Towards Personalized Adaptive Learning Using Artificial Intelligence and Physiological Signals

30th, Oct. 2025

Cheolkyu Shin

HALLYM UNIVERSITY

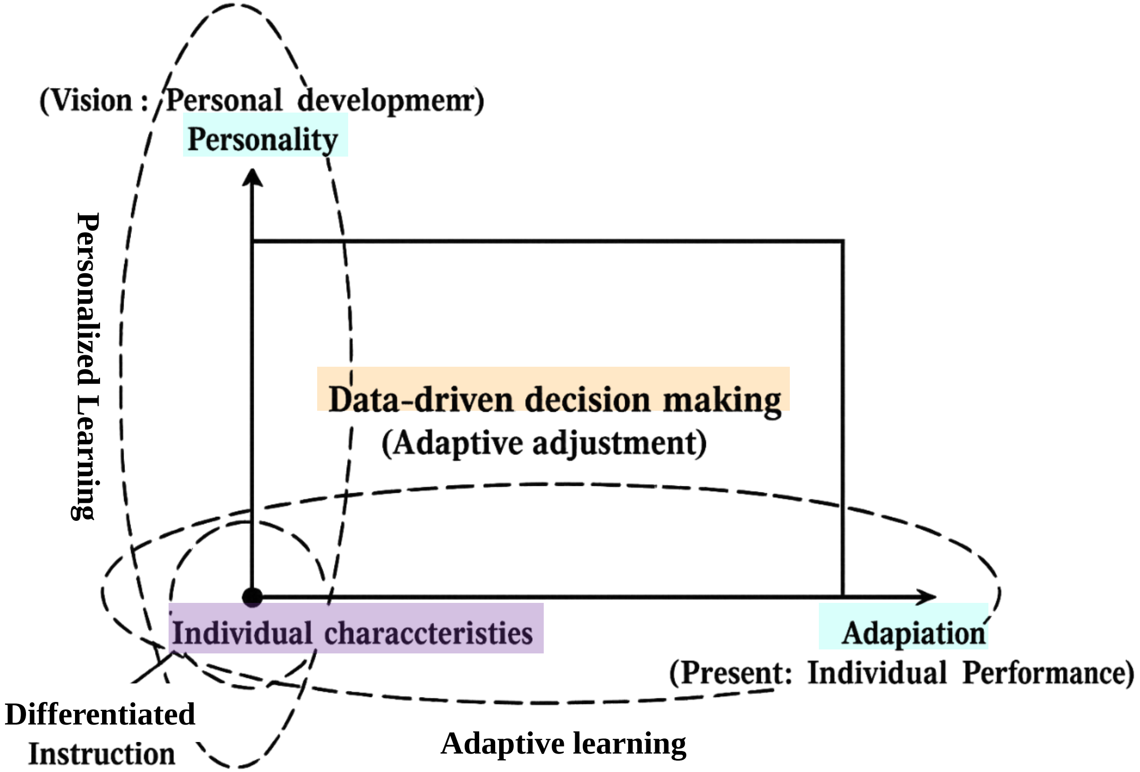
Contents

- Personalized Adaptive Learning (PAL)
- Recent study on AI-based PAL using physiological signals
- How to realize PAL?

Personalized Adaptive Learning (PAL)

Personalized Adaptive Learning (PAL)?

- PAL integrates personalization with adaptation.
- Data-driven decision making serves as the central hub for all approaches.
- Each learner is unique and constantly changing, which requires real-time monitoring.

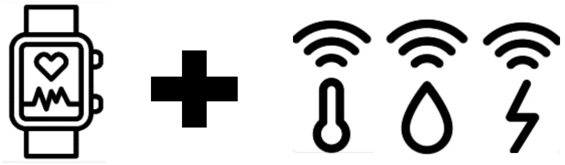


Peng et al. (2019). Personalized adaptive learning: an emerging pedagogical approach enabled by a smart learning environment. Smart Learning Environments

Personalized real-time monitoring for PAL

- Environmental & biometric data – assessing learners' conditions in real time
  - Using wearable sensing and Internet of Things (IoT) technologies
- Adaptive feedback – supporting both instructors and learners

Wearables IoT



→ Learner state real-time monitoring → Adaptive feedback

Recent study on AI-based PAL using physiological signals

HALLYM UNIVERSITY

Relevance of physiological signal to learner states

Laboraory for AI & Network

- Extensive research has already demonstrated clear associations between physiological signals and learner states.

