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Research Article

Digital Burnout Risk Classification Based on Doomscrolling and Fear of Missing Out Using the Mamdani Fuzzy Method

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Abstract:
Introduction: Intensive digital technology use among university students may contribute to Digital Burnout, particularly when accompanied by doomscrolling and Fear of Missing Out (FOMO). This study classifies Digital Burnout risk into low, moderate, and high categories using these two digital-behavior factors. **Method**: A Mamdani Fuzzy Inference System was implemented in MATLAB using Doomscrolling and FOMO as inputs and Digital Burnout as the output. Data were collected through validated self-report questionnaires from 414 students, resulting in 408 valid records. The system employed nine IF–THEN rules, trapezoidal and triangular membership functions within a normalized [0,100] domain, centroid defuzzification, and twelve parameter-adjustment iterations. **Results and Discussion**: The ground-truth distribution showed that 47.5% of students were categorized as having high Digital Burnout, 30.1% moderate, and 22.3% low. The optimal fuzzy configuration achieved 67.89% accuracy and a macro F1-score of 0.6725. The High category achieved very high precision of 0.9688 but moderate recall of 0.6392, indicating that some high-risk students remained undetected. Classification accuracy was higher among gamers (77.19%) than general respondents (61.18%). **Conclusion**: The Mamdani Fuzzy approach demonstrates the feasibility of classifying Digital Burnout risk from Doomscrolling and FOMO; however, its moderate accuracy and reliance on self-reported, non-clinical labels indicate that it should be considered an exploratory prototype requiring independent validation and expert-reviewed rules before practical deployment.

Keywords: Classification, Digital Burnout, Doom scrolling, Fear of Missing Out, Fuzzy Mamdani.

Dataset link: https://drive.google.com/drive/folders/19bT9rs2jh6OvyKG59WQTtZn-ehm7tZ0s

1. Introduction

Technology and internet use have become inseparable from daily life, and university students aged 18–25 are among the most active users for both academic and entertainment purposes [1], [2]. Without adequate self-regulation, however, excessive digital engagement can produce Digital Burnout a state of physical, emotional, and mental exhaustion rooted in Maslach and Jackson's burnout framework, but manifested here through compulsive online engagement [4], [5]. Empirical evidence supports the scale of this problem: a study of 925 Turkish university students found 84.3% used the internet more than four hours daily, with above-average Digital Burnout scores significantly correlated with stress ($r = 0.585$, $p < 0.01$) [6]. Digital Burnout is thus a widespread, not isolated, issue among students.

Among the many digital behaviors linked to burnout, doomscrolling and Fear of Missing Out (FOMO) stand out as two of the most prevalent and psychologically consequential. Doomscrolling the habitual, repeated consumption of negative online content has been shown to heighten psychological distress [22], [23], with roughly 58% of students falling into the moderate-to-high category, spending three to five hours daily on this behavior [9]. FOMO, the anxiety of missing out on information or social experience, drives compulsive connectivity [11] and is linked to social media addiction, cyberslacking, and reduced academic performance [13], [14], [26]. Doomscrolling and FOMO are also empirically linked to one another ($r = 0.377$, $p < 0.01$) [8], suggesting they reinforce a shared pattern of compulsive, anxiety-driven digital engagement that plausibly underlies Digital Burnout.

Similar patterns are observed among Universitas Mulawarman students, where both heavy social media users and online gamers show signs of difficulty concentrating, anxiety when separated from their smartphones, and late-night social media use. However, no systematic instrument currently exists to identify students' Digital Burnout risk level, limiting early detection and intervention.

Prior studies have examined pieces of this problem but not built a classification model that captures it. Göldağ [6] established a Digital Burnout-internet addiction relationship but did not classify risk levels. Rahmadiani and Helmi [2] linked FOMO to academic achievement without addressing Digital Burnout. Prokopowicz and Mikołajewski [15] built a Mamdani Fuzzy burnout classifier from the Maslach Burnout Inventory, but for a general population, not students, and without digital-behavior predictors. No existing study, to our knowledge, has used doomscrolling and FOMO arguably the two most behaviorally proximal and empirically correlated digital habits linked to student burnout as inputs to a Digital Burnout classification model. This is the gap the present study addresses.

We focus deliberately on these two variables rather than a broader multifactorial model. Digital Burnout is undeniably influenced by additional factors (e.g., sleep quality, offline stressors, personality traits), and we do not claim doomscrolling and FOMO fully explain it. Rather, they were selected because (a) both are specifically digital behaviors as opposed to general psychological traits making them directly actionable for a digital-wellbeing intervention; (b) both have validated, purpose-built measurement scales [10], [21] suited to fuzzy linguistic modeling; and (c) their empirically established correlation with each other and with burnout-related distress [6], [8] provides a defensible basis for a first-generation classification model. This scope is treated as a starting point rather than a complete etiological account, and is revisited as a limitation in the Discussion and Conclusion.

