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FUZZY RNR: A MAMDANI DECISION SUPPORT SYSTEM FOR PRISONER ASSESSMENT AND REHABILITATION IN CENTRAL JAIL KHUZDAR

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Abstract
Smart prisoner assessment and rehabilitation planning are key to public safety and successful reintegration. Standard assessment processes tend to have difficulties with complexity, subjectivity, and subtle interplay between criminogenic and responsivity factors, soft interventions that are not necessarily optimally adjusted to the individual. This study designs and tests a Mamdani fuzzy logic decision support system for holistic prisoner assessment and rehabilitation program recommendation based on the Risk-Need-Responsivity (RNR) model. The system combines several attributes, such as crime severity, psychological effect, repeat-offender status, educational level, need for substance misuse, need for mental health, social support, work history, motivation, cultural variables, and in-prison conduct, and represents them using Gaussian and triangular membership functions to portray inherent imprecision. A rule-based inference engine, based on criminological literature and expert opinion, controls the inference engine. This study evaluated the system using a dataset collected from the Central Jail in Khuzdar. Results show robust categorization across RNR profiles (low/medium/high risk, need, responsivity) and context-sensitive recommendations for rehabilitation intensity (none, low, moderate, intensive). Distributional and sensitivity analyses confirm stability and highlight rules with the largest influence on outcomes. The resulting tool is transparent, interpretable, and adaptable, and can help correctional professionals assign more precise, culturally sensitive interventions in resource-constrained correctional settings.

1. INTRODUCTION

Accurate assessment and targeted rehabilitation are central to modern correctional practice because they directly affect recidivism rates and community safety. The **Risk-Need-Responsivity (RNR)** framework linking intervention intensity to offender risk, criminogenic needs, and responsivity characteristics remains the dominant evidence-based model [1]. Instead, widespread adoption and practical application remain challenging. Significant studies report that more than two-thirds of released prisoners in the U.S. are rearrested within three years, underscoring the need for more precise and individualized involvement strategies [2]. These scales, while helpful, reduce complex offender profiles to simplifications. They cannot incorporate qualitative or unpredictable factors like motivation or social support, and they frequently incorporate static scoring cuts that do not take into account the subtle interactions of behavioral, psychological, and social factors[3]. In resource-poor and culturally delicate environments like Balochistan, complexity is magnified by [4], [5] They give rise to a larger demand for adaptive, context-aware assessment systems[6].

Fuzzy logic offers an attractive methodological solution. Zadeh first introduced fuzzy set theory [7] Who allowed for reasoning with uncertainty and the expression of linguistic variables. Mamdani fuzzy inference systems (MFIS) capture expert knowledge as interpretable "if then" rules that are particularly well adapted for decision support systems at the place of intersection of qualitative judgment with quantitative measure[8]. Making them especially suitable for decision support in domains where qualitative judgment and quantitative measures intersect. Previous work has shown the utility of fuzzy logic in clinical decision support and rehabilitation contexts [9]. Suggesting its potential for offender assessment. This study addresses two major gaps: (1) the lack of transparent, interpretable systems that handle imprecision in RNR-based assessments, and (2) the absence of culturally grounded decision-support tools for correctional settings in Pakistan. To fill these gaps, we design and evaluate a Mamdani fuzzy inference system that integrates criminological attributes and expert rules to classify prisoners into RNR profiles and recommend tailored rehabilitation programs[10]. The contributions are a Fuzzy logic–based framework, Real-world evaluation, and Sensitivity analysis.

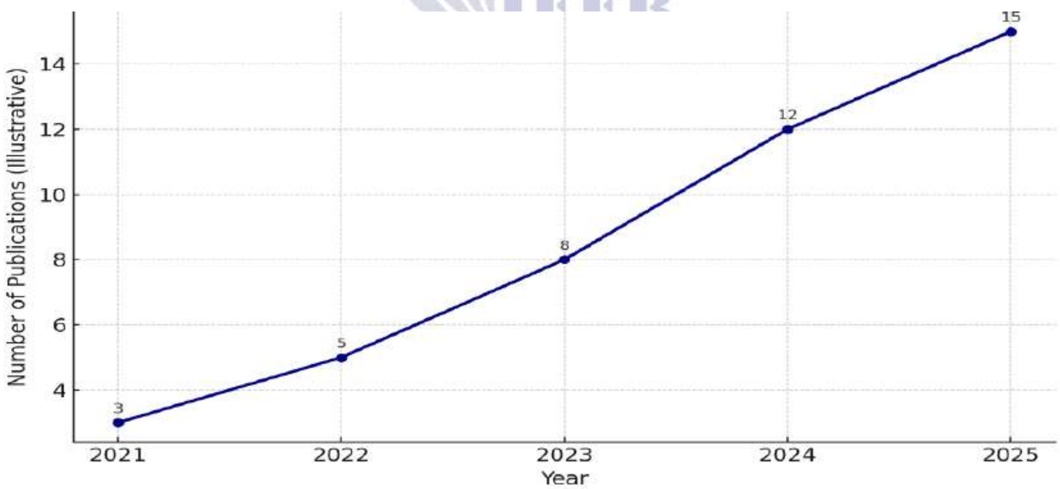

Figure 1: Trend of Fuzzy Logic Applications in Prison/Criminal Justice (2021–2025) [11].

Figure 1. Trend of Fuzzy Logic Applications in Prison and Criminal Justice. The line graph shows the increasing academic interest in implementing fuzzy logic in prisons and criminal justice systems over the last five years. This study has expanded from early conceptual studies to practical applications, such as offender risk assessment or crime prediction, as well as digital rehabilitation programs. It discloses the obligation of fuzzy logic as an

effective method to deal with these situations, blending expertise and facilitating decision-making processes within prison settings.

This study is also unique because it combines the Risk-Need-Responsivity model and the Mamdani fuzzy inference system as a whole to handle the fuzziness of crime offender attributes in an interpretable and explicit fashion, as used by [1], [7], [8]. Using real data from the Central Jail district in Khuzdar and nearby facilities, it provides one of the first context-sensitive decision-support tools for prisoner assessment in Pakistan [4], [5]. The contributions include a fuzzy RNR model, empirical validation with sensitivity analysis, and culturally grounded rehabilitation recommendations. Future work will extend the model with longitudinal data and integration into correctional information systems for broader scalability.

2. Literature Review

Risk-Need-Responsivity (RNR) Model

The RNR model is the most powerful framework for correctional interventions, guiding offender assessment and rehabilitation planning [12]. Its three principles are briefly listed in Table 1.

