



## A Fuzzy Inference System for Assessing Parental Mental Health and Postpartum Depression

Saumya Richa\* and Zahoor Lone

**ABSTRACT:** The transition to parenthood is a critical emotional and psychological adjustment period for both mothers and fathers; however, conventional assessment tools often reduce complex mental-health experiences into rigid categorical scores. To overcome these limitations, this study developed and evaluated a Mamdani-type Fuzzy Inference System (FIS) for assessing parental mental health after childbirth. The model integrated four key psychosocial indicators—postpartum depression (EPDS), parenting stress (PSS), perceived social support (MSPSS), and emotional regulation (ERQ)—and applied expert-defined fuzzy rules to generate a continuous mental-health index using linguistic categories (low, moderate, high). The system was tested on cross-sectional data from 400 parents in Aurangabad, Bihar. Results showed that most participants fell within the moderate mental-health range, with fathers demonstrating slightly higher risk compared to mothers. The findings highlight the advantage of fuzzy logic in capturing nuanced emotional variations compared to traditional Likert-based scoring. While the cross-sectional design limits causal inference, the model demonstrates significant potential for early risk detection and supports gender-inclusive, culturally sensitive postpartum mental-health interventions.

**Keywords:** Fuzzy Inference system, postpartum depression, emotional regulation, parental mental health, parenting stress, social support, gender variations.

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\* Corresponding author.  
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## 1. Introduction

Depression is a complex mental disorder whose symptoms often overlap, making diagnosis challenging. It is generally characterized by persistent sadness, loss of interest, and impaired functioning, and in severe cases may involve suicidal thoughts lasting for at least two weeks [1]. The transition to parenthood introduces significant psychological, emotional, and social adjustments for both mothers and fathers [2]. Mothers face physical recovery, hormonal changes, and sleep disruption, while fathers frequently encounter financial pressure and new role responsibilities [2]. Globally, postpartum depression affects 10–20% of mothers regardless of socioeconomic background [3], and this prevalence increases to 20–40% in developing countries due to inadequate healthcare services [4]. Paternal postpartum depression has also gained attention, with symptoms reported in approximately 10–15% of new fathers; however, stigma and gender expectations contribute to underreporting [5]. These figures highlight the urgent need for comprehensive, sensitive, and inclusive mental-health assessment tools.

Standard psychometric instruments such as the Edinburgh Postpartum Depression Scale (EPDS), Parenting Stress Scale (PSS), and Multidimensional Scale of Perceived Social Support (MSPSS) have significantly improved postpartum screening practices. However, traditional Likert-based scoring can reduce complex emotional variations into rigid categorical boundaries, which risks oversimplifying individual mental-health states [6]. Fuzzy scales, in contrast, acknowledge the subjective and continuous nature of psychological experiences by assigning degrees of membership rather than fixed values [6,7]. This flexibility allows subtle differences in emotional states to be captured more accurately than with fixed categories.

Beyond biological and emotional processes, postpartum depression is shaped by sociocultural forces. Research from developing countries identifies family conflict, marital tension, unwanted infant gender, limited social support, and infant health complications as major contributors [8]. Such factors indicate that family pressures and social norms significantly influence postpartum mental health.

**Figure 1. Major psychosocial risk factors for postpartum depression, highlighting family-related stressors and gender preference concerns.**

