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FUZZY LOGIC FOR MANAGING COMPLEX UNCERTAINTY IN PREDICTIVE AND DECISION SUPPORT SYSTEMS

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Abstract:

This paper addressed how fuzzy logic can represent and handle uncertainty across diverse prediction and decision-support applications. Six fuzzy logic systems were examined, covering case of diabetes risk prediction, personalized diet recommendation, rainfall prediction, supply-demand identification in online food delivery, educational decision support, and air quality assessment. For each case study, relevant characteristics were extracted, including uncertain input factors, membership function selection, fuzzy rule bases, inference process, and output interpretation. The analysis was conducted to identify recurring and specific patterns in the representation of uncertainty processing. The findings reveals that fuzzy systems across the six applications share a common reasoning structure that transforms imprecise input information into interpretable outputs through membership functions, rule-based reasoning, and fuzzy inference, while differing in the selection of uncertainty-related variables, membership function configurations, and rule structures according to case requirements. Based on the identified patterns, a generalized uncertainty-aware fuzzy inference framework is projected to illustrate the systematic progression of fuzzy reasoning to interpretable prediction, recommendation, assessment, or decision-support outputs. The findings also demonstrate the adaptability of fuzzy logic in representing gradual and imprecise information across diverse application domains. The proposed framework provides a conceptual foundation for the development of future fuzzy inference systems and

offers practical guidance for researchers and practitioners developing for uncertainty-based applications in the future endeavours.

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Uncertainty, Fuzzy Decision Making, Fuzzy Prediction, Fuzzy Logic, Fuzzy Inference System



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Introduction

In today's fast-paced and increasingly complex environment, industrial development, business growth, and healthcare institutions require competent and rational prediction and decision-support systems. During the planning process, decision-makers are often required to choose between two or more alternatives. Within the framework of cognitive processes, individuals can generate a wide range of alternatives before making a choice. Experts suggest that when evaluating available alternatives, decision-makers should consider psychological needs, personal preferences, and desired values. From a cognitive perspective, decision-making should be viewed as a continuous process that is influenced by and connected to an individual's immediate environment. Many cognitive processes exhibit an unpredictability that defies the predictions of probability theory and randomness, and this uncertainty may be difficult to explain. Since Lotfi Zadeh got his start in fuzzy sets theory, the latter field has grown to include soft computing, which incorporates techniques, such as fuzzy systems with neural networks and genetic algorithms (Charanarur et al., 2023).

At the heart of this shift is fuzzy logic, a mathematical framework that permits the representation of uncertainty and imprecision in a manner that closely approximates human cognition. Fuzzy logic addresses these challenges by allowing for "computing with words," where linguistic variables replace numerical values, enabling the usage in combination with other mathematical systems to represent the intricate interactions between variables that occur in everyday language (Najib, et al., 2026). Because of the lack of comprehensive data sets for modelling, fuzzy logic may be used to reflect the subjective uncertainty in the real applications sector. Fuzzy logic provides a mechanism for transforming such information into meaningful prediction or decision outputs.

An architecture of a fuzzy logic system is divided into four main blocks. The first block is fuzzification which transforms crisp inputs into linguistic fuzzy sets, next is knowledge base which comprises a rule base of IF-THEN rules and a database of membership function. The third block is inference engine where the engine applies fuzzy reasoning to derive output fuzzy sets, and the last block is defuzzification converting fuzzy outputs to crisp control actions. The common approaches of fuzzy consequents use Mamdani FIS, and the crisp-output function applied the concept of Takagi–Sugeno FIS. In decision applications, Mamdani FIS with triangular or trapezoidal membership functions (MFs) is popular due to interpretability (Negnevitsky, 2005). For instance, IF–THEN rules can be formulated to represent relationships between input variables and predicted outcomes, such as “*IF attendance is High AND assignment performance is Good THEN academic performance is High*”. Similarly, in a decision-support system, rules can be used to recommend an appropriate course of action, such as “*IF household income is Low AND number of dependents is High AND financial burden is High THEN zakat assistance priority is High*”. The key design choices include MFs shape or overlap, rule evaluation, and defuzzification method which the centroid or Centre of Gravity (COG) is most common applied (Silvestri et al., 2025). With the help of an expert system and various defuzzification techniques, it is possible to reduce the quantity of error that is generated. There are several advantages to using fuzzy logic systems, including the fact that they can work with input data that have been corrupted in any way (Han and Qin, 2021)

