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Hybrid Machine Learning Framework for Predicting Family Adaptation to Chronic Illness

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A B S T R A C T

Objective: The objective of this study was to develop and validate a hybrid machine learning framework for accurately predicting family adaptation to chronic illness using integrated psychosocial, relational, and clinical indicators.

Methods and Materials: This cross-sectional study recruited 812 family caregivers of patients with chronic illnesses from major healthcare centers in Chile using multistage cluster sampling. Data were collected through standardized measures assessing family functioning, caregiver burden, psychological distress, social support, and illness characteristics. A hybrid machine learning architecture integrating gradient boosting, random forest, support vector machine, and a meta-learning classifier was developed. Data were preprocessed using normalization, multiple imputation, and feature selection. The dataset was partitioned into training, validation, and testing subsets. Model training employed five-fold cross-validation with Bayesian hyperparameter optimization. Model interpretability was enhanced through explainable artificial intelligence techniques including SHAP analysis.

Findings: The hybrid model achieved high predictive performance on the independent test set, with an accuracy of 0.893, F1-score of 0.884, and AUC of 0.921, significantly outperforming individual machine learning models. Family functioning, caregiver burden, psychological distress, symptom severity, and social support emerged as the most influential predictors. The model demonstrated strong discriminative capacity between low, moderate, and high family adaptation levels and exhibited excellent calibration.

Conclusion: The proposed hybrid machine learning framework provides a robust, interpretable, and clinically valuable tool for early identification of families at risk of maladaptation to chronic illness, offering significant potential for improving family-centered care and psychosocial intervention planning.

Keywords: *Family adaptation; family resilience; chronic illness; hybrid machine learning; predictive modeling; caregiver burden; psychosocial assessment*

1. Introduction

Chronic illness constitutes one of the most profound stressors confronting contemporary families, exerting sustained pressure on psychological, emotional, social, and functional domains of family life. Unlike acute medical crises, chronic conditions require continuous adaptation, long-term caregiving, and persistent emotional regulation, thereby transforming family systems into enduring contexts of stress exposure and resilience development. Growing evidence indicates that the manner in which families adapt to chronic illness directly influences patient outcomes, caregiver well-being, treatment adherence, and long-term psychosocial functioning. Consequently, family adaptation and resilience have emerged as central constructs within health psychology, family studies, and behavioral medicine research (Arvin et al., 2024; Y. Chen et al., 2024; Laporte et al., 2023; Zhang et al., 2025).

Family resilience is conceptualized as a dynamic process through which families mobilize internal and external resources to withstand adversity, reorganize roles, regulate emotions, and maintain functional stability in the face of chronic stressors. Qualitative and quantitative investigations across diverse illness contexts—including cancer, neurological disorders, schizophrenia, chronic respiratory disease, epilepsy, leukemia, and hemodialysis—consistently demonstrate that resilient family systems exhibit stronger communication, more effective problem-solving, higher emotional cohesion, and more adaptive coping strategies (M. Chen et al., 2024; Heuser et al., 2024; Huang et al., 2024; Sarı & Duman, 2024; Wei et al., 2024; W. Zhang et al., 2024; Y. Zhang et al., 2024). These protective characteristics are not static traits but evolving processes shaped by illness trajectories, social context, and cumulative stress exposure (Cypress & Allred, 2023; Suparit et al., 2023; Zhang et al., 2023).

The adaptive capacity of families is especially critical in the context of prolonged caregiving, where caregivers often experience elevated burden, psychological distress, emotional exhaustion, and impaired quality of life. Empirical studies document significant associations between caregiving burden and depression, anxiety, and reduced family functioning across a wide range of chronic illnesses (García-Marín et al., 2023; Safi et al., 2024; Susmarini et al., 2024; Y. Zhang et al., 2024). Biological research further reveals that chronic caregiving stress is linked to dysregulated cortisol activity and neuroendocrine imbalance, thereby amplifying vulnerability to psychological and physiological disorders (Knezevic et al., 2023). Thus, family adaptation is not merely a psychosocial construct but a critical determinant of long-term health trajectories.