Table 1. Core Principles of the RNR Model

Principle	Description	References
Risk	Match intervention intensity to the offender's risk level. Over-treatment of low-risk individuals may increase recidivism.	[12], [13]
Need	Focus on criminogenic needs (e.g., substance abuse, antisocial attitudes, unemployment).	[14][15], [16]
Responsivity	Use cognitive-behavioral approaches (general) and tailor interventions to individual factors such as motivation, culture, and learning style (specific).	[17][18], [19], [20]

Table 1 reflects the Risk, Need, and Responsivity (RNR) model. Balancing program intensity against offender risks is advanced by the Risk principle, criminogenic needs targeting (e.g., drug use or unemployment) by Need, and tailoring programs to personal characteristics by Responsivity in efforts to maximize program effectiveness.

2.2 Fuzzy Logic Systems

Fuzzy logic, introduced by Zadeh [21],[20]. Seeks to deal with uncertainty and linguistic variables. The Mamdani Fuzzy Inference System (MFIS), commonly used in decision support systems, comprises fuzzification, rule evaluation, aggregation, and defuzzification [22],[23].

Advantages of Fuzzy Logic in Corrections:

I. Models vagueness in terms like “high risk” or “moderate need.”
II. Transparent reasoning through IF–THEN rules.
III. Integrates expert knowledge directly.
IV. Robust to incomplete or noisy data [22], [24]

2.3 Applications in Criminology

Fuzzy logic has been applied to offender management, but often in a limited scope. Examples include:

Table 2. Applications of Fuzzy Logic in Criminology

Domain	Contribution	Limitations	Reference
Offender Classification	Categorizes offenders by risk and crime severity.	Focuses mainly on static factors.	[24]
Dynamic Risk Modeling	Incorporates behavior, motivation, and substance abuse.	Lacks integration with full RNR.	[25]
Program Matching	Aligns rehabilitation with offender profiles.	Limited cultural sensitivity.	[26]

Table 2 summarizes key approaches in offender assessment. Offender Classification categorizes

individuals by risk and crime severity but relies heavily on static factors. Dynamic Risk Modeling incorporates behavioral elements like motivation and substance abuse, though it often misses full RNR integration. Program Matching links rehabilitation programs with offender profiles but shows limited cultural adaptability.

2.4 Criminogenic Attributes and Rule Derivation

Input variables in this research (e.g., crime severity, repeat offense, education, motivation, substance abuse, social support, cultural factors) are consistent with criminological literature [12],[14]. Rules are derived from RNR principles, empirical findings, and contextual insights relevant to Balochistan [9].

2.5 Cultural Considerations

Cultural background influences offenders' perceptions, motivation, and receptiveness to rehabilitation. Ignoring cultural risks and program ineffectiveness, especially in collectivist societies like Balochistan [26]. Incorporating culture as a responsive factor ensures contextual sensitivity. Current research often isolates risk or needs assessment and neglects responsivity and cultural dimensions. Few systems operationalize the full RNR framework in an integrated fuzzy model. This study bridges the gap by developing a Mamdani fuzzy inference system that unifies risk, need, and responsivity while embedding cultural context, offering one of the first decision-support tools tailored to Pakistan's correctional environment.

3. Methodology

3.1. Overall System Architecture

The system is built on a **Mamdani Fuzzy Inference System (MFIS),** selected for its interpretability and ability to incorporate expert knowledge. It comprises four interconnected sub-systems, aligned with the **Risk-Need-Responsivity (RNR) model:**

I. **Risk Assessment System**: evaluates the likelihood of reoffending.
II. **Need Assessment System**: identifies criminogenic needs requiring intervention.
III. **Responsivity System**: determines readiness and suitability for rehabilitation.
IV. **Rehabilitation Recommendation System**: integrates outputs from the three subsystems to recommend tailored rehabilitation programs.

The outputs of the first three systems (risk, need, responsivity) are crisp numerical values, which become direct inputs to the recommendation system, ensuring a **sequential and integrated pipeline.**

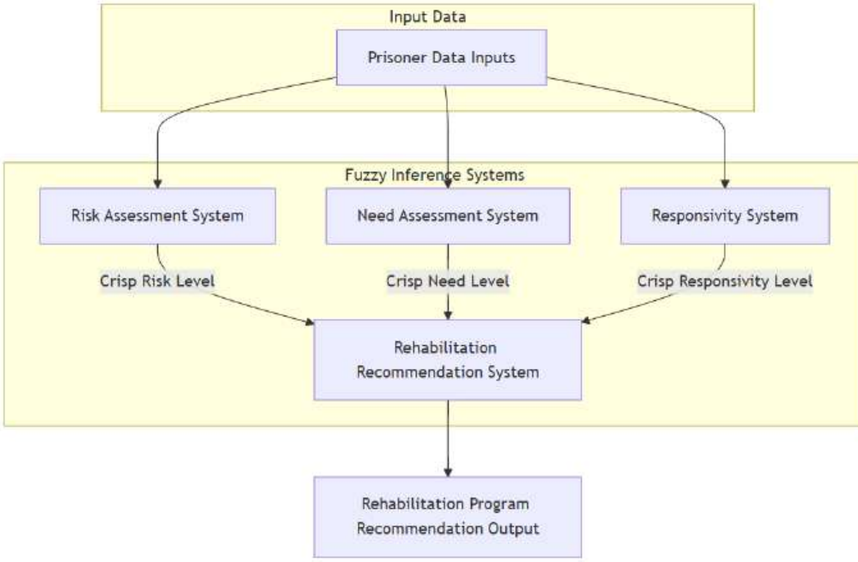

Figure 3. 1 Overall System Architecture Diagram

Figure 3.1 visually represents the four interconnected fuzzy systems (Risk, Need, Responsivity, and Rehabilitation Recommendation) as distinct blocks. Arrows show the flow of information, particularly how the crisp outputs from Risk, Need, and Responsivity feed into the Rehabilitation Recommendation system. It should clearly illustrate the sequential and integrated nature of the assessment pipeline.

3.2. Dataset Acquisition and Preparation

The dataset was obtained from **Central Jail Khuzdar,** representing diverse prisoner profiles with demographic, criminal, psychological, and behavioral attributes. Key features *include* age, gender, education, marital status, crime type, crime severity, psychological impact, repeat offender status, substance abuse, mental health need, social support, motivation, and prison behavior. The Data preparation involved:

I. Handling missing values (e.g., assigning a neutral score for psychological impact).
II. Mapping categorical values (e.g., “High,” “Low”) to numerical ranges suitable for fuzzy processing.
III. Normalizing variables into consistent scales for inference.