Fuzzy sets and fuzzy logic have been proven to be useful tools in the fields of management and decision sciences, predictions and support recommendations in various fields. As example, in environmental prediction case, Janarthanan et al. (2021) suggested that Mamdani-based fuzzy inference systems can be effectively used to predict rainfall as variables (temperature, humidity, and wind speed) are correlated with the help of linguistic rules. Prediction of Air Quality Index (AQI) with uncertainty and imprecise environmental data and achieve high prediction accuracy (Shafii et al., 2021; Zulkifli and Idris, 2024). In decision-making problem, fuzzy logic has been applied successfully in various problem such as diabetes diagnosis (Abdullah, et al., 2018), nutrition and diet Selection (Lakshmi et al., 2023; Mulla et al., 2019, Amiri and Hasan, 2023), online supplier selection (Sureeyatanapas and Damapong, 2024, Bei et al., 2025) and selection and optimization of educational trajectories (Tarasyev et al. 2018; Yüksel, et al., 2023).

Drawing from these diverse applications, existing studies tend to focus on applications, leaving a gap in understanding how fuzzy uncertainty modelling represented in the context of problem assessment, prediction, decision-making. It remains unclear which fuzzy system characteristics are commonly adopted across domains, and which characteristics are shaped by domain-specific requirements. For example, in health-related prediction it could be representation of uncertainty through personal and clinical risk factors, whereas for environmental prediction it could be continuously relying on meteorological conditions. Therefore, a systematic comparative between different case is needed to identify recurring and domain-specific patterns in the representation and processing of uncertainty. In addition, the diversity of FIS has resulted in different setting of membership functions, rule-base structures, inference mechanisms, defuzzification methods, and output interpretation. Thus, the research gap address twofold which are how fuzzy logic is used to represent uncertainty in prediction and decision-support applications. Next, the absence of a generalized conceptual framework for applying FIS to new prediction/decision tasks by identifying specific FIS characteristics. This paper fills these gaps by detailing the design and implementation of six FIS-based projects from different domains, comparing their fuzzy components, and proposing a high-level framework for handling uncertainty in similar contexts. The rest of the paper is organized as follows: Section 2 reviews

how fuzzy logic handles uncertainty, Section 3 explains analysis methodology, Section 4 summarizes case studies analysis, Section 5 presents cross-study uncertainty comparisons, Section 6 introduces the generalized FIS framework and Section 7 concludes with implications.

Fuzzy Logic for Handling Uncertainty

This section will discuss the role of fuzzy uncertainty in prediction and decision making.

Uncertainty in Prediction and Decision Making

Uncertainty can be defined as the lack of the exact knowledge that would enable us to reach a perfectly reliable conclusion (Stephanou and Sage, 1987). The main sources of uncertain knowledge are weak implications, imprecise language, missing data and combining the views of different experts. Classical logic permits exact reasoning (True or False), unfortunately most real-world problems contain inexact, incomplete or even unmeasurable data. Several numeric and non-numeric methods have been developed to deal with uncertainty in rule-based (Bhatnagar and Kanal, 1986). Fuzzy logic reflects how people think in sense of words, human decision making and common sense. As a result, it is leading to new, more human, intelligent systems. For example, a fuzzy rule might state, “IF rainfall chance is *high* AND humidity is *medium*, THEN anticipate *heavy rain*”. Each condition of linguistic variables is a fuzzy concept. This is how fuzzy rules handle and capture the imprecise knowledge inputs. In practice, this approach has proven effective and has been applied extensively in prediction and decision support system because it can operate on linguistic terms and partial truths.