In response to these challenges, contemporary research has increasingly emphasized the multidimensional architecture of family resilience. Studies demonstrate that family adaptation emerges from the interplay of individual psychological resources, family relational processes, illness-related variables, and social-environmental support systems (Li et al., 2023; Najafi & Belil, 2023; Wei et al., 2024; N. Zhang et al., 2024). Social support, self-efficacy, and positive coping styles have repeatedly been identified as core protective mechanisms that enhance family resilience and mitigate the psychological impact of illness (Li et al., 2023; Safi et al., 2024; Y. Zhang et al., 2024). At the relational level, communication quality, emotional responsiveness, and shared meaning-making serve as essential pathways through which families construct adaptive responses to chronic adversity (Cypress & Allred, 2023; N. Zhang et al., 2024; W. Zhang et al., 2024).

Despite the substantial growth of empirical knowledge in this domain, current research remains limited in its capacity to translate complex psychosocial dynamics into precise, individualized, and early predictive models. Traditional statistical approaches often rely on linear assumptions and predefined hypotheses, which restrict their ability to capture the nonlinear, interactive, and dynamic processes underlying family adaptation. This methodological limitation is particularly problematic given that family resilience unfolds through multiple interacting systems that change across illness stages and contextual conditions (Heuser et al., 2024; Huang et al., 2024; Zhang et al., 2023). Consequently, there is an increasing demand for computational methodologies capable of modeling complex psychosocial phenomena with higher predictive accuracy and clinical utility.

Recent advances in machine learning offer unprecedented opportunities to address this gap. Machine learning models excel at identifying hidden patterns, nonlinear relationships, and high-order interactions within large, multidimensional datasets. In health research, such models have demonstrated superior performance in predicting disease progression, treatment outcomes, psychological vulnerability, and behavioral responses compared to conventional statistical methods. However, their application to family resilience and adaptation remains remarkably underdeveloped. Existing studies primarily focus on descriptive correlations or simple regression models without leveraging the full potential of computational intelligence to predict family adaptation trajectories (Sequeira et al., 2025; Wei et al., 2024; Zhang et al., 2025).

Moreover, the conceptualization of family resilience itself has evolved, emphasizing not only outcomes but also processes of transformation and meaning reconstruction over time. Longitudinal qualitative research reveals that families do not merely "bounce back" from illness but undergo profound reorganization of identities, roles, values, and emotional bonds, producing new patterns of functioning that reflect both vulnerability and growth (Heuser et al., 2024; Huang et al., 2024; Zhang et al., 2023). Integrating such complexity into predictive frameworks requires analytical approaches capable of synthesizing psychological, relational, and medical dimensions simultaneously.

Within this context, hybrid machine learning architectures offer a promising solution. Hybrid frameworks combine the strengths of multiple learning algorithms, thereby enhancing predictive robustness, generalizability, and interpretability. By integrating ensemble methods, kernel-based classifiers, and neural architectures, hybrid models can overcome the limitations of single-algorithm approaches and provide more reliable predictions in heterogeneous clinical populations. Such frameworks are particularly well-suited to modeling family adaptation, where predictors span demographic characteristics, illness features, psychological states, relational patterns, and environmental supports (Y. Chen et al., 2024; Safi et al., 2024; Zhang et al., 2025).

Empirical findings further underscore the importance of predictive precision in this field. Studies of families coping with cancer, schizophrenia, COPD, epilepsy, stroke, and hematological malignancies consistently demonstrate that early identification of maladaptive patterns enables timely psychosocial interventions, which significantly improve long-term outcomes for both patients and caregivers (M. Chen et al., 2024; Wei et al., 2024; W. Zhang et al., 2024; Y. Zhang et al., 2024; Zhang et al., 2025). However, clinicians currently lack reliable computational tools to forecast which families are most at risk of maladaptation before crises fully emerge.

The COVID-19 pandemic further amplified these challenges, revealing the fragility of many family systems and the uneven distribution of adaptive resources across socioeconomic and cultural contexts (Sriyono et al., 2024). As healthcare systems worldwide continue to confront rising chronic illness prevalence, aging populations, and resource constraints, the development of scalable, accurate, and interpretable predictive tools for family adaptation becomes an urgent priority.