Because Digital Burnout is subjective, gradual, and shaped by individual perception, a method that can handle this uncertainty rather than force a crisp cutoff is needed. Simpler alternatives exist but each has a specific drawback here: threshold-based scoring, logistic regression, and ordinal classification all assign a single crisp category per case, so two students separated by one point near a cutoff (e.g., normalized scores of 39 vs. 41) are treated as categorically different despite a negligible real difference; decision trees impose similarly rigid, axis-aligned splits and risk overfitting given only two predictors. The Mamdani Fuzzy method, by contrast, represents each input through overlapping membership functions, allowing partial membership in adjacent categories, and its linguistic IF-THEN rules mirror the qualitative reasoning a counselor might use-both properties suited to a construct as gradual as Digital Burnout [16]. This method-which translates linguistic, rule-based reasoning into a computable system [16] has demonstrated strong performance on subjective, perception-based classification tasks such as academic performance monitoring [25] and student stress detection at 80% accuracy [20]. Digital Burnout levels (low, moderate, high) are classified here using the validated Digital Burnout Scale (DBS) [17], consistent with prior empirical work [4], [6].

It is worth emphasizing that the primary contribution of this study is not the Mamdani Fuzzy method itself, which is a well-established technique in control and decision systems, but its systematic application to a combination not previously examined in the classification literature: doomscrolling and FOMO as joint inputs for Digital Burnout risk among university students. This study therefore aims to classify Universitas Mulawarman students' Digital Burnout levels into low, moderate, and high categories based on doomscrolling and FOMO patterns using the Mamdani Fuzzy method, offering an initial, interpretable risk-screening prototype to inform future development of student mental health support tools in higher education.

2. Method

Data Collection and Instruments

This study employed primary data collected through an online questionnaire using Google Forms distributed to active students of Universitas Mulawarman aged 18–25 years who actively use social media and/or play online games. For the purpose of group comparison, respondents were categorized as Gamer if they self-reported playing online or mobile games in response to a binary screening question ("Apakah Anda bermain game online/mobile game?" — Yes/No), regardless of reported gaming duration. Those who answered "Yes" were subsequently asked to report their average daily gaming duration (categorized as <1 hour, 2–4 hours, 4–6 hours, or more than 6 hours), which was used descriptively to characterize the Gamer group's engagement level rather than as a threshold for group inclusion. Respondents who answered "No" to the initial screening question were categorized as General social media users. This classification was based entirely on self-report and was not independently verified through objective play-time tracking, which represents a limitation of the group comparison analysis.The sample size was determined using the Slovin formula with a population of 32,254 students and a 5% margin of error, resulting in a minimum sample size of 400 respondents. Respondents were selected using a purposive sampling technique based on predefined inclusion criteria. The overall research procedure is illustrated in **Figure 1**.

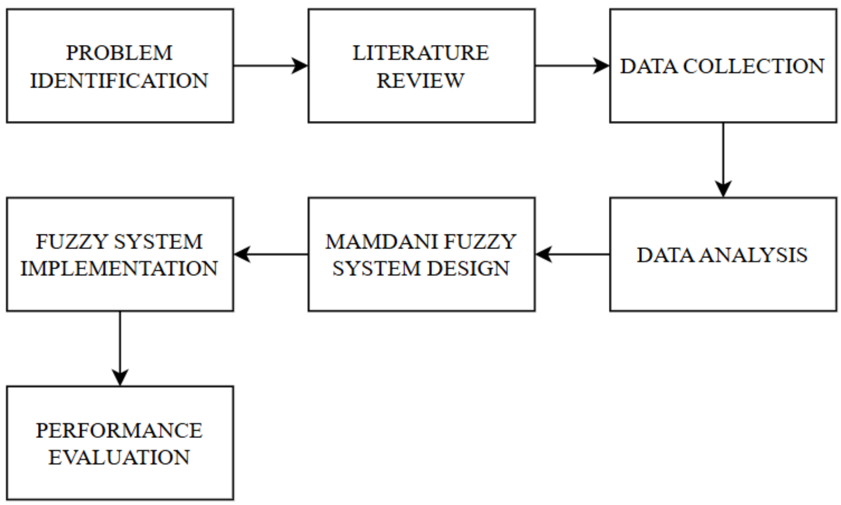

Figure 1. Research Framework

Three validated instruments were adapted in this study. The first instrument was the Social Media Doomscrolling Scale [10], consisting of 12 items measuring six dimensions: salience, mood modification, tolerance, withdrawal symptoms, conflict, and relapse. The second instrument was the Fear of Missing Out Scale (FOMO Scale) [21], consisting of 10 items assessing the level of anxiety associated with missing information and social activities. The third instrument was the Digital Burnout Scale (DBS) [17], consisting of 24 items covering three subscales: digital aging, digital deprivation, and emotional exhaustion. All instruments employed a five-point Likert scale ranging from Strongly Disagree (1) to Strongly Agree (5). Validity testing was conducted using the Pearson Product-Moment Correlation, while reliability testing was performed using Cronbach's Alpha through SPSS. An item was considered valid if the calculated correlation coefficient exceeded the critical value at a significance level of 0.05, and an instrument was considered reliable if $\alpha > 0.70$.

Ethical Considerations

This study collected data through an online self-report questionnaire distributed via Google Forms to active students of Universitas Mulawarman. Respondents completed the questionnaire based on their own willingness to access and fill out the shared form. No formal informed consent form, structured anonymity protocol, or institutional ethical clearance was implemented prior to data collection, as this was not standard practice for non-clinical, self-report survey research of this nature at the authors' institution at the time of the study.

