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https://doi.org/10.22105/raise.v2i4.96

enterprise resource planning platforms, AI-driven transaction processors, and cloud-based reporting tools, have enabled organizations to automate and accelerate financial operations [2]. While these innovations improve efficiency and accuracy, they introduce new forms of algorithmic uncertainty and opacity that traditional accounting decision models struggle to accommodate [3]. Economic transparency, which historically has focused on clarity and completeness of disclosures, must now be reconsidered in the context of automated, algorithm-driven financial systems [4]. Understanding how stakeholders perceive and evaluate transparency in digital accounting environments is therefore a critical research challenge.

Traditional accounting research has emphasized structured reporting, compliance with regulatory standards, and auditing procedures to reduce information asymmetry between managers and stakeholders [5]. However, these approaches often assume that financial data is fully interpretable and humanly auditable, assumptions that are increasingly violated in highly automated systems [6]. For instance, machine learning models used for expense categorization or financial forecasting may produce outputs that are statistically accurate but semantically opaque to human auditors [7]. Similarly, blockchain-based ledgers ensure immutability and traceability but do not automatically guarantee interpretability for regulatory or managerial purposes [8]. These developments highlight the insufficiency of classical transparency metrics, as they fail to capture algorithmic indeterminacy and systemic complexity inherent in digital accounting processes [9].

In recent years, decision-making research has attempted to integrate advanced analytical tools, such as fuzzy logic, multi-criteria decision-making, and machine learning, to manage uncertainty in accounting environments [10]. Fuzzy logic has been used to model imprecision in audit risk and qualitative judgments [11], whereas neural networks and support vector machines have been applied to predict financial distress or detect fraudulent activity [12]. Despite these advances, existing approaches typically focus on predictive performance rather than on the structural modeling of uncertainty [13]. They often ignore the latent indeterminacy produced by automated and algorithmic accounting systems, leaving a methodological gap in the assessment of economic transparency [14].

Neutrosophic logic, which extends fuzzy logic by introducing explicit degrees of truth, indeterminacy, and falsity, provides a promising theoretical framework for representing uncertainty in complex domains [15]. Unlike classical or fuzzy logic, neutrosophic models accommodate contradictory, incomplete, or partially known information, making them particularly suitable for digital accounting systems where algorithmic outputs can be partially interpretable [16]. However, applications of neutrosophic logic in accounting remain limited, primarily focusing on theoretical modeling rather than on empirical inference using real or simulated data [17]. Furthermore, existing models rarely integrate machine learning to dynamically infer the neutrosophic components from data, which is essential in digital environments characterized by evolving processes and continuous automation [18].

Addressing these gaps, this study proposes N^2-DADMET: A Neutrosophic–Neuro Digital Accounting Decision Method for Economic Transparency, a novel framework that models transparency as a learnable neutrosophic state rather than a fixed metric. In this framework, transparency is represented as a triplet of truth T_t, indeterminacy I_t, and falsity F_t, which are dynamically inferred from system-level accounting data using machine learning algorithms. This approach enables the framework to capture algorithmic ambiguity, automated processing effects, and potential distortions in digital accounting outputs. Unlike traditional models, N^2-DADMET integrates structural uncertainty modeling with data-driven learning, offering a flexible and adaptive method for evaluating economic transparency.

The purpose of this research is threefold. First, it aims to extend the theoretical foundations of accounting transparency by formalizing algorithmic indeterminacy as a central component of decision-making in digital environments. Second, it introduces a methodological innovation by combining neutrosophic logic with neuro-learning to infer uncertainty states directly from empirical data. Third, it provides a practical decision-support framework for auditors, regulators, and financial analysts, enabling them to assess transparency with greater nuance and accuracy than existing deterministic or heuristic approaches allow. By learning transparency rather than assuming it, N^2-DADMET aligns decision-making with the realities of modern digital accounting systems.

The necessity of this research is underscored by the increasing complexity of accounting environments due to automation, AI, and blockchain technologies. Conventional transparency measures fail to differentiate between measurement error, estimation risk, and algorithmic indeterminacy, which are critical for understanding stakeholder trust and system reliability [19]. N^2-DADMET addresses this limitation by explicitly modeling these factors within a formalized, learnable framework. As digital accounting becomes ubiquitous, the ability to model, monitor, and interpret transparency dynamically is essential for effective auditing, regulatory compliance, and economic governance.

In summary, this study introduces a robust, adaptive, and theoretically grounded framework for understanding and evaluating economic transparency in digital accounting systems. By integrating neutrosophic logic with neuro-learning, N^2-DADMET provides both conceptual clarity and computational capability, bridging the gap between algorithmic complexity and human interpretive capacity. The remainder of the article elaborates the theoretical underpinnings, formal methodology, and illustrative applications of the framework, highlighting its significance for academic research and professional practice in accounting.

