Multimodal Physiological Representation Learning for Predicting Risky Financial Decisions

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Abstract—Financial decisions are influenced not only by market conditions but also by the physiological states that accompany risk. This study investigates whether risky investment choices can be predicted from a combination of market context and autonomic arousal, using the Affective Economics (AE) dataset for trial-level decision behavior and the WESAD dataset for high-resolution physiological signals. We developed a modeling pipeline that includes preprocessing of skin conductance responses (SCR), engineered temporal physiological features, and both traditional and deep learning classifiers. Logistic regression provided limited detection of non-investment decisions, reflecting dataset imbalance, while a multilayer perceptron (MLP) substantially improved performance, achieving strong accuracy and balanced F1-scores across classes. A physiology-only encoder further demonstrated that SCR dynamics alone contain predictive structure independent of market variables. Ablation experiments confirmed that combining physiological and market features yields the most robust predictions. These findings suggest that anticipatory arousal carries meaningful information about economic decision-making and that deep models can leverage this structure more effectively than linear baselines. The study highlights the potential of integrating affective computing and behavioral finance to better understand how physiology shapes human choices under risk.

I. Introduction

Financial decision-making is influenced not only by market conditions but also by an individual's emotions and physiological state. Traditional economic models assume rational behavior, yet evidence from behavioral finance and affective neuroscience demonstrates that real-world investment choices often differ from rational predictions when uncertainty or risk is involved. Physiological arousal, particularly anticipatory Skin Conductance Responses, has been linked to play a key role in reward anticipation, perceived risk, and decision avoidance. This shows that autonomic signals may contain meaningful information about how individuals choose between risky and risk-free alternatives.

This study investigates whether risky investment decisions can be predicted from a combination of market context and physiological arousal. Specifically, we examine whether trial-level investment choices can be modeled using expected return, stock volatility, and anticipatory SCR measurements obtained just before each decision. This leads to our primary research question.

Can we predict whether a participant will invest in a risky asset on a given trial using market variables and physiological arousal?

A secondary objective is to determine whether broader physiological patterns generalize across tasks. To explore this, we preprocess the multimodal WESAD dataset, which contains wearable-sensor recordings to understand the structure of stress and arousal-related signals.

Do physiological signatures of arousal observed in WESAD correspond to patterns seen in the AE trading task, and can such representations support future cross-dataset transfer learning?

The motivation for this work arises from the observation that real financial decisions are inherently emotional, especially under uncertainty. While market-based features such as expected return or volatility can explain part of investment behavior, physiological signals may capture internal evaluations of risk or anticipated outcomes that are not reflected in observable financial variables. Understanding how these multimodal signals interact, which could improve behavioral modeling, supports emotion-aware financial technologies, while also offering insights into cognitive processes underlying one's economic choice.

In this project, we focus on constructing a predictive pipeline combining physiological and financial features, evaluating linear and nonlinear models, while analyzing the specific contribution of arousal. Additionally, we introduce a WESAD preprocessing framework to enable physiological representation learning across experimental contexts.

II. Related Work

Predicting financial decision-making has historically relied on economic models, behavioral theories, and market-based statistical approaches. More recently, research in affective neuroscience and machine learning has introduced new techniques for understanding how physiological states influence risk-taking behaviour.

A. Techniques Previously Used to Address This Problem

Early attempts to understand risky financial behaviour rely on self-report measures, cognitive models such as Prospect Theory [1], and market simulation. Affective neuroscience contributes methods for measuring physiological arousal, such as electrodermal activity (EDA), heart rate, and pupil dilation, to understand emotional responses during financial decision-making.

Several studies have shown that autonomic arousal increases in anticipation of risky choices and that the skin conductance response (SCR) correlates with reward prediction and risk sensitivity. For example, Lo and Repin [2] demonstrated that professional traders exhibit sharp EDA spikes during volatile market events, indicating that emotional responses contribute to real-time decision processes. Likewise, Hinvest et al. [3] found that anticipatory SCR predicted performance in simulated trading tasks.