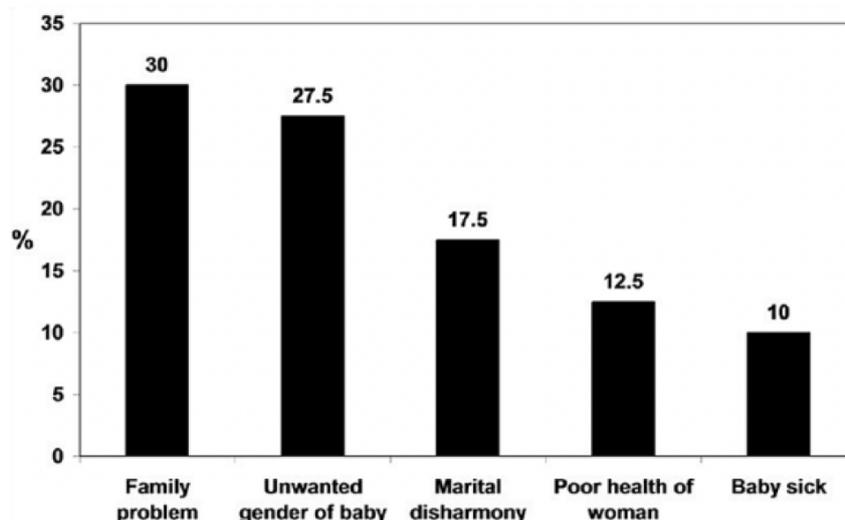


Figure 1: \*

*Adapted from Shriram et al. (2019) — Open Source*

## 2. Theoretical and Conceptual Foundation

Psychological constructs such as anxiety, stress, and depression exist along a continuum rather than as strict categories. Fuzzy set theory, introduced by Zadeh (1965), supports this understanding by enabling partial membership to multiple categories [9]. The membership function  $\mu_A(x)$  assigns values from 0 (no membership) to 1 (full membership), reflecting the degree to which an element belongs to a fuzzy set. This approach represents psychological uncertainty more accurately than binary classification models [9,10,11].

Fuzzy logic applies these principles through natural-language IF–THEN rules, similar to clinical reasoning (e.g., “IF stress is high AND support is low THEN sadness is high”) [12].

### 2.1. Psychological Constructs Underpinning the Fuzzy Model

Emotional regulation refers to the ability to monitor and modify emotional responses according to situational demands [13]. Effective regulation increases resilience, whereas maladaptive strategies elevate depression risk [14,15]. Multidimensional Perceived Social Support measures perceived support from family, friends, and significant others [16], and high support has been shown to reduce postpartum stress and depressive symptoms [17]. The Parenting Stress Scale evaluates emotional burden and conflict associated with parenting [18], which is closely linked to anxiety, depression, and family-relationship challenges [19]. These psychological variables converge in relation to postpartum depression, commonly measured by Edinburgh Postpartum Depression Scale [20], with symptoms such as sadness, fatigue, irritability, and reduced pleasure.

### 2.2. Computational Integration: Fuzzy Logic in Parental Mental Health

This study employs a Mamdani-type Fuzzy Inference System (FIS) to assess postpartum mental health using MSPSS, PSS, and ERQ as inputs to predict depression risk (EPDS). Each input is categorized into Low, Moderate, and High fuzzy subsets. Expert-defined IF–THEN rules (e.g., “IF Stress is High AND Support is Low THEN Depression Risk is High”) generate a fuzzy mental-health index that is defuzzified into a crisp score for interpretation. Unlike regression approaches, this model improves interpretability, handles nonlinear interactions, and reduces diagnostic rigidity.

### 2.3. Conceptual Framework for Fuzzy Modeling

Fuzzy set theory and fuzzy logic form the theoretical foundation of the Mamdani-type Fuzzy Inference System (FIS) employed in this study to assess parental mental health following childbirth.

1. **Fuzzy Set:** Developed by Zadeh (1965) — Any fuzzy modeling is based on a fuzzy set. It allows for partial membership instead of a strict ‘in’ vs. ‘out’ dichotomy [21]. For example, a person might have a membership value of 0.7 in the category “depressed” and 0.3 in the category “not depressed,” while in traditional sets, membership is restricted to 1 or 0. In this study, fuzzy subsets represent Low, Moderate, and High Social Support (MSPSS); Mild, Moderate, and Severe Depression (EPDS); and Low and High Parenting Stress (PSS).
2. **Fuzzy Logic:** The Reasoning Framework (Zadeh, 1972) — Fuzzy logic enables reasoning through natural language, based on IF–THEN rules, allowing degrees of truth between 0 and 1 rather than strict binary outcomes [22].
3. **For instance:** IF Stress is High AND Social Support is Low, THEN Depression Risk is High. This framework aligns with real-world psychological decision-making, where emotional states are uncertain and overlapping.
4. **Mamdani Fuzzy Inference System (FIS):** The Application Layer (Mamdani, 1975) — The Mamdani model converts psychological input variables into interpretable output using fuzzy rules [23]. It consists of four major steps:
  - Fuzzification — transforms crisp values (e.g., EPDS score) into fuzzy membership values;
  - Rule Evaluation — applies expert IF–THEN rules;
  - Aggregation — combines outputs of all rules;
  - Defuzzification — converts the final fuzzy surface to a precise numerical score (e.g., 0.56 representing moderate depression risk).