Data Preprocessing

The collected raw data underwent three preprocessing stages. First, data cleaning was performed to identify and remove respondents exhibiting straight-lining response patterns, defined as providing the same response value for all questionnaire items. Second, data transformation was conducted by calculating the total scores for each variable: Doomscrolling (sum of 12 items; range 12–60), FOMO (sum of 10 items; range 10–50), and Digital Burnout (sum of 24 items; range 24–120). Third, min–max normalization was applied to standardize all variables into the domain [0,100] using the following equation [15]:

$$Normalized\ Score = \frac{Actual\ Score - Minimum\ Score}{Maximum\ Score - Minimum\ Score} \times 100 \quad (1)$$

Following normalization, the ground truth labels were established based on normalized Digital Burnout scores using the following thresholds: Low (≤ 40), Moderate ($40 <$ score ≤ 60), and High (> 60). These thresholds were determined proportionally within the [0,100] domain and are consistent with the approaches adopted by Prokopowicz and Mikołajewski [15] and Sutisna et al. [20].

It is important to note that these threshold-based labels represent a behavioral risk classification derived from self-reported questionnaire scores, not a clinical diagnosis of burnout. The DBS is a validated psychometric instrument, but the classification output in this study should be interpreted as an indication of relative risk level based on digital behavior patterns, rather than a diagnostic determination requiring clinical confirmation by a psychologist or mental health professional [17]. The system is intended as a screening or early-detection aid, not a replacement for professional clinical assessment.

Mamdani Fuzzy System Design

The Mamdani Fuzzy Inference System was designed with two input variables, namely Doomscrolling (X_1) and FOMO (X_2), and one output variable, Digital Burnout (Y). All variables were defined within the normalized domain [0,100] and implemented using the MATLAB Fuzzy Logic Toolbox. The complete variable definitions are presented in **Table 1**.

Table 1. Input and Output Variable Definitions

Type	Variable	Number of Items	Original Score Range	Domain	Linguistic Categories
***Input* (X)**	Doomscrolling (X1)	12	12-60	[0, 100]	Low, Moderate, High
	FOMO (X_2)	10	10-50	[0,100]	Low, Moderate, High
***Output* (Y)**	*Digital Burnout* (Y)	24	24-120	[0,100]	Low, Moderate, High

Fuzzy logic provides a mathematical framework for handling uncertainty and imprecision in human reasoning, as originally introduced by Zadeh [26], which forms the theoretical foundation of fuzzy inference systems. Membership functions were designed using trapezoidal functions (trapmf) for the Low and High categories and triangular functions (trimf) for the Moderate category. A 15-point overlap zone between adjacent categories was incorporated to represent uncertainty, which is a fundamental characteristic of fuzzy logic [16]. The same parameters were applied to all variables because they shared an identical normalized domain, as presented in **Table 2**.

Table 2. Membership Function Parameters

Variable	Category	Function	Parameters
***Doomscrolling*(X_1)**	Low	trapmf	[0, 0, 25, 40]
	Moderate	trimf	[25, 50, 75]
	High	trapmf	[60, 75, 100, 100]
FOMO(X_2)	Low	trapmf	[0, 0, 25, 40]
	Moderate	trimf	[25, 50, 75]

Variable	Category	Function	Parameters
	High	trapmf	[60, 75, 100, 100]
***Digital Burnout*(Y)**	Low	trapmf	[0, 0, 25, 40]
	Moderate	trimf	[25, 50, 75]
	High	trapmf	[60, 75, 100, 100]

It is acknowledged that Digital Burnout may be influenced by additional factors beyond doomscrolling and FOMO, such as screen time duration, academic workload, sleep quality, and general social media addiction. This study deliberately limits its input variables to doomscrolling and FOMO as an initial, focused model designed to test the feasibility of a fuzzy-based classification approach using two behaviorally proximal and psychometrically validated digital-behavior predictors. Broader multivariate models incorporating additional predictors are recommended for future research.

Rule Base

With two input variables and three linguistic sets for each variable, a total of $3 \times 3 = 9$ IF–THEN rules were established. The rule formulation assumed that an increase in one or both input variables would lead to a higher level of Digital Burnout. This assumption is supported by Satici et al. [8], who reported a significant positive correlation between Doomscrolling and FOMO ($r = 0.377$; $p < 0.01$), both of which contribute to psychological distress. The initial rule base is presented in **Table 3**.

Table 3. Initial Rule Base Configuration

Rule	*Doomscrolling*	FOMO	*Digital Burnout*
R1	Low	Low	Low
R2	Low	Moderate	Low
R3	Low	High	Moderate
R4	Moderate	Low	Low
R5	Moderate	Moderate	Moderate
R6	Moderate	High	High
R7	High	Low	Moderate
R8	High	Moderate	High
R9	High	High	High

The rule base in this study was formulated based on theoretical assumptions and prior empirical correlations reported in the literature [8], [15], rather than direct validation by domain experts. Given that Digital Burnout is a psychological construct, future refinement of the rule base should involve structured validation by clinical psychologists, student counselors, or mental health researchers to strengthen the ecological and clinical validity of the classification rules.