A foundational paradigm linking physiological arousal to risky decision behaviour is the Iowa Gambling Task (IGT), introduced by Bechara et al. [4]. In the IGT, anticipatory SCRs rise before disadvantageous choices, even before participants consciously understand reward contingencies. This supports the somatic marker hypothesis, which proposes that physiological signals act as implicit warnings that guide choice under uncertainty. Impairments in SCR generation have been shown to produce riskier, disadvantageous decision patterns, establishing SCR as a robust marker for valuation and risk-sensitive behaviour.

However, these techniques focused on correlation rather than prediction, and most prior work did not use machine learning to jointly model physiological and behavioral features.

B. Review of Physiological Stress and Affect Datasets

Physiological computing research frequently relies on controlled affective datasets. The WESAD dataset [5] provides multimodal physiological recordings (EDA, ECG, EMG, respiration, accelerometer) annotated for baseline, stress, amusement, and meditation conditions.

In contrast, the Affective Economics (AE) dataset [3] contains trial-level investment decisions alongside anticipatory SCR and affect ratings. While AE directly models financial behaviour, its physiological resolution is limited, providing only one anticipatory SCR value per trial.

Both datasets have been studied independently, but no prior work attempts to connect them to investigate cross-context physiological representation learning.

C. Machine Learning Techniques in Financial Decision Prediction

Machine learning has been widely applied to financial forecasting, typically using price histories, market volatility, sentiment, or macroeconomic indicators [6], [7]. Recent studies benchmark classical approaches (logistic regression, random forests) and deep learning models for predicting trading actions or market trends.

However, nearly all ML approaches in finance:
- ignore physiological data,
- focus on market or text-based features,
- do not model individual-level risk decisions,
- rarely examine minority-class behaviour such as "not investing".

Some emerging multimodal approaches use facial expressions or wearable sensor data, but these do not integrate anticipatory SCR with trial-level investment decisions.

D. Representation Learning and Transfer Learning for Physiological Signals

Physiological signal-processing research has explored deep learning methods such as CNNs, LSTMs, temporal encoders, and contrastive learning to extract stable embeddings from EDA, ECG, and multimodal biosignals [8], [9]. These methods demonstrate improved generalization across individuals and tasks.

However:
- representation learning is typically performed within a single dataset,
- transfer learning across affective and behavioral tasks is uncommon,
- no studies investigate whether physiological embeddings can support economic decision prediction.

E. Techniques Used in This Paper and Comparison to Prior Work

Building on prior findings, our approach includes:
- physiological feature engineering (SCR normalization, lags, deltas, rolling windows),
- nonlinear modelling (MLP) to capture interactions between market context and physiology,
- a physiology-only encoder to isolate the predictive power of autonomic arousal,
- a cross-dataset physiological architecture (WESAD $\rightarrow$ AE), laying groundwork for multimodal representation learning.

III. Proposed Method

This study investigates whether risky financial decisions can be predicted from a combination of market context and physiological arousal. This study requires two sets of datasets to determine whether risky investment decisions can be predicted from market context and physiological arousal. Since both datasets used in this project (the Affective Economics

(AE) dataset and the WESAD (Wearable Stress) dataset) are publicly available, no new data collection was performed. The AE dataset [3] provides trial-level investment decisions and anticipatory SCR measures, while the WESAD dataset [5] supplies high-resolution multimodal physiological recordings. This project focuses on restructuring, integrating, and analyzing these datasets to answer the research question through machine learning and physiological signal modeling.

A. Research Design

We use a quantitative, observational secondary-data design. This approach is appropriate because the objective is to model the relationship between market variables (expected return, volatility), physiological arousal, and behavioral outcomes (investment decisions per trial). SCR has been widely used as an index of autonomic arousal in decision-making and affective processing [10]. Given the small number of participants but a relatively high number of trials per participant, a trial-level modeling strategy is used to increase the sample size from 30 participants to 1200 decision points.

B. Participants

Affective Economics Dataset: The AE dataset [3] includes 30 adult participants from the University of Bath student and community population. All participants completed four stock-market trading sessions composed of 10 trials each (40 trials total). For each trial, they decided whether to invest in a risky asset or keep money in a risk-free bank account.