This model allows nonlinear interactions among parenting stress, emotional regulation, and social support to predict postpartum depression more flexibly than fixed-category assessments.

### 2.4. Aim of the Study

This study aimed to design a Mamdani-type Fuzzy Inference System (FIS) incorporating EPDS, MSPSS, PSS, and ERQ to evaluate postpartum mental health in parents. The model compared fuzzy outcomes between mothers and fathers and assessed its performance in relation to traditional statistical methods. By supporting more interpretable and continuous assessment of emotional well-being, the fuzzy framework facilitates early identification of psychological risk and encourages father-inclusive, culturally sensitive, and human-centered mental-health interventions.

## 3. Methodology

### 3.1. Study Design

A quantitative cross-sectional design was used, integrating standardized psychological assessment with a Mamdani-type Fuzzy Inference System (FIS) to estimate postpartum depression risk among parents. Fuzzy modeling was selected because it accommodates vague and continuous emotional states such as depression, stress, and perceived support, which are not suitably represented by rigid categorical scoring frameworks.

### 3.2. Participants

The study included 400 parents (200 mothers and 200 fathers) recruited from public and private healthcare facilities in Aurangabad district, Bihar, India. Participants were selected through multistage sampling at the block level, followed by purposive sampling within primary health centers. Data were collected from parents 6–24 months postpartum.

#### **Inclusion criteria:**

- Biological mothers or fathers aged 22–35 years,
- Having a child aged 6–24 months, and
- Willingness to provide informed consent.

**Exclusion criteria:**

- Parents with a previous psychiatric diagnosis
- History of substance dependence
- Presence of severe physical illness

Written consent was obtained, and the Institutional Research Ethics Committee at Lovely Professional University granted ethical approval.

### 3.3. Sociodemographic Characteristics

A demographic questionnaire was developed to collect essential background information from parents, informed by previous research and related literature. The data gathered included participants' age, locality, occupation, monthly income, mode of delivery, child's gender, family structure (nuclear or joint), and parity, indicating whether they were experiencing parenthood for the first time (primiparous) or had more than one child (multiparous).

### 3.4. Psychological Tools

There are a total of four standardized psychological tools used as input variables in the fuzzy inference model. Each scale was chosen for its robust psychometric properties, conceptual relevance to parental mental health, and suitability for fuzzy-logic modeling.

1. **Emotional Regulation Questionnaire (ERQ):** The Emotional Regulation Questionnaire (ERQ) Gross and John (2003) assesses two key emotion regulation strategies: cognitive reappraisal (6 items) and expressive suppression (4 items) [24]. Responses are rated on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The Scale showed a good internal reliability: cognitive reappraisal ( $\alpha = 0.79$ ) and expressive suppression ( $\alpha = 0.73$ ). Higher scores on cognitive reappraisal reflect more adaptive emotional regulation, whereas higher scores on expressive suppression reflect less adaptive strategies.
2. **Edinburgh Postpartum Depression Scale (EPDS):** The EPDS is a widely used 10-item self-report screening tool developed by Cox et al. (1987) to assess postpartum depressive symptoms [20]. With a total score range of 0–30, higher scores indicate greater symptom severity. Cut-off ranges classify depression as minimal (0–6), mild (7–13), moderate (14–19), and severe (20–30). The scale demonstrates strong internal consistency ( $\alpha = 0.83$ ) and cross-cultural validity [25]. In this paper, the EPDS served as the primary measure of depressive symptoms and was used as a benchmark for validating the fuzzy model.
3. **Multidimensional Scale of Perceived Social Support (MSPSS):** MSPSS was constructed by Zimet et al. (1988) to measure perceived adequacy of social support from three sources: family, friends, and significant others [16]. It consists of 12 items rated on a 7-point Likert scale, ranging from 1 (very strongly disagree) to 7 (very strongly agree). Total scores range from 12–84, with higher scores reflecting greater perceived social support: (12–35) Low support, (36–60) Moderate support, (61–84) High support. The scale shows excellent reliability ( $\alpha = 0.85$ – $0.91$ ) and strong test-retest stability. In this study, MSPSS functioned as a moderator to examine the buffering effect of social support on postpartum emotional adjustment.
4. **Parenting Stress Scale (PSS):** The scale developed by Berry and Jones (1995) is used to measure parental stress related to parenting experiences both positively and negatively [18]. These 18 items were responded to on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Items 1, 2, 5, 6, 7, 8, 17, and 18 are reverse-scored. The PSS possesses good internal consistency ( $\alpha = 0.83\text{--}0.86$ ) and construct validity [26]. In the fuzzy model, this variable represents stress intensity, an important input variable that influences postpartum mental health outcomes.