Inference and Defuzzification Process

The Mamdani Fuzzy inference process consisted of four stages. First, fuzzification converted crisp input values into membership degrees within the interval [0,1] according to the predefined membership functions. Second, rule evaluation employed the AND operator with the minimum (MIN) method to determine the firing strength of each rule. Third, aggregation utilized the maximum (MAX) method to combine all activated rule outputs. Finally, defuzzification was performed using the centroid method within the Mamdani inference framework [16] to transform the aggregated fuzzy set into a crisp output value z^*:

$$z^* = \frac{\sum_{j=1}^{n} z_j \mu(z_j)}{\sum_{j=1}^{n} \mu(z_j)} \quad (2)$$

The resulting crisp value was categorized according to the predefined thresholds: z* ≤ 40 (Low), 40 < z* ≤ 60 (Moderate), and z* > 60 (High).

Model Evaluation

Model performance was evaluated by comparing the classification results generated by the fuzzy system with the established ground truth using a 3×3 confusion matrix. The evaluation metrics included accuracy, precision, recall, and F1-score for each category (Low, Moderate, and High) [24]. In addition to overall performance evaluation, a comparative analysis was conducted between general social media users and online game users to identify differences in Digital Burnout characteristics across the two groups. If the classification accuracy was not satisfactory, iterative adjustments of membership function parameters and rule base configurations were performed until the optimal model configuration was achieved.

It should be noted that the parameter and rule-base optimization process (12 iterations, reported in the Results section) and the final accuracy evaluation were both conducted on the same set of 408 respondents. As no independent train–test split or cross-validation procedure was applied, the reported accuracy may be optimistic and should be interpreted as an in-sample fit rather than a generalizable predictive performance measure. Future work should validate this model using a held-out test set or k-fold cross-validation to obtain an unbiased estimate of classification performance.

3. Result and Discussion

Data Collection and Instrument Validation

The data collection process yielded 414 active students from Universitas Mulawarman aged 18–25 years, exceeding the minimum target of 400 respondents. Among them, 173 respondents were active online game users (Gamer group), while 241 respondents were general social media users (General group). The majority of respondents were female (65%), predominantly 21 years old (24.2%), and most reported using social media for more than four hours per day (78%).

Validity testing using the Pearson Product-Moment Correlation indicated that all questionnaire items across the three variables had calculated correlation coefficients greater than the critical value (r-table = 0.096) at a significance level of 0.05 with df = 412. Therefore, all items were considered valid. Reliability testing using Cronbach's Alpha demonstrated excellent internal consistency for all instruments, as shown in **Table 4**.

Table 4. Reliability Test Results

Variable	*Cronbach's Alpha*	Description
Doomscrolling	0,947	Reliable
FOMO	0,952	Reliable
Digital Burnout	0,964	Reliable

Data Preprocessing and Ground Truth Distribution

The data cleaning stage identified six respondents exhibiting straight-lining response patterns. These respondents were excluded from further analysis, consisting of four respondents from the General group and two from the Gamer group. Consequently, the final dataset consisted of 408 valid respondents (171 Gamers and 237 General users). Subsequently, total scores were calculated for each variable and normalized to the domain [0,100] using the min–max normalization equation (1). The original score ranges were Doomscrolling (min = 12, max = 56), FOMO (min = 10, max = 50), and Digital Burnout (min = 24, max = 120).

Based on the categorization of normalized Digital Burnout scores, the ground truth distribution is presented in Table 5. Most students were classified in the High Digital Burnout category (47.5%), indicating a substantial level of digital exhaustion, consistent with the finding that most respondents spent more than four hours per day on social media.

Table 5. Ground Truth Distribution of Digital Burnout

Category	Frequency	Frequency
Low	91	22,3%
Moderate	123	30,1%
High	194	47,5%
Total	**408**	**100%**

Mamdani Fuzzy Implementation and Baseline Configuration Results

The Mamdani Fuzzy Inference System (FIS) was developed and implemented using the MATLAB Fuzzy Logic Toolbox. An initial overlap region of 15 points was defined between adjacent linguistic categories to accommodate uncertainty in the classification process. For all variables normalized to the domain [0,100], trapezoidal membership functions (trapmf) were assigned to the Low and High categories, whereas the Moderate category was represented using a triangular membership function (trimf). The mathematical formulations of the membership functions for the initial configuration are given below:

$$\mu Low(x) = \begin{cases} 1 & x \leq 25 \\ \dfrac{40 - x}{40 - 25} & 25 < x \leq 40 \\ 0 & x > 40 \end{cases}$$

$$\mu Moderate(x) = \begin{cases} 0 & x \leq 25 \ or \ x \geq 75 \\ \dfrac{x - 25}{50 - 25} & 25 < x \leq 50 \\ \dfrac{75 - x}{75 - 50} & 50 < x < 75 \end{cases}$$

$$\mu High(x) = \begin{cases} 0 & x \leq 60 \\ \dfrac{x - 60}{75 - 60} & 60 < x \leq 75 \\ 1 & x > 75 \end{cases}$$

