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# Uncertainty-Aware Appraising of User Interfaces in Human Computer Interactions: Blending Tree Soft Sets and Neutrosophic Computational Methodological

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**Abstract**
Human Computer Interactions (HCI) is a multifaceted discipline that focuses on designing, appraising, and implementing interactive computer systems to improve accessibility, usability, and user experience. Herein, we focus on appraising user interfaces (UIs) in HCI. This process is characterized by ambiguities, feedback from users, and other conflicting criteria. Moreover, it must all be addressed in this intricate and diverse process. By blending a set of computational techniques such as Multi-Criteria Decision-Making (MCDM) approaches with soft computing techniques (SCTs), this study suggests a unique model for appraising UIs prototypes. By adding indeterminacy to fuzzy logic, neutrosophic offers a strong way to deal with the ambiguities and uncertainties that come from user appraisals. Conversely, soft sets used to illustrate and examine how evaluation criteria and UI choices relate to one another. The suggested architecture allows for a thorough and methodical assessment of UI prototypes by fusing such techniques with MCDM methods like entropy - multi-objective optimization on the basis of simple ratio analysis (MOOSRA). These techniques are deployed for the first time in this problem. Ultimately, the proposed model excels in balancing different appraisal features in comparison to traditional fuzzy MCDM methods. This study provides a scalable and adaptable model for UI appraisal, which improves stakeholder inclusivity. Also, it enables designers to create UIs that are not only functional and efficient but also engaging, accessible, and aligned with user needs. In this context, our constructed model proves its efficacy through deploying it on case study for platforms of healthcare organization that need to adopt optimal UI that meet user needs amongst alternatives of UIs prototypes.

Keywords: Human Computer Interactions (HCI); user interfaces (UIs); soft computing techniques (SCTs); Multi-Criteria Decision-Making (MCDM)

## 1. Introduction

This section contains several ingredients to furnish a thorough overview of human-computer interaction. Each section covers relevant information on this study's objectives and driving forces.

### 1.1 Widened overview

More than ever [1] Human-computer interaction (HCI) is a top priority as it determines how individuals will engage with digital systems, which are now an essential part of our daily lives.
In line with [2], HCI first appeared in the early 1980s as "man-machine interaction," but it later changed its name based on [3] to "Human-Computer Interaction" to represent the increasing importance of computers in our day-to-day interactions.

The term HCI may be described from a variety of perspectives. For instance [4] The study of HCI is a multidisciplinary branch that focuses on how humans and computers interact. According to [5] HCI's beginnings may be found in the early days of computing, when the main goal was to get machines to work. But as computers proliferated, the necessity of making them easier to use became evident. This transformation motivates the emergence of HCI[6] , integrating knowledge from design, psychology, computer science, and other fields to develop systems that follow human capabilities and requirements. Wherein the goal of HCI [7] is to comprehend, assess, and create for various human experiences, such as enjoyment, mindfulness, productivity, learning, fun, immersion, and behavior modification.

Since 2000, HCI has shifted from traditional usability tests to studying user experience, emphasizing humans' role in design and interaction. Interactivity, a core HCI concept, has become crucial, with different types of interactivities (source, medium, and message) affecting user engagement and system evaluation. Recent research focuses on psychological effects and optimal levels of interactivity to enhance user experience [8].

According to prior studies of [9],[10],[11]; The notion of HCI is related to other terms described in Fig 1.

