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Predicting Emotional Dysregulation Using Machine Learning: The Role of Digital Rumination, Sleep Variability, Cognitive Load Reactivity, and Social Micro-Withdrawal

Hayato. Ichikawa[1], Shimoguri. Hasegawa[2*], Oleksandr. Panchenko[3], Vitalii. Stankevych[4]

[1] School of Health Sciences, Kobe University, 7-10-2 Tomogaoka Suma, Kobe 654-0142, Japan
[2] Department of Psychiatry, University of Occupational and Environmental Health, Kitakyushu, Fukuoka 8078555, Japan
[3] Sleep and Health Research Program, Department of Psychiatry, University of Arizona College of Medicine, Tucson, Arizona, US
[4] Anxiety Disorders Clinic, McMaster University Medical Centre, Hamilton, Ontario, Canada

*** Corresponding author email address**: shimoguri.hasegawa@med.uoeh-u.ac.jp

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ABSTRACT

Objective: The present study aimed to develop and validate a machine learning model to predict emotional dysregulation based on digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal among young adults.

Methods and Materials: This quantitative predictive study was conducted on a sample of 428 young adults in Japan using a multimodal data collection approach integrating self-report measures, ecological momentary assessment, and passive digital tracking over a six-week period. Emotional dysregulation was assessed using a validated scale, while predictor variables included digital rumination, sleep variability derived from wearable actigraphy, cognitive load reactivity measured through task-based and self-report indices, and social micro-withdrawal operationalized via behavioral smartphone data. Data preprocessing involved normalization, missing data imputation, and feature engineering. Multiple machine learning algorithms, including random forest, support vector machine, gradient boosting, and XGBoost, were trained and evaluated using a 70-15-15 data split. Model performance was assessed using RMSE, MAE, and R^2, and interpretability was enhanced through SHAP analysis to determine feature importance and interaction effects.

Findings: The results indicated that the XGBoost model achieved the highest predictive accuracy ($R^2 = 0.76$), outperforming other algorithms. Digital rumination emerged as the strongest predictor, followed by social micro-withdrawal, cognitive load reactivity, and sleep variability. Significant interaction effects were observed, particularly between digital rumination and social micro-withdrawal, as well as between digital rumination and sleep variability, indicating synergistic influences on emotional dysregulation. SHAP analysis revealed nonlinear relationships and threshold effects, demonstrating that higher levels of digital rumination and behavioral disengagement substantially increased the likelihood of elevated emotional dysregulation.

Conclusion: The findings highlight the effectiveness of machine learning approaches in capturing the complex and interactive determinants of emotional dysregulation, emphasizing the central role of digitally mediated cognitive and behavioral processes alongside physiological variability. Integrating digital rumination, sleep patterns, cognitive load sensitivity, and micro-level social behaviors provides a comprehensive framework for understanding emotional dysregulation in contemporary contexts and offers valuable implications for targeted, data-driven mental health interventions.

Keywords: *Emotional Dysregulation, Machine Learning, Digital Rumination, Sleep Variability, Cognitive Load Reactivity, Social Micro-Withdrawal*

1. Introduction

Emotional dysregulation has emerged as a central construct in contemporary psychological science, reflecting difficulties in the monitoring, evaluation, and modulation of emotional responses across contexts. It is increasingly conceptualized as a transdiagnostic mechanism underlying a wide spectrum of mental health conditions, including anxiety, depression, and behavioral disorders, thereby positioning it as a critical target for both theoretical modeling and applied intervention (Daros & Ruocco, 2021; Doom et al., 2021). The significance of emotional dysregulation is particularly pronounced in young adults, a developmental stage characterized by heightened emotional reactivity, identity formation processes, and increased exposure to environmental stressors. Within this developmental window, the interplay between cognitive processes, social environments, and behavioral patterns becomes especially salient in shaping emotional functioning (Giletta, 2026; Vedechkina et al., 2022). Despite extensive theoretical and empirical work, the complexity and dynamic nature of emotional dysregulation necessitate more integrative and predictive approaches capable of capturing nonlinear interactions among multiple contributing factors.