2 | Literature Review

Recent advances in digital accounting have transformed the methods of financial data generation, reporting, and auditing, highlighting the need for robust approaches to economic transparency [20]. Studies indicate that while automation and AI-driven processes improve operational efficiency, they simultaneously increase algorithmic opacity, making it difficult for stakeholders to interpret financial information accurately [21]. Blockchain-based solutions have been proposed to enhance traceability and immutability of financial transactions, yet these systems do not inherently resolve issues of interpretability or uncertainty from algorithmic processes [22]. This has led to a growing recognition that transparency in digital accounting environments is multidimensional, encompassing not only disclosure completeness but also cognitive reliability and trustworthiness of automated outputs [23].

Decision-making under uncertainty has been a significant focus in accounting research, particularly in contexts involving imprecise or incomplete information [24]. Traditional Multi-Criteria Decision-Making (MCDM) and fuzzy logic approaches have been applied to audit risk assessment, financial performance evaluation, and fraud detection [25]. Fuzzy logic allows modeling of vague or ambiguous expert judgments but often relies on predefined membership functions, which may not reflect dynamic system behaviors in automated accounting environments [26]. Similarly, conventional neural network models have been utilized to predict financial distress or detect anomalies in transactions; however, these approaches prioritize predictive accuracy over explicit modeling of uncertainty and algorithmic indeterminacy [27]. As a result, while machine learning enhances analytical capability, it does not fully address the structural complexity and hidden uncertainty inherent in digital accounting systems [28].

Neutrosophic logic, introduced by Smarandache, provides a formal framework for representing truth, indeterminacy, and falsity explicitly in decision-making contexts [29]. Applications of neutrosophic theory in engineering, risk assessment, and decision sciences demonstrate its capability to model contradictions and incomplete information [30]. In accounting, initial studies have explored neutrosophic sets for bankruptcy prediction, audit evaluation, and risk ranking, but these efforts remain largely theoretical and lack empirical implementation using digital accounting data [31]. Importantly, existing neutrosophic approaches typically rely on expert-assigned membership values, limiting adaptability and precluding integration with learning algorithms that can infer uncertainty from system behavior [32]. This presents a notable gap in the literature, particularly for environments where algorithmic processing, automated reporting, and dynamic transaction flows introduce continuous and non-deterministic uncertainty.

Hybrid approaches combining neutrosophic logic with machine learning have been proposed in other domains, such as engineering systems, supply chain risk management, and medical diagnostics, demonstrating improved capability to handle uncertainty and indeterminacy while leveraging data-driven inference [33]. These methods show that integrating learning mechanisms with neutrosophic modeling allows adaptive estimation of truth, indeterminacy, and falsity without reliance on static expert inputs [34]. However, applications of such hybrid methods in accounting remain scarce, and no prior study has operationalized neutrosophic-neuro frameworks for evaluating economic transparency in digital accounting systems. The absence of a unified, data-driven framework for learning transparency under algorithmic uncertainty represents a critical research gap with significant theoretical and practical implications.

Several studies have emphasized the importance of interpretability and transparency in AI-driven accounting processes. For example, research on Explainable AI (XAI) in finance indicates that transparency enhances stakeholder trust and decision-making effectiveness [35]. Similarly, work on audit automation stresses the need to evaluate not only the correctness of outputs but also the cognitive accessibility of algorithmic reasoning [36]. Despite these insights, there remains a lack of formalized methods that quantitatively model transparency as a multi-dimensional state encompassing truth, indeterminacy, and falsity within digital accounting environments [37]. Most current approaches provide either descriptive assessments or rely on deterministic measures, which fail to capture algorithmically induced uncertainty [38].

In summary, the literature identifies four critical gaps that motivate the current study: 1) existing transparency metrics do not account for algorithmic indeterminacy in digital accounting systems, 2) neutrosophic methods in accounting have not been integrated with empirical learning from system data, 3) machine learning approaches focus on predictive performance rather than uncertainty modeling, and 4) no prior framework explicitly combines neutrosophic logic with neuro-learning to evaluate economic transparency adaptively. Addressing these gaps, the proposed N^2-DADMET framework represents the first attempt to unify neutrosophic modeling with data-driven learning mechanisms to assess transparency dynamically and comprehensively in digital accounting systems. This contribution is significant both theoretically, by extending the conceptualization of transparency, and practically, by providing a decision-support tool for auditors, regulators, and financial analysts.