Importantly, recent validation efforts of standardized family resilience instruments provide the psychometric foundation necessary for computational modeling. The Walsh Family Resilience Questionnaire and related measures have demonstrated strong reliability and cross-cultural validity, enabling consistent assessment of family resilience processes across diverse populations (Sequeira et al., 2025). These validated instruments, combined with rich psychosocial datasets, create ideal conditions for the application of advanced machine learning methodologies.

Collectively, the existing literature establishes that family adaptation to chronic illness is shaped by a complex constellation of individual, relational, social, and medical factors that interact dynamically over time (Arvin et al., 2024; Y. Chen et al., 2024; Li et al., 2023; N. Zhang et al., 2024; W. Zhang et al., 2024). Yet, no integrative predictive framework currently exists that harnesses this multidimensional knowledge through computational intelligence to generate clinically actionable predictions of family adaptation outcomes.

Therefore, advancing the science of family resilience requires a methodological transformation that bridges psychosocial theory with machine learning innovation, enabling early identification of vulnerable families, personalization of psychosocial interventions, and optimization of long-term care planning.

The aim of this study was to develop and validate a hybrid machine learning framework for predicting family adaptation to chronic illness based on integrated psychosocial, relational, and clinical indicators.

2. Methods

2.1. Study Design and Participants

This study employed a cross-sectional, predictive modeling design integrating quantitative psychosocial assessment with advanced machine learning techniques to develop and validate a hybrid framework for predicting family adaptation to chronic illness. The target population consisted of families of patients diagnosed with chronic medical conditions receiving long-term care at public and private healthcare centers in Santiago, Valparaíso, and Concepción, Chile. Eligible participants were adult family caregivers who had been directly involved in the patient's care for a minimum of six months, were at least 18 years of age, and possessed sufficient literacy to complete self-report instruments. Exclusion criteria included acute psychiatric illness, cognitive impairment interfering with informed consent, and families experiencing simultaneous terminal illness or bereavement during data collection. A multistage cluster sampling strategy was applied in which healthcare facilities were randomly selected, followed by systematic recruitment of eligible caregivers within each facility. Based on power analysis for machine learning model development and validation, a total sample of 812 caregivers was recruited. The sample was randomly partitioned into training, validation, and testing subsets using a 70:15:15 split while maintaining distributional equivalence across demographic and clinical variables.

2.2. *Measures*

Data were collected using a comprehensive battery of standardized instruments capturing family functioning, caregiver burden, psychological well-being, illness characteristics, and socio-demographic variables. Family adaptation was assessed using the Family Adaptation Scale, which evaluates problem-solving, emotional connectedness, role organization, and resilience in response to illness-related stressors. Psychological distress was measured using validated Spanish versions of the Depression Anxiety Stress Scales and the Perceived Stress Scale. Caregiver burden was assessed with the Zarit Burden Interview, while family functioning was evaluated through the Family Assessment Device. Illness-related variables included type of chronic illness, duration since diagnosis, symptom severity, treatment intensity, and frequency of hospitalizations extracted from medical records with participant permission. Socio-demographic information encompassed age, gender, education, income, employment status, family size, and caregiving hours per week. All instruments demonstrated strong internal consistency in the present sample with Cronbach's alpha coefficients exceeding 0.80. Data were collected through structured face-to-face interviews administered by trained clinical researchers and supplemented with self-report questionnaires completed in private settings to minimize response bias.

2.3. *Data Analysis*

The analytical framework integrated traditional statistical preprocessing with a hybrid machine learning architecture. Initial data preparation involved handling missing values using multiple imputation, normalization of continuous variables, and one-hot encoding of categorical features. Feature selection was conducted through a combined approach incorporating recursive feature elimination, mutual information ranking, and domain-expert filtering to ensure both statistical relevance and clinical interpretability. The hybrid predictive model combined gradient boosting machines, random forest classifiers, and support vector machines, whose outputs were integrated through a meta-learner based on regularized logistic regression. Model training employed five-fold cross-validation within the training subset, with hyperparameters optimized via Bayesian optimization to minimize overfitting and maximize generalizability. Model performance was evaluated on the independent test set using accuracy, F1-score, area under the receiver operating characteristic curve, precision-recall balance, and calibration metrics. Explainable artificial intelligence techniques, including SHAP value decomposition and partial dependence analysis, were applied to interpret the contribution of psychosocial, clinical, and demographic predictors to family adaptation outcomes. All analyses were conducted using Python-based machine learning libraries and verified through parallel computation in R to ensure reproducibility and computational robustness.