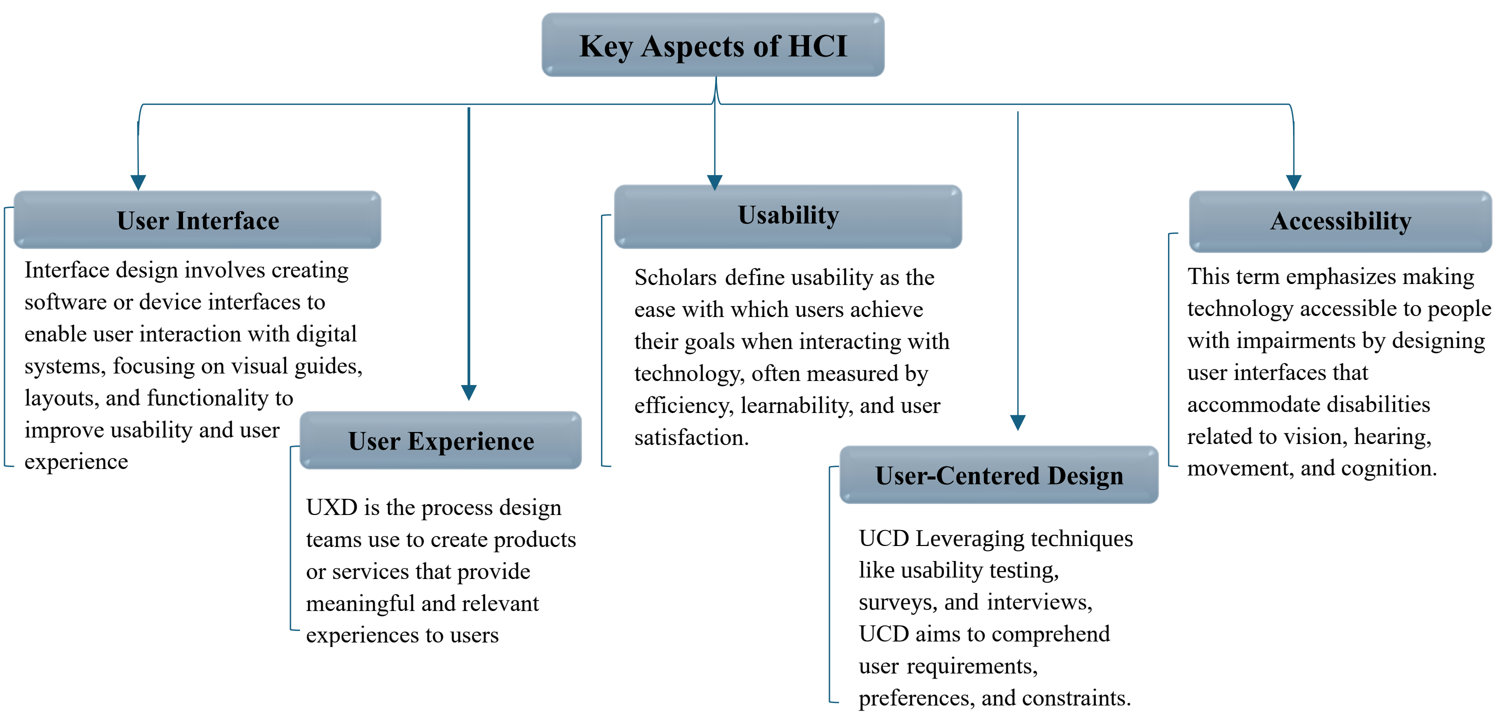


Fig 1. Key Aspects Related to Human Computer Interaction

key aspects declared preceding are contributed to the appraisal process for HCI. The creation of efficient, user-friendly systems that improve overall usability and satisfaction while enabling ongoing technological design development and improvement depends on the appraisal of HCI[12]. The approaches to the appraisal methods are mentioned in table 1.

Table 1. Appraisal Methodologies

| Method | Description | Benefits | Limitations | When to Use |
|---|---|---|---|---|
| **Heuristic Evaluation** | Experts use established guidelines (e.g., Nielsen's heuristics) to identify usability issues. | Quick, cost-effective, identifies common usability problems. | Relies on expert knowledge, may miss context-specific issues. | Early design, prototyping, existing interfaces. |
| **Cognitive Walkthrough** | Evaluates how easy it is for new users to learn a task. | Focuses on first-time user experience, identifies learning curve issues. | Can be time-consuming, requires detailed task scenarios. | Early design, complex tasks, new user interfaces. |
| **Pluralistic Walkthrough** | Involves users, developers, and designers discussing usability. | Collaborative approach, diverse perspectives, identifies various issues. | Requires coordination and facilitation, may lead to conflicting opinions. | Early design, iterative development, team consensus. |
| **Card Sorting** | Users organize information into categories to understand mental models. | Reveals user's information architecture, improves navigation. | Limited to information organization, may not address other usability issues. | Information architecture design, website navigation. |
| **A/B Testing** | Comparing two versions of a design to see which performs better. | Data-driven decisions, optimizes for specific metrics. | Limited to comparing variations, may not explain underlying issues. | Post-launch optimization, website content, marketing campaigns. |
| **Eye Tracking** | Analyzing user eye movements to understand attention and interaction. | Detailed insights into user attention, identifies visual hierarchy issues. | Requires specialized equipment, can be expensive. | Visual design, information layout, advertising effectiveness. |
| **Task Analysis** | Breaking down user tasks into steps to understand goals and interactions. | Identifies user goals and steps, improves task efficiency. | Can be time-consuming, requires detailed task scenarios. | Complex workflows, task-oriented applications. |
| **Perspective Based User Interface Inspection** | Enhancing usability by addressing varied user group experiences. | Addresses diverse user needs, inclusive design. | Requires diverse user representation, can be complex to manage. | Diverse user base, accessibility considerations. |
| **Formal Usability Inspections** | Evaluating a product against predefined criteria or guidelines. | Systematic evaluation, ensures | Requires trained experts, may be rigid in application. | Compliance requirements, standardized interfaces. |

| | | | | |
|---|---|---|---|---|
| | | adherence to standards. | | |

The presented study focuses on appraisal methods that can be adapted to address uncertainty in user interactions and evaluations (see table 2).

Table 2. Uncertainty-Aware Appraisal Methodologies

| Method | Description | Benefits | Limitations | When to Use | Uncertainty Handling |
|---|---|---|---|---|---|
| Surveys/Questionnaires (Uncertainty-Modified) | User feedback with uncertainty scales. | Captures user uncertainty. | Relies on self-reporting. | Post-launch. | High (with fuzzy logic) |
| Expert Reviews (Uncertainty -Modified) | Expert judgments with uncertainty ranges. | Incorporates expert uncertainty. | Requires consistent scales. | Complex systems. | High (with neutrosophic logic) |
| Cognitive Walkthrough (Uncertainty -Modified) | Task learning with probabilistic paths. | Models uncertain user decisions. | Requires detailed scenarios. | Early design. | High (with probabilistic branching, fuzzy logic) |
| Task Analysis (Uncertainty -Modified) | Task steps with uncertain transitions. | Models task uncertainty. | Requires detailed scenarios. | Complex workflows. | High (with probabilistic/fuzzy transitions) |
| Fuzzy Cognitive Maps (FCMs) | Models uncertain mental models. | Visualizes uncertain relationships. | Requires expert knowledge. | Complex interactions. | High |
| Bayesian Networks | Models probabilistic user behavior. | Predicts behavior with uncertainty. | Requires large datasets. | Behavior patterns. | High |

## 1.2 Motivation

As a result of the ongoing development of technology, UIs in HCI have become more intricate and varied. As the main interface between users and digital systems, UIs must be carefully designed and appraised to guarantee usability, accessibility, and user satisfaction. But because of the inherent ambiguities, subjective user input, and numerous conflicting criteria, appraising UIs is difficult undertaking. More reliable, adaptable, and data-driven methodologies are becoming more and more necessary as traditional assessment techniques frequently fail to handle these complications.

Modern UIs and emerging technologies like Internet of Things (IoT), virtual reality (VR), and augmented reality (AR) provide new opportunities and challenges for UI design and appraisal, as they must address the diverse users' needs across multiple domains, user groups, technology constraints and many hierarchical criteria and indeterminacy, which traditional appraisal techniques often struggle with. These obstacles are the motivation for conducting this study, which in turn tries to bridge this gap by integrating TrSS, SVNS, and MOOSRA, to offer a new approach to UI appraisal under uncertainty.

