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A Novel Decision-Making Framework For Cybersecurity Risk Assessment Using Interval-Valued Intuitionistic Fuzzy Soft Sets

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Abstract: Cybersecurity risk evaluation is a sophisticated decision-making challenge characterized by uncertainty and ambiguous expert opinions. Conventional models, which depend on exact numerical values, inadequately address the intrinsic vagueness of these evaluations. This paper introduces a comprehensive framework based on Interval-Valued Intuitionistic Fuzzy Soft Sets (IVIFSS), which is adept at managing such uncertainty by concurrently reflecting an expert's levels of belief, disbelief, and indecision for each criterion through intervals. We outline the IVIFSS model along with its aggregation techniques—restricted union and intersection—to amalgamate assessments from various experts, providing formal demonstrations of their algebraic characteristics. A comprehensive numerical case study evaluating IT infrastructure elements illustrates the framework's applicability. The findings reveal a clear prioritization of assets, with the customer database server identified as the most critical component. A comparative evaluation against alternative fuzzy methodologies presented in tabular format highlights the enhanced expressiveness and robustness of the proposed model. This research concludes that the IVIFSS framework offers a systematic, mathematically rigorous, and exceptionally effective approach for ranking cybersecurity risks, surpassing traditional methods.

***Index Terms* -** Cybersecurity, Risk Assessment, Interval-Valued Intuitionistic Fuzzy Soft Sets, Multi-Criteria Decision-Making, Uncertainty, Algebraic Properties.

1. INTRODUCTION

The increasing prevalence and sophistication of cyber threats have rendered comprehensive risk assessment an indispensable element of organizational defense strategies. This procedure encompasses the identification of critical assets, assessment of threats based on factors such as probability and impact, and the prioritization of mitigation strategies. Nevertheless, a considerable challenge arises from the qualitative and subjective nature of the information provided by security professionals. Assertions regarding a threat's "high probability" or a vulnerability's "significant impact" are intrinsically ambiguous. Conventional models that compel experts to allocate a single, exact figure (e.g., 8/10) are insufficient, as they overlook the expert's confidence level and the underlying uncertainty within their own evaluations.

To represent such ambiguity, Zadeh (1965) [19] proposed fuzzy set theory, which assigns a degree of membership to various elements. Atanassov (1986) [5] built upon this with Intuitionistic Fuzzy Sets (IFS) [11,15,16], incorporating a non-membership degree to clearly depict an expert's skepticism, with the difference serving as a measure of hesitancy. Molodtsov's soft set theory [14] offered a parameterization mechanism that is particularly suited for multi-criteria issues. The integration of these theories culminated in the robust Interval-Valued Intuitionistic Fuzzy Soft Set (IVIFSS) [4,9,15], wherein both membership and non-membership are expressed as ranges rather than singular values. This enables an expert to articulate their confidence as "ranging from 70% to 80%," providing a significantly more nuanced and vivid portrayal of human evaluation.

Although utilized in diverse sectors such as supply chain management and renewable energy planning [2,13], the application of Interval-Valued Intuitionistic Fuzzy Soft Sets (IVIFSS) in the realm of cybersecurity risk assessment is still predominantly uncharted. Recent literature emphasizes the underutilization of fuzzy methodologies in cybersecurity, despite their inherent capacity to effectively address uncertainties in expert judgment [5]. Additionally, although recent investigations have employed Intuitionistic Fuzzy Sets (IFS) for risk evaluation [2], the comprehensive potential of the interval-valued extension to encapsulate ranges of expert confidence remains largely unexploited within this field. This paper addresses this deficiency by proposing a specialized IVIFSS framework that enables security teams to capture refined expert insights, amalgamate various viewpoints, and distinctly prioritize risks. The primary contributions include: (1) the formal implementation of IVIFSS to cybersecurity risk metrics, supported by mathematical demonstrations of aggregation properties, (2) the application of restricted union and intersection for the synthesis of expert evaluations, (3) a practical illustration that provides clear, actionable risk prioritization, and (4) a comparative assessment showcasing superiority over current fuzzy approaches.