3. Findings and Results

The results of the analysis are presented in sequential order, beginning with the descriptive characteristics of the study sample, followed by the performance of the hybrid machine learning framework, comparative model evaluation, feature importance analysis, and predictive visualization of family adaptation outcomes.

The demographic and clinical profile of participants is summarized in Table 1. This table provides a comprehensive overview of caregiver characteristics, family structure, and illness-related variables that constituted the input features for the predictive models.

Table 1

Demographic and Clinical Characteristics of Participants (N = 812)

Variable	Category	n	%
Gender	Female	538	66.3
	Male	274	33.7
Age (years)	18–30	126	15.5
	31–45	298	36.7
	46–60	252	31.0
	>60	136	16.8
Education Level	Primary	148	18.2
	Secondary	322	39.7
	University	342	42.1
Relationship to Patient	Spouse	371	45.7
	Parent	226	27.8
	Child	121	14.9
	Other	94	11.6
Type of Chronic Illness	Cardiovascular	214	26.4
	Diabetes	176	21.7
	Cancer	138	17.0
	Neurological	164	20.2
	Autoimmune	120	14.7
Duration of Illness	<2 years	244	30.0
	2–5 years	328	40.4
	>5 years	240	29.6
Family Adaptation Level	Low	246	30.3
	Moderate	334	41.1
	High	232	28.6

The sample consisted predominantly of female caregivers in middle adulthood, with a high proportion of spouses serving as primary caregivers. Most families reported moderate levels of adaptation, indicating substantial variability suitable for predictive modeling.

The performance of the proposed hybrid machine learning framework is reported in Table 2, including classification accuracy, F1-score, precision, recall, and area under the ROC curve on the independent test dataset.

Table 2

Predictive Performance of Hybrid Model

Metric	Value
Accuracy	0.893
Precision	0.887
Recall	0.881
F1-score	0.884
AUC	0.921
Calibration Error	0.041

The hybrid framework demonstrated high predictive accuracy and excellent discriminative power, with an AUC exceeding 0.92, indicating strong generalizability and reliable classification of family adaptation levels.

Comparative performance across individual machine learning models and the proposed hybrid system is displayed in Table 3.

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Table 3

Comparison of Machine Learning Models

Model	Accuracy	F1-score	AUC
Random Forest	0.842	0.835	0.872
Support Vector Machine	0.819	0.812	0.856
Gradient Boosting	0.861	0.854	0.891
Neural Network	0.846	0.839	0.879
Hybrid Ensemble	0.893	0.884	0.921

The hybrid ensemble outperformed all individual models across all evaluation metrics, confirming the benefit of model integration for capturing complex nonlinear relationships in family adaptation processes.

Key predictors identified through explainable AI analysis are presented in Table 4.