Table 3. 1 Summary of Fuzzy System Inputs and Outputs

System	Variable	Type	Range	Linguistic Terms	Description
Risk Assessment	Crime Severity	Input	[0–10]	Minor, Moderate, Severe	Severity of committed crime
	Psychological Impact	Input	[0–10]	Low, Moderate, High	Impact of crime on victims
	Repeat Offender	Input	[0–5]	No, Yes	Whether the prisoner is a repeat offender
	Education Level (Risk)	Input	[0–6]	Low, Medium, High	Educational background (risk context)

	Risk Level	Output	[0–100]	Low, Medium, High	Overall risk of reoffending
Need Assessment	Substance Abuse	Input	[0–3]	None, Low, Moderate, High	Substance abuse needs
	Mental Health	Input	[0–3]	None, Low, Moderate, High	Mental health needs
	Social Support	Input	[0–2]	Low, Moderate, High	Strength of support network
	Employment History	Input	[0–2]	Unfavorable, Neutral, Favorable	Employment stability/history
	Need Level	Output	[0–10]	Low, Medium, High	Overall criminogenic needs
Responsivity	Motivation	Input	[0–2]	Low, Moderate, High	Motivation for rehabilitation
	Education Level (Resp)	Input	[0–6]	Low, Medium, High	Educational background (responsivity context)
	Cultural Factor	Input	[0–1]	Low, High	Cultural influence on responsiveness
	Prison Behavior	Input	[0–2]	Poor, Average, Good	Conduct within prison
	Responsivity Level	Output	[0–10]	Low, Medium, High	Overall rehabilitation responsiveness
Rehabilitation Recommendation	Risk Level (Crisp)	Input	[0–100]	Low, Medium, High	From the Risk system
	Need Level (Crisp)	Input	[0–10]	Low, Medium, High	From the Need system
	Responsivity Level (Crisp)	Input	[0–10]	Low, Medium, High	From the Responsivity system
	Recommendation	Output	[0–10]	None, Low, Moderate, Intensive	Suggested rehabilitation intensity

Table 3.1 systematically lists all input and output variables for each of the four fuzzy systems. For each variable, include its name, type (Antecedent/Consequent), numerical universe of discourse, and a brief description of its meaning. This provides a quick reference for all variables in the system.

3.3 Fuzzy System Design Input/Output Variables

The fuzzy model was implemented using scikit-fuzzy (Python). Each subsystem defines inputs, outputs, membership functions, and fuzzy rules. All subsystems use linguistic variables mapped to numerical universes of discourse.

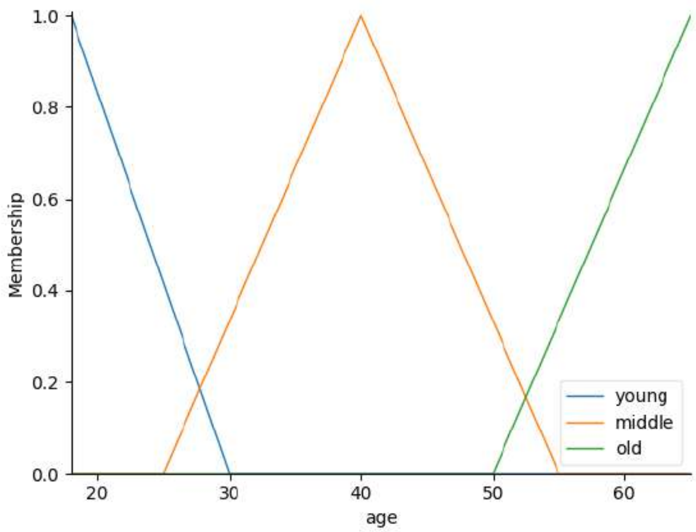

Figure 3. 2 Membership Functions for Age

Figure 3.2 illustrates the membership functions for the variable *Age*, where numerical values are mapped into linguistic categories (e.g., Young, Middle, Old). These functions enable the fuzzy system to interpret age ranges in a gradual and human-like manner rather than with strict cutoffs.

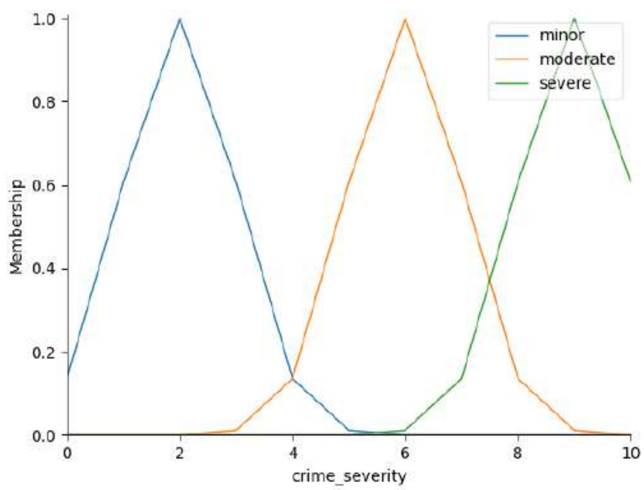

Figure 3. 3 Membership Functions for Crime Severity

Figure 3.3 illustrates the membership functions for Crime Severity, which categorize offenses into linguistic categories such as Minor, Moderate, and Severe. These functions capture the gradual transition between severity levels, supporting more flexible and human-like risk assessment.

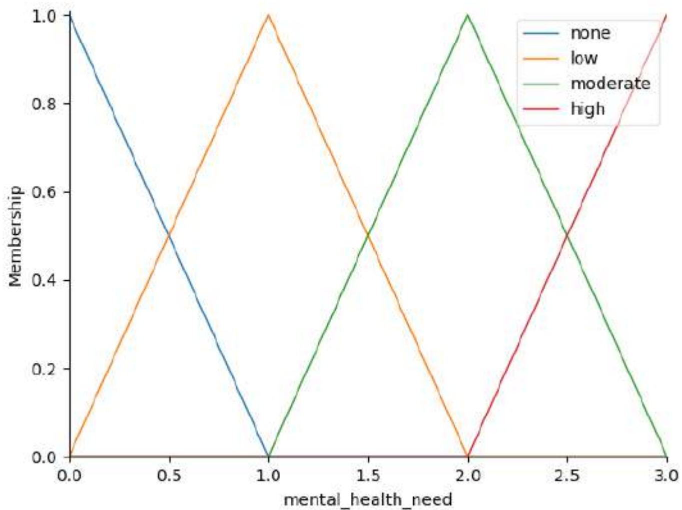

Figure 3. 4 Membership Functions for Mental Health Need

Figure 3.4 depicts the membership functions for *Mental Health Need*, dividing it into categories such as None, Low, Moderate, and High. These functions allow the fuzzy system to represent varying levels of psychological support required by prisoners in a gradual, interpretable manner.