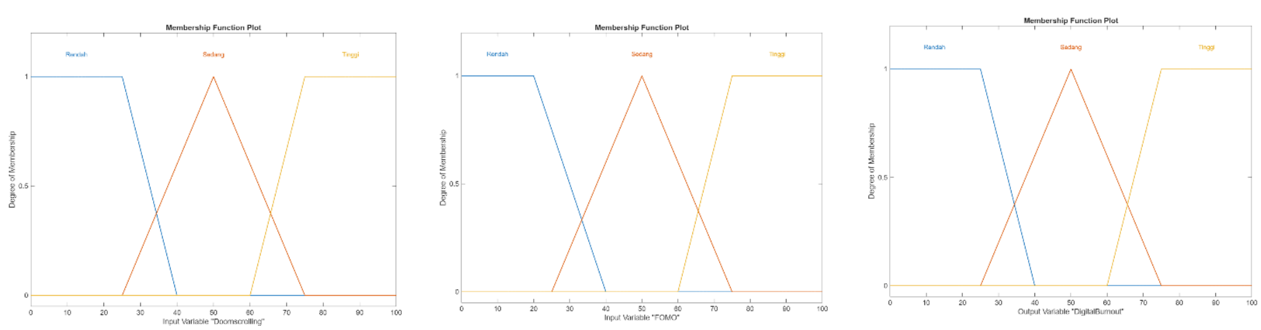

Figure 2. Membership Functions of Input and Output Variables (Initial Configuration)

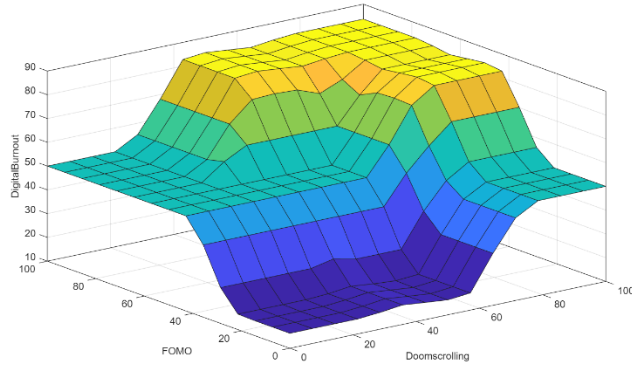

Figure 3. Surface View of the Relationship Between Doomscrolling, FOMO, and Digital Burnout

As illustrated in Figure 3, the Digital Burnout score tends to increase monotonically as Doomscrolling and FOMO scores increase, indicating a positive relationship between the input and output variables. The smooth transitions among categories demonstrate the capability of the Mamdani Fuzzy system to generate gradual output changes rather than abrupt classifications typically produced by conventional classification methods.

Example of Mamdani Fuzzy Inference

To illustrate the inference process, the first respondent was selected, with normalized values of Norm_DS = 29.17 and Norm_FOMO = 32.50. The fuzzification results are shown in **Table 6**.

Table 6. Fuzzification Results for the Sample Respondent

Variable	Normalized Value	μ_Low	μ_Moderate	μ_High
Doomscrolling (Norm_DS)	29,17	0,72	0,17	0,00
FOMO (Norm_FOMO)	32,50	0,50	0,30	0,00

Using the minimum (MIN) operator, four of the nine rules were activated, as presented in **Table 7**.

Table 7. Rule Strengths (α-Predicates) for the Sample Respondent

Rule	Doomscrolling	FOMO	Output DB	Strength
R1	Low (0,72)	Low (0,50)	Low	0,50
R2	Low (0,72)	Moderate (0,30)	Low	0,30
R3	Low (0,72)	High (0,00)	Moderate	0,00
R4	Moderate (0,17)	Low (0,50)	Low	0,17
R5	Moderate (0,17)	Moderate (0,30)	Moderate	0,17
Rule	**Doomscrolling**	**FOMO**	**Output DB**	**Strength**
R6	Moderate (0,17)	High (0,00)	High	0,00
R7	High (0,00)	Low (0,50)	Moderate	0,00
R8	High (0,00)	Moderate (0,30)	High	0,00
R9	High (0,00)	High (0,00)	High	0,00

The aggregation stage using the maximum (MAX) operator produced:

μ_Low = max(R1, R2, R4) = max(0,50; 0,30; 0,17) = 0,50

μ_Moderate = max(R3, R5, R7) = max(0,00; 0,17; 0,00) = 0,17

μ_High = max(R6, R8, R9) = max(0,00; 0,00; 0,00) = 0,00

Defuzzification using the centroid method with representative values of Low = 20, Moderate = 50, and High = 80 yielded:

$z^* = (20×0,50 + 50×0,17 + 80×0,00) / (0,50 + 0,17 + 0,00)$

$= 18,50 / 0,67 = 27,61$

Since z^*=27.61≤40, the respondent was classified as having Low Digital Burnout. The same procedure was automatically applied to all 408 respondents using MATLAB.

Baseline Classification Results

Under the baseline configuration, the system classified 214 respondents (52.5%) as Low, 64 respondents (15.7%) as Moderate, and 130 respondents (31.9%) as High Digital Burnout. Compared with the ground truth distribution, the system tended to classify more respondents into the Low category because rules R2 and R4 were initially assigned Low outputs. The confusion matrix is presented in **Table 8**.

Table 8. Global Confusion Matrix of the Baseline Configuration (408 Samples)

Actual / Predicted	Low	Moderate	High
Low	**85**	5	1
Moderate	88	**32**	3
High	41	27	**126**

Of the 91 actual Low instances, 85 were correctly classified. Of the 123 actual Moderate instances, only 32 were correctly classified, while 88 instances were misclassified as Low. For the 194 actual High instances, 126 were correctly classified. Overall, 243 out of 408 samples were correctly classified, resulting in a global accuracy of 59.56%. The class-wise evaluation metrics are presented in **Table 9**.