Fuzzy Interpretation of Uncertainty

Fuzzy reasoning includes two distinct parts: evaluating the rule antecedent (the IF part of the rule) and implication or applying the result to the consequent (the THEN part of the rule). In fuzzy systems, where the antecedent is a fuzzy statement, all rules fire to some extent, or partially (Negnevitsky, 2005). If the antecedent is true to some degree of membership (MFs) to quantify vagueness, then the consequent is also true to that same degree. In fuzzy theory, fuzzy set A of the universe X is defined by function $\mu_A(x)$ called the MFs of set A (Zadeh, 1965)

$$\mu_A(x): X \rightarrow [0,1] \quad (1)$$

Where

$$\begin{aligned} \mu_A(x) &= 1 \text{ if } x \text{ is totally in } A; \\ \mu_A(x) &= 0 \text{ if } x \text{ is not totally in } A; \\ 0 &< \mu_A(x) < 1 \text{ if } x \text{ is partly in } A; \end{aligned}$$

Thus, this set allows a continuum of possible choices. Consider for example in men's height, the universe of discourse of consists of three sets which are short, average and tall. In fuzzy logic, a man who is 180cm tall is a member of the average men set with a degree of membership of 0.1, and at the same time, he is also a member of the tall men set with a degree of 0.3. This means that a man of 180cm tall has partial membership in multiple sets.

Fuzzy Inference for Prediction and Decision Support

Fuzzy inference can be defined as a process of mapping from a given input to an output, using the theory of fuzzy sets. The general process (refer Figure 1) is:

1. Fuzzification: Convert crisp inputs into fuzzy membership degrees via the defined MFs.
2. Rule Evaluation: Apply a set of IF-THEN rules, where each rule's antecedent clauses are evaluated using AND/OR operators to produce a fuzzy output contribution.
3. Aggregation: Combine the fuzzy outputs of all rules into a single fuzzy set for each output variable.
4. Defuzzification: Convert the aggregated fuzzy output back into a crisp value. The resulting crisp output is then used as the prediction or decision result.

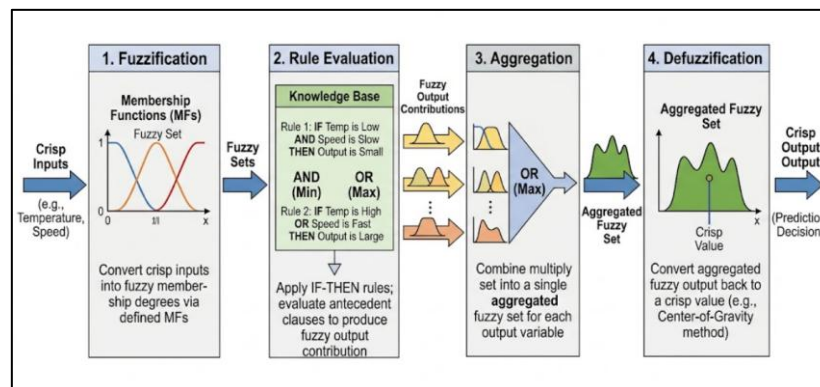


Figure 1: General Process of a Fuzzy Inference System (FIS)

Source: The image was generated with the assistance using Gemini Edu based on conceptual designs provided by the authors.

Methodological Approach for Uncertainty Analysis

This section will briefly discuss selection of case studies and information extraction. The methodological process consists of three stages: (i) selection of case studies, (ii) systematic information extraction, and (iii) cross-domain comparative analysis.

Selection of Case Studies

This study adopts a structured qualitative approach to examine how fuzzy logic is applied to handle uncertainty in prediction, recommendation, assessment, and decision-support systems. Six fuzzy logic-based undergraduate projects were selected as case studies based on their relevance to uncertainty-oriented represent different applications. The selection was guided by the application must employ a FIS or fuzzy logic as a core modelling approach and the application must address prediction, recommendation, assessment, or decision-support problems involving uncertain or imprecise information. Table 1 presents the selected case studies and their respective objectives.