3.5 Membership Functions

I. **Gaussian membership functions**: used for continuous/subjective inputs in the Risk subsystem (e.g., crime severity, psychological impact).

II. **Triangular membership functions**: used in the Need, Responsivity, and Recommendation subsystems for efficiency.

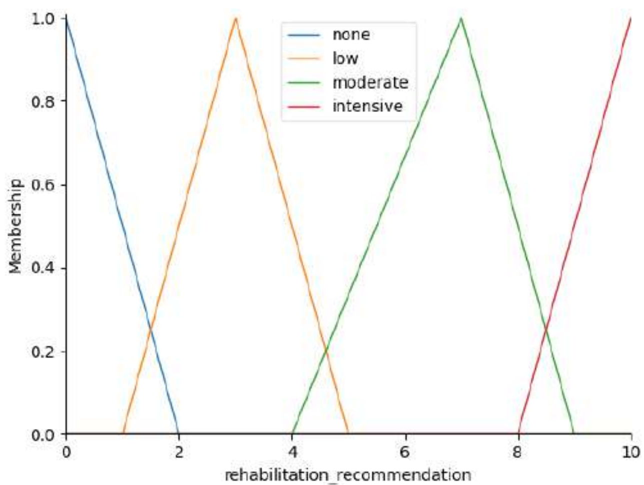

Figure 3. 5 Membership Functions for Rehabilitation Recommendation

Figure 3.5 presents the membership functions for *Rehabilitation Recommendation*, categorized as None, Low, Moderate, and Intensive. These functions enable the fuzzy system to align program intensity with the prisoner's assessed risk, need, and responsivity profiles.

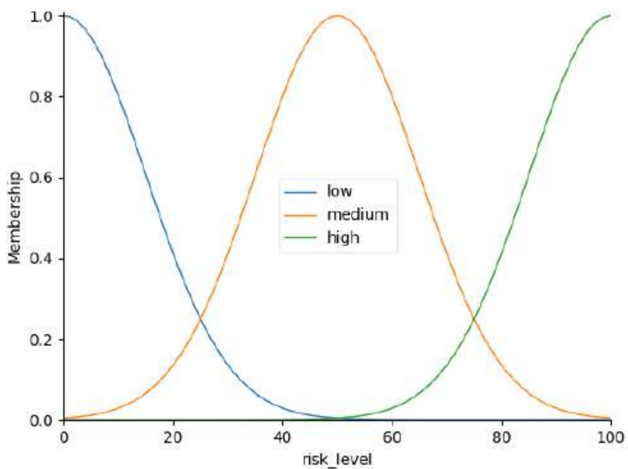

Figure 3. 6 Membership Functions for Risk Level

Figure 3.6 shows the membership functions for Risk Level, classified into Low, Medium, and High. These functions help the fuzzy system quantify the likelihood of reoffending in a gradual and interpretable way.

3.6 Fuzzy Rules

The rule base encodes criminological principles, expert insights, and RNR guidelines. Each subsystem has a set of IF–THEN rules (43 total). A representative subset is shown below.

Table 3. 2 Sample Fuzzy Rules

System	Rule ID	Fuzzy Rule (IF-THEN Statement)	Justification (Brief)
Risk Assessment	Rule 4	IF Crime Severity is Severe AND Psychological Impact is High, THEN Risk Level is High.	Severe crimes with high victim impact are strong indicators of high reoffending risk.
	Rule 5	IF Repeat Offender is Yes AND Crime Severity is Severe, THEN Risk Level is High.	Consistent with the Risk Principle: prior criminal history and severe offenses increase risk.
	Rule 11	IF Education Level is High AND Repeat Offender is No, THEN Risk Level is Low.	Higher education and no prior history suggest a lower risk of future offending.
Need Assessment	Rule 1	IF Substance Abuse Need is High AND Mental Health Need is High, THEN Need Level is High.	Co-occurring severe criminogenic needs require intensive intervention.
	Rule 3	IF Mental Health Need is None AND Substance Abuse Need is None AND Social Support is High, THEN Need Level is Low.	Absence of key criminogenic needs and strong support indicate low overall need.
Responsivity	Rule 1	IF Motivation is High, AND Prison Behavior is Good, AND Cultural Factor is Low, THEN the Responsivity Level is High.	Highly motivated individuals with good behavior and no cultural barriers are highly responsive.

	Rule 4	IF Cultural Factor is High AND Prison Behavior is Poor, THEN Responsivity Level is Low.	Significant cultural barriers combined with poor behavior indicate low responsiveness to standard interventions.
Rehabilitation Recommendation	Rule 1	IF Rehab Risk Level is High AND Rehab Need Level is High AND Rehab Responsivity Level is Low, THEN Rehabilitation Recommendation is Intensive.	High-risk, high-need individuals, especially with low responsivity, require the most intensive and tailored programs.
	Rule 6	IF Rehab Risk Level is Low AND Rehab Need Level is Low, THEN Rehabilitation Recommendation is None.	Low-risk, low-need individuals may not require formal programs, aligning with the Risk Principle.
	Rule 9	IF Rehab Responsivity Level is Low AND Rehab Need Level is High, THEN Rehabilitation Recommendation is Intensive.	Despite low responsivity, high needs necessitate intensive effort, potentially with specialized approaches.

Table 3.2 presents a small, representative sample of fuzzy rules from each of the four systems (e.g., 2-3 rules per system). For each rule, provide its full "IF-THEN" statement. This helps readers grasp the logic of the rule without needing to list all 43 rules.

3.7. Data Processing and Analysis

The pipeline for processing each prisoner record consists of:

I. **Input Mapping**: Converting raw dataset values to fuzzy-compatible scales.
II. **Fuzzy Inference**: applying the rule base to compute crisp outputs for risk, need, and responsivity.
III. **Integration**: feeding these outputs into the recommendation system.
IV. **Categorization**: mapping numerical scores back into linguistic labels (e.g., Low, Medium, High).

4.2. Fuzzy Assessment Distributions

Upon processing the dataset through the Mamdani Fuzzy Inference Systems, the prisoners were categorized into distinct levels for Risk, Need, Responsivity, and Rehabilitation Recommendation. The distributions of these assessments provide a high-level overview of the

3.8 Sensitivity Analysis

A simplified sensitivity analysis was conducted by testing reduced rule subsets. Results showed that **core rules drive most outputs**, while secondary rules fine-tune recommendations.

4 Results

4.1 Dataset Overview

The dataset comprised **437 prisoner records** with demographic (Age, Gender, Education, Marital Status), criminal (Crime Type, Severity, Repeat Offender, Prior Convictions, Sentence Length), and behavioral/social features (Psychological Impact, Prison Behavior, Cultural Factor, Substance Abuse Need, Social Support, Motivation, Mental Health Need). The variety of minor to severe crimes, differing education levels, and behavioral attributes provided a **comprehensive basis** to test the model's ability to handle heterogeneous prisoner profiles.

prisoner population's characteristics as evaluated by the fuzzy model.