Recent advances in digital technology have fundamentally transformed the psychological landscape in which emotional processes unfold. The ubiquity of smartphones, social media platforms, and online communication channels has introduced novel forms of cognitive engagement and social interaction, many of which are implicated in emotional dysregulation. Digital rumination, defined as repetitive negative thinking triggered or maintained by online experiences, represents one such emerging construct that extends traditional models of rumination into digitally mediated contexts. Contemporary evidence suggests that rumination operates as a core mechanism linking cognitive vulnerability to emotional distress, with its digital manifestation amplifying exposure frequency and persistence of maladaptive thought patterns (Wang et al., 2025; Wong et al., 2023). Moreover, the immersive and often algorithmically curated nature of digital environments may reinforce attentional biases and emotional reactivity, thereby exacerbating dysregulation processes (Arouch et al., 2025; Yousef et al., 2025). These findings underscore the necessity of incorporating digitally grounded cognitive constructs into predictive models of emotional functioning.

In parallel, sleep has been consistently identified as a foundational regulator of emotional processes. Beyond absolute sleep duration, recent research emphasizes the importance of sleep variability, referring to fluctuations in sleep timing and quality across days, as a critical determinant of emotional stability. Irregular sleep patterns have been associated with impaired emotion regulation capacity, heightened stress sensitivity, and increased vulnerability to psychopathology (Webb, 2023; Xu, 2025). The bidirectional relationship between sleep and emotional functioning suggests that variability in sleep may both contribute to and result from emotional dysregulation, creating a feedback loop that intensifies psychological distress. Furthermore, digital behaviors such as late-night screen use and continuous connectivity have been shown to disrupt circadian rhythms, thereby linking digital engagement directly to sleep-related dysregulation mechanisms (Adawi & Waseem, 2025; Lu et al., 2024). Integrating sleep variability into predictive frameworks thus provides a critical physiological dimension to understanding emotional dysregulation.

Another key factor in the contemporary emotional ecology is cognitive load reactivity, which reflects individual differences in emotional responses to cognitively demanding situations. High cognitive load environments, particularly those characterized by multitasking and information overload, are increasingly prevalent in digitally mediated contexts. Individuals who exhibit heightened reactivity to cognitive load may experience greater emotional exhaustion, reduced attentional control, and impaired regulatory capacity (Howard et al., 2024; Jiang, 2025). This construct aligns with emerging evidence linking cognitive strain to emotional instability and maladaptive coping strategies, suggesting that cognitive load reactivity may function as both a vulnerability and amplification mechanism in emotional dysregulation. Moreover, the integration of cognitive and emotional processes within complex environments highlights the need for models that capture dynamic interactions rather than isolated effects (Abdolmohamadi, 2025; Lunov et al., 2025).

Social behavior, particularly subtle forms of withdrawal and disengagement, also plays a crucial role in emotional regulation processes. Social micro-withdrawal refers to small-scale, often transient reductions in social engagement, such as delayed responses to messages, decreased initiation of communication, or avoidance of social interaction opportunities. While not as overt as social isolation, these micro-level behaviors may signal underlying emotional distress and contribute to the maintenance of dysregulation. Research indicates that patterns of reduced social engagement are associated with increased depressive symptoms, loneliness, and maladaptive emotional processing (Chen, 2025; Peçanha et al., 2025). In digital contexts, social micro-withdrawal may be both a consequence of negative online experiences and a coping strategy for managing emotional overload, thereby reinforcing cycles of disengagement and dysregulation (Giannakopoulos & Prassou, 2025; Huang et al., 2025). The nuanced nature of these behaviors necessitates sophisticated measurement approaches capable of capturing subtle variations in social interaction patterns.

The convergence of these factors—digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal—reflects the multifaceted nature of emotional dysregulation in the digital age. Importantly, these constructs do not operate independently; rather, they interact in complex and potentially nonlinear ways. For instance, excessive digital rumination may disrupt sleep patterns, which in turn heightens cognitive load sensitivity and promotes social withdrawal, creating a cascading effect on emotional regulation. Such interdependencies challenge traditional linear modeling approaches and call for more advanced analytical techniques capable of capturing high-dimensional relationships. Recent developments in machine learning offer promising avenues for addressing these challenges, enabling the integration of diverse data sources and the identification of complex patterns that may not be detectable באמצעות conventional statistical methods.