Table 1: Case Studies Selection

No	Field	Projects and its objective
1	Healthcare	Type 2 Diabetes Mellitus (T2DM) Prediction System (Fahrudin et al., 2025): A fuzzy classifier that predicts the risk or presence of type-2 diabetes from patient features.
2	Nutrition	Personalized Diet Recommendations (Robert et al., 2025): A dietary system that recommends nutrition plans based on individual health profiles and lifestyle factors.
3	Environment	Fuzzy Logic Application in Rainfall Prediction (Hasni et al., 2025): A fuzzy model mapping weather inputs to expected rainfall amount.
4	Logistics	Smart Supply-Demand Identification System for Online Food Delivery using Fuzzy Logic (Zaki et al., 2025): A system that assesses real-time supply-demand imbalance in a food delivery platform using fuzzy rules.
5	Education	Fuzzy Logic Application in Educational Decision Making (Hasbullah et al., 2025): A system predict the probability that a student will switch their programme, considering uncertainties and individual preferences.
6	Environmental Monitoring	Fuzzy Logic Application in Air Quality Measurement System (Junaidi et al., 2025): A FIS that computes an Air Quality Index (AQI) from sensor readings.

Information Extraction

The extracted information (refer Figure 2) was subsequently examined through the domains to identify common and specific approaches for uncertainty representation. The analysis considered on how different an application problem to translate uncertain or imprecise input conditions into linguistic fuzzy sets and actionable outputs. This approach enables this study to identify recurring patterns in fuzzy reasoning while highlighting differences arising from the characteristics of each application domain.

Problem → Objectives → Input Factors → Type of Uncertainty → Uncertainty Handling Mechanism → Membership Functions → Fuzzy Sets → Rule Base → FIS Type → Defuzzification → Output → Implementation → Limitations

Figure 2: General Information Extraction

Case Studies Analysis

This section provides a summary of the information extracted from each project. The projects are categorized into four main system types which are prediction-oriented systems, recommendation-oriented systems, decision-support systems, and environmental assessment systems. The extracted information is presented in Table 2 to Table 5.

Prediction-Oriented Systems**Table 2. Information Extraction of Prediction-Oriented Fuzzy Logic Systems**

Criteria	Type 2 Diabetes Mellitus (T2DM) Prediction System (Fahruddin et al., 2025)	Fuzzy Logic Application in Rainfall Prediction (Hasni et al., 2025)
Problem	Traditional diagnosis may rely on threshold values that may not adequately represent borderline or gradual health conditions.	Crisp numerical values are incapable of capturing the progressive changes and unpredictability of weather patterns.
Input Factors	Age, BMI, Family History	Wind Speed, Temperature
Type of Uncertainty	Variation in health/risk factors	Variation in environmental/weather conditions
Uncertainty Handling	Fuzzy representation of risk conditions	Fuzzy representation of weather conditions
Mechanism		
Membership Functions	Triangular and Trapezoidal MFs	Triangular MFs
Fuzzy Sets	Age: Very young, Young, Middle, Old BMI: Underweight, Normal, Overweight, Obese Family History: Low, Medium, High	Wind Speed: Very Low, Low, Normal, High, Very High Temperature: Very Low, Low, Normal, High, Very High
Rule Base	48 IF–THEN rules	25 IF–THEN rules
FIS Type	Mamdani	Mamdani
Defuzzification	Center of Gravity (COG) Method	Center of Gravity (COG) Method
Output	Risk Level: Low, Medium, High, Very High	Rainfall (%): Very Low, Low, Normal, High, Very High.
Execution	MATLAB Simulation and GUI	MATLAB Simulation and GUI
Limitations	The model is limited to three selected input factors, which may restrict the representation of other potentially relevant risk conditions.	The limited selection of meteorological inputs may reduce the ability of rainfall prediction under varying weather conditions.