4.3 Risk Assessment Distribution

The application of the Risk Assessment System resulted in the categorization of prisoners into Low, Medium, and High Risk levels.

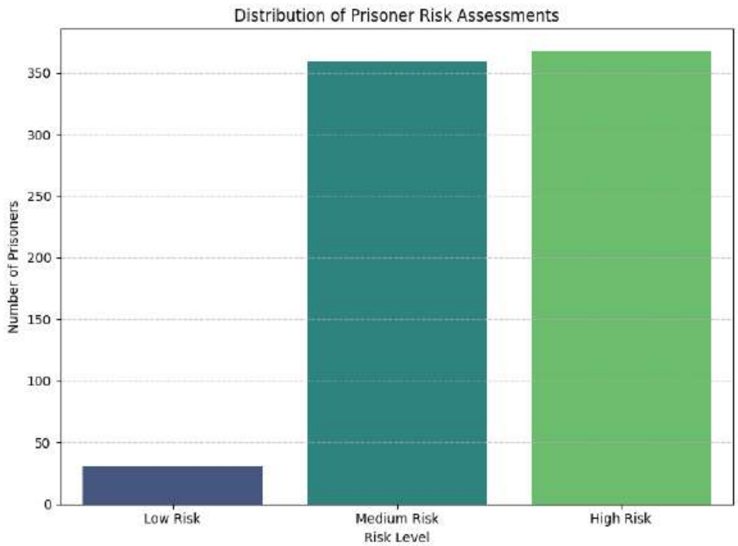

Figure 4. 1 Distribution of Prisoner Risk Assessments

Figure 4.1 indicates that a substantial portion of the prisoner population falls into the 'Medium Risk' category, suggesting a need for targeted interventions that balance security concerns with rehabilitation efforts. The presence of 'High Risk' individuals underscores the importance of intensive supervision and specialized programs, while 'Low Risk' individuals may benefit from less restrictive or community-based approaches.

4.4 Need Level Distribution

The Need Assessment System evaluated prisoners across various criminogenic needs, categorizing their overall Need Level as Low, Medium, or High. Figure 5.2 illustrates this distribution.

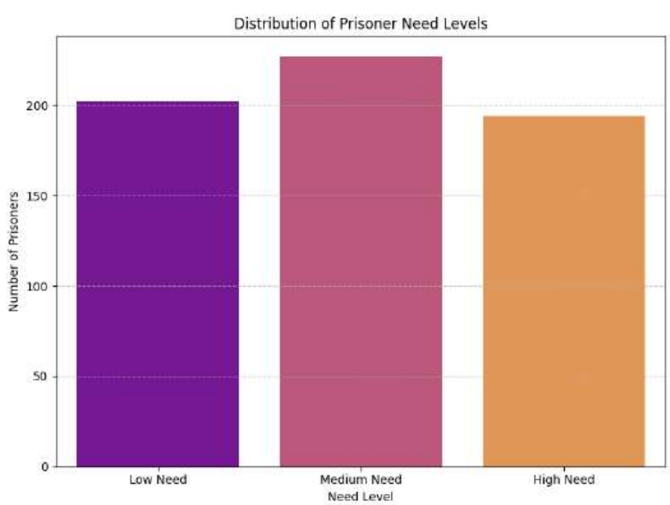

Figure 4. 2 Distribution of Prisoner Need Levels

Figure 4.2 shows the distribution of need levels, highlighting the prevalence of specific criminogenic factors within the prison population. A significant number of prisoners were identified with 'Medium' to 'High' needs, particularly in areas such as substance abuse, mental health, and employment history. This finding emphasizes the necessity of comprehensive need-based interventions to address the root causes of criminal behavior.

4.5 Responsivity Distribution

The Responsivity System assessed each prisoner's potential responsiveness to rehabilitation programs, considering factors like motivation, education, cultural background, and prison behavior. The resulting distribution is shown in Figure 5.3.

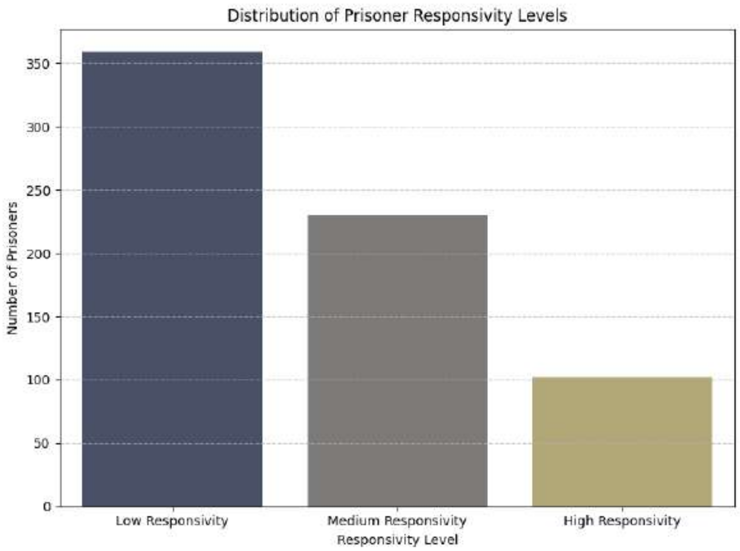

Figure 4. 3 Distribution of Prisoner Responsivity Levels

Figure 4.3: The responsivity distribution reveals varying degrees of readiness and capacity among prisoners to engage with interventions. A notable proportion of individuals exhibited 'Medium Responsivity,' suggesting that while they may benefit from standard programs, some tailoring might be beneficial. The presence of 'Low Responsivity' individuals underscores the need for highly individualized, culturally sensitive, and perhaps more intensive pre-program interventions to enhance their engagement.

4.6 Rehabilitation Recommendation Distribution

Integrating the crisp outputs from the Risk, Need, and Responsivity assessments, the Rehabilitation Recommendation System provided tailored program suggestions (None, Low, Moderate, Intensive). Figure 5.4 presents this distribution.

Figure 4. 4 Distribution of Rehabilitation Recommendations

Figure 4.4 The distribution of rehabilitation recommendations reflects the system's ability to differentiate between prisoners requiring minimal intervention and those necessitating comprehensive, multi-faceted programs. The observed proportions across the categories demonstrate that the fuzzy system can effectively match the intensity of the recommended program to the assessed RNR profile of each prisoner, aligning with the core principles of effective correctional practice.