Machine learning approaches have gained increasing traction in psychological research due to their capacity to model nonlinear relationships, handle large datasets, and optimize predictive accuracy. In the context of emotional dysregulation, these methods allow for the simultaneous consideration of multiple predictors and their interactions, providing a more holistic understanding of underlying mechanisms. Studies have demonstrated the utility of machine learning in predicting mental health outcomes, identifying risk profiles, and informing personalized interventions (Carter et al., 2025; Marano et al., 2025). Furthermore, the incorporation of explainable artificial intelligence techniques, such as Shapley Additive Explanations (SHAP), enhances the interpretability of models, bridging the gap between predictive performance and theoretical insight (Melvin et al., 2025; Tagliaferri et al., 2025). This methodological shift aligns with broader trends in psychological science toward data-driven, integrative frameworks that leverage technological advancements.

The relevance of these approaches is further underscored by the growing body of literature highlighting the psychological impact of digital environments. Problematic media use, social media fatigue, and technology-related stress have been linked to a range of adverse outcomes, including emotional dysregulation, aggression, and depressive symptoms (Carter et al., 2025; Huang et al., 2025). Additionally, constructs such as fear of missing out (FoMO) and assessment anxiety have been shown to mediate the relationship between digital engagement and mental health outcomes, illustrating the complex pathways through which technology influences emotional functioning (Ntumi et al., 2025; Yao et al., 2025). These findings reinforce the importance of adopting multidimensional models that account for both cognitive and behavioral aspects of digital interaction.

At the same time, individual differences in coping strategies, metacognitive processes, and emotional awareness further modulate the impact of these factors on emotional regulation. For example, variability in coping styles has been shown to influence how individuals respond to stress and digital demands, with maladaptive strategies exacerbating emotional dysregulation (Conway et al., 2024; Howard et al., 2024). Similarly, metacognitive processes related to attention and self-regulation play a critical role in shaping responses to cognitive load and digital stimuli (Lunov et al., 2025). The interplay between these individual

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differences and environmental factors highlights the need for personalized and context-sensitive models of emotional dysregulation.

Despite these advances, several gaps remain in the literature. First, there is a lack of integrative studies that simultaneously examine multiple digital, cognitive, physiological, and social predictors of emotional dysregulation within a unified framework. Second, existing research often relies on cross-sectional designs and traditional statistical methods, limiting the ability to capture dynamic and nonlinear relationships. Third, the application of machine learning in this domain, while growing, remains underutilized, particularly in studies that incorporate multimodal data sources such as ecological momentary assessment and passive behavioral tracking. Addressing these gaps is essential for advancing both theoretical understanding and practical intervention strategies.

Therefore, the present study seeks to bridge these gaps by employing a machine learning approach to predict emotional dysregulation based on digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal in a sample of young adults. The integration of these constructs within a predictive modeling framework allows for the examination of both individual and interactive effects, providing a comprehensive understanding of emotional dysregulation in contemporary digital contexts. The aim of this study is to develop and validate a machine learning model that predicts emotional dysregulation based on digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal.

2. Methods and Materials

2.1. Study Design and Participants

This study employed a quantitative, predictive research design grounded in supervised machine learning methodologies to model emotional dysregulation as a function of multidimensional behavioral and cognitive indicators. The target population consisted of young adults residing in Japan, selected due to their high engagement with digital environments and susceptibility to fluctuating emotional states in technologically saturated contexts. A total of 428 participants were recruited through stratified random sampling from universities and urban community networks in Tokyo and Osaka. Inclusion criteria required participants to be between 18 and 30 years of age, to have daily access to a smartphone, and to report no current diagnosis of severe psychiatric disorders that could confound emotional regulation patterns. Participants provided informed consent in accordance with institutional ethical guidelines, and data collection was conducted over a six-week observational window to capture temporal variability in behavioral and affective patterns.