Recommendation-Oriented Systems**Table 3. Information Extraction of Recommendation-Oriented Fuzzy Logic System**

Criteria	Personalized Diet Recommendations (Robert et al., 2025)
Problem	Conventional dietary planning systems is their inability to take account of the imprecision and variability of human health data.
Input Factors	Hunger Level, Activity Level, BMI, Health Goal
Type of Uncertainty	Variation in individual nutritional requirements
Uncertainty Handling	Fuzzy representation of personal factors
Mechanism	
Membership Functions	Triangular MFs
Fuzzy Sets	Hunger Level: Low, Medium, High Activity Level: Low, Moderate, High BMI: Underweight, Normal, Overweight

Rule Base	Health Goal: Weight Loss, Maintain, Weight Gain
FIS Type	81 IF–THEN rules
Defuzzification	Mamdani
Output	Center of Gravity (COG) Method
	Recommended Calorie Intake: Low, Medium, High
	Nutrient Balance: Low Protein, Balanced, High Protein
Execution	MATLAB Simulation and GUI
Limitations	Required to focus on refining the system's rules to provide more personalized diet recommendations.

Decision-Support Systems

Table 4. Information Extraction of Decision-Support Fuzzy Logic Systems

Criteria	Smart Supply-Demand Identification System for Online Food Delivery using Fuzzy Logic (Zaki et al., 2025)	Fuzzy Logic Application in Educational Decision Making (Hasbullah et al., 2025)
Problem	Incomplete or inaccurate data under the various activities and natural conditions in Supply-Demand Relationship (SDR) Identification for online food delivery.	Imbalance between the education cost and future earnings can lead to financial pressure, dissatisfaction or even dropout.
Input Factors	Rider Load, Weather Condition, Acceptance Rate	Perspective Directions, Budget Support possibility, Expected Salary Level
Type of Uncertainty	Variation in supply-demand fluctuations	Variation in education indicators
Uncertainty Handling Mechanism	Fuzzy rule-based assessment	Fuzzy rule-based assessment
Membership Functions	Triangular and Trapezoidal MFs	Triangular MFs
Fuzzy Sets	Rider Load: Low, Middle, High. Weather Condition: Good, Bad, Extreme. Acceptance Rate: Small, Middle, Large	Perspective Directions: Low, Middle, High Budget Support possibility: Low, Middle, High Expected Salary Level: Low, Middle, High
Rule Base	27 IF–THEN rules	27 IF–THEN rules
FIS Type	Mamdani	Mamdani
Defuzzification	Center of Gravity (COG) Method	Center of Gravity (COG) Method
Output	SDR Level: Relaxed, Normal, Tight.	Educational Path Change: Very Low, Low, Middle, High, Very High
Execution	MATLAB Simulation and GUI	MATLAB Simulation and GUI
Limitations	Required to focus on tuning the system's MFs to provide more flexible SDR level output.	Improvements of the model by additional inputs such as academic performance, personal interest or labour market trends to enhance the accuracy of decisions.

Table 5. Information Extraction of Environmental Fuzzy Logic System

Criteria	Fuzzy Logic Application in Air Quality Measurement System (Junaidi et al., 2025)
Problem	Unable to provide a realistic assessment of air quality due to environmental factors like temperature, humidity, and sensor calibration errors.
Input Factors	PM ₁₀ , CO, NO ₂
Type of Uncertainty	Continuous variation in environmental condition
Uncertainty Handling Mechanism	Fuzzy representation of air-quality conditions
Membership Functions	Triangular and Trapezoidal MFs
Fuzzy Sets	PM10: Excellent, Good, Moderate, Poor, Very Poor, Severe CO: Excellent, Good, Moderate, Poor NO ₂ : Excellent, Good, Moderate, Poor
Rule Base	96 IF–THEN rules
FIS Type	Mamdani
Defuzzification	Center of Gravity (COG) Method
Output	AQI: Good, Moderate, Unhealthy, Very Unhealthy, and Hazardous
Execution	MATLAB Simulation and GUI
Limitations	Improvement of additional input pollutants, real-time sensor integration and machine learning methods for adaptive rule optimization.