–: no established relationship

Physiological Signal	Cognitive Load	Fatigue	Emotional Arousal
HRV (Heart Rate Variability)	High [Shaffer]	Moderate [Srinivasan]	High [Shaffer]
GSR (Galvanic Skin Response)	Low [Nourbakhsh]	-	High [Boucsein]
EEG (Electroencephalography) bands	High [Teplan]	High [Harmony]	Moderate [Lendner]
BP (Blood pressure)	Low [Dimsdale]	Low [Newton]	High [Lovallo]
SpO_2 (Oxygen saturation)	Low [Hornbein]	Moderate [Davies]	-
HR (Heart Rate)	Moderate [Solhjoo]	Low [Nelesen]	High (AHA)
RR (Respiration rate)	Moderate [Hirokazu]	Low [Grassmann]	High [Kluger]
Skin Temperature	-	Moderate [González-Alonso]	High [Herborn]

Shaffer et al. (2017). HRV metrics and norms.
Srinivasan et al. (2024). HRV as an indicator of fatigue.
Nourbakhsh et al. (2012). GSR for cognitive load measurement.
Boucsein (2012). Electrodermal Activity.
Teplan (2002). Fundamentals of EEG measurement.
Harmony (2013). Functional significance of delta oscillations.
Lendner et al. (2020). EEG marker of arousal level.
Dimsdale (2008). Psychological stress and cardiovascular disease.
Newton et al. (2009). Lower ambulatory BP in chronic fatigue syndrome.
Lovallo (2015). Stress and Health: Biological and Psychological Interactions.
Hornbein (2001). The high-altitude brain.
Davies et al. (2023). In-ear SpO_2 for classification of cognitive workload
Solhjoo et al. (2019). HR and HRV correlate with clinical reasoning and cognitive load.
Nelesen et al. (2008). Relationship between fatigue and cardiac functioning
AHA (American Heart Association) (2022). All about heart rate (pulse)
Hirokazu et al. (2021). Validity of physiological measures for cognitive load
Grassmann et al. (2016). Respiratory changes in response to cognitive load.
Kluger et al. (2024). A dynamic link between respiration and arousal.
González-Alonso et al. (1999). Body temperature and fatigue.
Herborn et al. (2015). Skin temperature reveals intensity of acute stress.

Physiological signals and psychological states

Laboraory for AI & Network

- Physiological signals vary in measurement methods.
  - Wrist PPG (smartwatch) and wearable patches offer the highest comfort for continuous monitoring.

Signals	HRV	GSR	EEG band	BP	SpO_2	HR	RR	Skin Temp.
Sensor type(s)	Wrist PPG, ECG patch	Wrist band, finger electrodes	EEG headband/cap	Arm/ wrist cuff	Wrist PPG, finger clip	Wrist PPG	Chest belt, patch sensor, Wrist PPG	Wrist/ear sensor, patch
Wearability	High	Moderate	Low	Low	Moderate/High	High	Moderate/High	High

- PSI (Psychological State Identification) dataset includes 1000 students' psychological states.

ID	HRV (ms)	GSR (μS)	EEG Bands (δ,α,β)	BP (mmHg)	SpO2 (%)	HR (BPM)	Ambient Noise (dB)	Cognitive Load	Mood State	Psychol. State	RR (BPM)	Skin Temp. (ºC)	Focus Dur. (s)	Task Type	Age	Gender	Education Level	Study Major
1	33.03	1.03	[0.75, 1.42, 0.61]	114/79	98.43	98	56.86	Low	Anxious	Stressed	21	34.56	27	Exam	22	Female	Postgraduate	Engineering
2	49.91	1.34	[0.55, 1.85, 0.37]	113/86	98.94	70	45.34	Low	Neutral	Stressed	21	35.35	282	Assignment	23	Male	Undergraduate	Arts
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1000	49.00	1.38	[0.63, 0.94, 2.46]	129/79	95.09	96	31.45	Low	Anxious	Relaxed	17	34.35	94	Exam	23	Male	Undergraduate	Arts