2.2. Measures

Data collection was conducted using a multimodal assessment framework integrating self-report psychometric instruments, ecological momentary assessment (EMA), and passive digital behavioral tracking. Emotional dysregulation, as the dependent variable, was operationalized using the Difficulties in Emotion Regulation Scale (DERS), adapted and validated for Japanese populations. Digital rumination was assessed through a newly developed scale capturing repetitive negative thinking triggered by online interactions, combined with EMA prompts delivered three times daily via a mobile application. Sleep variability was quantified using wearable actigraphy devices that recorded sleep duration, latency, and fragmentation, from which intra-individual variability indices were computed. Cognitive load reactivity was measured through a combination of a laboratory-based dual-task paradigm and self-reported perceived mental effort in response to cognitively demanding daily situations, collected via EMA. Social micro-withdrawal was operationalized using passive smartphone data, including response latency to messages, frequency of social app usage decline, and reduced initiation of digital communication, complemented by a brief self-report inventory assessing subtle avoidance behaviors in social contexts. All instruments underwent preliminary reliability and validity checks within a pilot sample prior to full-scale deployment.

2.3. Data analysis

Data analysis was conducted using a comprehensive machine learning pipeline designed to optimize predictive accuracy while maintaining interpretability. Raw data were first preprocessed through normalization, missing value imputation using multiple imputation techniques, and temporal alignment of EMA and passive data streams. Feature engineering procedures were applied to derive higher-order indicators, such as variability indices, lagged effects, and interaction terms among predictors. The dataset was then partitioned into training, validation, and test sets using a 70-15-15 split. Multiple supervised learning algorithms were implemented, including random forest,

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gradient boosting machines, support vector machines, and extreme gradient boosting (XGBoost), to model emotional dysregulation scores. Model performance was evaluated using cross-validation procedures and metrics such as root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). To enhance model interpretability, Shapley Additive Explanations (SHAP) were employed to quantify the contribution of each predictor variable to the model's output. Hyperparameter tuning was performed using grid search optimization, and model robustness was assessed through sensitivity analyses. This integrative analytical approach enabled both high predictive precision and theoretically meaningful interpretation of the relative influence of digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal on emotional dysregulation.

3. Findings and Results

The final sample consisted of 428 participants from Japan, all of whom completed the full six-week data collection protocol. The mean age of participants was 23.84 years (SD = 3.12), with an age range of 18 to 30 years. The sample included 221 females (51.64%), 198 males (46.26%), and 9 participants (2.10%) who identified as non-binary or preferred not to disclose gender. In terms of educational status, 72.43% were undergraduate students, 18.69% were graduate students, and 8.88% were employed young adults not currently enrolled in formal education. The majority of participants (64.02%) reported daily smartphone usage exceeding 5 hours, reflecting a highly digitally engaged cohort. Baseline screening indicated that emotional dysregulation scores were normally distributed across the sample, with no extreme outliers after preprocessing. Compliance with ecological momentary assessment prompts exceeded 91%, and wearable sleep tracking adherence was 95%, indicating high data integrity across modalities.

Table 1

Descriptive Statistics and Correlations Among Study Variables

Variable	Mean	SD	1	2	3	4	5
1. Emotional Dysregulation	87.46	14.28	1.00				
2. Digital Rumination	31.72	6.85	0.61	1.00			
3. Sleep Variability	1.84	0.52	0.47	0.39	1.00		
4. Cognitive Load Reactivity	26.15	5.94	0.54	0.48	0.36	1.00	
5. Social Micro-Withdrawal	18.93	4.67	0.58	0.52	0.33	0.45	1.00

The results presented in Table 1 indicate that all predictor variables were positively and moderately correlated with emotional dysregulation. Digital rumination demonstrated the strongest association ($r = 0.61$), followed by social micro-withdrawal ($r = 0.58$) and cognitive load reactivity ($r = 0.54$), while sleep variability showed a moderate but meaningful relationship ($r = 0.47$). Intercorrelations among predictors were also significant, particularly between digital rumination and social micro-withdrawal ($r = 0.52$), suggesting overlapping but distinct behavioral mechanisms. The distribution of means and standard deviations indicates sufficient variability across constructs, supporting their suitability for predictive modeling. Multicollinearity diagnostics confirmed that variance inflation factors remained below critical thresholds, allowing all variables to be retained in subsequent machine learning analyses.