All scales demonstrated strong reliability in the present study (Cronbach’s  $\alpha = 0.80\text{--}0.90$ ).

### 3.5. Data Preprocessing

- Missing values were treated using mean substitution.
- Raw psychometric scores were normalized into the range [0–1] using min-max scaling.
- Fuzzy membership categories (Low, Moderate, High) were defined based on empirical score distribution.
- Separate datasets were created for mothers and fathers to assess gender differences.

### 3.6. Fuzzy Modeling Framework

A Mamdani-type Fuzzy Inference System (FIS) was constructed to predict the risk of postpartum depression among parents based on four psychological input variables: depression (EPDS), parenting stress (PSS), perceived social support (MSPSS), and emotional regulation (ERQ). The system classifies the output into three linguistic categories: Low, Moderate, and High fuzzy postpartum depression risk. Fuzzy modeling was chosen because it represents mental-health states on a continuous spectrum rather than rigid categorical boundaries, enabling a more realistic depiction of psychological variability.

Triangular membership functions were assigned to EPDS and MSPSS because of their nonlinear emotional interpretation, whereas threshold-based linguistic partitions were applied to PSS and ERQ due to their more linear scoring characteristics. The model structure and variable specifications are summarized in Table 1. The FIS was initially implemented in Microsoft Excel to develop a transparent, rule-based prototype for conceptual demonstration, and SPSS 27 was used for additional statistical analyses, including a chi-square test.

Table 1: Description of input and output variables used in FIS to assess the parents’ mental health status.

Variable	Type	Linguistic Categories	Membership Structure	Score Range	Psychological Interpretation
EPDS (Depression)	Input	Low, Moderate, High	Triangular fuzzy sets	0–30	Higher scores indicate more severe depressive symptoms. Overlapping triangular functions represent smooth transitions between mild, moderate, and severe states.
PSS (Parenting Stress)	Input	Low, Moderate, High	Threshold-based fuzzy partitions	18–90	Reflects increasing levels of parental stress. Higher scores correspond to greater stress with linear categorization.
MSPSS (Social Support)	Input	Low, Moderate, High	Triangular fuzzy sets	12–84	Measures perceived social support from family, friends, and significant others. Higher support indicates better emotional well-being.
ERQ (Emotional Regulation)	Input	Low, Moderate, High	Threshold-based fuzzy partitions	10–70	Represents ability to manage emotions (reappraisal and suppression). Higher scores indicate better emotional regulation.
Fuzzy Depression Index (PPD Risk)	Output	Low, Moderate, High	Defuzzified output (0–1)	0–1	Overall risk of postpartum depression calculated using centroid defuzzification to yield a representative single value.