2. METHOD

2.1 Theoretical Foundation

This subsection delineates the critical mathematical principles that underpin the proposed framework. The definitions advance from basic set theories to the more intricate structures employed in this research.

Definition 2.1 Fuzzy Set (FS) [16,19]**:** This was the first mathematical model to capture partial truth, moving beyond the classical binary (yes/no) logic. It allows an element to be a member of a set to a certain degree.

Let U be a universal set then a fuzzy set A in U define as:

$$A=\left\{\left\langle x,\mu_A(x)\right\rangle \middle| x\in U\right\}$$

Where, $\mu_A(x):U\to[0,1]$ is a membership function of x in A. The value of $\mu_A(x)$ denotes the degree of belongingness of x to the fuzzy set A.

Definition 2.2 Intuitionistic Fuzzy Set (IFS) [5,11]**:** IFS is a generalization of fuzzy sets that separately quantifies an expert's belief (μ), disbelief (υ), and uncertainty (π), providing a more nuanced model of human judgment.

Let U be a universal set then an Intuitionistic fuzzy set A in U define as:

$$A=\left\{\left\langle x,\mu_A(x),\upsilon_A(x)\right\rangle \middle| x\in U\right\}$$

Where, $\mu_A(x):U\to[0,1]$ and $\upsilon_A(x):U\to[0,1]$ is a membership and non-membership function of x in A, respectively, satisfying the condition $0\le\mu_A(x)+\upsilon_A(x)\le1$ for all $x\in U$.

The value $\pi_A(x)=1-\mu_A(x)-\upsilon_A(x)$ is called the hesitancy margin of x in A, representing the degree of indeterminacy or uncertainty.

Definition 2.3 Interval-Valued Intuitionistic Fuzzy Set (IVIFS) [4,11]**:** IVIFS is a further generalization where membership and non-membership are represented as intervals. This is particularly powerful for capturing the range of an expert's confidence, making it exceptionally suitable for modeling group opinions or individual uncertainty.

Let U be a universe of discourse. An interval-valued intuitionistic fuzzy set A in U is define as:

$$A=\left\{\left\langle x,\left[\mu_A^L(x),\mu_A^U(x)\right],\left[\upsilon_A^L(x),\upsilon_A^U(x)\right]\right\rangle \middle| x\in U\right\}$$

Where, $\left[\mu_A^L(x),\mu_A^U(x)\right]\subseteq[0,1]$ is the interval-valued membership function;

$\left[\upsilon_A^L(x),\upsilon_A^U(x)\right]\subseteq[0,1]$ is the interval-valued non-membership function

These interval satisfying the condition $0\le\mu_A^U(x)+\upsilon_A^U(x)\le1$ for all $x\in U$.

The interval-valued hesitancy margin is calculated as $\left[\pi_A^L(x),\pi_A^U(x)\right]=\left[1-\mu_A^U(x)-\upsilon_A^L(x)\right]$.

Definition 2.4 Soft Set [12,14]**:** Soft set theory provides a flexible framework for dealing with uncertainty by parameterization. It allows us to define different "views" or "criteria" (parameters) on the same universal set.

Let U be a universal set and E be a set of parameters then a pair (F,E) is called soft set over U if F is a mapping given by $F:E\to P(U)$, where $P(U)$ is the power set of U.

In other word a soft set is a parameterized family of the subset of the universal set U. For any parameter $e\in E$, $F(e)$ is considered the set of e-approximate element of the soft set.

Definition 2.5 Fuzzy Soft Set [11,19]**:** This is a hybrid model combining fuzzy sets and soft sets. For each parameter, we do not have a crisp set of elements, but a fuzzy set describing the degree to which each element satisfies that parameter.

Let U be a universal set and E be the set of parameters. Let $F(U)$ denote the set of all fuzzy subset of U. A pair of (F,E) is called a fuzzy soft set over U if F is a mapping given by $F:E\to F(U)$.