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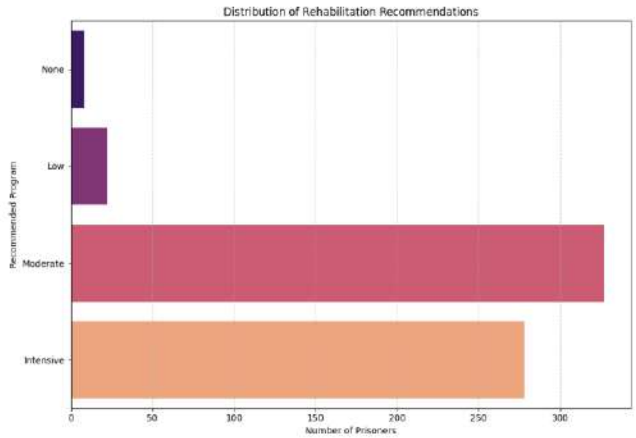

Figure 4.4 Distribution of Rehabilitation Recommendation

Table 4.1: Summary of Assessment Distributions

Assessment Type	Categories	Key Observations
Risk	Low, Medium, High	Majority Medium, critical share High
Need	Low, Medium, High	Many Medium–High needs (substance abuse, mental health)
Responsivity	Low, Medium, High	Mostly Medium; Low cases need tailored support
Recommendation	None, Low, Moderate, Intensive	Ranges across all levels; Intensive for high-risk/high need

Table 4.1 shows how the system bridges raw attributes to actionable rehabilitation guidance.

4.7 Membership Function Visualizations

To illustrate the fuzzification process and the linguistic interpretation of numerical inputs and outputs, representative membership function plots are presented. Figure 5.5 displays examples of Gaussian membership functions used in the Risk Assessment System, while Figure 5.6 shows triangular membership functions from the Need or Responsivity systems.

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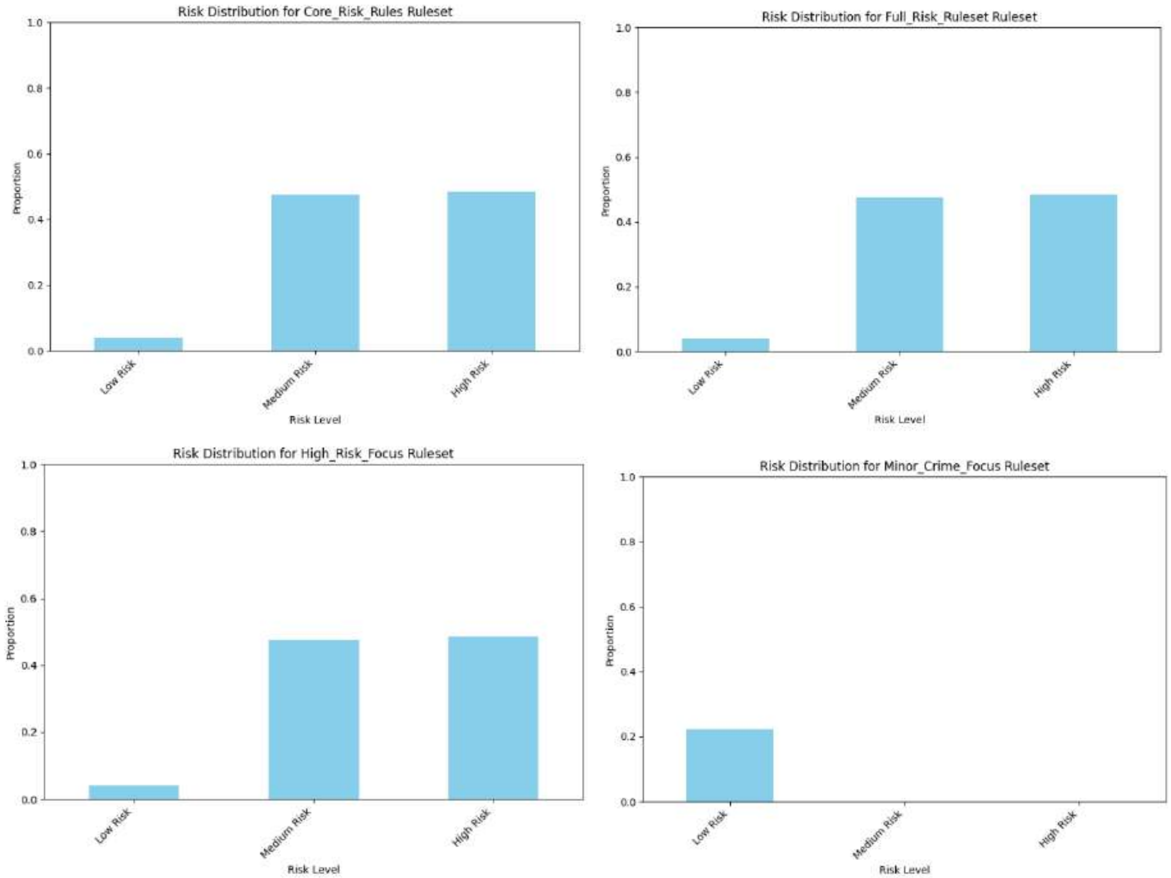

Figure 4.5 Sensitivity Analysis of Risk Assessment (Comparative Bar Plots for Rule Subsets)

The sensitivity analysis in Figure 4.5 for risk assessment revealed that while the overall trends remained consistent, certain rule subsets, particularly those emphasizing Repeat offender and Severe Crime Severity, led to a higher proportion of individuals categorized as 'High Risk.' Conversely, subsets focusing on Education Level and Minor Crime Severity tended to increase the 'Low Risk' category. This indicates that the model's output is responsive to the emphasis placed on different criminogenic factors within the rule base, affirming the importance of carefully curated rules.

4.8 Need Level Sensitivity

The impact of varying rule sets on the Need Level distribution is shown in Figure 5.8.