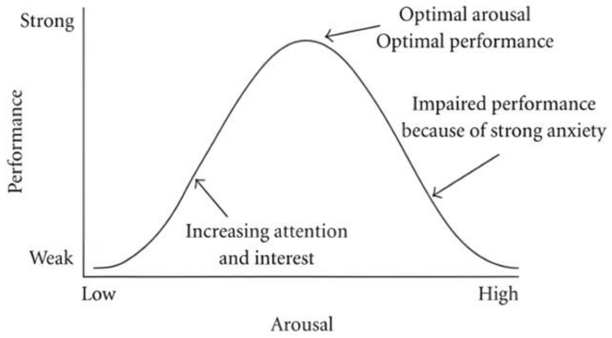
https://www.kaggle.com/datasets/ziya07/psychological-state-identification-dataset

PPG: Photoplethysmography, ECG: Electrocardiography

Difficulty adaptation policies for PAL

Rule-Based Policy

- Yerkes-Dodson-Based Policy (YDBP)



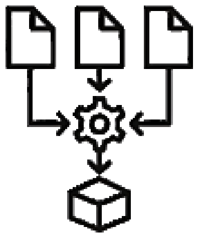
  - Step 1: Calculate arousal metrics from physiological signals
  - Step 2: Adapt difficulty based on arousal state
    - Too low / too high arousal → Low difficulty
    - Moderate but unbalanced arousal → Medium difficulty
    - Moderate & balanced arousal → High difficulty
- Distance-Based Policy (DBP)
  - Step 1: Measure deviation from baseline physiological state
  - Step 2: Adapt difficulty based on deviation size
    - Small deviation (near baseline) → High difficulty
    - Moderate deviation → Medium difficulty
    - Large deviation (far from baseline) → Low difficulty

AI-Based Policy (AIBP)

- AIBP simulates future learner states using AI models and selects the difficulty level that balances performance and fatigue.

Step 1

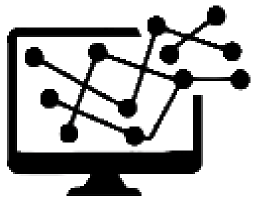
State Construction



Collect and encode physiological signals and learning performance to construct the learner's current state

Step 2

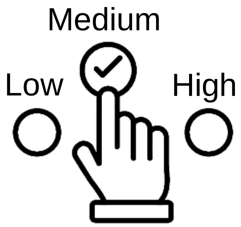
Multi-Step Simulation



Predict future performance and fatigue trajectories using a RF/XGB models under candidate difficulty sequence

Step 3

Policy Execution



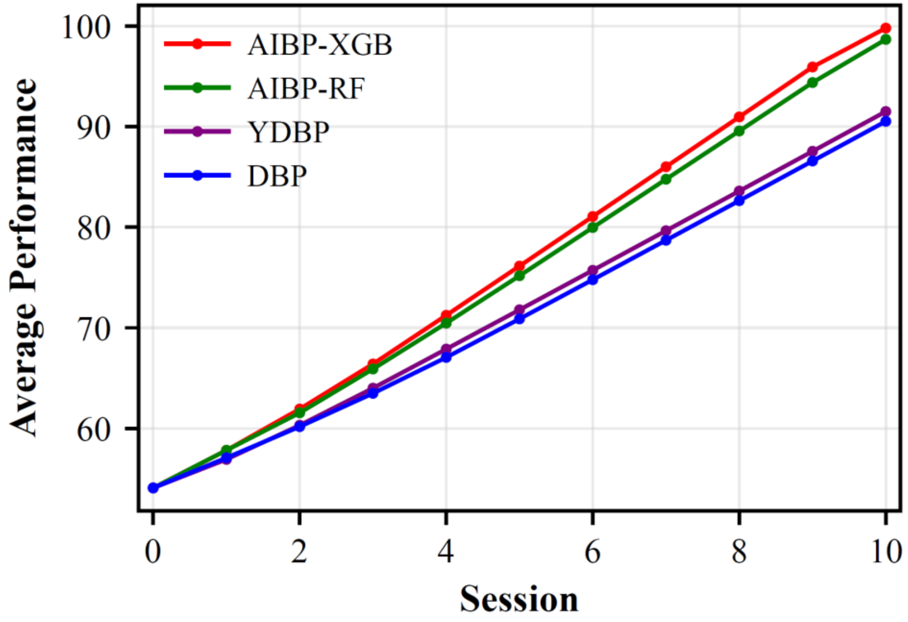
Select the optimal difficulty level based on simulated outcomes and apply it to the current learning session