In this light, the intention of this study is to investigate how MCDM and soft computing might be used to evaluate user interfaces for HCI. The goal of the study is to overcome the drawbacks of conventional techniques and offer a more reliable, adaptable, and user-centered approach to UI appraisal by creating and implementing a soft intelligent model. By making it possible to create user interfaces (UIs) that are not only practical and effective but also interesting, approachable, and in line with user requirements, the study's conclusions might further the field of human-computer interaction. This study provides the first integration of TrSS (hierarchical criteria modeling) with SVNS (indeterminacy handling) and MOOSRA (ranking), which outperforms conventional evaluation techniques when dealing with conflicting criteria. The proposed technique enables designers to quantify trade-offs (e.g., usability vs. security) and prioritize inclusive UI features.

### 1.3 Map of Conducted Study

Fig 2 illustrates the structure of our study. Also, the purpose of each section and its sub section.

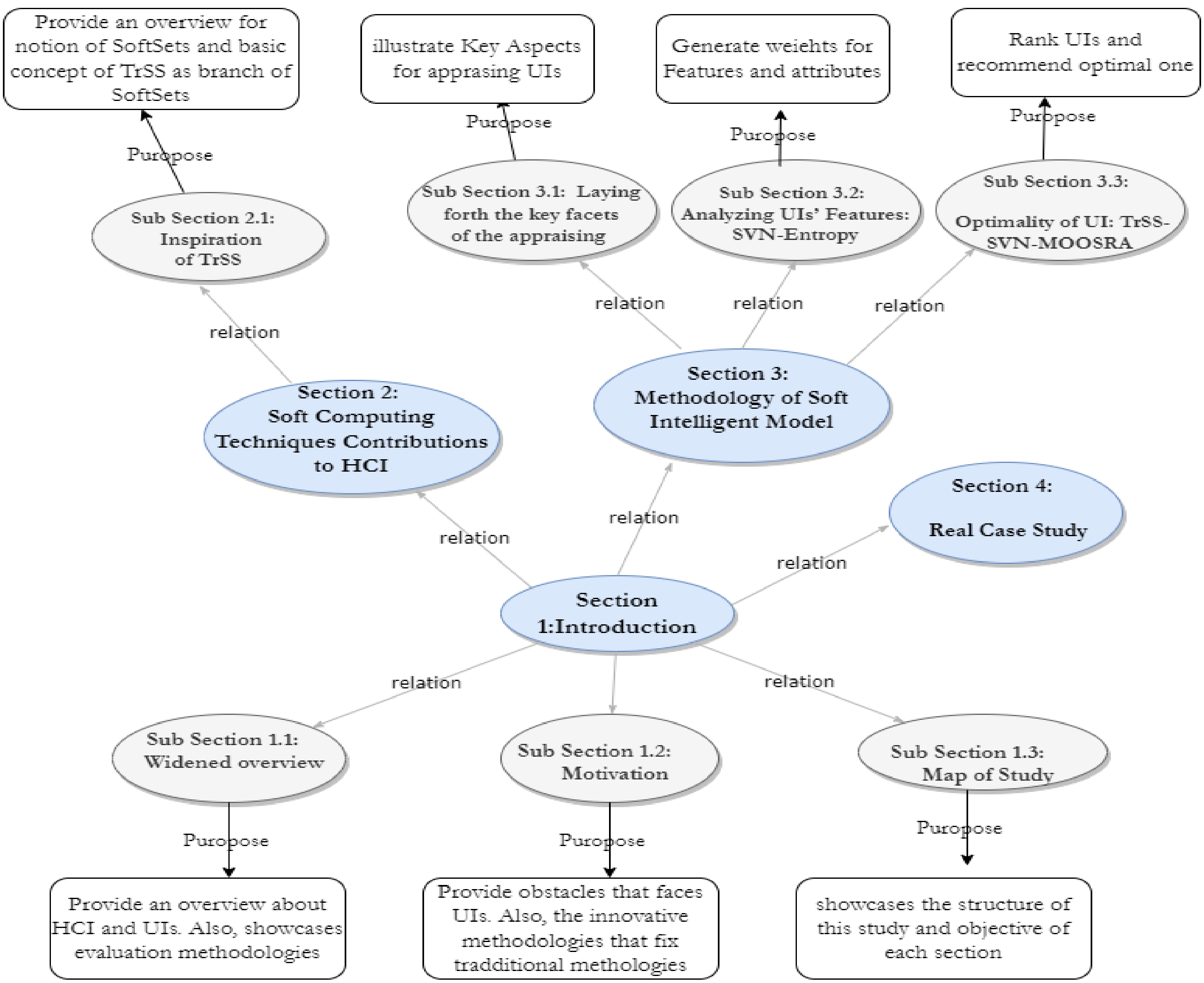

Fig 2 Map of Study

## 2. Soft Computing Techniques Contributions to HCI

The swift advancement of algorithms and intelligent techniques has led to the adaptation of novel strategies for complexity by emulating and drawing inspiration from natural behaviors[13]. These techniques are used in various directions. **First direction**: *Seeking for optimal solution amongst set of solutions*: Swarm intelligence systems that mimic the movements and behaviors of birds and other creatures are one example. **Second direction**: *Seeking for optimal solution through evaluating process for foggy circumstances*: for instance, uncertainty techniques as fuzzy theory that can handle incomplete information and its extensions, such as IFS and neutrosophic. **Third direction**: *Solving complex problems that human beings can't solve*: Using neural networks (NNs) to simulate the human brain and thinking.

The three directions mentioned previously fall under so-called soft computing techniques (SCTs). In other words, SCTs encompasses a variety of intelligence techniques to provide solutions characterized by endurance, resilience, and relatively inexpensive.

Accordingly, Pratihar [14] leveraged SCTs as effective tools to improve HCI through rendering systems more intelligent, adaptable, and user-focused. Given human behavior is complicated and unpredictable [15], SCTs are especially useful for creating interfaces that can learn from and adjust to user preferences and situations. In the same vein [16] indicated that collaborating SCTs into HCI, scholars and practitioners can develop systems that are not only more efficient but also more intuitive and responsive to user needs.

Generally speaking, we are leveraging SCTs' capabilities in HCI during appraisal process to support experts in vague situations. Accordingly, we integrate soft sets family (Tree SoftSet-TrSS) by uncertainty theory (Single Value Neutrosophic-SVN) to construct a soft intelligent model. This model volunteered to evaluate user interfaces (UIs) (See Fig 3).