Table 2

Machine Learning Model Performance Comparison

Model	RMSE	MAE	R^2
Random Forest	8.92	6.71	0.68
Support Vector Machine	9.47	7.12	0.63
Gradient Boosting	8.36	6.28	0.72
XGBoost	7.94	5.89	0.76

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Table 2 presents the comparative performance of four supervised machine learning algorithms in predicting emotional dysregulation. Among the tested models, XGBoost demonstrated the highest predictive accuracy, with the lowest RMSE (7.94) and MAE (5.89), alongside the highest explained variance ($R^2 = 0.76$). Gradient boosting also performed strongly, achieving an R^2 of 0.72, while random forest yielded moderate predictive power. The support vector machine exhibited comparatively lower performance across all evaluation metrics. These findings suggest that ensemble-based boosting algorithms are particularly effective in capturing the nonlinear and interaction effects inherent in psychological and behavioral data. The superiority of XGBoost informed its selection for subsequent interpretability and feature importance analyses.

Table 3

Feature Importance Based on SHAP Values (XGBoost Model)

Predictor Variable	Mean SHAP Value
Digital Rumination	0.42
Social Micro-Withdrawal	0.36
Cognitive Load Reactivity	0.31
Sleep Variability	0.27

The SHAP-based feature importance results in Table 3 reveal that digital rumination emerged as the most influential predictor of emotional dysregulation, followed by social micro-withdrawal and cognitive load reactivity. Sleep variability, while still significant, exhibited comparatively lower predictive contribution. The magnitude of SHAP values indicates the average impact of each feature on model output, demonstrating that cognitive-affective processes linked to digital engagement play a central role in emotional dysregulation. Notably, the relative importance of social micro-withdrawal underscores the behavioral manifestation of disengagement as a critical mechanism. These findings highlight the multidimensional and interactive nature of emotional dysregulation, with both cognitive and behavioral components contributing meaningfully.

Table 4

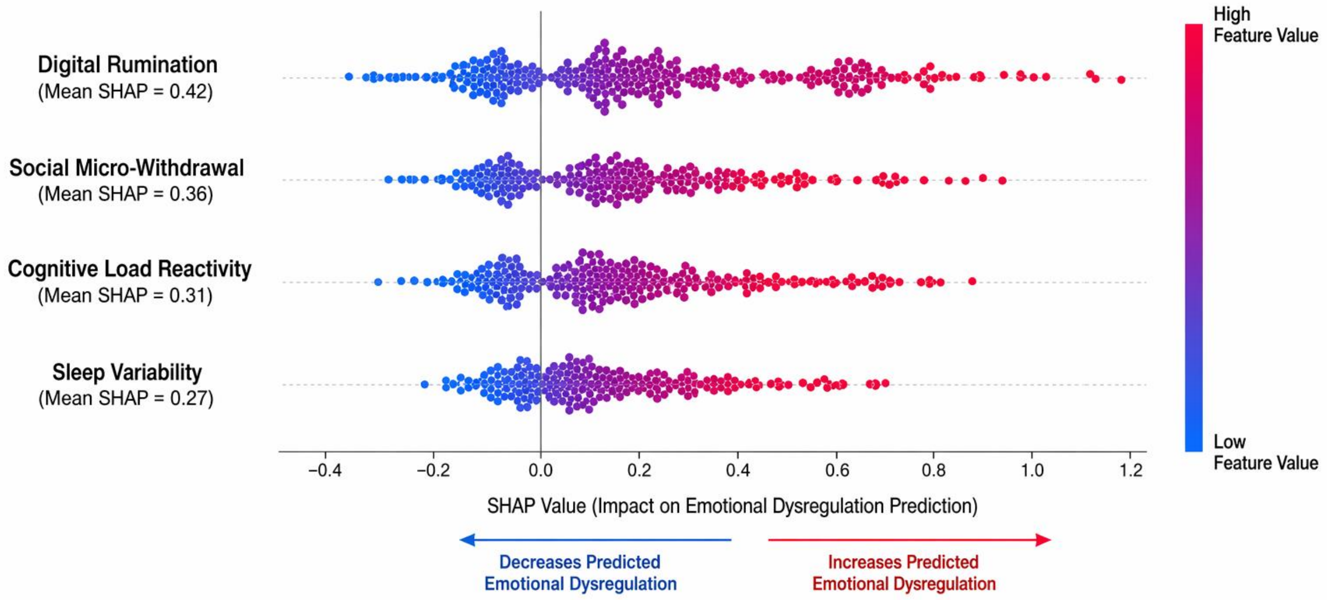
Interaction Effects Between Key Predictors (Derived Features)