Cross-Study Uncertainty Analysis

The selected applications indicate that uncertainty is present in different forms of prediction, recommendation, decision-support, and environmental assessment systems. The systems share a common fuzzy reasoning process in which uncertain input conditions are represented using linguistic variables, then processed through rule evaluation (IF-THEN rules), and transformed into interpretable outputs. The analysis and discussion focus on input uncertainty, linguistic representations, rule-based reasoning, and output interpretation.

Input Uncertainty

Through the six applications, uncertainty primarily originates from the continuous variation of input conditions (refer Table 6). However, the source of uncertainty differs according to the objective and application. Healthcare and education involve variations between individuals, while rainfall and air quality are influenced by changing environmental conditions. In the online food delivery system, uncertainty is associated with random supply and demand, whereas the diet recommendation system reflects differences in individual body requirements. Despite these differences, all systems use fuzzy representation to transform uncertain input conditions into linguistic variables.

Table 6. Analysis of Input Uncertainty

Application	Input Factors	Nature of Uncertainty	Fuzzy Representation
Diabetes Prediction	Health/Risk	Variation among individual	Linguistic Fuzzy sets

Rainfall Prediction	Weather/Environmental	Continuous unpredictable variation	and weather	Linguistic sets	Fuzzy
Diet Recommendations	Personal/nutritional	Individual requirements	dietary	Linguistic sets	Fuzzy
Online Food Delivery	Supply and demand	Fluctuating supply	demand and	Linguistic sets	Fuzzy
Educational decision	Student/educational	Differences in performance/conditions	in	Linguistic sets	Fuzzy
Air quality Assessment	Environmental parameters	Continuous variation	parameters	Linguistic sets	Fuzzy

Linguistic Representation

A common characteristic identified throughout the selected systems is the use of linguistic variables to represent uncertain conditions. Instead of assigning an input exclusively to a single crisp value, fuzzy membership functions allow an input to belong to multiple linguistic categories with different degrees of membership. The linguistic representation differs according to the meaning of the variables in each application (refer Table 7). In healthcare applications, linguistic categories may represent levels of risk, while environmental systems may use categories associated with rainfall or air-quality environmental conditions. Similarly, recommendation and decision-support applications may use linguistic terms to describe personal requirements, supply-demand conditions, or educational indicators. This variation demonstrates the flexibility of fuzzy logic in adapting the representation of uncertainty to different domains. However, the underlying principle remains consistent of continuous or imprecise information is transformed into meaningful fuzzy categories before being processed by the inference system.

Table 7. Linguistic Representation Across Application Domain

Application	Example Crisp Input	Linguistic Category & MFs degree	Interpretation of Fuzzy Sets
Diabetes Prediction	Age (years old) = 28	Very Young ($\mu = 1.0$)	The input exhibits a MFs of 1.0 in the <i>Very Young</i> category
Rainfall Prediction	Temperature = 0.85 (37°C)	High ($\mu = 0.6$) and Very High ($\mu = 0.4$)	The input exhibits a MFs of 0.6 in the <i>High</i> category and 0.4 in the <i>Very High</i> category
Diet Recommendations	Activity Level = 9	High ($\mu = 0.75$)	The input exhibits a MFs of 0.75 in the <i>High</i> category
Online Food Delivery	Acceptance Rate = 0.35	Small ($\mu = 0.25$) and Middle ($\mu = 0.5$)	The input exhibits a MFs of 0.25 in the <i>Small</i> category and 0.5 in the <i>Middle</i> category
Educational decision	Budget support possibility = 0.7	Medium ($\mu = 0.33$)	The input exhibits a MFs of 0.33 in the <i>Medium</i> category
Air quality Assessment	PM ₁₀ = 40	Good ($\mu = 0.71$) and Moderate ($\mu = 0.29$)	The input exhibits a MFs of 0.71 in the <i>Good</i> category and 0.5 in the <i>Moderate</i> category