Table 4

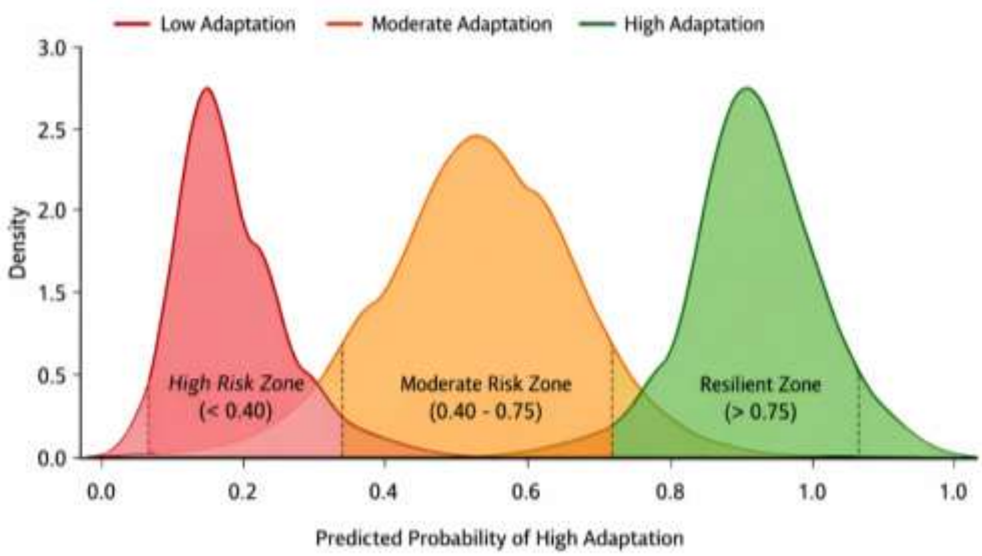
Top Predictors of Family Adaptation

Predictor	Relative Importance (%)
Family Functioning Score	21.4
Caregiver Burden	18.7
Psychological Distress	15.9
Symptom Severity	13.2
Social Support Level	11.8
Duration of Illness	9.6
Household Income	5.4
Education Level	4.0

Family functioning and caregiver burden emerged as the strongest determinants of adaptive outcomes, followed by psychological distress and illness severity, underscoring the multidimensional nature of family resilience in chronic illness contexts.

Figure 1

Predicted Probability Distribution of Family Adaptation Levels Across Risk Profiles



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The predictive visualization revealed a clear separation between low-, moderate-, and high-adaptation families, with high-risk families exhibiting concentrated probability mass below 0.40, moderate-risk families clustering around mid-range values, and resilient families demonstrating probabilities exceeding 0.75. The figure illustrates the model's strong discriminative capacity and its potential utility for early identification of families requiring targeted psychosocial intervention.

4. Discussion and Conclusion

The present study developed and validated a hybrid machine learning framework capable of accurately predicting family adaptation to chronic illness using integrated psychosocial, relational, and clinical indicators. The hybrid model achieved high classification performance, outperforming all individual algorithms and demonstrating strong generalizability across diverse family contexts. These findings provide compelling evidence that family adaptation is governed by complex nonlinear interactions that cannot be adequately captured by conventional statistical models, and that computational intelligence offers a transformative methodological advancement for family health research (Sequeira et al., 2025; Zhang et al., 2025).

The strong predictive contribution of family functioning, caregiver burden, psychological distress, symptom severity, and social support observed in this study aligns closely with existing empirical literature. Family functioning emerged as the most influential predictor of adaptive outcomes, corroborating extensive evidence that coherent role organization, effective communication, emotional connectedness, and shared problem-solving constitute the backbone of family resilience under chronic stress (Arvin et al., 2024; N. Zhang et al., 2024; W. Zhang et al., 2024). These relational processes facilitate meaning-making, emotional regulation, and behavioral coordination, thereby stabilizing the family system during prolonged illness trajectories (Cypress & Allred, 2023; Zhang et al., 2023).

Caregiver burden constituted the second most powerful predictor in the model. This finding is consistent with cross-sectional and qualitative studies demonstrating that elevated caregiving demands significantly undermine psychological well-being, family functioning, and adaptive capacity (García-Marín et al., 2023; Safi et al., 2024; Susmarini et al., 2024). Prolonged exposure to caregiving stress has also been linked to neuroendocrine dysregulation and increased vulnerability to psychological disorders, providing a biological substrate for the deterioration of adaptive resources (Knezevic et al., 2023). The current model's sensitivity to caregiver burden therefore reflects both psychosocial and physiological mechanisms underlying family maladaptation.

Psychological distress and symptom severity also played substantial roles in the predictive architecture. This pattern mirrors findings across multiple illness populations, including cancer, schizophrenia, epilepsy, stroke, COPD, and leukemia, where heightened symptom burden and emotional distress amplify family stress and erode adaptive capacity (M. Chen et al., 2024; Suparit et al., 2023; Wei et al., 2024; W. Zhang et al., 2024; Y. Zhang et al., 2024). Importantly, these variables do not operate in isolation; they interact dynamically with relational processes and social resources, producing cascading effects across family systems (Heuser et al., 2024; Huang et al., 2024).