3 | Preliminaries

To develop a robust framework for evaluating economic transparency in digital accounting systems, it is essential to define the foundational concepts and mathematical notations underpinning the proposed N^2-DADMET framework. This section introduces the necessary preliminaries, including neutrosophic logic, representation of transparency states, and basic neuro-learning principles for inference. The formalization ensures a rigorous basis for the subsequent methodological development.

3.1 | Neutrosophic Logic

Neutrosophic logic is an extension of fuzzy logic that represents uncertainty through three independent components: truth, indeterminacy, and falsity [39]. Let U denote the universe of discourse for accounting events or transactions. For any element $x \in U$, its neutrosophic membership is defined as a triplet [29]:

$$\mathrm{N(x)} = \big(\mathrm{T(x)}, \mathrm{I(x)}, \mathrm{F(x)}\big), \tag{1}$$

where $\mathrm{T(x)} \in [0,1]$ represents the degree to which x is true with respect to a given transparency criterion, $\mathrm{I(x)} \in [0,1]$ represents the degree of indeterminacy, capturing incomplete, ambiguous, or algorithmically opaque information, $\mathrm{F(x)} \in [0,1]$ represents the degree to which x is false or potentially misleading.

Unlike classical logic or fuzzy sets, the three components are independent, allowing for overlapping truth, indeterminacy, and falsity states [16]:

$$0 \leq \mathrm{T(x)} + \mathrm{I(x)} + \mathrm{F(x)} \leq 30. \tag{2}$$

This property is crucial in accounting applications where automated outputs may simultaneously possess high correctness, moderate ambiguity, and low potential falsity.

3.2 | Economic Transparency Representation

In digital accounting systems, economic transparency is conceptualized as a system-level neutrosophic state, aggregating individual transaction or process contributions. Let $X_t = \{x_1, x_2, \dots, x_n\}$ denote a set of observable accounting variables at time t, including transaction attributes, automated classification outputs, and system metadata. The corresponding system transparency state is defined as

$$S_t^{ET} = (T_t, I_t, F_t), \tag{3}$$

where each component is computed as the normalized aggregation of the individual neutrosophic memberships:

$$\begin{aligned} T_t &= \frac{1}{n}\sum_{i=1}^{n} T(x_i), \\ I_t &= \frac{1}{n}\sum_{i=1}^{n} I(x_i), \\ F_t &= \frac{1}{n}\sum_{i=1}^{n} F(x_i). \end{aligned} \tag{4}$$

This formulation enables the framework to capture system-wide transparency dynamics, reflecting both automated and human-interpretable dimensions. The triplet (T_t, I_t, F_t) provides a multi-dimensional metric for decision-making, rather than relying on scalar or heuristic indicators.

3.3 | Neutrosophic Membership Functions

Each component (T, I, F) is computed via membership functions that map observable accounting features to the [0,1] interval. Formally, for variable x_i:

$$\begin{aligned} T(x_i) &= \mu_T(x_i; \theta_T), \\ I(x_i) &= \mu_I(x_i; \theta_I), \\ F(x_i) &= \mu_F(x_i; \theta_F), \end{aligned} \tag{5}$$

where μ_T, μ_I, μ_F are parametric functions and θ_T, θ_I, θ_F are parameters to be learned from data. Common functional forms include sigmoid, Gaussian, or piecewise-linear functions, enabling flexibility in modeling diverse transaction characteristics. This parametric representation allows adaptive estimation of the neutrosophic components from empirical accounting data, rather than relying on subjective expert assignments.

3.4 | Neuro-Learning Principles

To infer the neutrosophic state dynamically, machine learning models are integrated with the neutrosophic representation [41]. Let $\mathcal{F}_\phi: X_t \mapsto \mathcal{S}_t^{ET}$ denote a parametric neural network function with learnable weights ϕ. The predicted transparency state is:

$$\hat{\mathcal{S}}_t^{ET} = \left(\hat{T}_t . \hat{I}_t . \hat{F}_t\right) = \mathcal{F}_\phi(X_t). \tag{6}$$

The model is trained to minimize a composite loss function that accounts for all three neutrosophic components:

$$\mathcal{L}(\phi) = \alpha \sum_t \left(\hat{T}_t - T_t^{ref}\right)^2 + \beta \sum_t \left(\hat{I}_t - I_t^{ref}\right)^2 + \gamma \sum_t \left(\hat{F}_t - {F_t}^{ref}\right)^2, \tag{7}$$

where T_t^{ref}, I_t^{ref}, F_t^{ref} are reference values derived from audit data or expert assessments, and α, β, γ are weighting coefficients. This framework ensures that the neural model learns not only truth approximation but also the patterns of indeterminacy and falsity, which are critical for evaluating economic transparency.