Definition 2.6 Intuitionistic Fuzzy Soft Set (IFSS) [5,11]**:** IFSS combines the parameterization power of soft sets with the expressive capability of IFS, allowing for the modeling of belief, disbelief, and hesitancy across multiple criteria.

Let U be universal set and E be a set of parameters . If $IF(U)$ denote the set of all intuitionistic fuzzy subsets of U. A pair of (F,E) is called an intuitionistic fuzzy soft set over U if F is a mapping given by $F:E\to IF(U)$.

Definition 2.7 Interval-Valued Intuitionistic Fuzzy Soft Set (IVIFSS) [4]**:** The IVIFSS framework, which serves as the foundation of this study, embodies the most comprehensive architecture within this context. It utilizes: Parameterization derived from soft set theory to address various criteria. Belief, Disbelief, and Hesitancy from IFS to effectively represent expert evaluations. Interval Values from IVIFS to encapsulate the spectrum and ambiguity inherent in those evaluations. This positions it as an extremely robust instrument for intricate Multi-Criteria Decision-Making (MCDM) challenges amid uncertainty, such as assessments of cybersecurity risks.

Let U be universal set and E be a set of parameters . If $IVIF(U)$ denote the set of all interval-valued intuitionistic fuzzy subsets of U. A pair of (F,A) is called an interval-valued intuitionistic fuzzy soft set over U, where $A\subseteq E$ and F is a mapping given by $F:A\to IVIF(U)$.

For any parameters $e\in A$, $F(e)$ is an IVIFS of U and can be written as:

$$F(e)=\left\{\frac{\left\langle x,\left[\mu_{F(e)}^{L}(x),\mu_{F(e)}^{U}(x)\right],\left[\upsilon_{F(e)}^{L}(x),\upsilon_{F(e)}^{U}(x)\right]\right\rangle}{x}:x\in U\right\}$$

2.2 Problem Formulation

The issue of cybersecurity risk assessment is articulated within the organized paradigm of interval-valued intuitionistic fuzzy soft set theory, aimed at methodically tackling the intrinsic uncertainties associated with expert evaluations. The scope of discussion encompasses three essential IT assets that constitute the foundation of the organization's digital framework: $U=\{a_1,a_2,a_3\}$ where a_1 represent the customer database server, a_2 denotes public facing web server and a_3 signifies the internal HR workstation. These assets were chosen based on their diverse degrees of exposure, significance to business functions, and potential ramifications in the event of security incidents. The evaluation criteria are established through an extensive parameter set $E=\{e_1,e_2,e_3\}$, where e_1 signifies High Likelihood of Attack, reflecting the chance of security breaches; e_2 denotes High Impact of Breach, assessing the possible repercussions of successful intrusions; and e_3 represents Inadequate Existing Controls, analyzing the efficacy of current security protocols. To guarantee a comprehensive evaluation, several expert teams contribute their assessments: Team 1 (Network Security Team) concentrates on technical threat parameters $A=\{e_1,e_2\}$, while Team 2 (Compliance & Risk Team) evaluates control and impact parameters $B=\{e_2,e_3\}$, with parameter e_2 acting as a shared evaluation standard that facilitates comparative analysis and integration of various expert insights. This methodical framework lays a solid groundwork for employing IVIFSS operations to amalgamate multi-dimensional risk evaluations and produce actionable security prioritizations.

2.3 Aggregation Operations and Mathematical Proofs

In order to consolidate expert insights, it delineate two fundamental operations for IVIFSSs (F,A) and (G,B) within a shared universe U, where $C=A\cap B$. These operations correspond with the aggregation functions effectively utilized in contemporary MCDM research employing IVIFS [10].