### 2.1 Inspiration of TrSS

The technique of TrSS is suggested by Smarandache [17] who is the founder of uncertainty theory is neutrosophic. The objective of TrSS is to illustrate the relationship between attributes and sub-attributes of patients and SVDs. Hence, the technique's basic aspects and relationship formed according to [18]

- Assum $\mathfrak{H}$ be a universe of discourse, and $\mathcal{H}$ a non-empty subset of $\mathfrak{H}$, with the powerset of $\mathcal{H}$ P($\mathcal{H}$).
- Suppose $\partial$ be a set of attributes for main nodes as $\partial = \{ \partial_1, \partial_2, \ldots, \partial_n\}$ where n ≥ 1 and considering attributes of $\partial$ resident at the first level.

- Accordingly, sub-attributes of the main attributes are located in the second level as sub-nodes $\partial_1$ symbolled as $\{ \partial_{1-1}, \partial_{1-2}, \ldots, \partial_{1-n}\}$ also, sub-attributes of $\partial_2$ expressed as $\{ \partial_{2-1}, \partial_{2-2}, \ldots, \partial_{2-n}\}$.
- Considering $\partial$ is root and located at level zero, sequentially nodes of level 1, level 2, up to level n are inherent of $\partial$. Moreover, Tree Soft is expressed as F: P(Tree($\partial$)) ⟶ P($\mathcal{H}$).

We choose TrSS as they can represent the hierarchical nature of the criteria in some HCI appraisal scenarios (e.g., Flexibility ⟶ Rigid/Adaptive/Customize). And unlike other techniques, TrSS supports multi-level dependencies and scalability without performance loss.

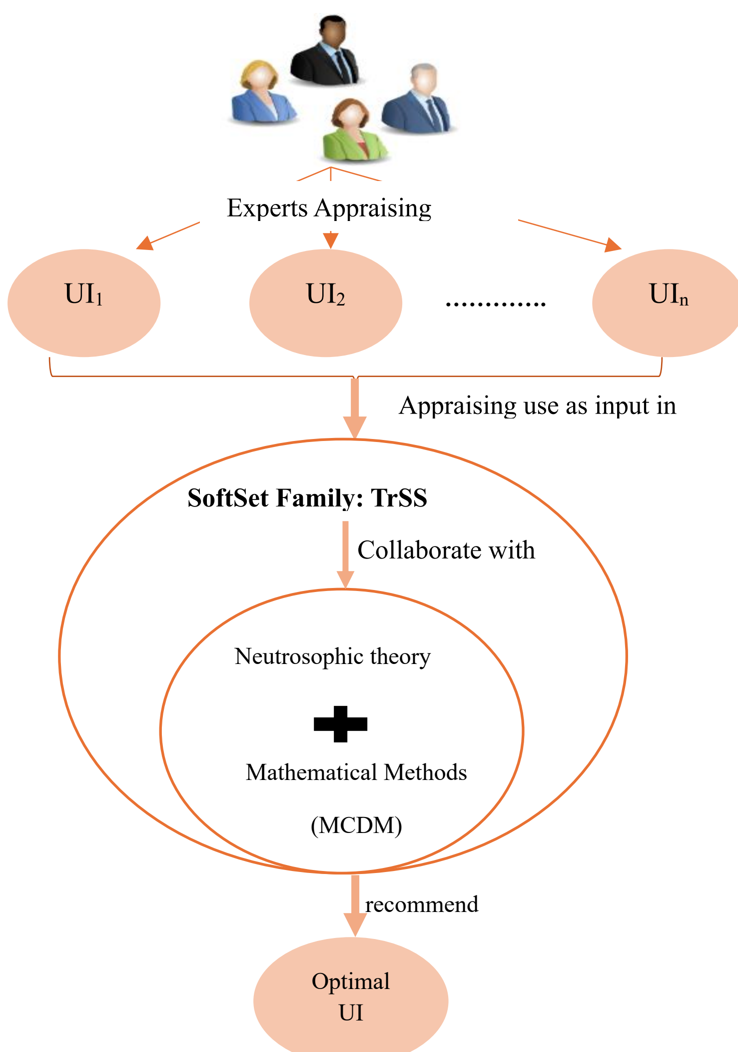


Fig 3. Collaboration of SoftSets Family with Uncertainty Theory

## 3. Methodology of Soft Intelligent Model

Herein, we exhibit the procedures of constructing the proposed model's workflow (see figure 4). As well as the role of each technique that contributes to constructing the model through the following:

### 3.1 Laying forth the key facets of the appraising procedure

- Set of alternatives (UIs) = {.UI1, UI2…UIn} are determining to volunteer into appraising process.
- The main UIs features (Fn)={F1,F2…Fn} and attributes (An)={A1.1,A1.2….An.m} are determined to appraise UIs.
- The expert panel is forming to contribute to the appraising process for UIs based on its features and attributes.