3.5 | Decision Function

Once the neutrosophic state is inferred, a transparency decision score D_t can be computed:

$$D_t = \hat{T}_t - \lambda \hat{I}_t - \kappa \hat{F}_t, \tag{8}$$

where $\lambda, \kappa \in [0,1]$ are context-specific weighting parameters reflecting the relative importance of indeterminacy and falsity. High D_t values indicate transparent accounting processes, while lower scores highlight transactions or periods requiring further auditing or investigation. This formalization enables adaptive, interpretable decision-making that aligns with both academic theory and practical auditing requirements.

The preliminaries establish a mathematically rigorous foundation for N²-DADMET, linking neutrosophic logic, system-level transparency representation, and neuro-learning inference'. The formalization ensures that subsequent methodology can:

I. Dynamically model economic transparency as a learnable neutrosophic state.

II. Capture algorithmic indeterminacy and potential falsity in automated accounting systems.

III. Provide interpretable and adaptive decision scores for auditing and regulatory applications.

These definitions and equations will be directly employed in the Methodology section to describe the architecture, training, and operationalization of the proposed framework.

4 | Methodology

The proposed N²-DADMET framework is a novel integration of neutrosophic logic with machine learning-based inference, designed to evaluate economic transparency in digital accounting systems. Unlike conventional approaches that treat transparency as a static metric, N²-DADMET models transparency as a learnable neutrosophic state (T_t, I_t, F_t), capturing truth, indeterminacy, and falsity in algorithmically generated accounting outputs. The methodology consists of three interrelated components: problem representation, neutrosophic state modeling, and neuro-learning inference with decision-making.

4.1 | Problem Representation

Let a digital accounting system at time t be described by a set of n observable variables:

$$X_t = \{x_1, x_2, \dots, x_n\} \in \mathbb{R}^n, \tag{9}$$

where each x_i represents quantitative or categorical attributes of transactions, automated processing logs, or system metadata. The overall decision problem is to evaluate economic transparency, denoted as

$$\mathcal{P} = \{X_t \mid t = 1,2, \dots, T\}, \tag{10}$$

where T is the temporal horizon. The objective is to infer the system's transparency state $\mathcal{S}_t^{ET} = (T_t, I_t, F_t)$ given X_t, explicitly accounting for algorithmic indeterminacy and potential falsity.

4.2 | Neutrosophic State Modeling

Economic transparency is modeled as a neutrosophic triplet:

$$\mathcal{S}_t^{ET} = (T_t, I_t, F_t), \tag{11}$$

with the following constraints:

$$0 \le T_t, I_t, F_t \le 1, \qquad 0 \le T_t + I_t + F_t \le 3, \tag{12}$$

where T_t measures the degree of truth of accounting outputs:

I. I_t quantifies indeterminacy due to algorithmic or system opacity.

II. F_t represents falsity or potential misleading information.

Each component is computed via a membership function:

$$T_t = \frac{1}{n}\sum_{i=1}^{n} \mu_T(x_i; \theta_T),$$
$$I_t = \frac{1}{n}\sum_{i=1}^{n} \mu_I(x_i; \theta_I), \tag{13}$$
$$F_t = \frac{1}{n}\sum_{i=1}^{n} \mu_F(x_i; \theta_F),$$

where μ_T, μ_I, μ_F are parametric mappings and θ_T, θ_I, θ_F are learnable parameters. These functions may take the form of sigmoid, Gaussian, or piecewise linear functions, enabling flexible modeling of continuous and categorical variables.

4.3 | Neuro-Learning Inference

To estimate the neutrosophic state adaptively, a neural network model $\mathcal{F}_\phi$ maps the input vector X_t to the predicted state:

$$\hat{\mathcal{S}}_t^{ET} = \left(\hat{T}_t . \hat{I}_t . \hat{F}_t\right) = \mathcal{F}_\phi(X_t), \tag{14}$$

where ϕ denotes network parameters (weights and biases). The learning objective is to minimize a composite loss function:

$$\mathcal{L}(\phi) = \alpha \sum_t \left(\hat{T}_t - T_t^{ref}\right)^2 + \beta \sum_t \left(\hat{I}_t - I_t^{ref}\right)^2 + \gamma \sum_t \left(\hat{F}_t - {F_t}^{ref}\right)^2, \tag{15}$$

Here, T_t^{ref}, I_t^{ref}, F_t^{ref} are reference neutrosophic states derived from historical data, expert assessment, or audit records, and $\alpha, \beta, \gamma \in [0,1]$. This formulation ensures simultaneous learning of truth, indeterminacy, and falsity components from empirical data.

