MCSB 2026 · MODELLING & COMPUTING IN SYSTEMS BIOLOGY

A Preliminary Study on Emotion-Aware EEG-Based Music Recommendation & *Neurofeedback*

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POSTER #27

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MACRO F1 · HEADLINE MODEL

0.6819

raw_mamba2_allch_8s, repeated subject-disjoint, 5 seeds (42–46). SD ±0.1073.

`macro F1 = accuracy = 0.6819`

VS. RANDOM CHANCE

2.7×

Over the 0.25 four-class baseline. Best-of-leaderboard across seven model families.

DECODED DIRECTLY FROM

14 ch · 8 s

Raw EEG @ 128 Hz, 8-second windows, 50% overlap. Four GAMEEMO classes.

SYSTEM OVERVIEW

01 Closed-loop BCI

01 EEG headset
Emotiv EPOC+, 14 electrodes, 128 Hz continuous stream during gameplay.

02 Mamba2 decoder
Selective state-space model on raw 8 s windows — no hand-crafted bandpower.

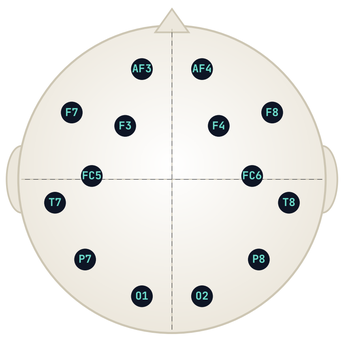
03 Affect estimate
Posterior over four V/A classes: Boring, Calm, Horror, Funny.

04 Music & feedback adaptation
Policy adapts tempo, valence, intensity; optional neurofeedback cue.

05 Updated EEG segment
Next 8 s window closes the loop, online, every step.

↻ LOOP CLOSES BACK TO STEP 01

14-channel scalp montage

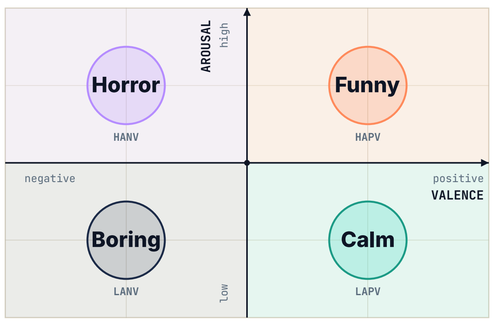


ANTERIOR FRONTAL	AF3 · AF4
FRONTAL	F7 · F3 · F4 · F8
FRONTO-CENTRAL	FC5 · FC6
TEMPORAL	T7 · T8
PARIETAL	P7 · P8
OCCIPITAL	O1 · O2

Emotiv EPOC+ montage, 14 saline-soaked felt sensors, 128 Hz. All channels enter the model unaltered.

TASK STRUCTURE

02 Four affect classes



GAMEEMO labels mapped onto the valence–arousal plane. Each gameplay session evokes one quadrant.

ARCHITECTURE & TRAINING

03 raw_mamba2_allch_8s

Architecture	Mamba2 selective SSM · 6 layers · hidden 192 · state 128
Input	raw EEG · 14 ch · 128 Hz · 8 s win · 50% overlap
Optimizer	AdamW · cosine warm restarts · bf16 AMP
Regularisation	dropout · weight decay · label smoothing
Augmentation	MixUp · gaussian noise · amplitude scaling · time shift · channel dropout
Output	softmax over 4 classes (HANV / HAPV / LANV / LAPV)

EVAL TRACK	SPLIT	SEEDS	METRICS
subject-disjoint repeated, 5 seeds	18 / 4 / 5 train / val / test subjects	42–46 test held to final fold	macro F1 secondary: accuracy

EVAL HYGIENE
All preprocessing, model selection, and early-stopping decisions use only train + validation subjects.

DISCUSSION

04 Takeaways

01 Raw full-channel EEG carries 4-class affect information.
No bandpower features, no hand-crafted descriptors — the SSM learns directly from time-domain signal.

02 Mamba2 SSMs are promising for EEG sequence modelling.
Outperforms TCN, ResNet, residual-2048×5, and Random Forest baselines on the same protocol.

03 Subject-disjoint evaluation is non-negotiable.
EEG models otherwise memorise subject signatures and inflate apparent generalisation.

04 Fold spread (0.55 → 0.86) → subject adaptation is the next problem.
Per-user calibration, uncertainty estimation, and cross-dataset pretraining are the open levers.

05 Next: real-time closed-loop validation.
Does online affect estimation actually drive useful music adaptation and measurable anxiety reduction?