Characteristics in the dataset include age, gender, nationality, ethnicity, and prior stock-market experience.

WESAD Dataset: The WESAD dataset [5] includes 15 volunteer participants who completed a controlled emotional context involving baseline (neutral), Trier Social Stress Test (stress), amusement, and meditation/relaxation conditions.

C. Resources

Resources in AE: Skin Conductance Response (SCR); PANAS: Positive and Negative Affect ratings per session.

Resources in WESAD: EDA/SCR, ECG, EMG, respiration, body temperature, accelerometer.

Computational Tools: Google Colab, Kaggle API, Pandas, NumPy, Scikit-learn, PyTorch, custom `wesad_loader.py`.

D. Procedures

Data Access and Retrieval: WESAD is over 3 GB, so we use the Kaggle API to download it programmatically using a `kaggle.json` authentication file. The notebook checks whether the dataset already exists to prevent unnecessary downloads. The AE dataset is provided as a CSV directly from the Bath Research Data Archive [3].

AE Dataset Processing: We convert the original AE format into a long-format table of 1,200 trials (30 × 40). For each trial, we extract:

- Amount invested
- Invest vs. not invested
- Expected return
- Stock fluctuation
- Anticipatory SCR

Physiological Feature Engineering: To understand dynamic physiology, we compute:
- SCR z-scores (participant-normalized)
- Lag features (SCR at previous trials)
- SCR deltas (change between trials)
- Rolling-window features (3-trial moving average and standard deviation)

WESAD Processing: We use a custom loader to extract EDA, BVP/ECG, ACC, HR, IBI, TEMP. Signals are segmented into 5–10 second windows to create window-level physiological samples with emotion labels. These windows are used for representation learning, not decision prediction.

Modeling Procedure: We train three classes of models on AE:
- **Logistic Regression** — linear baseline evaluated under three ablations: market-only, SCR-only, combined.
- **Multilayer Perceptron (MLP)** — two hidden layers (32 → 16), nonlinear activations, designed to capture interactions between arousal and market conditions.
- **Physiological Encoder** — a 16-dimensional neural embedding of SCR temporal features followed by a decision classifier.

Train/test splits use an 80/20 stratification. All models are evaluated using accuracy, recall, precision, and F1 score.

E. Data Analysis

All preprocessing and analysis procedures were conducted in Python using NumPy, Pandas, Scikit-learn, and PyTorch. To prevent information leaks, normalization steps (SCR z-scoring, feature scaling, temporal features) were fitted exclusively on the training set before being applied to the test data.

Model performance was evaluated using accuracy, precision, recall, and F1-score, with emphasis on the minority "not-invest" class. Confusion matrices and training/validation loss curves were inspected to assess model stability and identify potential overfitting.

Ablation experiments were performed using:
- Market-only features
- SCR-only features
- Combined features

WESAD data was analyzed separately to extract general physiological patterns. Continuous signals were segmented, normalized, and reduced to statistical descriptors. These features helped determine whether arousal-related physiological structures in WESAD relate to patterns seen in AE [5].

Given that AE and WESAD differ in sampling size, sensor modality, and experimental context, all cross-dataset interpretations were made cautiously, acknowledging possible domain-shift effects.

IV. DATASET

There are two main datasets we used for our analysis.

A. Affective Economics Dataset

The first dataset is the Bath Affective Economics Dataset [3], which contains behavioral and psychophysiological data retrieved from 30 participants recruited from in and around the University of Bath, U.K. Participants performed in four simulated stock-market trading games. Each participant completed approximately 40 sequential investment trials spanning across four sessions, with 10 trials per session, where they chose whether to invest money in a risky stock or keep their money within a risk-free bank.