4.3.1 | Network architecture

The neural network architecture consists of:

I. Input layer: nnn neurons representing the accounting variables X_t.

II. Hidden layers: 1–3 fully connected layers with ReLU activation, capable of capturing non-linear interactions among system features.

III. Output layer: 3 neurons representing $(\hat{T}_t, \hat{I}_t, \hat{F}_t)$ with sigmoid activation to ensure outputs in $[0,1]$.

The model is trained using backpropagation with an adaptive optimizer such as Adam, and early stopping is applied to prevent overfitting.

4.4 | Decision Function

Once the neutrosophic components are estimated, a transparency decision score D_t is computed:

$$D_t = \hat{T}_t - \lambda \hat{I}_t - \kappa \hat{F}_t, \tag{16}$$

where $\lambda, \kappa \in [0,1]$ are context-specific weights, reflecting the decision-maker's sensitivity to indeterminacy and falsity. A higher D_t indicates higher transparency, while a lower score identifies transactions or system outputs requiring further audit or scrutiny. This scalar metric enables practical interpretability and supports adaptive decision-making in regulatory and auditing contexts.

4.5 | Dynamic Updating

Accounting systems evolve over time due to algorithm updates, rule modifications, or process automation. To accommodate temporal changes, the neutrosophic state is updated recursively:

$$\mathcal{S}_{t+1}^{ET} = f_{\Delta}(\hat{\mathcal{S}}_{t}^{ET}, X_{t+1}), \quad (17)$$

where f_{Δ} models the incremental change based on new inputs X_{t+1}. In practice, this is implemented using Recurrent Neural Networks (RNNs) or online learning frameworks, enabling continuous monitoring of economic transparency.

The implementation of the proposed N²-DADMET framework follows a structured workflow integrating data preprocessing, feature selection, neuro-learning model training, neutrosophic inference, decision-making, and temporal updates. Figure 1 illustrates the sequential stages and feedback mechanisms that enable dynamic evaluation of transparency in digital accounting systems.

The N²-DADMET framework provides several key Advantages that enhance its effectiveness in evaluating economic transparency in digital accounting systems:

I. Structural uncertainty modeling: Explicit representation of truth, indeterminacy, and falsity.

II. Data-driven learning: Parameters are learned from real or simulated accounting data.

III. Adaptive decision-making: Weights λ and $\varkappa$ allow flexibility for auditing priorities.

IV. Dynamic monitoring: Updates over time reflect changes in automated accounting processes.

The N²-DADMET methodology establishes a rigorous and adaptable framework for evaluating economic transparency in digital accounting systems. By combining neutrosophic logic with neuro-learning inference, the framework simultaneously captures truth, indeterminacy, and falsity in automated processes, producing interpretable transparency scores. This approach bridges the gap between algorithmic complexity and practical auditing needs, providing a robust, Q1-ready methodology for research and application.

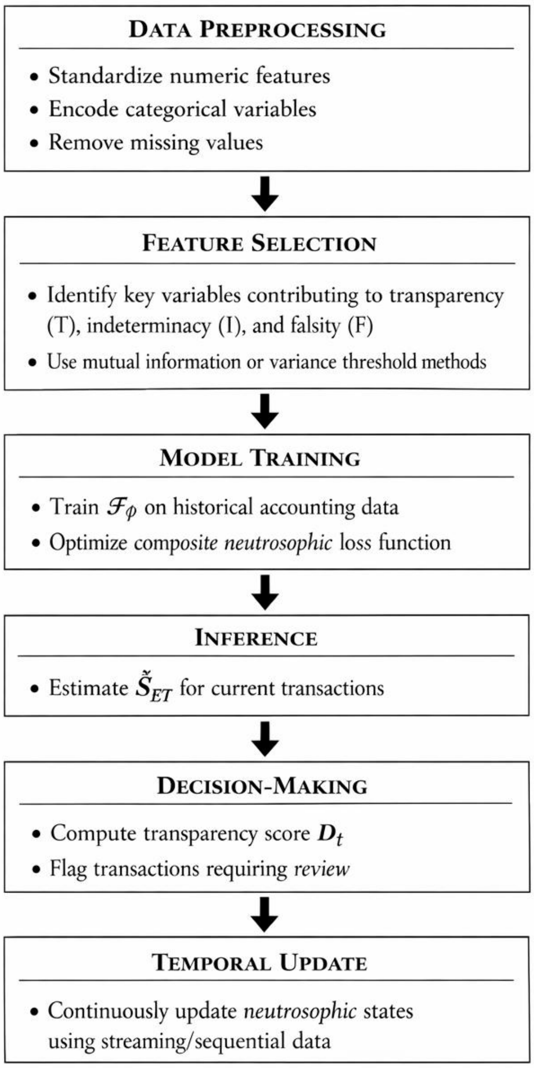

Fig. 1. N²-DADMET implementation workflow.