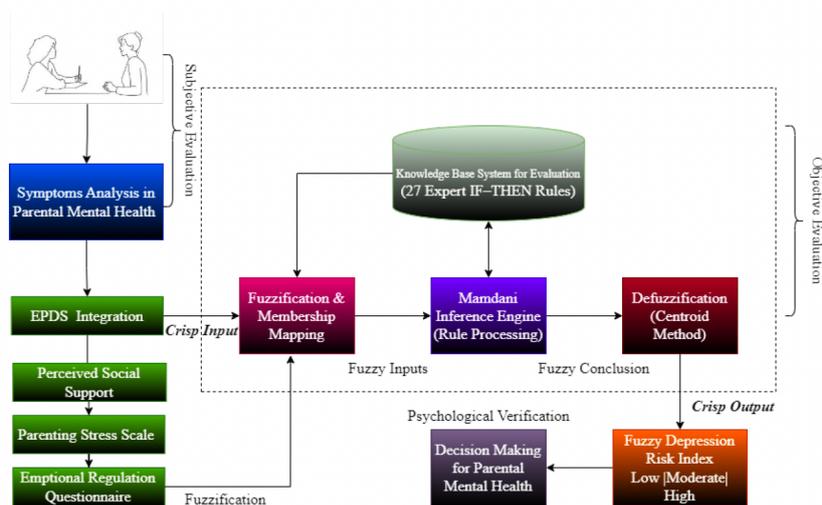


Figure 2: Architecture of the Mamdani-type Fuzzy Inference System (FIS) for Estimating Postpartum Depression Risk.

Table 1 presents the fuzzy input and output variables of the model, their linguistic categories, and the membership structures. Triangular fuzzy sets were used for variables carrying nonlinear psychological interpretation (EPDS, MSPSS), whereas threshold-based partitions were employed for linear variables (PSS, ERQ). Thus, the model applies fuzzy sets to nuanced psychological indicators and thresholds to directly measured quantitative variables.

Fig. 2 illustrates the workflow integrating psychological assessment with fuzzy-logic-based computational modeling. Input variables, Perceived Social Support (MSPSS), Parenting Stress (PSS), Emotional Regulation (ERQ), and Depression (EPDS), are converted into fuzzy membership values during the fuzzification stage. A knowledge base composed of 27 expert-defined IF-THEN rules and the Mamdani inference engine processes the fuzzy inputs to generate fuzzy conclusions. The centroid defuzzification method produces a Crisp Output represented as the Fuzzy Depression Risk Index (Low, Moderate, High), supporting psychological verification and clinical decision-making for parental mental-health assessment after childbirth.

### 3.7. Rule-Based and Inference Mechanism

The fuzzy inference model employed 27 IF-THEN rules, generated by combining three key input variables, depression (EPDS), parenting stress (PSS), and perceived social support (MSPSS), each represented by three linguistic levels (Low, Moderate, High), resulting in  $3^3 = 27$  rules. Although Emotional Regulation (ERQ) was included as an input factor, it was not added to the rule base to avoid excessive complexity (which would otherwise require 81 rules) and to preserve clinical interpretability. Representative rules include:

- IF depression is high AND stress is high AND support is low THEN PPD risk is high.
- IF depression is low AND stress is low AND support is high THEN PPD risk is low.

Rule aggregation used the min-max composition, and the centroid method produced a continuous output score (0–1). Separate models were developed for mothers and fathers to examine gender-related differences.

### 3.8. Model Validation and Comparison

Model performance was assessed by comparing the Fuzzy Depression Index with raw psychometric scores using Pearson correlation ( $r$ ). Negative correlations with EPDS and PSS and positive correlations

with MSPSS and ERQ confirmed theoretical consistency. Root Mean Square Error (RMSE) was used to compare predictive accuracy with logistic regression, demonstrating satisfactory performance and interpretability.

### 3.9. Ethical Considerations

Written informed consent was obtained from all participants. The Institutional Research Ethics Committee of Lovely Professional University approved the study protocol. Confidentiality and anonymity were strictly maintained throughout. Participants were free to withdraw at any time.

Table 2: Fuzzy Data Processing Workflow

Stage	Description	Output/Notes
Input	Import EPDS, PSS, MSPSS, ERQ raw scores (n = 400)	Raw Psychological Data
Fuzzification	Convert crisp values into membership values (0–1)	Example: EPDS – Low (0–8), Moderate (7–18), High (15–30)
Inference Rules	Apply 27 expert-defined IF–THEN rules for fuzzy reasoning	Separate models for mothers and fathers
Defuzzification	Centroid method to compute final fuzzy depression index	Output range: 0 (Low) to 1 (High)
Validation	Correlate fuzzy scores with traditional scale scores	Evaluates predictive performance and interpretability

Table 2 summarizes the sequential workflow of the fuzzy inference system used to assess postpartum depression (PPD) risk. Raw psychological scores were first fuzzified, processed through 27 IF–THEN rules, and then defuzzified to generate a continuous depression-risk index. Model validation using correlation analysis demonstrated strong agreement with traditional psychometric measures, confirming reliability and interpretability. This approach integrates psychological theory with computational fuzzy logic to capture nonlinear variations in parental mental health. By combining emotional regulation, perceived social support, and parenting stress, the model enables a more sensitive and nuanced assessment of PPD risk than conventional categorical methods, supporting clearer and more informed clinical decision-making.