Interaction Term	Contribution Score
Digital Rumination × Sleep Variability	0.29
Cognitive Load Reactivity × Micro-Withdrawal	0.26
Digital Rumination × Micro-Withdrawal	0.33
Sleep Variability × Cognitive Reactivity	0.21

Table 4 illustrates the contribution of interaction effects derived through feature engineering processes. The interaction between digital rumination and social micro-withdrawal demonstrated the highest contribution (0.33), suggesting that individuals who both ruminate digitally and withdraw socially are at substantially greater risk of emotional dysregulation. Similarly, the interaction between digital rumination and sleep variability indicates that cognitive over-engagement in digital contexts may exacerbate the destabilizing effects of irregular sleep patterns. These interaction effects provide deeper insight into the synergistic mechanisms underlying emotional dysregulation, beyond the additive influence of individual predictors.

Figure 1

SHAP Summary Plot of Predictor Contributions to Emotional Dysregulation



Note. Each dot represents one participant. The position on the x-axis indicates the SHAP value, showing how much the feature contributed to increasing (positive) or decreasing (negative) the model's prediction for emotional dysregulation. The color of each dot represents the original feature value, with red indicating higher values and blue indicating lower values.

The SHAP summary plot (Figure 1) visually illustrates the distribution and magnitude of each predictor's contribution across all observations in the XGBoost model. The plot demonstrates that higher levels of digital rumination consistently correspond to increased emotional dysregulation scores, with a steep gradient indicating strong influence. Social micro-withdrawal and cognitive load reactivity show similarly directional effects, although with slightly more dispersion across participants, reflecting heterogeneity in behavioral responses. Sleep variability exhibits a more moderate slope, yet remains a consistent contributor. Importantly, the visualization reveals nonlinear thresholds, particularly for digital rumination, beyond which the probability of elevated emotional dysregulation sharply increases. This pattern supports the presence of tipping points in digital-cognitive engagement, where cumulative exposure may lead to disproportionate emotional consequences.

4. Discussion

The present study aimed to develop a predictive model of emotional dysregulation using machine learning by integrating four emerging and theoretically relevant constructs: digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal. The findings demonstrated that emotional dysregulation could be predicted with substantial accuracy, particularly through ensemble-based algorithms such as XGBoost, which yielded the highest explanatory power among tested models. This result underscores the complex, nonlinear, and interaction-driven nature of emotional dysregulation, supporting the appropriateness of machine learning approaches for modeling psychological phenomena that are inherently multifactorial. The high predictive performance aligns with prior research indicating that psychological outcomes, especially those linked to digital behavior and cognitive-emotional processes, benefit from data-driven, integrative modeling strategies (Carter et al., 2025; Marano et al., 2025).

Among the predictors, digital rumination emerged as the most influential variable, exhibiting the strongest contribution to emotional dysregulation across all analyses. This finding is consistent with the conceptualization of rumination as a core transdiagnostic process that amplifies negative affect through repetitive and maladaptive cognitive loops (Daros & Ruocco, 2021; Wong et al., 2023). The extension of rumination into digital contexts appears to intensify its impact, likely due to the continuous availability of triggering stimuli and the reinforcing mechanisms embedded within social media platforms. Empirical evidence suggests that digital environments facilitate persistent engagement with emotionally salient content, thereby prolonging rumination cycles and exacerbating emotional distress (Arouch et al., 2025; Yousef et al., 2025). Furthermore, the strong predictive role of digital rumination aligns with studies linking rumination to depressive symptoms, anxiety, and maladaptive coping, reinforcing its centrality in emotional dysregulation processes (Wang et al., 2025; Yu et al., 2025).