Yerkes & Dodson (1908). Relation of stimulus strength to habit-formation

Breiman (2001). Random forests (RF), Chen et al.(2016). XGBoost (XGB)

Session-wise average performance

- All policies exhibit monotonic improvements as the number of sessions increases, demonstrating the effectiveness of adaptive difficulty adjustment in enhancing learner performance.



Policy	Final Mean ± Std	Final vs. Initial Gain (%)	Avg Gain (Sessions 1–3) (%)
AIBP-XGB	99.79 ± 0.55	84.49	7.59
AIBP-RF	98.67 ± 1.84	82.42	7.29
YDBP	91.50 ± 1.15	69.17	6.11
DBP	90.52 ± 1.35	67.36	5.79

Repeated measure ANOVA

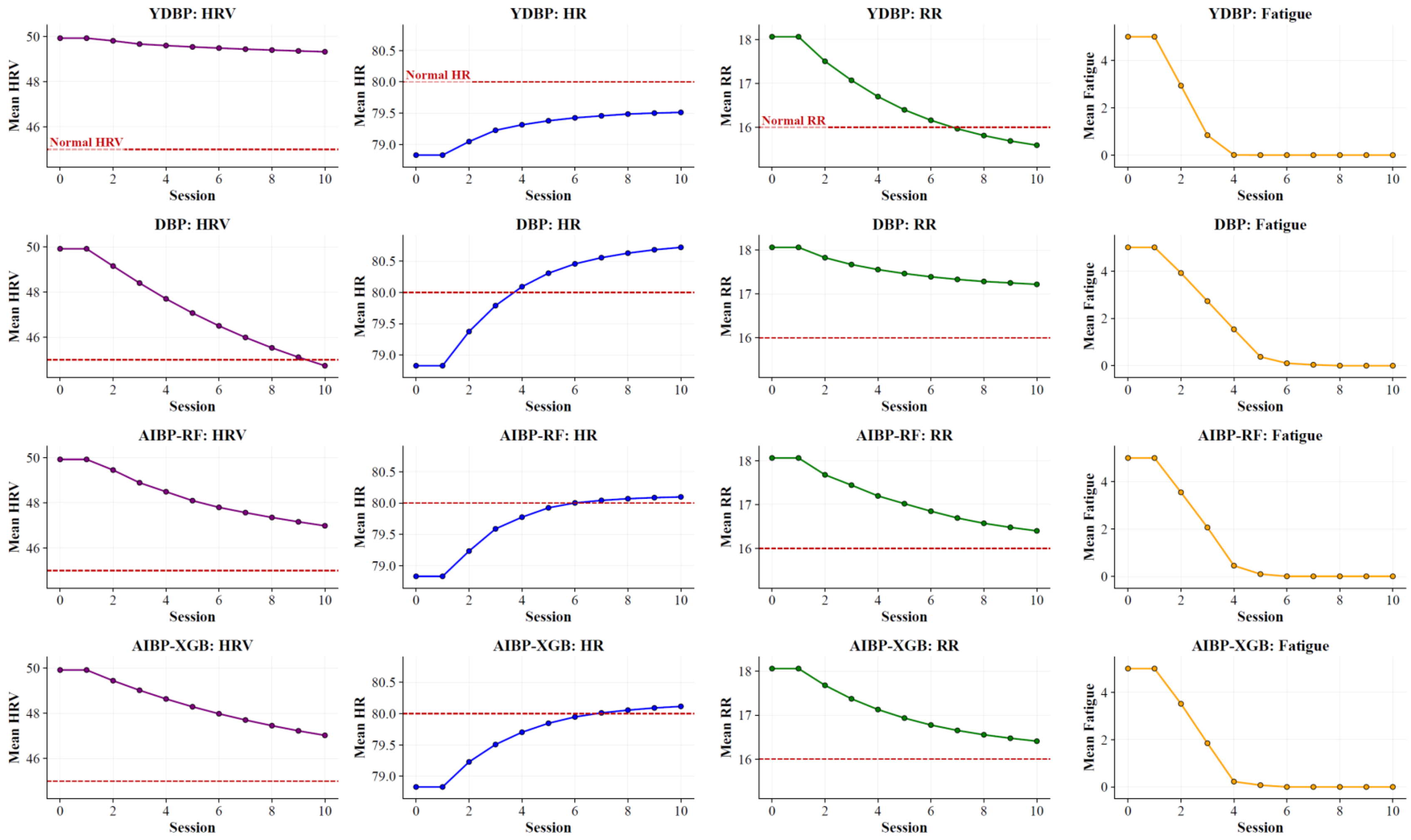
Source	Degree of Freedom	F-statistic	P-value	η_G^2
Policy	3.2997	20975.836	< 0.001	0.91