## 4. Results

### 4.1. Socio-demographic Characteristics

Table 3: Socio-demographic Characteristics (N = 400)

Variable	Categories	n	%
Gender	Mothers	200	50.0
	Fathers	200	50.0
Locality	Rural	180	45.0
	Urban	220	55.0
Occupation	Working	148	37.0
	Not working	252	63.0
Child Gender	Girl	128	32.0
	Boy	272	68.0
Delivery Type	Premature	259	64.8
	Full-term	141	35.3
Birth Order	First child	162	40.5
	Second child	238	59.5
Family Type	Nuclear	106	26.5
	Joint	294	73.5
Relationship with Family	Supportive	297	74.3
	Moderate	78	19.5
	Unsupportive	25	6.3
Relationship with Husband	Good	360	90.0
	Not too good	40	10.0
Type of Marriage	Arranged	341	85.3
	Love	59	14.8
Age	25–28	157	39.3
	28–33	144	36.0
	33–40	99	24.8

Participants Characteristics: Table 3 summarizes participant demographics. The highest proportion of parents were aged 25–28 years (39.3%), followed by 28–33 years (36%). Regarding family context, 73.5% lived in joint families. Supportive family relationships were reported by 74.3%, while 90% described good marital relationships. A majority (59.5%) were second-time parents. These demographic indicators contextualize the predominance of the Moderate mental well-being category identified through fuzzy analysis.

### 4.2. Development of a Mamdani-Type Fuzzy Inference Model

A Mamdani-type Fuzzy Inference System (FIS) was constructed using EPDS, PSS, MSPSS, and ERQ as input variables. Each variable was transformed into fuzzy linguistic categories (Low, Moderate, High) using membership functions, enabling continuous emotional representation. A total of 27 IF–THEN rules constituted the rule base. For example:

**IF** depression is high **AND** stress is high **AND** support is low **THEN** mental health is poor.

The centroid method generated a continuous output fuzzy index ranging between 0 and 1.

### 4.3. Gender-Based Comparison of Fuzzy Classification

Table 4: Fuzzy Classification by Gender (N = 400)

Group	Poor	Moderate	Good	Total
Mothers	3 (1.5%)	197 (98.5%)	0	200
Fathers	7 (3.5%)	192 (96.0%)	1 (0.5%)	200

Table 4 presents the application of the fuzzy model to 400 parents (200 mothers, 200 fathers) with three fuzzy-defined mental-health categories: Poor, Moderate, and Good. Most participants fell into the Moderate category, indicating a generally balanced but sensitive emotional adjustment. A slightly higher percentage of fathers was classified as Poor compared to mothers, suggesting greater emotional vulnerability among men during the postpartum transition. A chi-square test showed no significant association between gender and fuzzy mental-health category,  $\chi^2(2, N=400) = 2.66, p = .26$ . Although nonsignificant, descriptive trends support recent findings on underrecognized paternal distress and demonstrate the fuzzy model’s sensitivity to subtle psychological variations that mean-based methods may overlook.

### 4.4. Validation of the Fuzzy Model

Table 5: Validation of the Fuzzy Model through Correlation with Psychometric Scales

Variable	Correlation (r)	Interpretation
EPDS	0.43	Moderate positive alignment with depressive severity
PSS	-0.05	Weak negative association, nonlinear effects
MSPSS	0.13	Weak positive influence of support
ERQ	0.72	Strong positive effect; most influential predictor

Table 5 shows the strongest association with emotional regulation ( $r = .72$ ), underscoring its role as a major determinant of postpartum emotional well-being. The model demonstrated moderate sensitivity to depressive symptoms (EPDS;  $r = .43$ ), while weaker correlations with PSS and MSPSS reflected the complex, nonlinear interaction of stress and support. Overall, the fuzzy model offered high interpretability and psychological realism by producing linguistically meaningful labels (e.g., “Moderate well-being”), unlike traditional regression methods that rely on fixed coefficients.