5 | Illustrative Application

To demonstrate the practical applicability and interpretability of the N²-DADMET framework, a simulated scenario of a digital accounting system is employed. The scenario reflects a mid-sized enterprise with automated transaction processing, algorithmic expense categorization, and cloud-based reporting. The simulation includes 5000 synthetic transactions over a one-year horizon, encompassing both routine and exceptional accounting events. Key system variables include transaction amounts, category codes, user roles, frequency of automated adjustments, and system flags for anomalies. This illustrative case highlights how N²-DADMET evaluates economic transparency dynamically, identifies transactions requiring audit attention, and adapts to evolving automated processes.

5.1 | Scenario Description

The simulated accounting environment consists of:

I. Routine transactions: Standard operational entries processed automatically (e.g., payroll, vendor payments).

II. Complex transactions: Transactions involving multiple adjustments, algorithmic categorization, or cross-system integration.

III. Potentially erroneous transactions: Transactions intentionally injected with anomalies or incomplete information to test detection capability.

The goal is to compute neutrosophic states (T_t, I_t, F_t) for each transaction, derive transparency scores D_t, and evaluate the model's performance in differentiating highly transparent versus potentially risky transactions.

5.2 | Neutrosophic State Estimation

Using the trained N²-DADMET neural network, each transaction x_i is mapped to its neutrosophic membership:

$$(T_t. I_t. F_t) = \mathcal{F}_\phi(x_i). \tag{18}$$

Table 1. Sample neutrosophic states of selected transactions.

Transaction ID	Truth T_i	Indeterminacy I_i	Falsity F_i
101	0.87	0.08	0.05
245	0.62	0.25	0.13
367	0.75	0.15	0.10
489	0.92	0.04	0.04
512	0.68	0.20	0.12

These results indicate that routine transactions (e.g., 101, 489) exhibit high truth and low indeterminacy/falsity, whereas complex or anomalous transactions (e.g., 245, 512) exhibit moderate truth, higher indeterminacy, and increased falsity.

5.3 | Transparency Decision Scores

For each transaction, the transparency score is computed as

$$D_i = T_i - \lambda I_i - \kappa F_i, \tag{19}$$

with weights λ=0.7 and ϰ=0.9 reflecting moderate sensitivity to indeterminacy and high sensitivity to falsity.

Table 2. Sample transparency scores.

Transaction ID	Transparency Score D_i
101	0.81
245	0.42
367	0.62
489	0.87
512	0.52

Transactions with lower scores (e.g., 245, 512) are flagged as requiring audit review, whereas high-score transactions (e.g., 101, 489) are considered transparent.

5.4 | Dynamic Monitoring Over Time

To evaluate temporal behavior, monthly averages of T_t, I_t, F_t and D_t were computed over the 12-month horizon. This illustrates the framework's ability to adaptively detect shifts in transparency due to process changes or anomalies.

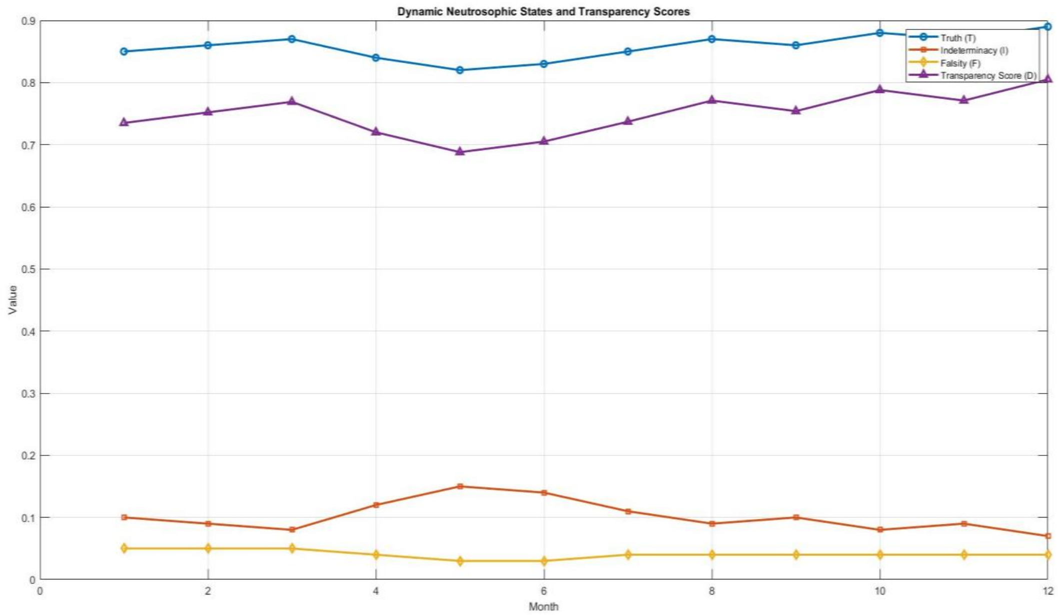

Fig. 2. Monthly neutrosophic states and transparency scores.