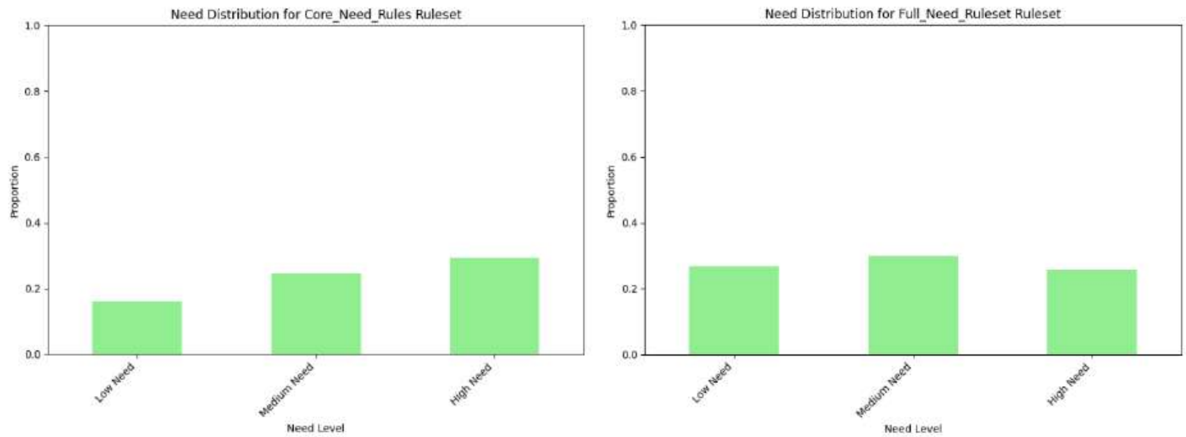

Figure 4. 6 Sensitivity Analysis of Need Level (Comparative Bar Plots for Rule Subsets)

The analysis for need assessment demonstrated in Figure 4.6 that rules prioritizing Substance Abuse need and Mental_Health_Need led to a greater concentration of prisoners in the 'High Need' category. This confirms the direct impact of these critical criminogenic factors on the overall need assessment and highlights the model's ability to reflect the severity of these issues.

4.9 Sensitivity Analysis Findings

The sensitivity analysis was conducted to evaluate the robustness of the fuzzy model to variations in its rule base. By comparing assessment distributions under different subsets of rules, insights were gained into the influence of specific rule groups on the overall outcomes. The analysis focused on the Risk, Need, Responsivity, and Rehabilitation Recommendation systems.

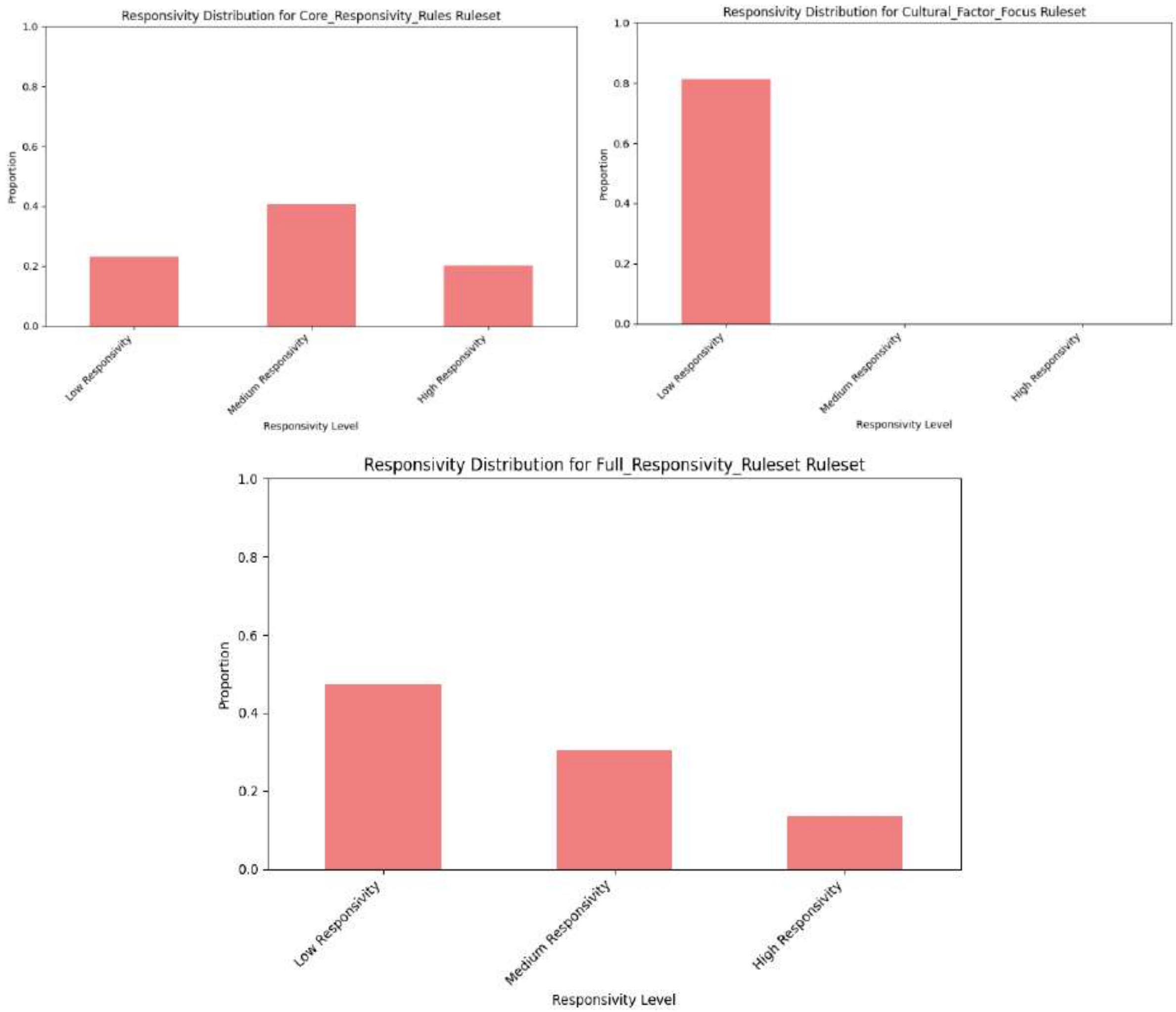

Figure 4. 7 Sensitivity Analysis of Responsivity Comparative Bar Plots for Rule Subsets

Figure 4.7 shows the sensitivity analysis for responsivity, which revealed that rules incorporating Cultural Factor significantly influenced the proportion of individuals categorized as 'Low Responsivity.' When these rules were more heavily weighted or exclusively used, more individuals were shifted towards lower responsivity levels, underscoring the model's capacity to account for contextual barriers to rehabilitation. This finding validates the emphasis placed on cultural considerations in the system's design.

4.10 Rehabilitation Recommendation Sensitivity

Finally, the sensitivity of the Rehabilitation Recommendation to changes in its underlying rule base is presented in Figure 5.10.