⚠ LIMITATIONS

01 Single dataset (GAMEEMO).
No cross-dataset validation yet — domain shift to real-world EEG is untested.

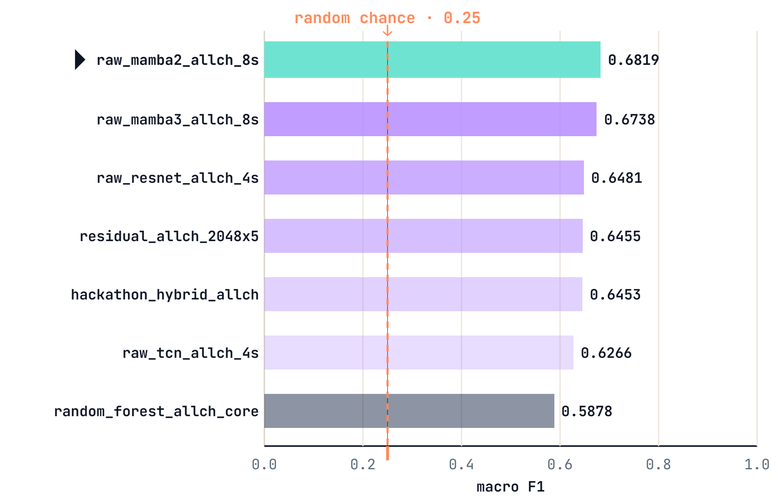
02 Consumer-grade hardware.
14-channel saline-sensor setup limits spatial resolution; clinical-grade rigs may show different patterns.

03 No closed-loop validation yet.
The music recommendation and neurofeedback claims are architectural — the affective decoder works, the loop itself is future work.

05 Results

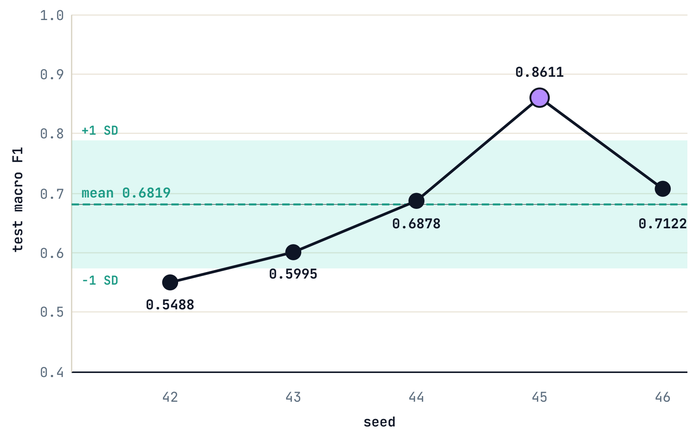
Repeated subject-disjoint, 5 seeds. Test sets held out until final fold evaluation.

A Full-channel benchmark



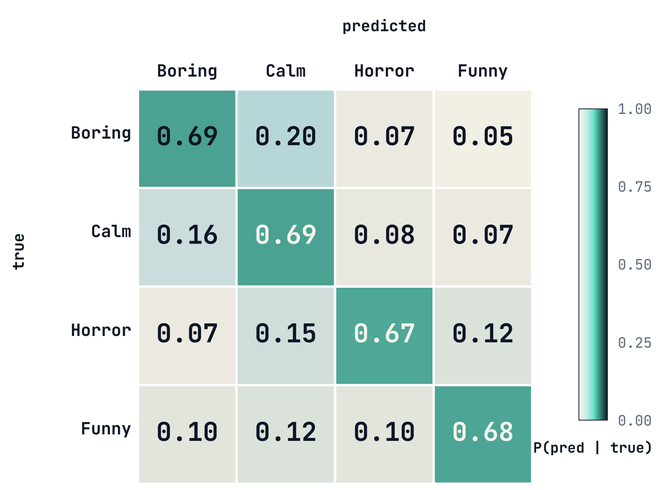
raw_mamba2_allch_8s leads the seven-family leaderboard. Dashed line marks the 0.25 random-chance baseline.

B Fold-by-fold stability



Inter-subject variability remains a barrier — fold spread runs from 0.5488 (seed 42) to 0.8611 (seed 45).

C Confusion structure



Row-normalised mean confusion. Largest off-diagonal mass is Boring↔Calm (low-arousal axis), as expected.

PER-CLASS PERFORMANCE

06 Class scores

CLASS	PRECISION	RECALL	F1	F1 BAR (0 .5 1)	SUPPORT
HANV · Horror	0.7543	0.6669	0.7022		365
HAPV · Funny	0.7410	0.6844	0.7005		365
LANV · Boring	0.6646	0.6866	0.6721		365
LAPV · Calm	0.6368	0.6899	0.6526		365

All four classes above chance. Horror & Funny lead in F1; Calm is the hardest — consistent with the low-arousal valence ambiguity in the confusion matrix.

CITATIONS

07 Selected references

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CODE & DATA

- Dataset: GAMEEMO (Alakus et al., 2020) — publicly available.
- Code, configs, and model checkpoints: available on request.
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