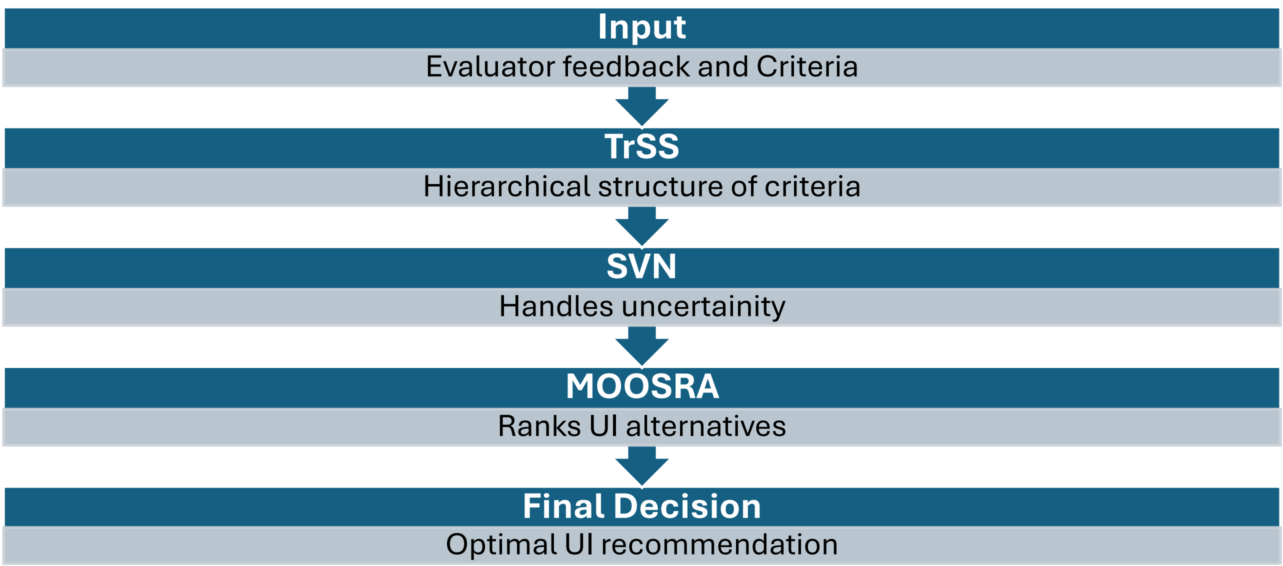


Fig 4. Proposed hybrid framework for UI appraisal.

### 3.2 Analyzing UIs' Features: SVN-Entropy

This procedure's goal is to provide weights for the features and attributes of UIs. Therefore, to create weights, SVNSs are mixed with the entropy of MCDM approaches. In the following step of the alternatives ranking process, the produced weights are bothersome. To achieve the goal, we employ several procedures.

- Transforming the utilized linguistic terms of DMs into Neutrosophic values based on SVN scale which mentioned in [19] .Thereby, Neutrosophic decision matrices are constructed based on the rating of DMs.
- The score function in Eq.(1) is embraced for converting the constructed matrices into crisp matrices.

$$\boldsymbol{s}(\sigma_{\text{ij}}) = \frac{(2+\alpha-\beta-\theta\ )}{3} \quad (1)$$

Where $\alpha$, $\beta$, $\theta$ refers to truth, false, and indeterminacy respectively.

- Aggregate the crisp matrices into a compiled matrix based on Eq.(2).

$$\wp_{ij} = \frac{(\sum_{j=1}^{N} \sigma_{ij})}{Z} \quad (2)$$

Where $\sigma_{ij}$ refers to the value of the criterion in the matrix, Z refers to the number of decision-makers.

- Eq.(3) is utilized in the compiled matrix to normalize it to construct a normalized matrix.

$$\mathbb{N}or_{ij} = \frac{\wp_{ij}}{\sum_{j=1}^{m} \wp_{ij}} \quad (3)$$

Where $\sum_{j=1}^{m} \wp_{ij}$ indicates the sum of each criterion in the compiled matrix per column.

- Eq.s(4),(5) are contributed to compute entropy.

$$En_{j} = -h \sum_{i=1}^{m} \mathbb{N}or_{ij} \ln \mathbb{N}or_{ij} \quad (4)$$

where,

$$h = \frac{1}{\ln(N)} \quad (5)$$

N refers to utilized alternatives

- Finally, the weights of features are generated by employing Eq. (6)

$$\omega_{j} = \frac{1 - En_{j}}{\sum_{j=1}^{n}(1 - En_{j})} \quad (6)$$

Algorithm1 illustrates the pseudo code for integrating SVN with entropy.

**Algorithm 1: SVN-Entropy Method**

{
//The following pseudocode is to generate weights for UIs' features
Input: num_alternatives # Number of alternatives (rows)
num_Features # Number of features (columns)
num_attributes # Number of attributes (columns)
Output: Generate array of weights for Features and attributes
Create decision matrices $X^{K}$, Transform Neutrosophic $X^{K}$ to crisp $\sigma_{ij\ K}$
Generate normalized matrix $\mathbb{N}or_{ij}$ = decision_matrix ($\wp_{ij}$) / sum_values$\sum_{j=1}^{m} \wp_{ij}$
Calculate entropy for each feature ($En_{j}$).
Generate Features' weights.
Weight= create array (num _features).
Weight_feature=(1- entropy(feature)) / (sum(1- entropy(feature))
Return weights
}

## 3.3 Optimality of UI: TrSS-SVN-MOOSRA

Herein, three techniques are integrated to rank UIs prototypes. Each technique plays a vital role in solving the problem of selection. **TrSS** is utilized to determine and employ a set of attributes to obtain the most appropriate UIs. While **SVNSs** are harnessed for supporting MOOSRA in uncertain environments and ambiguity of information during the ranking process, **MOOSRA** is also utilized to balance trade-oofs and handle situations where non-beneficial (e.g., cost) and beneficial (e.g., usability) criteria exist. While Entropy weighting provides algorithm transparency by reducing bias by prioritizing criteria with high variability (e.g., user engagement). Algorithm 2 illustrates the pseudo code for integrating TrSS-SVN with MOOSRA.

- Constructing Neutrosophic decision matrices for each DM to evaluate UIs based on attributes which determined by TrSS.
- Transforming Neutrosophic decision matrices into de-neutrosophic decision matrices through using Eq.(1).
- Eq.(2) is utilized for the second time to aggregate these matrices into an aggregated matrix.
- Normalizing the aggregated matrix based on Eq.(8).

$$\mathrm{Nor_{ij}} = \frac{\mathrm{v_{ij}}}{\left[\sum_{\mathrm{j}}^{\mathrm{m}} \mathrm{v_{ij}}\right]^{1/2}} \quad (8)$$

- Compute weighted decision matrix based on Eq.(9).

$$\mathrm{weighted\_matrix_{ij}} = \mathrm{Nor_{ij}} * \omega_{\mathrm{j}} \quad (9)$$

- Calculating ration as in Eq.(10) to obtain final rank for alternatives.

$$\mathrm{Ratio} = \frac{\sum_{\mathrm{j=1}}^{\mathrm{B}} \mathrm{Nor_{ij}}}{\sum_{\mathrm{j=1}}^{\mathrm{NB}} \mathrm{Nor_{ij}}} \quad (10)$$