Pairwise comparisons with Bonferroni correction. All pairwise differences were statistically significant at $p < 0.001$ (Bonferroni adjusted).

Policy A	Policy B	Cohen's d
AIBP-XGB	AIBP-RF	0.83
AIBP-XGB	YDBP	9.19
AIBP-XGB	DBP	8.97
AIBP-RF	DBP	5.04
AIBP-RF	YDBP	4.67
YDBP	DBP	0.78

Physiological signals and fatigue dynamics

- AIBP improves learning performance and supports better physiological states, with signals closer to normal ranges and faster fatigue reduction than YDBP and DPB.



Lessons from the study

- Biometric data as personal information
  - Practical strategies are required to ensure secure and ethical use in PAL.

- Adaptive feedback through AI-based PAL
  - Needs to support explainability and transparency for both instructors and learners.
  - For example, it should clarify how each physiological signal contributes to difficulty selection when multiple signals are used.

- Limited environmental & biometric data
  - Current study relies on the PSI dataset (1,000 students); some signal distributions appear narrower or shifted compared to typical ranges, and the dataset provides single-timepoint recordings rather than longitudinal trajectories.

How to realize PAL?

HALLYM UNIVERSITY

Physiological signal reliability & accessibility in PAL

Laboraory for AI & Network

- Reliability of wearable signals
  - Accuracy drops under motion/stress
  - Signal quality affected by skin tone, anatomy, and usage habits

- Technical / physical accessibility
  - Unequal access across schools & learners (cost, infrastructure)

- Socio-ethical accessibility
  - Requires informed consent, privacy protection, data ownership clarity

PAL model explainability and transparency

- AI-driven policies
  - High accuracy but “black-box” → trust & fairness concerns

- Transparency challenges
  - Physiological signals: noisy, context-dependent, vary across individuals
  - Decisions perceived as arbitrary or unfair

- Possible approaches
  - Post-hoc XAI (e.g., SHAP, LIME) → feature attribution
  - Human-in-the-loop oversight → trust, fairness, accountability

Standardization in learning analytics

LAIN
Laboraory for AI & Network

- Standardized data schemas
  - Consistent labels (cognitive/affective states)
  - Timestamp alignment across modalities
  - Sensor metadata for comparability
- Benchmark datasets
  - Richer multimodal signals, longitudinal sessions, diverse learner populations
- Integration with existing standards (xAPI, Caliper)
  - Interoperability across EdTech systems
  - Cross-institutional collaboration & scalability

“Technology should support education, not lead it.”

Q&A