Table 9. Global Model Evaluation Metrics – Baseline Configuration

Class	Precision	Recall	F1-Score
Low	0,3972	0,9341	0,5574
Moderate	0,5000	0,2602	0,3422
High	0,9692	0,6495	0,7778
Macro average	0,6221	0,6146	0,5591
Global Accuracy: 59.56%			

Parameter Adjustment Iterations

Since the baseline accuracy of 59.56% did not meet the predefined performance threshold, twelve parameter adjustment iterations were conducted. The optimization process focused on two aspects of the fuzzy system: (1) variations in the membership function overlap region (10, 15, and 20 points) and (2) variations in the output assignments of rules R2 and R4 (Default, Alternative A, Alternative B, and Alternative C). The accuracy comparison for all iterations is presented in **Table 10**.

Table 10. Accuracy Comparison Across Model Iterations

Iteration	*Overlap*	R2 *Output*	R4 *Output*	Global Accuracy	Gamer Accuracy	General Accuracy	Description
1	15	Low	Low	59,56%	74.85%	48.52%	Balanced
2	20	Low	Low	59,31%	75.44%	47,68%	Balanced
3	10	Low	Low	60.05%	74.27%	49,79%	Balanced
4	15	Moderate	Moderate	67.65%	77.78%	60.34%	Balanced
5	20	Moderate	Moderate	66.42%	78,36%	57.81%	Balanced
6	**10**	**Moderate**	**Moderate**	**67,89%**	**77.19%**	**61.18%**	**Balanced (Optimal)**
7	15	Low	Moderate	63.73%	76.61%	54.43%	DS Dominant

Iteration	*Overlap*	R2 *Output*	R4 *Output*	Global Accuracy	Gamer Accuracy	General Accuracy	Description
8	20	Low	Moderate	63.48%	77.78%	53.16%	DS Dominant
9	10	Low	Moderate	64.22%	76.02%	55,70%	DS Dominan
10	15	Moderate	Low	63.48%	76.02%	54.43%	FOMO Dominant
11	20	Moderate	Low	62,25%	76.02%	52,32%	FOMO Dominant
12	10	Moderate	Low	63.73%	75.44%	55.27%	FOMO Dominant

Among the twelve iterations, the optimal configuration was obtained in Iteration 6, which employed a 10-point overlap and modified both R2 and R4 outputs to Moderate (Alternative A). This configuration achieved the highest global accuracy of 67.89%. Two consistent patterns emerged during the optimization process. First, the Alternative A configuration consistently produced the highest accuracy across all overlap levels, outperforming the Default configuration by approximately 4–8%. Second, a narrower overlap region (10 points) yielded higher classification accuracy than wider overlap regions (15 and 20 points) under the Alternative A configuration.

Final Configuration Results

Under the final configuration, the system classified 123 respondents (30.1%) as Low, 156 respondents (38.2%) as Moderate, and 129 respondents (31.6%) as High Digital Burnout. This distribution was considerably closer to the ground truth than the baseline configuration, particularly for the Moderate category, which increased substantially from 64 respondents (15.7%) to 156 respondents (38.2%). The confusion matrix of the final configuration is presented in **Table 11**.

Table 11. Global Confusion Matrix – Final Configuration (408 Samples)

Actual / Predicted	Low	Moderate	High
Low	**71**	19	1
Moderate	38	**82**	3
High	16	54	**124**

Of the 91 actual Low instances, 71 were correctly classified. Of the 123 actual Moderate instances, 82 were correctly classified. Of the 194 actual High instances, 124 were correctly classified. In total, 277 out of 408 samples were correctly classified, representing an improvement over the 243 correctly classified samples obtained under the baseline configuration. The evaluation metrics for the final configuration are presented in **Table 12**.

Table 12. Global Model Evaluation Metrics – Final Configuration

Class	Precision	Recall	F1-Score
Low	0,5680	0,7802	0,6574
Moderate	0,5290	0,6667	0,5899
High	0,9688	0,6392	0,7702
Macro average	0,6886	0,6954	0,6725
Global Accuracy: 67.89%			

Compared with the baseline configuration, the final model demonstrated improvements across all evaluation metrics. Global accuracy increased from 59.56% to 67.89%, while the macro-average F1-score improved from 0.5591 to 0.6725. While this represents a meaningful improvement, the final global accuracy of 67.89% remains moderate and should not be interpreted as indicating strong overall classification performance; model utility varies considerably across categories, as discussed below.

The model achieved its strongest result in the High category, with a precision of 0.9688 meaning that when the model predicts High Digital Burnout, this prediction is very likely to be correct. However, recall for the High category was only 0.6392, indicating that the model failed to identify approximately 36% of respondents who were actually experiencing High Digital Burnout (70 out of 194 actual High cases were misclassified, primarily into the Moderate category, as shown in Table 11). This recall limitation is a critical concern for the intended application of this system as an early-detection tool: a substantial proportion of genuinely high-risk students would not be flagged by the model, potentially leaving them without the attention or intervention that early detection is meant to provide. Consequently, while the model's high precision makes its High-category predictions trustworthy when they occur, its moderate recall means it cannot be relied upon as a comprehensive screening mechanism on its own, and should be interpreted as one input among several in any practical early-detection workflow.