**Algorithm 2: TrSS Based SVN-MOOSRA Method**

1. {
2. //The following pseudocode is to rank and recommend UIs prototypes
3. Input: num_alternatives # Number of alternatives (rows)
4. num_attributes # Number of attributes (columns)
5. Output: Ranking alternatives of UI prototypes
6. Implement TrSS:
7. Determine attributes of features
8. Create decision matrices $y^K$, Transform Neutrosophic $y^K$ to crisp $\mathrm{v_{ij}}_K$
9. Generate normalized matrix $\mathbb{N}\mathrm{or_{ij}}$ = decision_matrix ($\mathrm{v_{ij}}_K$) / (sqrt (sum_values$\sum_{\mathrm{j=1}}^{\mathrm{m}} \mathrm{v_{ij}}_K$))
10. Calculate weighted decision matrix ($\mathrm{weighted\_matrix_{ij}}$).
11. Calculate sum of normalized matrix based on its category #bencicial or non-beneficial
12. IF beneficial_attribute=sum_normalized[beneficial_attribute]
13. ELSE
14. Non_beneficial_attribute=sum_normalized[non_beneficial_attribute]
15. Calculate MOOSRA score

16. Rank UIs prototypes
17. Rank=Sort_ Descending [MOOSRA score]
18. Return rank of UIs prototypes
19. }

## 4. Real Case Study

Herein we implemented our constructed soft opting model in realistic to validate the efficacy of the constructed model.

### 4.1 Problem Description

We exhibit the problem that our constructed model is supposed to be applied through the following scenario.

| **Scenario: Select Optimal UI amongst set of prototypes** |
| --- |
| A reputable healthcare organization is moving to a totally digital system in order to boost administrative effectiveness, optimize clinical operations, and improve patient care. The company is working on a new Human-Computer Interaction (HCI) system as part of this program, which will be utilized by several stakeholders, such as physicians, nurses, patients, and administrative personnel. With distinct features and design philosophies, the organization has selected amongst five possible prototypes of user interface (UI) designs. It is the responsibility of a group of decision-makers (DMs) comprising medical professionals, IT specialists, and patient advocates to appraise various user interfaces and choose the best one. |

**Action:**

The decision-makers are required to assess the five user interface prototypes and choose the one that best serves the expectations of the organization. Numerous features including cost, security, scalability, usability, usefulness, accessibility, and user engagement, must be taken into account throughout the decision process. To guarantee that the selected user interface (UI) supports the objectives of the organization and offers the greatest experience for every user, it is difficult to strike a balance between these features.

**Proposition:**

Deploying the constructed soft intelligent model in the problem of appraising UIs prototypes. Support DMs in their decisions when they don't able to make decisions due to various reasons such as vague and uncertainty information. Also, avoid biases.

### 4.2 Soft Intelligent Model Implementation

#### 4.2.1 Key Aspects

- In our problem, five UIs prototypes are volunteered to be candidates. The appraisal process is conducted for **five UIs** through **three features** that branched into **nine attributes** as mentioned in Fig 5.

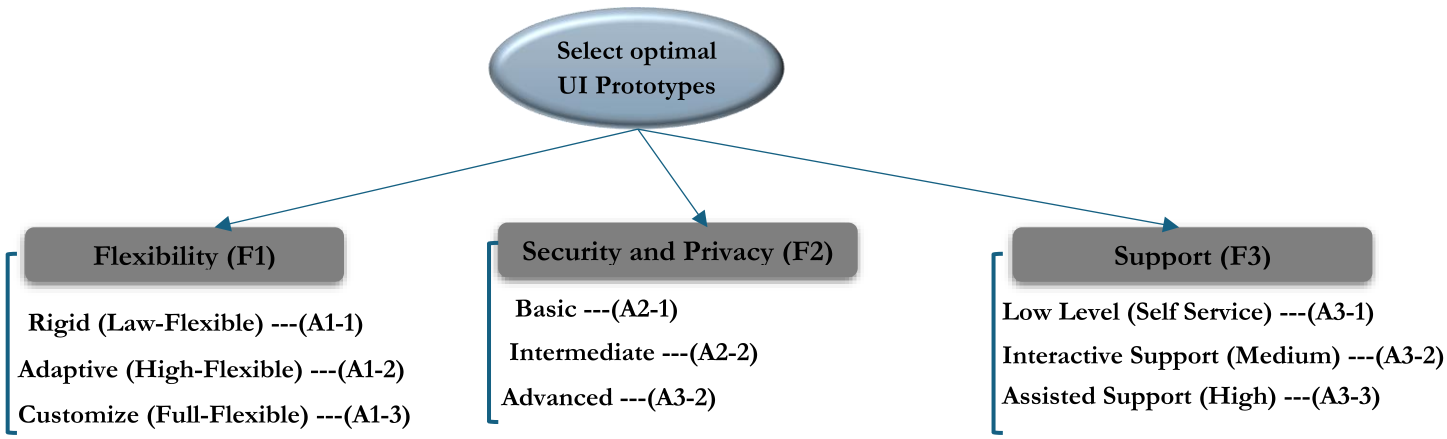


Fig 5. Tree Soft of UIs Features and its attributes

### 4.2.2 Weighting Features and attributes

- ➢ Deploying pseudo code of algorithm 1:
- Three Neutrosophic decision matrices are constructed based on DMs' scoring. Eq.(1) used to transform these matrices into crisp matrices.
- Aggregating these matrices into single matrix based on Eq.(2) as listed in Table 3.
- Normalizing the aggregated matrix through Eq.(3) and results listed in Table 4.
- Eq.(4) is implemented to compute entropy.
- Final Features' weights is obtained in Fig 6 through executing Eq.(6) which indicates that F2 has highest weight otherwise, F1 has lowest value

Table 3. Aggregated Matrix for Main Features

| | F1 | F2 | F3 |
|---|---|---|---|
| UI1 | 0.604444444 | 0.572222222 | 0.426666667 |
| UI2 | 0.816666667 | 0.577777778 | 0.716666667 |
| UI3 | 0.538888889 | 0.38 | 0.5 |
| UI4 | 0.705555556 | 0.805555556 | 0.65 |
| UI5 | 0.644444444 | 0.711111111 | 0.816666667 |