Social micro-withdrawal also demonstrated a substantial contribution to emotional dysregulation, ranking as the second most important predictor in the model. This finding highlights the significance of subtle behavioral indicators of disengagement in understanding emotional functioning. Unlike overt social isolation, micro-withdrawal reflects nuanced shifts in interaction patterns, which may serve as early markers of psychological distress. The observed relationship is consistent with research indicating that reduced social engagement, even at micro-levels, is associated with increased emotional vulnerability and depressive symptomatology (Chen, 2025; Peçanha et al., 2025). In digital environments, such withdrawal may be both a response to overwhelming stimuli and a coping mechanism, yet it paradoxically reduces access to social support, thereby perpetuating dysregulation (Giannakopoulos & Prassou, 2025; Huang et al., 2025). The strong interaction effect between digital rumination and social micro-withdrawal further suggests a synergistic mechanism, whereby cognitive over-engagement and behavioral disengagement co-occur to intensify emotional instability.

Cognitive load reactivity emerged as another significant predictor, emphasizing the role of cognitive-emotional interplay in emotional dysregulation. Individuals who exhibit heightened emotional responses to cognitively demanding situations appear more susceptible to dysregulation, likely due to diminished attentional control and increased mental fatigue. This finding aligns with studies demonstrating that cognitive overload contributes to emotional exhaustion and impaired regulation, particularly in environments characterized by constant information flow and multitasking demands (Howard et al., 2024; Jiang, 2025). The relevance of cognitive load reactivity is further supported by metacognitive frameworks, which highlight the role of attentional and regulatory processes in managing emotional responses (Abdolmohamadi, 2025; Lunov et al., 2025). The interaction between cognitive load reactivity and social micro-withdrawal observed in the present study suggests that individuals overwhelmed by cognitive demands may increasingly disengage socially, thereby reinforcing dysregulation cycles.

Sleep variability, while comparatively lower in direct contribution, remained a significant and consistent predictor of emotional dysregulation. This finding supports the growing body of literature emphasizing the importance of sleep regularity, rather than merely duration, in emotional functioning. Fluctuations in sleep patterns can disrupt circadian rhythms and impair neurobiological processes underlying emotional regulation, leading to increased emotional reactivity and reduced resilience (Webb, 2023; Xu, 2025). Moreover, the interaction between sleep variability and digital rumination suggests that irregular sleep may amplify the cognitive persistence of negative thoughts, creating a feedback loop that exacerbates dysregulation. This is consistent with evidence linking poor sleep quality to increased rumination and emotional distress (Adawi & Waseem, 2025; Wang et al., 2025). The integration of sleep variability into the predictive model thus adds a গুরুত্বপূর্ণ physiological dimension to the understanding of emotional dysregulation.

The interaction effects identified in the model provide critical insights into the dynamic and interconnected nature of the studied variables. The strongest interaction, observed between digital rumination and social micro-withdrawal, suggests that the co-occurrence of cognitive and behavioral dysregulation processes significantly elevates the risk of emotional instability. This finding aligns with ecological and systems-based models of psychopathology, which emphasize the interplay between internal cognitive processes and external behavioral patterns (Doom et al., 2021). Similarly, the interaction between digital rumination and sleep variability highlights the convergence of cognitive and physiological factors, suggesting that disruptions in one domain may amplify vulnerabilities in another. These results reinforce the necessity of adopting multidimensional frameworks that capture the complexity of emotional dysregulation in contemporary contexts.

The superior performance of the XGBoost model compared to other algorithms further underscores the importance of capturing nonlinear relationships and higher-order interactions in psychological data. Traditional statistical approaches may overlook such complexities, leading to incomplete or oversimplified models. The use of SHAP analysis in the present study enhances interpretability

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by quantifying the contribution of each predictor, thereby bridging the gap between predictive accuracy and theoretical understanding. This approach aligns with recent methodological advancements advocating for explainable artificial intelligence in psychological research, enabling researchers to derive meaningful insights from complex models (Melvin et al., 2025; Tagliaferri et al., 2025). The ability to identify key predictors and their interactions has significant implications for both theory development and intervention design.