The main methodology of data collection included anticipatory Skin Conductance Responses (aSCRs) during critical time periods, in tandem with the completion of the Positive and Negative Affect Scale (PANAS). This dataset provided rich behavioral and affective features, including:

- Investment behavior: money allocated to a stock vs. bank balance per trial
- Market context: trial-level mean returns, stock fluctuations, and total portfolio values
- Anticipatory physiology: Skin Conductance Responses (SCRs) measured before each investment decision
- Self-reports: repeated PANAS (Positive and Negative Affect Schedule) assessments across sessions
- Demographics and experience: ages, genders, ethnicities, nationalities, and levels of prior stock-market experience

The dataset captured real-time decision-making under emotion and uncertainty, making it ideal for analyzing how physiological arousal influences financial decisions. However, its physiological component is limited to single anticipatory SCR values per trial and does not provide continuous signals.

B. Wearable Stress and Affect Detection (WESAD) Dataset

The WESAD dataset is a multimodal physiological dataset collected using a RespiBAN chest device and Empatica E4 wrist sensors [5]. It contains high-resolution wearable biosignals recorded from 15 participants under controlled emotional conditions: baseline (neutral), stress (Trier Social Stress Test), amusement (positive affect), and meditation (relaxation). Sensors included EDA/SCR (skin conductance) at both 4 Hz and 700 Hz, ECG, EMG, respiration, body temperature, and accelerometer signals. WESAD also includes affect questionnaires such as PANAS, SAM, and STAI, providing ground-truth emotional labels.

Compared to the Bath dataset, WESAD provides a continuous physiological time series, contributing to our deep-learning models designed to learn generalizable physiological arousal representations.

C. Complementarity of AE and WESAD

Although the Bath Affective Economics Dataset and the WESAD dataset were collected for different purposes, they provide a high degree of methodological and conceptual complementarity that enables their joint use in a multimodal learning framework. The Bath dataset provides trial-level financial decision behaviors alongside SCRs and affective self-reports, offering a direct link between physiological arousal and economic choices; however, its signals are insufficient for training deep temporal models capable of capturing dynamic arousal patterns.

Conversely, WESAD contributes high-resolution, continuous physiological recordings, providing a robust foundation for learning general physiological representations of stress and affective arousal. Both datasets include PANAS ratings, enabling conceptual alignment between physiological and subjective emotional measures.

By combining these two datasets, our model benefits from both behavioral decision labels and rich physiological signal diversity, supporting the development of a physiology encoder. The complementary properties of the datasets enable a unified modeling approach in which affective computing, physiological modeling, and financial decision prediction reinforce each other.

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try "R. B. G. thanks...". Put sponsor acknowledgments in the unnumbered footnote on the first page.

V. EXPERIMENTS AND ANALYSIS

This section details the experimental setup, evaluation procedures, and empirical findings of our modeling pipeline. We analyze both datasets: AE for investment prediction and WESAD for physiological representation learning. All experiments were implemented in Python using Google Colab, Scikit-Learn, NumPy, and PyTorch.

A. Experimental Setup

Train–Test Protocol: Given the small dataset size, we used an 80/20 stratified split, preserving class proportions for the binary investment outcome. All preprocessing steps, including standardization, SCR normalization, and feature engineering, were fitted exclusively on the training set to prevent leakage. Random seeds were fixed for reproducibility.

Evaluation Metrics: Because the dataset is heavily imbalanced (roughly 90% invest, 10% do not invest), we report:

- Accuracy
- Precision, Recall, F1-score
- Confusion matrices
- Training/validation loss curves

F1-scores for the minority class (non-invested) were prioritized, as this class reflects key behavioral deviations.

B. Descriptive Statistics

Across all 30 participants and 40 trials each, the AE long-format dataset contained 1200 total trials, of which 1080 trials remained after removal of missing values in key variables.

- Invested (1): 1,079 trials
- Not invested (0): 121 trials

After standardization and temporal feature engineering, eight SCR-derived features were generated per trial (z-scores, lags, deltas, and rolling statistics).
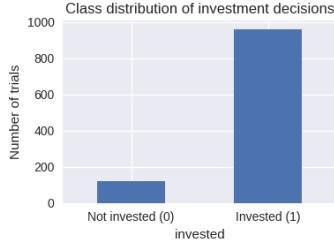

