

Using Deep Learning to Classify Family Functioning Profiles Based on Parental Attachment, Emotion Socialization, and Child Behavioral Outcomes

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1. Round 1

1.1. Reviewer 1

Reviewer:

The study's sample size (784 two-parent Greek families) is a notable strength and provides adequate statistical power for LPA and training a deep learning model, yet the inclusion criteria (cohabiting, native Greek, no severe diagnosis) restrict the sample to relatively normative, lower-risk families, which substantially limits the generalizability of the findings to more diverse, single-parent, migrant, or clinically complex populations and should be discussed more explicitly and critically in the limitations section.

The manuscript convincingly argues for potential clinical applications of profile-based classification, yet it does not adequately address interpretability and ethical considerations around using a "black-box" MLP in clinical decision-making; it would be highly valuable to incorporate interpretable ML techniques (e.g., SHAP values, feature importance analyses, prototypical family cases) and to discuss how misclassification—particularly between anxious-inconsistent and high-risk

families—would be managed in practice, as well as how the model would be adapted or recalibrated in non-Greek or higher-risk settings.

Response: Revised and uploaded the manuscript.

1.2. Reviewer 2

Reviewer:

The description of the LPA procedure is conceptually sound, but the manuscript does not sufficiently report core model-selection details (e.g., comparison of 2-, 3-, 4-class solutions, fit indices such as BIC, AIC, entropy, Lo-Mendell–Rubin tests, and class sizes), nor does it provide detailed parameter estimates for the profiles; without these, readers cannot adequately evaluate whether the three-profile solution is empirically optimal or whether the labels (“Adaptive,” “Anxious-Inconsistent,” “High-Risk/Avoidant-Punitive”) are fully justified by the quantitative patterns.

The operational characterization of the three family profiles remains somewhat descriptive and impressionistic, as the text relies on narrative labels (e.g., “avoidant-punitive”) rather than presenting clear tables or figures that show standardized means and confidence intervals for attachment dimensions, supportive/non-supportive emotion socialization, and SDQ subscales; providing such quantitative profile descriptions would greatly enhance interpretability, replicability, and potential clinical translation of the typology.

The introduction and discussion make strong claims about “intergenerational transmission,” “risk,” and “predictive” processes, yet the cross-sectional design only supports associational conclusions; the authors should temper causal language, explicitly acknowledge that profiles reflect contemporaneous patterns rather than developmental trajectories, and ideally outline how future longitudinal or cross-lagged designs would be necessary to substantiate the proposed causal mechanisms.

The deep learning component is an interesting and innovative addition, but the current reporting of the MLP model is insufficient for scientific reproducibility: key architectural and training details (number of layers and neurons, activation functions, optimizer, learning rate, batch size, number of epochs, regularization strategies such as dropout or weight decay, handling of missing data and class imbalance) are missing or only vaguely described, and should be reported systematically, preferably in a dedicated Methods subsection.

While the manuscript emphasizes the “exceptional overall classification accuracy” of the MLP and highlights an F1-score of 1.00 for the adaptive profile, it does not present full numerical performance metrics for the other classes (precision, recall, F1 for Profiles 2 and 3, overall accuracy with confidence intervals, and the full confusion matrix); these metrics should be fully reported (e.g., in Table 4) to allow readers to judge performance across profiles, especially for the clinically most relevant high-risk group.

From a methodological standpoint, the exclusive focus on a deep learning classifier without comparison to simpler, more interpretable baseline models (e.g., multinomial logistic regression, random forest, gradient boosting, support vector machines) weakens the claim that deep learning is necessary or superior in this context; I strongly recommend including one or more benchmark models and reporting whether the MLP yields a practically meaningful improvement in performance, along with a brief discussion of the trade-off between accuracy and interpretability.

Response: Revised and uploaded the manuscript.

2. Revised

Editor’s decision after revisions: Accepted.

Editor in Chief’s decision: Accepted.