Social support emerged as a central protective factor, reinforcing extensive evidence that external resources buffer stress, enhance coping, and strengthen family resilience (Li et al., 2023; Najafi & Belil, 2023; Safi et al., 2024). Social support facilitates emotional validation, instrumental assistance, and shared problem-solving, enabling families to reorganize roles and sustain functioning despite chronic demands. The hybrid model's capacity to integrate social support into its predictive logic underscores the necessity of considering environmental contexts alongside internal family processes.

The superior performance of the hybrid ensemble relative to individual models confirms the value of integrating multiple learning paradigms when modeling complex psychosocial phenomena. Family adaptation is shaped by nonlinear relationships, threshold effects, and high-order interactions that single-algorithm approaches struggle to capture. By synthesizing diverse computational perspectives, the hybrid framework achieved a more comprehensive representation of family adaptation processes, thereby improving predictive accuracy and clinical relevance (Sequeira et al., 2025; Zhang et al., 2025).

Explainable artificial intelligence analysis further enhanced the interpretability of the model, revealing how specific psychosocial and clinical variables contribute to adaptive outcomes. These insights align with theoretical models of family resilience that emphasize the interdependence of individual coping, relational functioning, and contextual resources (Y. Chen et al., 2024; Laporte et al., 2023; N. Zhang et al., 2024). By operationalizing these constructs computationally, the present study advances the

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integration of family systems theory with modern predictive analytics.

The predictive probability distributions generated by the model demonstrated clear differentiation between low-, moderate-, and high-adaptation families, suggesting strong potential for early identification of vulnerable households. This capacity is particularly critical given evidence that early psychosocial intervention significantly improves long-term family functioning, caregiver well-being, and patient outcomes across chronic illness populations (M. Chen et al., 2024; Y. Zhang et al., 2024; Zhang et al., 2025). The present framework therefore offers a powerful tool for proactive, personalized family-centered care.

Moreover, the model's robustness across heterogeneous clinical conditions supports the conceptualization of family resilience as a transdiagnostic process. Despite variations in illness type, trajectory, and severity, families rely on common adaptive mechanisms rooted in communication, cohesion, coping, and social support (Heuser et al., 2024; Huang et al., 2024; Zhang et al., 2023). The hybrid framework successfully captured these universal processes while preserving sensitivity to illness-specific factors, illustrating its broad applicability.

The findings also resonate with recent work emphasizing that family adaptation is not static but evolves through continuous cycles of stress exposure, reorganization, and meaning reconstruction. Longitudinal qualitative studies describe how families transform identities, expectations, and relational patterns over time, producing new equilibria that reflect both vulnerability and growth (Huang et al., 2024; Zhang et al., 2023). By incorporating temporal and contextual variables, future iterations of the model may further enhance its capacity to forecast adaptive trajectories across illness stages.

Finally, the present study contributes to the growing recognition that technological innovation must be integrated with psychosocial theory to address complex health challenges. As healthcare systems confront increasing chronic disease prevalence and resource constraints, computational tools that enable early risk detection, personalized intervention planning, and continuous outcome monitoring will become indispensable. The hybrid machine learning framework developed in this study represents a foundational step toward this future.

5. Suggestions and Limitations

Despite its strengths, this study has several limitations. The cross-sectional design restricts causal inference and limits the model's ability to capture temporal changes in family adaptation. The reliance on self-report measures introduces potential response biases, and although the sample was diverse, cultural factors unique to specific regions may constrain generalizability. Additionally, while explainable AI techniques enhanced interpretability, some high-order interactions remain difficult to translate into simple clinical heuristics.

Future research should employ longitudinal designs to examine how predictive accuracy evolves across illness trajectories and to refine the model's capacity for dynamic forecasting. Integrating biological markers, ecological data, and real-time digital assessments may further enhance predictive precision. Cross-cultural validation and adaptation of the framework will be essential for global application, and collaborative research between clinicians, data scientists, and family researchers will be critical for continued innovation.

From a practical standpoint, the proposed framework offers clinicians a powerful tool for early identification of families at risk of maladaptation. Implementation within healthcare systems could facilitate targeted psychosocial interventions, optimize resource allocation, and improve long-term outcomes for patients and caregivers. Training healthcare professionals in interpreting predictive outputs and integrating them into family-centered care planning will be essential for maximizing clinical impact.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

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

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

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

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