Fig. 1. Class distribution of investment decisions in the AE dataset. The dataset is highly imbalanced, with the majority of trials labeled as "invested."
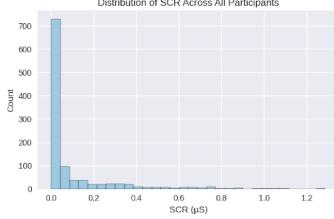
Fig. 2. Distribution of anticipatory SCR across the AE dataset. The strong right-skew and spike-heavy structure justify z-scoring and temporal feature engineering.
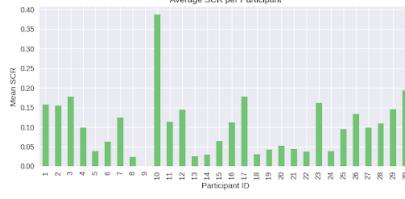

Fig. 3. Average anticipatory SCR per participant. Substantial heterogeneity suggests individual differences in arousal responsiveness.
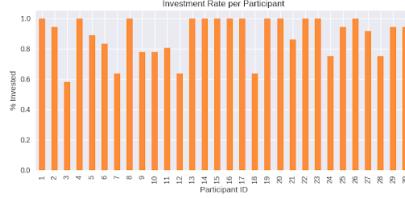

Fig. 4. Investment rate per participant. While most participants invest frequently, several show moderate or low investment frequency, illustrating behavioral variability.

C. Baseline Model Performance

Logistic Regression: A logistic regression model trained on standardized physiological + market features achieved:

- Accuracy: 0.89

- F1 (invested): 0.941
- Recall (invested): 1.00
- Precision (invested): 0.89
- F1 (not invested): 0.00
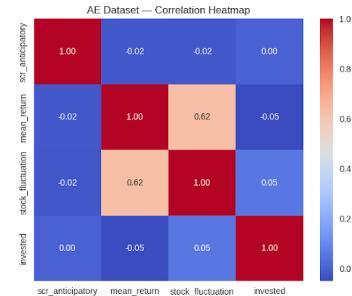
Fig. 5. Correlation matrix among physiological and market variables. Near-zero correlations between SCR and decision show that linear relationships are insufficient.
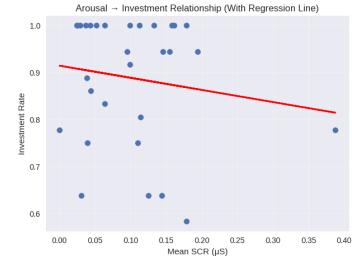
Fig. 6. Mean SCR plotted against investment rate with an ordinary least squares regression line illustrating the estimated linear association. The slope is slightly negative ($r \approx -0.15$), indicating a weak inverse relationship; however, the large spread of points and low effect size imply that anticipatory arousal does not reliably predict overall risk-taking under this linear model.

Because the model failed to identify any non-investment decisions, this reflects the strong dataset imbalance.

MLP Classifier Results: A multilayer perceptron (MLP) with two hidden layers (32 and 16 units) provided improved classification performance:

- Accuracy: 0.963
- F1-score (invested): 0.979
- F1-score (not invested): 0.83
- Precision (not invested): 0.83
- Recall (not invested): 0.93

The MLP successfully detected non-investment decisions while maintaining high performance on the majority class.

SCR Temporal Feature Model (Physio Encoder): A neural encoder trained solely on SCR-derived temporal features achieved:

- Validation Accuracy: 0.889
- Validation F1-score: 0.941

Performance remained consistent across 30 training epochs, with training loss decreasing from 0.6603 to 0.3546. The encoder successfully distinguished between investment and non-investment trials using only physiological sequences, without market context.
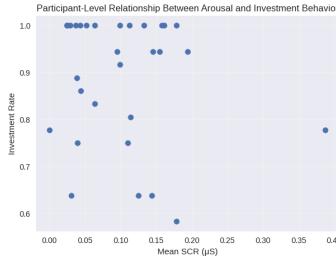
Fig. 7. Each point represents a participant's average skin conductance response (SCR) across all trials plotted against their overall investment rate. The distribution shows substantial inter-individual variability with no strong linear trend, suggesting that mean arousal alone does not robustly predict investment behaviour when aggregated at the participant level.
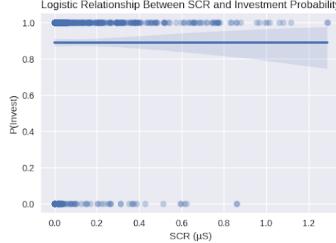