The findings of this study also contribute to the broader literature on digital mental health by highlighting the central role of digitally mediated cognitive and behavioral processes in emotional dysregulation. The integration of constructs such as digital rumination and social micro-withdrawal reflects the evolving nature of psychological experiences in the digital age. Previous research has documented the adverse effects of problematic media use, social media fatigue, and technology-related stress on mental health outcomes (Lu et al., 2024; Marano et al., 2025). The present study extends this literature by demonstrating how these factors interact with cognitive and physiological processes to predict emotional dysregulation. Additionally, the findings support person-centric and context-sensitive frameworks that emphasize the role of individual differences and environmental influences in shaping psychological outcomes (Carter et al., 2025; Yun & Kwak, 2025).

Furthermore, the results align with emerging evidence on the role of emotional dysregulation as a mediator in various psychological pathways. For instance, emotional dysregulation has been shown to mediate the relationship between guilt, shame, and behavioral disorders, as well as between digital engagement and mental health outcomes (Ntumi et al., 2025; Yu et al., 2025). The identification of key predictors in the present study provides valuable insights into the antecedents of emotional dysregulation, thereby informing potential intervention targets. By addressing factors such as digital rumination, sleep variability, and cognitive load reactivity, it may be possible to mitigate the downstream effects of emotional dysregulation on mental health.

In addition, the findings highlight the importance of considering boredom and emotional exhaustion as underlying mechanisms linking digital engagement to emotional dysregulation. Research suggests that boredom may drive excessive technology use, which in turn contributes to cognitive overload and emotional distress (Tagliaferri et al., 2025). Similarly, emotional exhaustion has been linked to impaired mental health and increased vulnerability to dysregulation, particularly in high-demand environments (Jiang, 2025). These mechanisms may operate in conjunction with the variables examined in the present study, further emphasizing the need for comprehensive models that integrate multiple dimensions of psychological functioning.

5. Conclusion

Overall, the present study provides robust evidence for the predictive utility of machine learning models in understanding emotional dysregulation and highlights the central role of digital, cognitive, behavioral, and physiological factors. The integration of these constructs within a unified framework offers a comprehensive perspective on emotional dysregulation in the digital age and underscores the importance of interdisciplinary approaches in psychological research.

6. Limitations & Suggestions

The study is not without limitations. First, the cross-sectional nature of the data limits the ability to infer causal relationships among the variables, and longitudinal designs are needed to examine temporal dynamics and directionality. Second, although multimodal data collection was employed, reliance on self-report measures for certain constructs may introduce response biases and affect measurement accuracy. Third, the sample, while relatively large, was restricted to young adults in Japan, which may limit the generalizability of the findings to other cultural or age groups. Fourth, despite the use of advanced machine learning techniques, model performance may still be influenced by unmeasured variables, such as personality traits or environmental stressors, which were not included in the present study.

Future research should adopt longitudinal and experimental designs to examine causal pathways and temporal interactions among digital rumination, sleep variability, cognitive load reactivity, and social micro-withdrawal. Expanding the scope of research to include diverse populations across different cultural contexts will enhance the generalizability of findings and allow for cross-cultural comparisons. Additionally, future studies should incorporate additional variables, such as personality traits, emotional intelligence, and environmental stressors, to develop more comprehensive predictive models. The integration of real-time data collection methods, such as continuous passive sensing and advanced ecological

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momentary assessment, may further improve the accuracy and ecological validity of predictive models. Finally, the application of hybrid modeling approaches that combine machine learning with theoretical frameworks may facilitate the development of more interpretable and theoretically grounded models of emotional dysregulation.

From a practical perspective, the findings of this study have important implications for mental health interventions and digital well-being strategies. Interventions targeting digital rumination, such as cognitive restructuring and mindfulness-based approaches, may help reduce maladaptive thought patterns and improve emotional regulation. Promoting regular sleep patterns and reducing sleep variability through behavioral interventions and digital hygiene practices may also enhance emotional stability. Additionally, strategies aimed at managing cognitive load, such as time management training and reduction of multitasking, may mitigate emotional reactivity. Finally, interventions designed to encourage healthy social engagement and reduce micro-withdrawal behaviors may strengthen social support networks and buffer against emotional dysregulation.

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Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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Authors' Contributions

All authors equally contributed in this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

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