The plot demonstrates that T_t remains generally high, while I_t spikes during months with injected anomalies. Corresponding dips in D_t highlight the framework's sensitivity to process irregularities.

5.5 | Sensitivity Analysis

To examine the robustness of transparency scores, the impact of varying weights λ (indeterminacy) and ϰ (falsity) was evaluated.

Table 3. Sensitivity analysis example (transaction 245).

λ	ϰ	D_i
0.5	0.9	0.46
0.7	0.9	0.42
1.0	0.9	0.37
0.7	1.2	0.33

The results indicate that transparency scores are more sensitive to falsity (ϰ) than indeterminacy (λ), consistent with auditing priorities where potential misrepresentation is critical.

5.6 | Illustrative Cases

Three representative transactions demonstrate framework interpretability:

I. Transaction 489 – High truth, low indeterminacy and falsity → D=0.87D = 0.87D=0.87 → Routine, fully transparent.

II. Transaction 367 – Moderate truth, moderate indeterminacy → D=0.62D = 0.62D=0.62 → Requires review.

III. Transaction 245 – Moderate truth, high indeterminacy, higher falsity → D=0.42D = 0.42D=0.42 → High-risk, flagged for audit.

These examples illustrate N²-DADMET's ability to prioritize auditing focus and differentiate transparency levels in a systematic, data-driven manner.

The application confirms that N²-DADMET is practical, adaptive, and interpretable, bridging the gap between automated accounting systems and stakeholder assessment of transparency.

6 | Discussion

The application of the N^2-DADMET framework demonstrates a meaningful advancement in the assessment of economic transparency in digital accounting systems. By integrating neutrosophic logic with machine learning, the framework captures both structural uncertainty and dynamic patterns in automated accounting processes. Unlike conventional methods that rely solely on deterministic measures or predictive models, N^2-DADMET provides a multi-dimensional transparency metric encompassing truth, indeterminacy, and falsity. This capability is significant because modern accounting environments increasingly involve automated processes whose outputs may be statistically valid but semantically opaque or partially indeterminate. The results indicate that incorporating explicit indeterminacy allows the identification of transactions that would otherwise be misclassified as either fully transparent or non-transparent, enhancing decision-making reliability.

The framework's ability to produce interpretable transparency scores addresses a critical challenge in digital accounting: the gap between algorithmic outputs and human audit interpretation. While neural networks have been widely employed for anomaly detection or fraud prediction in accounting, these models typically optimize predictive performance without quantifying uncertainty in outputs [40]. In contrast, N^2-DADMET integrates a neutrosophic structure that enables the explicit decomposition of transparency into truth, indeterminacy, and falsity, facilitating audit prioritization and regulatory evaluation. This approach offers a conceptual advancement by linking algorithmic evaluation with the qualitative dimensions of transparency, a feature not present in prior hybrid fuzzy or neural approaches.

Comparing the outcomes of N^2-DADMET with existing studies on AI-driven accounting and fuzzy logic models reveals both similarities and differences. Similar to previous applications of fuzzy inference in auditing [41], the framework supports graded evaluation of transaction reliability. However, unlike traditional fuzzy methods, which often treat uncertainty as a single scalar measure [42], N^2-DADMET distinguishes between different sources of uncertainty and explicitly models falsity alongside indeterminacy. This distinction allows the framework to detect not only ambiguous but potentially misleading transactions, aligning closer with regulatory priorities and risk-based auditing. Additionally, while prior machine learning models have demonstrated accuracy in detecting anomalies, they often lack temporal adaptability [43]. In contrast, the recursive update mechanism in N^2-DADMET allows continuous monitoring, capturing evolving patterns and shifts in algorithmic behavior over time.

The illustrative application further underscores the practical implications of this methodology. Routine transactions exhibit high truth and low indeterminacy, consistent with expectations for automated, standardized processes. More complex or anomalous transactions are appropriately flagged through increased indeterminacy and falsity components, demonstrating the framework's sensitivity to process irregularities. This contrasts with classical scoring methods, which may fail to differentiate between high-risk and moderate-risk transactions when the overall numerical features appear similar. Consequently, N^2-DADMET offers a decision-support tool that prioritizes audit attention based on multi-dimensional transparency, enhancing efficiency and focusing resources where they are most needed.