Definition 2.8 Restricted union (Pessimistic/Risk-Averse View): $(F,A)\cap_R(G,B)=(H,C)$ for $e\in C$ and $x\in U$:

$$\mu_{H(e)}^{L}(x)=\max\left(\mu_{F(e)}^{L}(x),\mu_{G(e)}^{L}(x)\right),\qquad \mu_{H(e)}^{U}(x)=\max\left(\mu_{F(e)}^{U}(x),\mu_{G(e)}^{U}(x)\right)$$

$$\upsilon_{H(e)}^{L}(x)=\min\left(\upsilon_{F(e)}^{L}(x),\upsilon_{G(e)}^{L}(x)\right)\qquad \upsilon_{H(e)}^{U}(x)=\min\left(\upsilon_{F(e)}^{U}(x),\upsilon_{G(e)}^{U}(x)\right)$$

This operation emphasizes the highest perceived threat, suitable for risk-averse strategy.

Theorem 2.1 (Closure Property): The operation of limiting both the union and intersection of two Interval-Valued Intuitionistic Fuzzy Soft Sets (IVIFSSs) results in the formation of yet another Interval-Valued Intuitionistic Fuzzy Soft Set (IVIFSS).

Proof:

Let $(H,C)=(F,A)\cup_R(G,B)$. It need to show that for any $e\in C$ and $x\in U$, $H(e)(x)$ is a valid IVIFS, i.e. $0\le\mu_{H(e)}^{U}(x)+\upsilon_{H(e)}^{U}(x)\le 1$.

From the definition:

$$\mu_{H(e)}^{U}(x)=\max\left(\mu_{F(e)}^{U}(x),\mu_{G(e)}^{U}(x)\right)$$

$$\upsilon_{H(e)}^{U}(x)=\min\left(\upsilon_{F(e)}^{U}(x),\upsilon_{G(e)}^{U}(x)\right)$$

Since $F(e)(x)$ and $G(e)(x)$ are IVIFS, we have:

$$\mu_{F(e)}^{U}(x)+\upsilon_{F(e)}^{U}(x)\le 1 \text{ and } \mu_{G(e)}^{U}(x)+\upsilon_{G(e)}^{U}(x)\le 1$$

Without loss of generation assume $\mu_{H(e)}^{U}(x)=\mu_{F(e)}^{U}(x)$ then:

$$\mu_{H(e)}^{U}(x)+\upsilon_{F(e)}^{U}(x)=\mu_{F(e)}^{U}(x)+\min\left[\upsilon_{F(e)}^{U}(x),\upsilon_{G(e)}^{U}(x)\right]\le\mu_{F(e)}^{U}(x)+\upsilon_{F(e)}^{U}(x)\le 1$$

In a like manner, the condition of non-negativity is satisfied. Consequently, $H(e)(x)$ qualifies as a legitimate IVIFS. The demonstration for the constrained intersection proceeds in a similar fashion.

Theorem 2.2 (Commutativity): The operations pertaining to the restricted union and intersection are characterized by their commutative nature, which indicates that the order in which these operations are performed does not affect the ultimate outcome, thus demonstrating a fundamental property within the realm of set theory.

Proof:

We need to show $(F,A)\cup_R(G,B)=(G,B)\cup_R(F,A)$

Let $(H,C)=(F,A)\cup_R(G,B)$ and $(K,C)=(G,B)\cup_R(F,A)$ where, $C=A\cap B$.

For any $e\in C$ and $x\in U$:

$$\mu_{H(e)}^{L}(x)=\max\left[\mu_{F(e)}^{L}(x),\mu_{G(e)}^{L}(x)\right]=\max\left[\mu_{G(e)}^{L}(x),\mu_{F(e)}^{L}(x)\right]=\mu_{K(e)}^{L}(x)$$

The same holds for μ^{U}, υ^{L} and υ^{U}. Thus $H(e)=K(e)$ for all $e\in C$ providing commutativity.

Theorem 2.3 (Idempotency): The operations of restricted union and intersection exhibit the property of idempotency, which means that when these operations are applied multiple times to the same set, the result remains unchanged after the first application, thereby demonstrating a fundamental characteristic of these mathematical functions in set theory.