Table 4. Normalized Matrix for Main Features

| | F1 | F2 | F3 |
|---|---|---|---|
| UI1 | 0.182611615 | 0.18781911 | 0.137191854 |
| UI2 | 0.24672709 | 0.189642597 | 0.230439443 |
| UI3 | 0.162806311 | 0.124726477 | 0.160771704 |
| UI4 | 0.213158778 | 0.264405543 | 0.209003215 |
| UI5 | 0.194696207 | 0.233406273 | 0.262593783 |

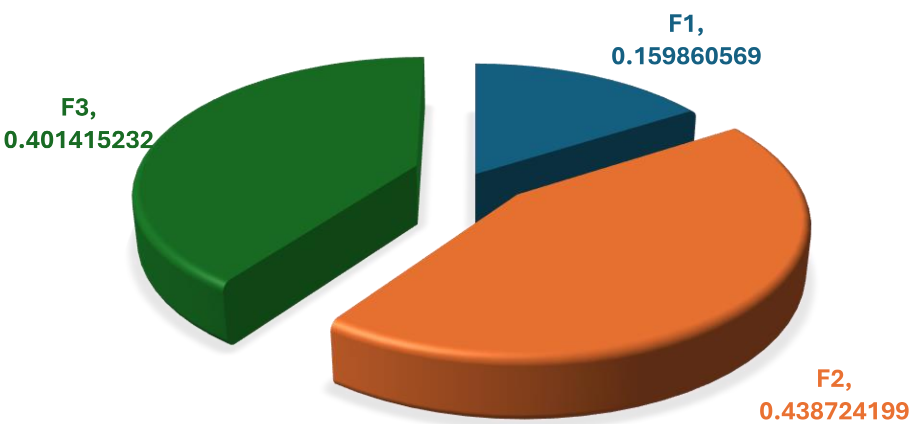


Fig 6. Final Features Weights

### 4.2.3 Recommend Optimal UI Prototype

➢ Implement TrSS technique

- Select group of attributes that are inherent of main features of UIs, to create Neutrosophic decision matrices.
- Eq.(1) is implemented to transform these matrices into crisp matrices and aggregate them into an aggregated matrix based on Eq.(2). The results are listed in Table 5.
- Eq.(8) is executed in an aggregated matrix to normalize it and represent in Table 6.
- Table 7 represents a weighted decision matrix through deploying Eq.(9) in normalized matrix.
- Rank UIs prototypes based on Eq.(10) where A1-1 is non-beneficial attribute otherwise A2-2 and A3-3 are beneficial attributes.
- Fig 7 exhibits that UI2 is the most comfortable and meets requirements for users. Accordingly, it is the optimal one otherwise UI4 is worst one

Table 5. Aggregated Matrix based on TrSS-SVN-MOOSRA

| | A1-1 | A2-2 | A3-3 |
|---|---|---|---|

| | | | |
|---|---|---|---|
| UI1 | 0.644444444 | 0.677777778 | 0.938888889 |
| UI2 | 0.498888889 | 0.838888889 | 0.966666667 |
| UI3 | 0.42 | 0.666666667 | 0.666666667 |
| UI4 | 0.598888889 | 0.611111111 | 0.726666667 |
| UI5 | 0.565555556 | 0.811111111 | 0.565555556 |

Table 6. Normalized Matrix based on TrSS-SVN-MOOSRA

| | A1-1 | A2-2 | A3-3 |
|---|---|---|---|
| UI1 | 0.522864888 | 0.417228757 | 0.532540721 |
| UI2 | 0.404769543 | 0.516406084 | 0.548296363 |
| UI3 | 0.340763668 | 0.410388941 | 0.378135423 |
| UI4 | 0.485903749 | 0.376189862 | 0.412167611 |
| UI5 | 0.458859014 | 0.499306545 | 0.320784884 |

Table 7. Weighted Decision Matrix based on TrSS-SVN-MOOSRA

| | A1-1 | A2-2 | A3-3 |
|---|---|---|---|
| UI1 | 0.172368462 | 0.074220292 | 0.131809535 |
| UI2 | 0.133436964 | 0.09186282 | 0.135709226 |
| UI3 | 0.112336687 | 0.073003566 | 0.09359257 |
| UI4 | 0.160183795 | 0.066919935 | 0.102015901 |
| UI5 | 0.151268184 | 0.088821005 | 0.079397697 |

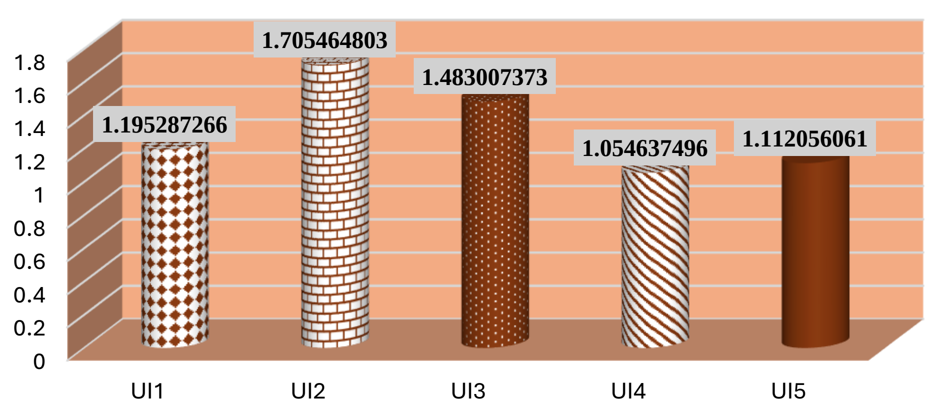

Fig 7. Rank UIs Prototypes

## 5. Conclusions

In HCI, appraising UIs is a crucial step that guarantees the creation of systems that are not only useful but also user-centric, accessible, and intuitive. Hence, this study has explored various methodologies that contributed to constructing a soft intelligent model for appraising UIs, emphasizing the importance of incorporating usability principles, user feedback. The constructed model exploited the soft computing technique particularly Neutrosophic theory (SVN) for dealing with the ambiguity, complexity, and inherent uncertainties related to system behaviors, user preferences, and appraisal criteria and features of UIs. As well as SVN integrated with other computational methods of MCDM where stakeholders and designers can consider and appraise several conflicting variables to choose the best user interface designs with greater objectivity and knowledge. These techniques are collaborating with the notion of softest especially TrSS during selecting set of attributes that contribute to construct decision matrices based on DMs.