Rule-Based Reasoning

The IF-THEN rules combine multiple linguistic conditions and provide a structured representation of the reasoning process. For example, a prediction-oriented system may use a rule that relates high-risk input conditions to a high predicted risk, while a recommendation system may relate a combination of personal characteristics to a suitable recommendation. The rule-based approach provides an interpretable mechanism for handling uncertainty because the relationship between input conditions and outputs can be explicitly examined. This differs from approaches where the decision process may be difficult to interpret. For example,

“If PM₁₀ is Poor (0.90) AND CO is Moderate (0.32) AND NO₂ is Moderate (0.70) THEN AQI is Very Unhealthy which Degree of activation = MIN (0.90, 0.32, 0.70) = 0.32”.

Across the selected applications, the number and structure of rules depend on the number of input variables and fuzzy sets. Therefore, more complex and uncertain information application may require a larger rule base to represent the possible combinations of input conditions and subsequently combined through fuzzy rules to determine the corresponding output. This indicates that the rule-based reasoning mechanism provides a common foundation for applying fuzzy logic across different prediction and decision-support domains.

Output Interpretation

The output interpretation is fuzzy reasoning transforms uncertain input conditions into interpretable linguistic or numerical outputs. The nature of the output, however, depends on the system objective. Prediction-oriented systems generate estimated conditions, recommendation-oriented systems provide suggested actions, decision-support systems assist users in selecting an appropriate decision, while environmental assessment provides an interpretation of the current environmental condition. This demonstrates the versatility of fuzzy logic as a robust mechanism for uncertainty management that seamlessly accommodates tailored rule bases and real case representations. Table 8 describe the overall output of the six-project conducted.

Table 8. Output Interpretation Across the Selected Systems

Application	System Orientation	Output Function	Decision Meaning
Diabetes Prediction	Prediction	Risk prediction	Indicates predicted diabetes risk
Rainfall Prediction	Prediction	Rainfall prediction	Indicates expected rainfall condition
Diet Recommendations	Recommendation	Recommendation	Suggests suitable dietary option
Online Food Delivery	Decision Support	Operational decision	Supports operational decision
Educational decision	Decision Support	Decision Support	Supports educational decision
Air quality Assessment	Assessment	Environmental assessment and monitoring	Indicates environmental condition

Discussion

Fuzzy Logic as An Uncertainty-Handling Approach

Fuzzy logic is well-suited to modelling uncertainty in various field of study. Designing fuzzy systems allow inputs to be partially true and/or partially false. This flexibility permits each system incorporate ambiguous information or knowledge successfully. For example, if a student's preparation is "*adequate*", the fuzzy education FIS can partially rule both "*good*" and "*poor*" categories, rather than forcing a single true/false consequence. Likewise, fuzzy AQI level computation can express air quality on a smooth scale rather than a crisp function. All inputs of cases are never forced into a single rigid value but are processed through graded membership. As a result, the fuzzy outputs tend to vary continuously with inputs, making the models more robust to noisy or intermediate data. This interpretive advantage handling non-binary and multi-valued evidence of fuzzy systems.

Though fuzzy logic's general principles are constant, the nature of uncertainty is specific. In meteorology, uncertainty conditions come from chaotic weather dynamics, in healthcare its biological variability, in education considers psychological factors and in logistics from market fluctuations. This diversity required customizing fuzzy sets and rules to each execution. For instance, what counts as "*high risk*" or "*poor*" category remain differs by each application thresholds. The number of linguistic terms also reflected the needs. It could be hundreds of rules or broader categories. This study highlights that each domain's experts must carefully map their uncertainties into fuzzy representations. Nevertheless, the underlying approach of mapping uncertain inputs through fuzzy sets was common to all.

Generalized Framework for Uncertainty FIS

Based on the analysis and having the similar fashion of FIS architecture, a generalized framework for uncertainty FIS is presented in Figure 3. The main novelty of the proposed framework lies in its cross-domain synthesis of the uncertainty-handling process rather than in the introduction of a new fuzzy inference algorithm. Conventional fuzzy inference architectures generally describe the computational sequence from fuzzification, rule evaluation, inference, and defuzzification. In contrast, the proposed framework extends this representation by explicitly linking the nature of application-specific uncertainty to the selection and configuration of fuzzy system components and to the interpretation of the final output. Thus, it provides a higher-level conceptual view of how a common fuzzy reasoning structure can be configured for different uncertainty-oriented applications.