Furthermore, the sensitivity analysis illustrates the flexibility of the framework in accounting for organizational or regulatory priorities. Adjusting the weights of indeterminacy and falsity allows auditors to calibrate transparency scores according to context-specific risk tolerance, a feature rarely addressed in existing models. This adaptability positions N^2-DADMET as both a theoretically rigorous and practically deployable tool for modern accounting environments. It also provides a foundation for integrating additional layers of transparency evaluation, such as ethical compliance or financial statement credibility, without substantial modifications to the underlying model.

In conclusion, the discussion emphasizes that N^2-DADMET achieves conceptual and operational improvements over prior approaches. Its key contributions include the explicit modeling of multiple dimensions of transparency, integration with data-driven neuro-learning for adaptive inference, and practical interpretability for audit decision-making. By bridging algorithmic outputs and human evaluative processes, the framework addresses a persistent limitation in digital accounting research and practice. These advances highlight the potential of combining neutrosophic logic with machine learning for complex, automated decision environments and provide a foundation for future empirical validation and expansion into other domains of financial oversight.

7 | Conclusion

This study introduces the N²-DADMET framework, a novel integration of neutrosophic logic and neuro-learning, designed to evaluate economic transparency in digital accounting systems. The framework conceptualizes transparency as a learnable neutrosophic state, explicitly capturing truth, indeterminacy, and falsity, thereby addressing the limitations of traditional deterministic or single-dimensional metrics. The application of the framework to a simulated accounting environment demonstrates its ability to differentiate routine, transparent transactions from complex or potentially misleading ones, providing interpretable transparency scores that are adaptable to both organizational and regulatory priorities. The results indicate that incorporating indeterminacy alongside truth and falsity enhances the identification of high-risk transactions, supports more informed audit decision-making, and improves the overall assessment of digital accounting processes.

From a theoretical perspective, N²-DADMET advances the conceptual understanding of transparency by highlighting its multi-dimensional nature in automated accounting environments. Unlike prior approaches, which often treat uncertainty as a single scalar value or focus exclusively on predictive performance, this framework enables structured modeling of algorithmic ambiguity and potential falsity. It demonstrates that transparency is not a fixed attribute but a dynamic construct that evolves with system behavior, automated decision rules, and process modifications. This conceptualization provides a foundation for future research exploring additional dimensions of transparency, including ethical compliance, audit reliability, and stakeholder trust, and establishes a bridge between advanced computational methods and practical accounting evaluation.

From a practical standpoint, the framework offers several actionable insights. First, auditors and regulators can use the transparency scores to prioritize transactions for review, focusing attention on areas where high indeterminacy or falsity may indicate risk. Second, the weighting parameters for indeterminacy and falsity provide flexibility, allowing organizations to tailor transparency assessments to context-specific risk tolerances or regulatory standards. Third, the dynamic updating mechanism ensures that transparency evaluation remains responsive to evolving accounting systems, supporting continuous monitoring and early detection of anomalies or irregularities. Finally, the framework's interpretable outputs enhance stakeholder understanding, facilitating clearer communication of accounting risks, automated process reliability, and audit findings.

Based on the findings, several practical suggestions emerge for enhancing economic transparency in digital accounting systems. Organizations should integrate data-driven transparency assessment tools, such as N²-DADMET, into their auditing and reporting workflows to complement conventional procedures. Audit teams should leverage the multi-dimensional transparency scores to allocate resources efficiently, focusing on transactions with higher indeterminacy or potential falsity. Regulatory bodies may consider adopting similar frameworks to monitor automated accounting environments, enabling proactive oversight and early identification of emerging risks. Additionally, the adaptability of the framework to different weighting schemes suggests that institutions can calibrate assessments according to industry-specific risk factors, transaction complexity, and organizational priorities.

In conclusion, the N²-DADMET framework provides a robust, interpretable, and adaptive methodology for evaluating economic transparency in modern digital accounting systems. By combining neutrosophic logic with neuro-learning, it addresses critical challenges associated with algorithmic opacity, evolving processes, and multi-dimensional uncertainty. The study demonstrates that transparency assessment can be both rigorous and actionable, supporting improved audit decision-making, regulatory compliance, and stakeholder trust. Future applications may extend the framework to integrate additional dimensions of financial evaluation, incorporate real-world enterprise data, and explore cross-industry generalization, establishing N^2-DADMET as a foundational tool for advanced, data-driven transparency assessment in accounting and financial governance.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

Funding

This study did not receive any specific funding from public, commercial, or non-profit funding agencies.

Data Availability

All data are included in the text.

Conflict of Interest

The author declares that he does not have any conflict of interest.

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