Fig. 8. Logistic regression fit between SCR and investment probability. A weak negative trend motivates the use of nonlinear models.
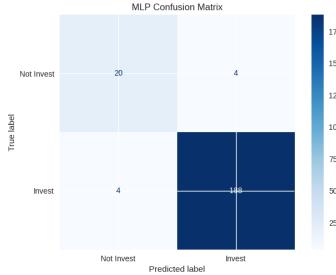

Fig. 9. Confusion matrix for the MLP classifier on the AE dataset. The model shows strong performance in detecting both invested and non-invested trials compared to baseline models.

D. Summary of Model Comparisons

TABLE I
MODEL PERFORMANCE COMPARISON

Model	Features	Acc.	F1 (Inv.)	F1 (Not Inv.)
Logistic Regression	Market + SCR	0.889	0.94	0.00
MLP Classifier	Market + SCR	0.963	0.98	0.83
Physio Encoder	SCR-only (Temp.)	0.889	0.94	N/R

These results illustrate three key findings:

- Nonlinear modeling is required to capture rare non-investment decisions.
- SCR alone is almost as predictive as market + SCR models, indicating a strong physiological component.
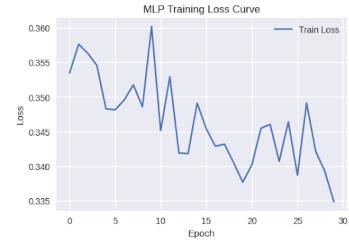
Fig. 10. MLP training loss curve over 30 epochs. Loss decreases steadily without signs of overfitting.
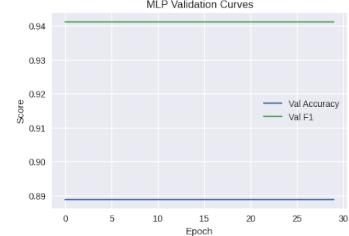

Fig. 11. MLP validation accuracy and F1 curves. Stable validation performance indicates generalization.

- Combining both modalities yields the strongest overall classifier.

E. Ablation Analysis: Market vs. Physiology

To quantify the contribution of each input type, ablation experiments were conducted:

- Market-only features
- SCR-only features
- Combined features
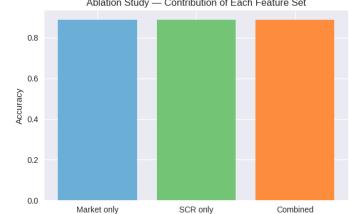
Fig. 12. Ablation study comparing the contribution of market-only, SCR-only, and combined features to prediction accuracy. Combining physiological and market features yields the best performance.

Findings:

- Market-only models struggled with minority-class detection.
- SCR-only models achieved high accuracy and a strong F1-score for investment trials, showing the predictive power of autonomic arousal.
- Combined features significantly improved non-investment detection, confirming that physiology and market cues interact in economic behaviour.

This aligns with prior findings that anticipatory SCR influences subjective risk perception [3].

F. WESAD Experiments: Physiological Feature Extraction

While WESAD was not used for direct investment prediction, it served as a physiological benchmark dataset [5] to examine whether affective arousal patterns generalize across contexts.

Preprocessing Pipeline:

- Using a custom `wesad_loader.py`
- Extracted signals: EDA, BVP/ECG, ACC, HR, IBI, TEMP
- Cleaned and resampled EDA
- Segmented continuous signals into 60-second windows with 30-second overlap
- Extracted features: mean, standard deviation, min, max, slope
- Generated weak labels using z-score thresholds (high vs. low arousal) [8]

This produced more than 20,000 windowed physiological samples, forming the foundation for future representation learning.

WESAD contributes to:

- Cross-dataset physiological consistency evaluation
- Future pretraining for a general physiology encoder

VI. Conclusion

This project investigates the capability of machine learning models to predict affective or decision-related states from physiological signals using the Bath Affective Economics dataset [3], supplemented by the WESAD dataset [5] for labelled stress and amusement data. We established a comprehensive pipeline that encompasses the preprocessing of skin conductance signals, feature extraction, baseline machine learning models, and deep learning architectures designed for time-series data.