Proof:

We need to show $(F,A)\cup_R(F,A)=(F,A)$

Let $(H,A)=(F,A)\cup_R(F,A)$ for any $e\in A$ and $x\in U$:

$$\mu_{H(e)}^{L}(x)=\max\left[\mu_{F(e)}^{L}(x),\mu_{F(e)}^{L}(x)\right]=\mu_{F(e)}^{L}(x)$$

The same holds for μ^{U}, υ^{L} and υ^{U}. Thus $H(e)=F(e)$ for all $e\in A$ providing idempotency.

3. RESULT

The established framework was meticulously employed to evaluate the three distinct assets, identified as a_1, a_2 and a_3 utilizing the specific parameters provided by two highly knowledgeable expert teams who possess extensive experience in this domain. The preliminary assessments derived from the IVIFSS methodology are presented in the subsequent section, showcasing the initial evaluations that have been conducted to ensure a comprehensive analysis of the aforementioned assets.

Table I: Initial Expert Assessments

Team	*Parameter*	*Asset*	*Membership [μ^L, μ^U]*	*Non-Membership [v^L, v^U]*
1 (F)	e_1: High Likelihood	a_1	[0.7, 0.8]	[0.1, 0.2]
		a_2	[0.8, 0.9]	[0.0, 0.1]
		a_3	[0.3, 0.5]	[0.4, 0.5]
	e_2: High Impact	a_1	[0.9, 1.0]	[0.0, 0.0]
		a_2	[0.6, 0.7]	[0.2, 0.3]
		a_3	[0.4, 0.6]	[0.2, 0.3]
2 (G)	e_2: High Impact	a_1	[0.8, 0.9]	[0.0, 0.1]
		a_2	[0.7, 0.8]	[0.1, 0.2]
		a_3	[0.5, 0.6]	[0.3, 0.4]
	e_3: Inadequate Controls	a_1	[0.6, 0.7]	[0.2, 0.3]
		a_2	[0.9, 1.0]	[0.0, 0.0]
		a_3	[0.2, 0.4]	[0.5, 0.6]

The execution of the restricted union was meticulously carried out on the prevalent parameter e_2, which is categorized as having a High Impact of Breach, in order to derive a comprehensive and risk-averse consolidated perspective that encapsulates the various facets of potential vulnerabilities. The findings and results stemming from this analytical process have been systematically compiled and are succinctly summarized in Table II, which serves as a pivotal reference point for stakeholders seeking to understand the implications of the data presented.

Table II: Result of Restricted Union on Parameter $e_2\left[(F,A)\cup_R(G,B)\right]$

Asset	*Aggregated IVIFS Value on e_2*	*Implied Risk Level*
a_1	[0.9, 1.0], [0.0, 0.0]	**Critical**
a_2	[0.7, 0.8], [0.1, 0.2]	**High**
a_3	[0.5, 0.6], [0.2,0.3]	**Medium**

In order to derive a conclusive overall ranking, a composite risk score was computed for each asset by averaging the upper membership (μ^U), the inverse of the lower non-membership $(1-\upsilon^L)$, and the inverse of the hesitancy $(1-\pi)$ across all three parameters (e_1, e_2, e_3). This defuzzification methodology aligns with approaches employed in contemporary IVIFS applications [7].

Table III: Composite Risk Scores and Final Asset Prioritization

Asset	*Composite Risk Score*	*Final Rank*	*Priority Level*
a_1	**0.90**	1	**Critical**
a_2	**0.88**	2	**High**
a_3	**0.51**	3	**Medium**

The findings derived from both the aggregation of a singular parameter and the composite scoring unambiguously highlight the Customer Database Server (a_1) as the paramount asset, succeeded by the Web Server (a_2). The HR Workstation (a_3) ranks significantly lower in importance. The comparative evaluation presented in Table 4 distinctly illustrates that the proposed IVIFSS framework offers the most thorough management of uncertainty and delivers superior flexibility in decision-making approaches, albeit at the cost of heightened computational complexity.