## 5. Discussion

### 5.1. Overview of Findings

Transitioning into parenthood involves significant emotional and psychological adjustments for both mothers and fathers. In the present study, a Mamdani-type Fuzzy Inference System (FIS) was employed to model the ambiguity and dynamic nature of parental mental health. This flexible computational framework integrates key psychological factors, including depressive symptoms, parenting stress, social support, and emotional regulation, while accounting for the continuous and nonlinear characteristics of emotional experiences. Through linguistic membership functions, the fuzzy model transforms rigid categorical assessments into more fluid and interpretable outputs that reflect the real-life continuum of parental emotional well-being. The demographic context of the sample further supports these fuzzy-based outcomes. A substantial proportion of participants were young parents (aged 25–28 years), many experiencing first-time parenthood, and the majority residing in joint family households, conditions associated with heightened adjustment demands as well as shared caregiving and emotional support. These characteristics correspond with the predominance of the Moderate mental-well-being classification observed in the model, suggesting that the fuzzy system accurately captured subtle emotional gradients shaped by sociocultural and familial influences.

## 5.2. Interpretation of Fuzzy Model Findings

The fuzzy inference approach addresses these limitations by allowing partial membership across emotional states. Rather than assigning an individual exclusively to one category (e.g., Moderate or Severe), the fuzzy model represents people as belonging to multiple categories with varying degrees (e.g., 0.6 Moderate and 0.4 Severe). This produces a more human-centered and realistic depiction of emotional functioning, enabling the detection of subtle psychological shifts and supporting more personalized mental-health interpretation. Unlike Likert-based approaches with discrete response options, fuzzy logic uses a 0–1 continuum, enabling smoother transitions and greater precision in representing emotional complexity [7]. This modeling approach aligns theoretically with Emotion Regulation Theory (Gross & John, 2003) and the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984), both of which emphasize the dynamic and context-dependent nature of psychological responses [24,27]. Thus, the fuzzy model enhances interpretive depth by transforming raw numerical responses into meaningful linguistic outcomes that better reflect actual emotional experience.

## 5.3. Gender-Based Emotional Differences

Although the chi-square analysis did not reveal a statistically significant association between gender and fuzzy-defined mental-health categories, the descriptive patterns indicated subtle emotional differences between mothers and fathers. These trends resonate with emerging research on paternal mental health [15,5]. For example, meta-analytic evidence estimates that approximately 8% of new fathers experience depressive symptoms [28], and recent screening studies report paternal postpartum depression (PPD) rates between 8–13%, emphasizing that men are frequently under-screened and under-diagnosed [29]. In this study, fathers had slightly higher fuzzy scores falling in the category of “Poor.” This suggests that men are suffering from more latent or under-recognized psychological strain following childbirth. The key strength of the fuzzy model is its power to detect this small variation in emotional states, even if traditional p-value-based statistics are not significant. Instead of depending on a statistical threshold, fuzzy modeling captures nuanced, qualitative, and contextual emotional differences. These findings align with prior evidence indicating that fathers’ postpartum challenges are often a mask of societal expectations, under-reporting, and unique patterns of emotional expression [30]. The fuzzy framework, therefore, offers a meaningful tool for recognizing paternal distress that might otherwise remain invisible in conventional assessment systems.

## 5.4. Validation Using Traditional Measures

Validation analyses demonstrated that the fuzzy mental-health index showed a strong positive correlation with emotional regulation ( $r = .72$ ) and a moderate correlation with depressive symptoms (EPDS;  $r = .43$ ). This suggests that parents with more adaptive emotional-regulation strategies tend to demonstrate better emotional well-being, supporting theoretical perspectives that emphasize the protective role of emotion regulation in buffering postpartum stress and depressive symptoms [24]. Evidence from recent studies further confirms that strategies such as cognitive reappraisal can significantly reduce the risk of perinatal depression and anxiety [31]. Weaker correlations were found between the fuzzy index and perceived social support ( $r = .13$ ) and parenting stress ( $r = -.05$ ), reflecting the complex and context-dependent nature of these variables. The impact of social support is highly influenced by cultural and family expectations [8], while parenting stress has been shown to predict poorer emotional health among parents [20], particularly among fathers who report lower emotional or practical support [32]. Together, these findings reflect that the fuzzy model fully captures the quantitative aspect of parental mental health and qualitative interdependencies between emotional, social, and behavioral domains. Unlike conventional regression-based methods that reduce relationships to single coefficients, the fuzzy inference system captures nonlinear dynamics and subtle shifts in psychological states, enhancing interpretive depth and real-world applicability.