The most notable improvement occurred in the Moderate category, where the F1-score increased from 0.3422 to 0.5899; however, this score still reflects considerable difficulty in distinguishing Moderate from adjacent categories, as discussed further below.The comparison of model performance across respondent groups is presented in **Table 13**.

Table 13. Evaluation Metrics Comparison Per Group – Final Configuration

Metric	Gamer	General
Accuracy	77,19%	61,18%
Macro Precision	0,6734	0,6784
Macro Recall	0,7102	0,6298
Macro F1-Score	0,6823	0,6052

The Gamer group achieved higher classification accuracy (77.19%) than the General group (61.18%) under the final configuration. To investigate this difference, an independent-samples comparison of the raw Doomscrolling and FOMO scores between the two groups was conducted. Because Shapiro-Wilk tests indicated that both variables were non-normally distributed in both groups ($p < 0.001$ for all four tests), the Mann-Whitney U test was used as the primary significance test, with Welch's t-test reported as a robustness check. The Gamer group reported significantly higher Doomscrolling scores ($M = 41.18$, $SD = 13.42$) than the General group ($M = 30.37$, $SD = 10.50$; Mann-Whitney $U = 29352.0$, $p < 0.001$; Welch's $t = 8.77$, $p < 0.001$; Cohen's $d = 0.92$, a large effect), and significantly higher FOMO scores (Gamer: $M = 32.69$, $SD = 12.67$; General: $M = 25.10$, $SD = 9.26$; Mann–Whitney $U = 27245.5$, $p < 0.001$; Welch's $t = 6.66$, $p < 0.001$; Cohen's $d = 0.70$, a large effect). Levene's test further indicated that the variance of both Doomscrolling and FOMO scores differed significantly between groups ($p < 0.001$ for both variables), with the Gamer group showing greater absolute variability (higher SD) than the General group. These results are discussed in relation to classification accuracy in the following section.

Discussion

The majority of Universitas Mulawarman students were classified in the High Digital Burnout category (47.5%), which is consistent with the findings of Göldağ [6], who reported that 84.3% of university students used the internet for more than four hours per day and exhibited above-average levels of Digital Burnout. The respondent characteristics observed in this study, where most participants spent more than four hours daily on social media, further support these findings.

As noted above, the Mamdani Fuzzy model achieved its highest precision in the High category (0.9688), but this must be considered alongside its comparatively low recall (0.6392) for the same category. High precision with moderate recall indicates a conservative classification pattern: the model rarely misclassifies a Low or Moderate case as High, but it also fails to flag a substantial share of true High-risk cases, most of which are instead classified as Moderate. For an early-detection application specifically, recall not precision is arguably the more critical metric, since the cost of missing a genuinely high-risk student (a false negative) is likely greater than the cost of a false alarm. This asymmetry between precision and recall in the High category is therefore a meaningful limitation of the current model configuration, and future refinement should explicitly prioritize improving recall for the High category, even if this requires accepting some reduction in precision.

Conversely, the model exhibited difficulty distinguishing between the Low and Moderate categories, as reflected by the relatively lower F1-score of the Moderate category (0.5899). Two possible explanations may account for this overlap. First, the fixed thresholds used to define the Low, Moderate, and High categories (≤40, 40–60, >60) may be too rigid relative to the actual, more continuous distribution of Digital Burnout risk in this population; a data-driven approach to threshold-setting (e.g., based on the empirical distribution of scores, or expert-informed cut-points) might produce categories with clearer separation. Second, the overlap may reflect a genuine limitation of the two-variable input space: doomscrolling and FOMO alone may not provide sufficient discriminative information to reliably separate Low from Moderate risk, particularly if other unmeasured factors (e.g., academic workload, sleep quality, or general social media use) also contribute meaningfully to this boundary. Distinguishing between these two explanations is not possible with the current dataset and model design, but both point to a similar recommendation: future work should test alternative thresholding strategies and expand the input variable set to determine which factor is primarily responsible for the observed overlap.

Although the optimal accuracy of 67.89% was lower than the 80% accuracy reported by Sutisna et al. for student stress classification using the Mamdani Fuzzy method, this discrepancy can be attributed to significant differences in research context. Sutisna et al. employed three objective academic indicators (GPA, attendance, and credit load), whereas the present study utilized two psychological and subjective variables (Doomscrolling and FOMO) [20]. Psychological variables generally exhibit greater individual variability and less clearly defined category boundaries, making them inherently more difficult to classify than structured academic indicators. This limitation is consistent with methodological validations showing that fuzzy rule-based models can reliably approximate subjective psychological scores despite inherent measurement uncertainty, though such models remain more sensitive to overlapping category boundaries than models built on objective, discrete indicators [28]. Furthermore, the imbalanced class distribution, in which the High category accounted for 47.5% of the dataset, likely contributed to the observed limitations in classification performance.

