TIHA-MLI v6.0: A Comparative Validation of Idiosyncratic Linear Models (MLI) for Affective Valence (EEG vs. Peripheral Signals)

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Abstract

Computational models of affect fail to generalize across subjects, challenging universal formula approaches. We present the final validation of the Hybrid Affective Integration Theory (TIHA) v6.0, which posits that affective experience is an **Idiosyncratic Linear Model (MLI)**. This framework was validated through a "model competition" on the multimodal DEAP dataset (N=32), comparing an EEG-based model (Central Nervous System - CNS) with a wearable model ("TIHA-Lite", Peripheral Nervous System - PNS).

Both models, using Ridge Regression (alpha=1.0), proved to be robust and statistically significant predictors of valence:

1. **EEG Model (CNS: Φ, E, S_{eeg}):** Achieved $R^2 = 0.1810$ ($p = 1.66\text{e-}11$).
2. **"TIHA-Lite" Model (PNS: HRV, EDA, S_{gsr}):** Achieved $R^2 = 0.0914$ ($p = 4.88\text{e-}11$).

The pivot to wearables is thus **validated and viable**, quantified by a 49.5% loss in predictive power. Both models are methodologically robust (max VIF ¡ 2.74). The "Idiosyncratic Paradox" is formally confirmed (non-universal weights, $p > 0.104$). **Integration (Φ)** is the primary driver of the EEG model. This paper validates the MLI framework across both signal domains (CNS and PNS) and invites engineering for Phase II.

Keywords: Affective computing, idiosyncratic modeling, EEG, HRV, EDA, PNS, valence, VIF.

1 INTRODUCTION

The challenge in affective computing is generalization failure. TIHA v6.0 posits that the solution is an **Idiosyncratic Linear Model (MLI)**. The hypothesis arose from the falsification of universal models ('Operator $\odot$) (v3.5, LOSO, $r \approx 0.04$).

The "Ontological Pivot" (v4.0) led to an MLI. An initial 4-component model (v4.6) ($R^2 \approx 0.229$) was discarded due to **high multicollinearity** (v4.7, VIF ≈ 6.96). A "model competition" (v4.8) identified a robust 3-component EEG model (Φ, E, S), validated in v5.1 ($R^2 = 0.181$, VIF¡2.74, Paradox $p > 0.104$).

This paper presents the **final validation (v6.0)**. We address the critical question of Phase III: Does the MLI framework function solely with peripheral signals (PNS)? We conducted a comparative validation on DEAP, contrasting the v5.1 EEG model with a new "TIHA-Lite" PNS model, using the dataset's existing HRV and EDA signals.

*Joint Independent Research Initiative, Brazil. Dated: November 8, 2025. DOI: 10.17605/OSF.IO/BJ2TS Repository (GitHub): `github.com/leandroantoniodasilvapacheco/TIHA-MLI-v6.0`.

2 METHODS

2.1 Dataset and Signals

We utilized the multimodal DEAP dataset [3] (N=32, 1280 total trials). Data were extracted per trial:

- **EEG Signals (CNS):** Channels 1-32.
- **PNS Signals (Peripherals):** Channel 37 (GSR/EDA) and Channel 39 (Plethysmograph/HRV).
- **Dependent Variables:** Hedonic Valence (V_H) and Eudaimonic Valence (V_E), normalized to [-1, 1].

2.2 Proxies (Independent Variables)

2.2.1 Model A (v5.1 EEG)

- Φ (Integration): Mean correlation in the alpha band (8-12 Hz).
- E (Entropy): Spectral Entropy (Welch PSD).
- S_{eeg} (EEG Surprise): Variance of the Fz signal.

2.2.2 Model B (v6.0 PNS "TIHA-Lite")

- HRV (Variability): RMSSD (Root Mean Square of Successive Differences) of plethysmograph peaks.
- EDA (Activation): Count of phasic peaks (SCRs) in the GSR signal.
- S_{gsr} (PNS Surprise): Variance of the GSR signal.

2.3 Analysis and Procedure

For each of the 32 subjects, two separate MLI models (Model A and B) were trained using Ridge Regression (alpha=1.0) to predict V_H and V_E. Metrics (R^2, MAE, r, VIF) were aggregated. The Idiosyncratic Paradox (H5) was tested on Model A. (Seed=42, Python/Scikit-learn/Statsmodels).

3 RESULTS

Execution of v6.0 (N=32) validated both models.

3.1 Model A (v5.1 EEG): Predictive and Robust

- **Predictive Power (V_H):** $R^2 = 0.1810$ ($p = 1.66\text{e-}11$), MAE=0.3858, $r = 0.4023$.
- **Predictive Power (V_E):** $R^2 = 0.1512$ ($p = 3.15\text{e-}10$).
- **Robustness (VIF):** SUCCESS (max VIF = 2.739 ¡ 5).
- **Driver:** Φ (Integration) (mean $|Beta| = 0.1356$).
- **Paradox:** SUCCESS (min p = 0.104 ¿ 0.05).

3.2 Model B (v6.0 PNS "TIHA-Lite"): Pivot Validated

- **Predictive Power (V_H):** $R^2 = 0.0914$ ($p = 4.88\text{e-}11$), MAE=0.4144, $r = 0.2870$.
- **(Predictive Power V_E):** (Similar analysis, $R^2 \approx 0.08_x$).
- **Robustness (VIF):** SUCCESS (max VIF = 1.097 ¡ 5).

3.3 Comparative Validation (EEG vs. PNS)

The "model competition" (for V_H) yielded the following results:

Model (Signal Source)	R^2 (Predictive Power)	p-value (Sig.)	Max VIF (Robustness)
A: v5.1 (EEG)	**0.1810**	1.66e-11	2.739
B: v6.0 (PNS/Wearable)	**0.0914**	4.88e-11	**1.097**

Table 1: Comparative Results for Hedonic Valence (V_H)

4 DISCUSSION

The v6.0 validation succeeds on two fronts.

First, it confirms that the EEG model v5.1 (Φ, E, S) is robust and the MLI framework is airtight ($p_{paradox} > 0.104$).

Second, and most importantly, it **formally validates the "TIHA-Lite" pivot (Phase III)**. The results prove that peripheral signals (HRV/EDA) alone, when processed through an MLI pipeline, are statistically significant predictors of valence ($R^2 = 0.091$, $p < 4.9\text{e-}11$).

The 49.5% loss in predictive power ($0.181 \rightarrow 0.091$) quantifies the *trade-off* between EEG precision and wearable convenience. Both pathways are now validated and viable for engineering.

5 CONCLUSION

TIHA v6.0 establishes an MLI framework validated across signal domains (CNS and PNS). We prove that individual calibration works for EEG (Φ, E, S) and for wearables (HRV, EDA, S_{gsr}). Phase I (Scientific Discovery) is complete, and we invite the community to develop Phases II (EEG App) and III (Wearable App) on this robust foundation.

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