## 5.5. Practical & Clinical Implications

The proposed fuzzy model provides a valuable framework for the early identification of parental emotional risk after childbirth. By translating complex psychometric scores into clear linguistic categories such as “Moderate well-being” or “High depression risk,” the model improves interpretability and supports

timely clinical decision-making. This clarity enables healthcare professionals to detect at-risk individuals more effectively and integrate early mental-health interventions into routine screening practices. The model also offers a flexible foundation for developing AI-based decision-support systems capable of generating personalized assessments using psychological and contextual factors. Importantly, the inclusion of both mothers and fathers promotes diagnostic equity and emphasizes that postpartum mental health is a shared experience, not limited to maternal concerns. Overall, the fuzzy framework demonstrates potential to strengthen early intervention strategies and inform evidence-based mental-health policies for new parents.

### 5.6. Theoretical Contributions

Fuzzy logic functions as an effective bridge between computational intelligence and psychological theory, enabling the quantification of complex constructs such as stress, social support, and emotional regulation with greater precision than traditional categorical approaches. By capturing variability and partial emotional states, the fuzzy framework offers improved psychological realism and analytic rigor for modeling nonlinear affective systems. This theoretical integration demonstrates the value of fuzzy logic as a human-centered approach for understanding dynamic postpartum emotional processes.

### 5.7. Limitations and Future Directions

This study employed a cross-sectional design, limiting causal inference and the ability to observe changes in emotional states over time. In addition, the fuzzy rules were based on theoretical and empirical literature rather than clinical validation, which may restrict generalizability, and reliance on self-report measures may introduce response bias. Future research should incorporate longitudinal designs, clinical validation, and potentially hybrid models such as adaptive neuro-fuzzy systems to enhance predictive accuracy and self-learning capability. Cross-cultural applications may further clarify how contextual factors shape postpartum emotional trajectories.

## 6. Conclusion

The present study successfully developed and applied a Mamdani-type Fuzzy Inference System (FIS) to assess parental mental health after childbirth by integrating depression, parenting stress, social support, and emotional regulation into a dynamic and interpretable computational framework. Unlike traditional psychometric methods that enforce rigid categorical boundaries, the fuzzy approach captures the fluid and context-specific nature of emotional states, providing a more realistic representation of postpartum mental well-being. Expert-defined rules and centroid defuzzification enabled a continuous well-being index, offering interpretable outputs meaningful for clinical assessment. Gender-based comparison indicated predominantly moderate emotional well-being among both mothers and fathers, with slightly lower well-being in fathers, highlighting the need for gender-inclusive screening practices. Model validation demonstrated strong alignment with emotional regulation ( $r = 0.72$ ), supporting its psychological credibility and reinforcing the theoretical relevance of emotion regulation in postpartum adaptation. The fuzzy model, therefore, bridges numerical precision with clinical interpretability, contributing a flexible and human-centered analytical tool capable of informing AI-supported mental-health monitoring. While the cross-sectional design limits causal inference, future longitudinal and adaptive neuro-fuzzy approaches may enhance predictive power and clinical utility. Overall, the study demonstrates the potential of fuzzy logic as a meaningful and innovative framework for psychological modeling and culturally relevant postpartum mental-health care.

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*Saumya Richa (Corresponding author),  
Department of Psychology,  
Lovely Professional University, Phagwara, Punjab, India.  
E-mail address: saumyaricha@gmail.com*

*and*

*Zahoor Lone,  
Department of Psychology,  
Lovely Professional University, Phagwara, Punjab, India.  
E-mail address: zahoor20966@lpu.co.in*