Table IV: Comparative Analysis of Fuzzy Methods for Cybersecurity Assessment

Method	*Uncertainty Handling*	*Expressiveness*	*Robustness to Input Variance*	*Decision Strategy Flexibility*	*Implementation Complexity*
Crisp Numbers	None	Low	Low	None	Very Low
Traditional Fuzzy Sets [2]	Partial (only membership)	Medium	Low	Low	Low
Intuitionistic Fuzzy Sets (IFS) [3]	Good (membership & non-membership)	High	Medium	Medium	Medium
IVIFSS (Proposed)	**Excellent (intervals for membership, non-membership, hesitancy)**	**Very High**	**High**	**High (Union/Intersection)**	High
Pythagorean Fuzzy Sets [14]	Very Good	Very High	High	Medium	High

4 DISCUSSION

The findings outlined in Section 3 illustrate the effectiveness of the IVIFSS framework. The distinct prioritization ($a_1 > a_2 > a_3$) offers a clear guideline for the allocation of resources. The elevated score for a_1 is attributed to the absolute assurance of significant impact (⟨[0.9,1.0],[0.0,0.0]⟩⟨[0.9,1.0],[0.0,0.0]⟩ on e_2) and considerable issues regarding other parameters. The strength of the IVIFSS model resides in its capacity to derive this conclusion from a comprehensive information framework that incorporates uncertainty, an aspect often overlooked by conventional approaches.

The framework effectively converts ambiguous expert evaluations into a clear, actionable hierarchy. The implementation of intervals enables experts to convey their confidence levels organically, resulting in more precise contributions. The aggregation methods offer adaptability: the restricted union proves optimal for worst-case scenarios, while the restricted intersection can be utilized to pinpoint risks that receive unanimous agreement from all experts, facilitating consensus-building. This dual methodology for addressing uncertainty presents a notable advantage over more basic fuzzy models [2]. The mathematical validations presented in Section 2.3 confirm the theoretical robustness of these aggregation methods, a factor that is often neglected in practical fuzzy research [8].

The comparative evaluation presented in Table 4 underscores the merits of the IVIFSS framework. Although Pythagorean Fuzzy Sets (PFS) [18] provide significant expressiveness, they lack the intrinsic ability to manage parameterization akin to soft sets, which is essential for organized MCDM challenges such as cybersecurity evaluation. The capacity of the IVIFSS framework to represent various degrees of confidence (intervals) enhances its resilience to the inherent variability in expert assessments when contrasted with methodologies relying on single values [17]. This aligns with the increasing demand for advanced uncertainty models in IT governance and risk management [3,9,19].

For cybersecurity professionals, this framework presents a systematic, verifiable, and mathematically rigorous approach to risk assessment. It transcends subjective discussions by offering a quantitative foundation based on qualitative inputs. The ultimate result, as illustrated in Table 3, directly supports strategic planning and budget justification for security measures. The method's adaptability indicates its potential to evaluate a broader array of assets and threats, akin to methodologies utilized in intricate project portfolio selection [1,6].

5. CONCLUSION

This research has effectively created and showcased an innovative IVIFSS framework for the assessment of cybersecurity risks. The model adeptly tackles the significant issue of uncertainty in expert evaluations by utilizing the robust capabilities of interval-valued intuitionistic fuzzy sets. The implementation of restricted union and intersection operations, supported by formal mathematical validations of their characteristics (closure, commutativity, idempotency), offers a systematic approach for amalgamating varied expert perspectives. The numerical case study produced a transparent and well-founded prioritization of assets, demonstrating the framework's practical relevance. The comparative evaluation illustrated its superiority over current fuzzy methodologies in terms of expressiveness and versatility.

Future endeavors will concentrate on integrating this framework with real-time threat intelligence feeds for adaptive risk assessment and developing a user-centric software application to automate the calculations, thereby rendering this method accessible to security experts lacking an extensive foundation in fuzzy mathematics. Additionally, investigating the potential integration of this IVIFSS framework with other MCDM techniques such as TOPSIS or DEMATEL, as indicated in recent scholarship, may augment its decision-making proficiency for extensive cybersecurity portfolios.

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