The Gamer group achieved higher classification accuracy (77.19%) than the General group (61.18%) under the final configuration. The statistical comparison reported above indicates that this difference is unlikely to stem from gamers exhibiting more consistent or less variable digital behavior — in fact, Levene's test showed that the Gamer group's Doomscrolling and FOMO scores were significantly more variable in absolute terms (higher SD) than those of the General group, contradicting a simple "greater consistency" explanation. Instead, a more plausible explanation is that the Gamer group's substantially higher mean scores on both Doomscrolling (Cohen's d = 0.92) and FOMO (Cohen's d = 0.70) shifted a larger proportion of their responses away from the ambiguous, overlapping region of the fuzzy membership functions near the category boundaries. A supplementary analysis of score proximity to the Low–Moderate and Moderate–High boundaries (within ±5 points of the normalized thresholds of 40 and 60) showed that only 11.7% of Gamer respondents' Doomscrolling scores and 9.9% of their FOMO scores fell within this ambiguous zone, compared to 21.9% and 28.3%, respectively, for the General group. Because fuzzy classification accuracy depends heavily on how far an input falls from overlapping membership regions, this lower proportion of boundary-region scores likely explains why the Gamer group was classified with higher accuracy, independent of any claim about behavioral consistency. This finding suggests that the model's differential performance across groups reflects the underlying score distributions relative to the fixed category thresholds, rather than a qualitative difference in the structure or predictability of gaming-related versus general digital behavior.

The findings of this study are consistent with those of Satici et al. [8], who reported a significant positive correlation between Doomscrolling and FOMO ($r = 0.377$, $p < 0.01$), with both variables contributing to increased psychological distress. Similarly, Göldağ [6] found a significant positive relationship between Digital Burnout and student stress levels ($r = 0.585$, $p < 0.01$). The results also support the work of Prokopowicz and Mikołajewski [15], who argued that the simultaneous presence of multiple adverse digital behavioral factors leads to higher burnout levels. This pattern is reflected in the Mamdani Fuzzy rule base, where the combination of High Doomscrolling and High FOMO consistently results in a High Digital Burnout classification.

4. Conclusion

This study developed a proof-of-concept Digital Burnout classification model based on the Mamdani Fuzzy method, using Doomscrolling and Fear of Missing Out (FOMO) as input variables. The system was implemented using the MATLAB Fuzzy Logic Toolbox with nine IF–THEN rules, trapezoidal (trapmf) and triangular (trimf) membership functions within the [0,100] domain, and centroid defuzzification.

Based on data collected from 408 valid respondents from Universitas Mulawarman, most students were classified into the High Digital Burnout category (47.5%), followed by the Moderate (30.1%) and Low (22.3%) categories. Through twelve parameter adjustment iterations, the optimal configuration was obtained using a 10-point overlap and Moderate outputs for rules R2 and R4. This configuration achieved the highest global accuracy of 67.89%, representing an improvement of 8.33 percentage points over the baseline accuracy of 59.56%.

The model demonstrated its strongest precision in the High category (0.9688), meaning its High-risk predictions were rarely false alarms; however, recall for this category was considerably lower (0.6392), indicating that a substantial share of genuinely High-risk students would go unflagged if this configuration were deployed as-is. This precision–recall asymmetry is an important caveat rather than a straightforward success. Group-based analysis further revealed that the Gamer group achieved higher classification accuracy (77.19%) than the General group (61.18%); supplementary statistical analysis indicated that this gap does not reflect greater behavioral consistency among gamers-the Gamer group's Doomscrolling and FOMO scores in fact showed significantly higher variance (Levene's test, $p < 0.001$) but rather that Gamers' significantly higher mean scores (Cohen's $d = 0.70–0.92$) placed a smaller proportion of their responses within the ambiguous zone near the fuzzy category boundaries.

Although the optimal accuracy of 67.89% did not reach the target threshold of 80%, this limitation is consistent with the inherently greater variability and less clearly defined category boundaries of subjective psychological constructs compared with objective academic indicators. Given these limitations-moderate global accuracy, asymmetric precision–recall in the High category, and unresolved overlap between Low and Moderate classes this study should be regarded as an early-stage prototype for fuzzy-based Digital Burnout classification, rather than a validated, ready-to-deploy early-detection system. Its current findings demonstrate feasibility and provide a methodological foundation, but the model has not yet been tested on unseen data, and its rule base was constructed analytically rather than reviewed or refined by clinical or counseling experts.

Future work should therefore prioritize: (1) validating the model on a larger independent, previously unseen sample to assess generalizability beyond the present dataset; (2) involving domain experts (e.g., clinical psychologists or student counselors) in reviewing and refining the fuzzy rule base and category thresholds; (3) incorporating additional input variables — such as social media usage duration, sleep quality, or academic workload to address the discriminative limitations of a two-variable input space, particularly for the Low–Moderate boundary; (4) benchmarking the Mamdani Fuzzy approach against standard machine learning classifiers (e.g., logistic regression, decision trees, or random forests) trained on the same data, to establish whether its interpretability advantage comes at a meaningful cost or benefit in predictive performance relative to these more common alternatives; (5) exploring adaptive approaches such as the Adaptive Neuro-Fuzzy Inference System (ANFIS), which may improve classification accuracy while retaining a degree of rule-based interpretability; and (6) incorporating a formal informed consent procedure, explicit anonymity and confidentiality protocols, and prior approval from an institutional ethics committee to strengthen the ethical rigor of the research design, given that psychological data was collected from a student population. Only after such validation and comparative benchmarking would the model be appropriate to recommend for practical use in student mental health services.

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