Overall, each technique harnessed in the constructed model plays a certain role to accomplish appraisal process.

According to the study's findings, incorporating SCTs into HCI improves both UX overall and the accuracy of UI appraising. Designers may produce UIs that are more accessible, intuitive, and flexible to meet the demands of a wide range of users by implementing these techniques. The viewpoints of all stakeholders, including people with special needs or impairments, are considered thanks to this method, which also promotes a more inclusive design process. In this context, we implemented our soft intelligent model on case study to validate the efficiency of it.

## References


[1] V. Sharma, N. Kumar, and B. Nardi, "Post-growth Human-Computer Interaction," *ACM Trans. Comput. Interact.*, vol. 31, no. 1, pp. 1–37, 2023, doi: 10.1145/3624981.

[2] L. Triantafyllopoulos, E. Paxinou, G. Feretzakis, D. Kalles, and V. S. Verykios, "Mapping How Artificial Intelligence Blends with Healthcare: Insights from a Bibliometric Analysis," *Futur. Internet*, vol. 16, no. 7, 2024, doi: 10.3390/fi16070221.

[3] N. Van Berkel, J. Opie, O. F. Ahmad, L. Lovat, D. Stoyanov, and A. Blandford, "Initial responses to false positives in AI-supported continuous interactions: A colonoscopy case study," *ACM Trans. Interact. Intell. Syst.*, vol. 12, no. 1, pp. 1–18, 2022.

[4] A. Rapp, "Human–Computer Interaction," in *Oxford Research Encyclopedia of Psychology*, 2023.

[5] K. Ranade, T. Khule, and R. More, "Object Recognition in Human Computer Interaction:- A Comparative Analysis," pp. 1–10, 2024, [Online]. Available: http://arxiv.org/abs/2411.04263

[6] R. Hamdani and I. Chihi, "Adaptive human-computer interaction for industry 5.0: A novel concept, with comprehensive review and empirical validation," *Comput. Ind.*, vol. 168, no. February, 2025, doi: 10.1016/j.compind.2025.104268.

[7] H. L. O'Brien, I. Roll, A. Kampen, and N. Davoudi, "Rethinking (Dis)engagement in human-computer interaction," *Comput. Human Behav.*, vol. 128, p. 107109, 2022, doi: 10.1016/j.chb.2021.107109.

[8] S. Sharmin *et al.*, "fNIRS Analysis of Interaction Techniques in Touchscreen-Based Educational Gaming," *arXiv Prepr. arXiv2405.08906*, 2024.

[9] A. Adel, V. Gay, and A. Ryan, "The Evaluation of the Usability in Mobile Applications," *Theory Pract. Mod. Comput.*, no. November, pp. 23–24, 2022, [Online]. Available: https://www.researchgate.net/publication/365873044

[10] L. Emma, "User-centered design to enhance accessibility and usability in digital systems .," no. December, 2024.

[11] E. Apostolidou and P. A. Fokaides, "Enhancing Accessibility: A Comprehensive Study of Current Apps for Enabling Accessibility of Disabled Individuals in Buildings," *Buildings*, vol. 13, no. 8, 2023, doi: 10.3390/buildings13082085.

[12] N. Samrgandi, "User Interface Design & Evaluation of Mobile Applications," *Int. J. Comput. Sci. Netw. Secur.*, vol. 21, no. 1, pp. 55–63, 2021, [Online]. Available: https://doi.org/10.22937/IJCSNS.2021.21.1.9

[13] E. Çakıt and W. Karwowski, "Soft computing applications in the field of human factors and ergonomics: A review of the past decade of research," *Appl. Ergon.*, vol. 114, no. August 2023, p. 104132, 2024, doi: 10.1016/j.apergo.2023.104132.

[14] D. K. Pratihar, *Soft computing: fundamentals and applications*. Alpha Science International, Ltd, 2013.

[15] V. N. Thiruvalar, R. Yamini, M. A. P. Manimekalai, I. W. Suryasa, and S. Sugapriya, "Enhancing User Experiences in Ubiquitous Soft Computing Environments with Fuzzy Agent Middleware," *J. Wirel. Mob. Networks J. Wirel. Mob. Networks This J. doesn't have a profile Res. yet. Interest. this journal? Get Notif. when it Act. its profile, start Get. Updat. I'm Interest.*, vol. 14, no. 3, pp. 25–35, 2023.

[16] D. Garg, G. K. Verma, and A. K. Singh, "EEG-based emotion recognition using MobileNet Recurrent Neural Network with time-frequency features," *Appl. Soft Comput.*, vol. 154, p. 111338, 2024.

[17] F. Smarandache, "New Types of Soft Sets: HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, and TreeSoft Set," *Int. J. Neutrosophic Sci.*, vol. 20, no. 4, pp. 58–64, 2023, doi: 10.54216/IJNS.200404.

[18] F. Smarandache, M. Mohamed, and M. Voskoglou, "Evaluating Blockchain Cybersecurity Based on Tree Soft and Opinion Weight Criteria Method under Uncertainty Climate," *HyperSoft Set Methods Eng.*, vol. 1, no. January, pp. 1–10, 2024, doi: 10.61356/j.hsse.2024.17850.

[19] I. El-Henawy, S. El-Amir, M. Mohamed, and F. Smarandache, "Modeling Influenced Criteria in Classifiers' Imbalanced Challenges Based on TrSS Bolstered by The Vague Nature of Neutrosophic Theory," *Neutrosophic Sets Syst.*, vol. 65, pp. 183–198, 2024.

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