Therefore, the findings indicate that a common fuzzy reasoning structure can be configured according to the characteristics and objectives of a particular application. This distinction is important because the proposed framework is intended to provide a generalized conceptual structure rather than a fixed model. The framework identifies the major stages that can be considered when developing an uncertainty-aware fuzzy system, while the specific fuzzy sets, membership functions, rules, inference mechanism, and output interpretation remain dependent on the application context.

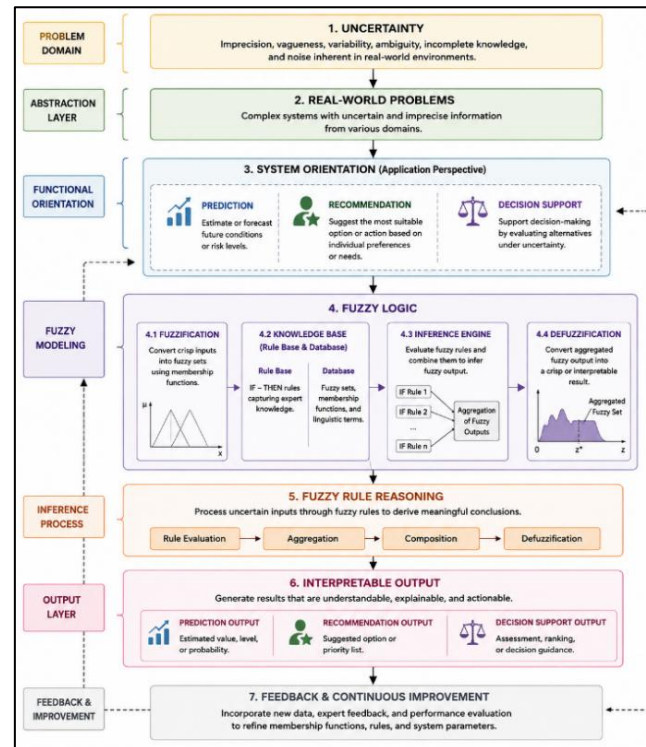


Figure 3: A Generalized Framework for Uncertainty FIS

Source: The image was generated with the assistance using ChatGPT based on conceptual designs provided by the authors.

Conclusion and Research Implications

This study demonstrates that the application of fuzzy logic as a computational approach for managing complex uncertainty across various fields of prediction and decision-support applications. Through six distinct case studies successfully implemented as functional MATLAB software with Graphical User Interfaces (GUIs), it can be concluded that, despite variations in their specific applications, each system relies on a unified underlying architecture. This architecture maps ambiguous input variables onto fuzzy linguistic sets and processes them through a Fuzzy Inference System (FIS) to generate actionable outputs. Each FIS was functionally validated by evaluating discrete input vectors directly through its respective GUI, confirming operational stability, logical flow, and output interpretability under interactive testing. However, these evaluations represent functional and operational testing rather than empirical validation of predictive accuracy or real-world effectiveness. Furthermore, this study highlights a key structural challenge of the FIS framework: as the number of input variables increases, the rule base can grow exponentially, increasing system dimensionality and limiting scalability. Although the evaluated systems addressed this challenge in their GUI implementations by prioritizing critical input combinations and performing manual rule pruning, scaling these systems to complex real-world environments necessitates more automated approaches. To address this limitation, future research should explore hybrid architectures that integrate data-driven machine learning and optimization algorithms, such as neuro-fuzzy systems, to automate rule tuning and reduce rule-base dimensionality. Ultimately, this research reaffirms fuzzy logic as an effective tool for reasoning under uncertainty, providing a flexible conceptual and computational framework for addressing a wide range of real-world applications.

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