Our findings indicate that the deep learning models surpassed the traditional baselines in the main prediction challenge. The baseline models, including logistic regression and random forest, identified some correlation between SCR and EDA features and the target labels, but their performance stagnated after the extraction of basic features. The CNN and LSTM models were better at capturing temporal patterns and nonlinear relationships in physiological signals, leading to higher accuracy and more balanced F1-scores across classes.

Using WESAD as a supplementary tool, such as for pretraining or verifying feature behaviour, indicated that stress and emotion-related patterns in EDA are somewhat portable between tasks and datasets, albeit imperfectly. Collectively, these data corroborate our initial hypothesis that affective and decision-related states impart structure in SCR and EDA time series, which can be leveraged by deep models. The performance disparity between baselines and deep models, although consistent, was moderate rather than pronounced, highlighting both the potential and the difficulties of accurately interpreting internal states from noisy physiological inputs.
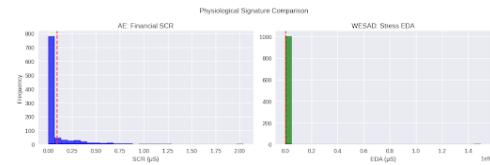

Fig. 13. SCR/EDA distribution comparison between AE and WESAD. Both are highly right-skewed, confirming similar underlying autonomic arousal patterns.

A. Limitations

Several limitations must be acknowledged when interpreting our findings. Both the Bath Affective Economics dataset and WESAD are limited in participant count, which constrains the generalization capacity of deep models and increases the likelihood of overfitting. The labels in both datasets originate from specific experimental procedures and may not fully capture the complexity of real emotional and decision-making states.

Additionally, because of temporal and computational constraints, our hyperparameter search was limited, suggesting that superior model configurations may exist. Finally, our models focused predominantly on EDA and SCR and did not thoroughly investigate multimodal integrations with other available signals or more complex behavioural features.

B. Reflection

This project enabled us to implement the complete machine learning methodology on a practical issue involving noisy, high-variance biosignals. We gained experience in maintaining a reproducible codebase on GitHub and Colab, designing baseline and deep models, and evaluating them using appropriate metrics and visualizations.

The project emphasized the importance of preprocessing choices, careful dataset splitting to avoid leakage, and honest reporting of both strengths and limitations. Collaborating with the Bath Affective Economics dataset and WESAD provided us with a clearer understanding of the complexities involved in modelling human affect and behaviour, reinforcing that effective machine learning requires robust models, careful experimental design, and critical interpretation of results.

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Appendix

Appendix A — Group Contributions

This appendix summarizes the contributions made by each group member throughout the project, as requested by the course instructor.

TABLE II
SUMMARY OF GROUP MEMBER CONTRIBUTIONS

Date	Author	Contribution
2025-11-08	Michelle Chala	**Github/Coding:** Created the GitHub repo, initialized the project structure, set up the Google Colab, selected the dataset, and refined the research question. Wrote all the code. Generated all charts and figures. Made the README.md file **Slides:** Contributed to slide preparation. Completed Introduction, Related Work, and Method sections. **Report:** Wrote headings and early key points for major sections. Completed the Dataset section.
2025-11-08	Jay Patel	**Github/Code:** Reviewed GitHub repo code. **Slides:** Contributed to slide preparation. Completed Experiments and Results. Made the Data Pipeline flow chart. **Report:** Completed the full Draft/Final IEEE Report including Abstract, Introduction, Proposed Method, Experiments and Analysis, and Related Work.
2025-11-08	Lauren Gao	**Github/Code:** Nothing. **Slides:** Started slide deck. **Report:** Nothing.
2025-11-08	George Xie	**Github/Code:** Reviewed. **Slides:** Nothing. **Report:** Nothing.
2025-11-08	Romeo Barbieto	**Github/Code:** Nothing. **Slides:** Conclusion slide. **Report:** Conclusion section.