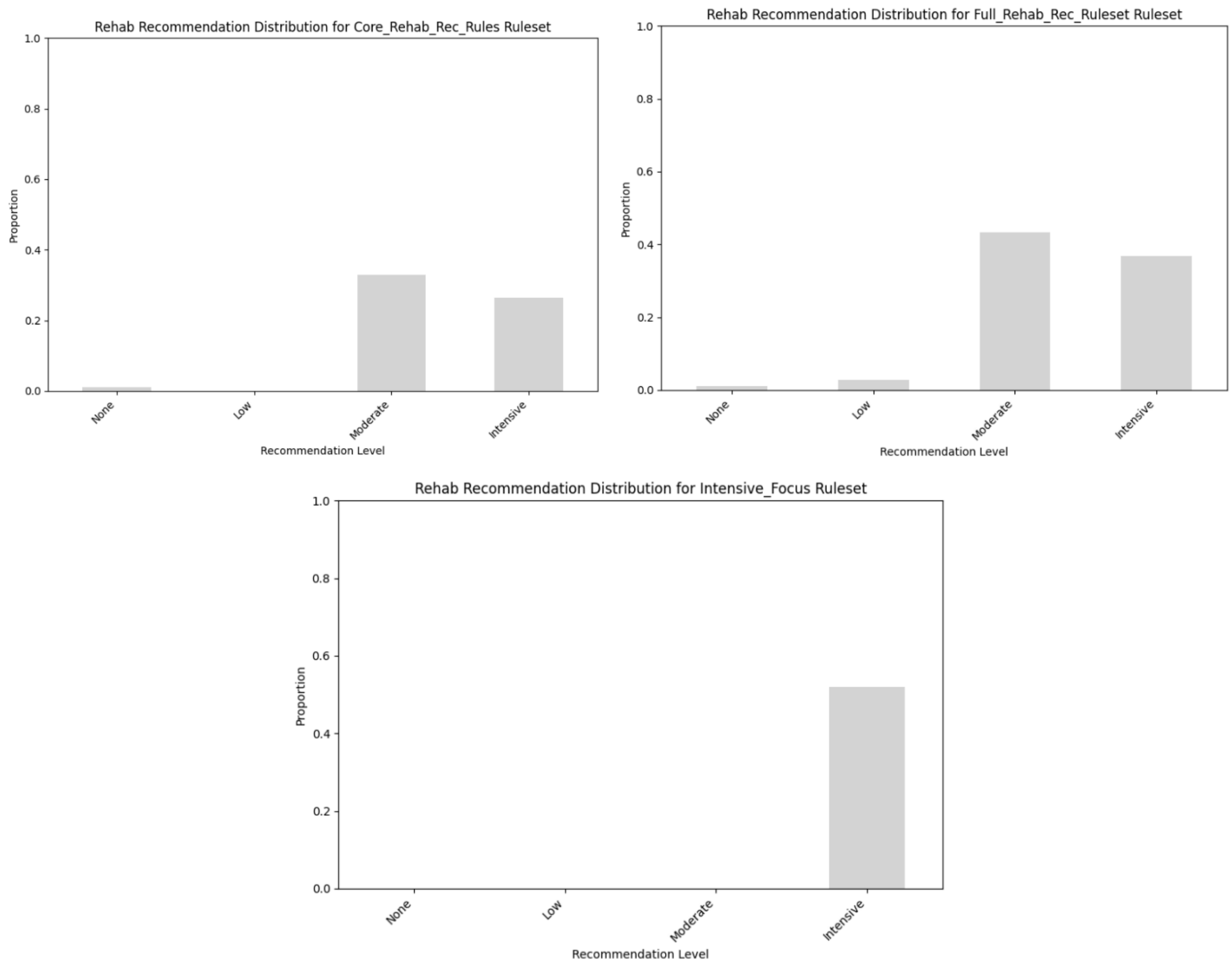

Figure 4. 8 Sensitivity Analysis of Rehabilitation Recommendation (Comparative Bar Plots for Rule Subsets)

Figure 4.8 represents the rehabilitation recommendation sensitivity analysis, which showed that rule subsets prioritizing 'High Risk' and 'High Need' input consistently led to a higher proportion of 'Intensive' recommendations. Conversely, rule sets focusing on 'Low Risk' and 'High Responsivity' tended to increase 'None' or 'Low' recommendations. This demonstrates the system's flexibility in adapting its recommendations based on the specific emphasis of its guiding logic, further validating its utility as a decision support tool.

5. Findings and discussion.

The decision support system based on fuzzy logic was able to produce refined judgments about risk, need, and responsivity, thereby making differentiated rehabilitation outcomes. A majority of the prisoners fell into the category of Medium Risk with Medium to Very High Needs, reflecting the need for strong, albeit personalized, interventions. Responsivity variation called for the adaptation of program delivery to motivation, education, and cultural background. Remarkably, the rate of low-responsivity cases, as elicited by culture, points to the need for culturally specific or preparation interventions to secure participation. Rehabilitation guidance supported the discrimination between prisoners who need very little monitoring and those who need strong, multi-dimensional programs, to align resources with the seriousness of need and risk, taking account of the capability of the individual to gain benefit. This influences the RNR approach:

I. **Risk:** Offenders are appropriately ranked as Low, Medium, and High Risk, and program intensity is adjusted accordingly.
II. **Need:** Criminogenic needs like substance use, mental health, and social support are targeted directly, as supported by evidence-based practice.
III. **Responsivity:** Considering motivation, instruction, behavior, and culture, the system provides customized interventions that correspond to personal style or style of engagement and learning.

It contributes value through the handling of uncertainty, interpretable rules, criminological expertise integration, as well as contextual, nuanced output. In practice, this results in more consistent judgments, customized interventions, rationalized allocation, as well as culture-sensitive measures of rehabilitation. It still has some areas of improvement, yet. The dataset, although representative, must be filled with longitudinal, real-world data. Rules, as well as membership functions, were theory-informed, rather than co-constructed, leaving some latitude to improve. The current model generates static, coarse recommendations, rather than dynamic, program-specific guidance. Finally, it was evaluated only based on logical, sensitivity, rather than long-term predictive measures, like reoffending.

6. Conclusion

This study introduced a fuzzy logic-based decision support system for the evaluation and rehabilitation of prisoners, based on the Risk-Need-Responsivity (RNR) framework. Using the Mamdani Fuzzy Inference System, it avoided the limitations of traditional methodologies through nuanced discrimination of risk, need, and responsivity, mixing criminogenic as well as cultural factors. It was also tested on the dataset provided by the Central Jail Khuzdar, producing personalized rehabilitation output, where most of the prisoners were recognized as medium-to-high risk, as well as needing cases. Sensitivity analysis confirmed the model's robustness and highlighted the influence of cultural and motivational factors on responsivity. The research contributes a transparent and interpretable framework that mirrors expert reasoning, improves assessment consistency, and supports culturally sensitive rehabilitation planning. Future work should focus on real-world validation with longitudinal data, system deployment for correctional staff, and the exploration of adaptive fuzzy models to enhance predictive power.

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