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PHYSIOLOGICAL RESPONSES OF NOVICE FLIGHT TRAINEES DURING DIFFERENT STAGES OF HELICOPTER SIMULATION TRAINING BASED ON PULSE RATE VARIABILITY

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Abstract. Physiological adaptation plays a critical role in skill acquisition during complex flight training processes, yet its dynamic changes across different training stages remain insufficiently understood. This study investigates physiological state changes in novice learners during helicopter flight simulation training and examines their association with skill acquisition. 14 participants without prior flight experience were recruited and completed a progressive four-stage training program, learning from basic helicopter control to independently executing the Helicopter Traffic Pattern. During the experiment, participants' Pulse-to-Pulse Interval (PPI) signals were continuously recorded, and Pulse Rate Variability (PRV) features were extracted. Statistical analyses were conducted to examine differences in PRV features across training stages. The results showed that PRV features changed significantly across training stages. These dynamic changes in PRV reflected variations in workload and the adaptive regulation of the autonomic nervous system across different stages of skill acquisition. The findings provide physiological evidence for optimizing training program design and support the development of real-time monitoring approaches for trainees' states.

Keywords: aviation safety, helicopter, novice flight training, physiological responses, wearable device.

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1. Introduction

With the rapid development of the civil aviation industry, the demand for pilots continues to grow. As the individuals directly responsible for aviation safety, pilots bear a significant mission to ensure flight safety (Zhang et al., 2022). The ab-initio flight training phase is not only the starting point of a pilot's career, but also the cornerstone for their subsequent development (Marques et al., 2023a). For novice flight trainees, who are in the earliest and most critical stage of skill acquisition, effective training evaluation is particularly important, as errors or deficiencies at this stage may persist throughout their professional development (Marques et al., 2023b). Scientific evaluation methods can quantify and assess the training effectiveness and skill level of pilots, providing them with personalized training feedback to further optimize the training process and offer more comprehensive and efficient flight instruction. Traditionally, the performance assessment of flight training relied on manual evaluation methods. This consumed significant human resources, and the evaluation process was tainted by numerous subjective factors, affecting the accuracy of the assessment results (Sun et al., 2023).

Currently, evaluation research based on flight data recorders has also received widespread attention. Wang et al. (2019) utilized flight quick access recorder (QAR) data to develop a risk-based evaluation model and system for assessing pilots' landing performance. Turetta et al. (2018) applied flight test data and artificial neural network techniques to develop and validate a mathematical model of pilot behavior during offset landing. Hebbar and Pashilkar (2017) analyzed pilot performance using flight simulator data from approach and landing scenarios, combining flight trajectory deviations and control strategies under various challenging conditions. However, due to the variability of trainee flight skills and the complexity of training scenarios, the actual data often suffers from poor quality and severe noise interference, making scientific and standardized data analysis difficult. Furthermore, flight data can only objectively present the pilot's behavioral performance during flight operations but not include the assessment of deeper physiological and psychological factors suggested by the iceberg theory (Sun et al., 2023). This limitation is even more pronounced for novice trainees, whose behavioral performance alone may not fully reveal their underlying workload, stress, or adaptability during different training stages.

In contrast, the utilization of physiological signals can effectively capture the physiological and psychological changes of pilots during training, providing instructors with additional objective information to deeply understand the changes in a pilot's state and skill development at different training stages, and offering a new method for pilot performance evaluation (Zhang et al., 2025). Borghini et al. (2017) developed a neuromeasurement method based on machine-learning algorithms to evaluate training progress, complementing standard performance evaluations. Some researchers have explored the correlation between pilots' physiological signals and flight operation behavior, further verifying the potential of physiological data in enhancing the effectiveness of pilot performance evaluation. Ji et al. (2022) employed Electroencephalography (EEG) to explore β-wave changes during take-off and landing, showing that variations in β potentials and their spatial distribution can be used to monitor and evaluate pilots' flight status in critical phases. Yuan et al. (2024) used functional near-infrared spectroscopy (fNIRS) in a flight simulator to analyze pilots' brain activity during turning tasks, showing that changes in oxyhaemoglobin concentration and related cortical regions can effectively classify and predict pilot operating behaviour. However, relatively few studies have specifically examined novice flight trainees, whose physiological responses may vary considerably across different training stages.

Pulse rate variability (PRV) is calculated from pulse-to-pulse interval (PPI) signals derived from photoplethysmography (PPG), providing a measure of the variability in successive pulse intervals (Yu et al., 2021). Previous studies have indicated that PRV can serve as a reliable surrogate for heart rate variability (HRV) obtained from electrocardiography (ECG), demonstrating good feasibility and accuracy (Schäfer & Vagedes, 2013). However, PRV and HRV are not completely interchangeable, as PRV may be influenced by peripheral vascular factors and signal artifacts that are not present in electrocardiography-derived HRV (Wang et al., 2024). PRV reflects the regulatory capacity of the autonomic nervous system (ANS) over cardiac rhythm, particularly the balance between sympathetic (excitatory) and parasympathetic (inhibitory) activity (Mejía-Mejía et al., 2020). Research has shown that PRV holds critical value in assessing pilots' physiological states, monitoring workload, and evaluating potential health risks, and it has been recommended that PRV be incorporated into routine assessments for pilots (Zhu et al., 2023). Compared with signals such as EEG or fNIRS, PRV is easier to acquire and less susceptible to motion artifacts, making it particularly suitable for flight simulation studies (Liu et al., 2025). Therefore, this study employs PRV to investigate the physiological responses of novice flight trainees during different stages of helicopter simulation training.

Despite the increasing use of physiological signals in flight training research, existing studies have mainly focused on experienced operators or specific flight tasks, with limited attention to novice trainees and the dynamic evolution of their physiological states across training stages. In particular, how physiological indicators reflect skill acquisition during progressive training remains unclear. To address this gap, the present study aims to investigate the stage-dependent changes in physiological responses during ab-initio helicopter simulation training and to examine their relationship with skill acquisition. Unlike traditional approaches that rely primarily on subjective evaluation or flight performance data, this study employs PRV as an objective physiological measure to capture autonomic regulation. By analyzing PRV features across four progressively increasing training stages, this study provides new insights into the dynamic adaptation process of novice trainees and offers a physiological basis for improving training evaluation and design.

2. Methods

This study proposes a PRV-based physiological evaluation framework to assess skill acquisition during helicopter simulation training, as shown in Figure 1. The framework integrates training stage design, physiological signal acquisition, feature extraction, and statistical analysis to quantify changes in autonomic regulation across different training stages.

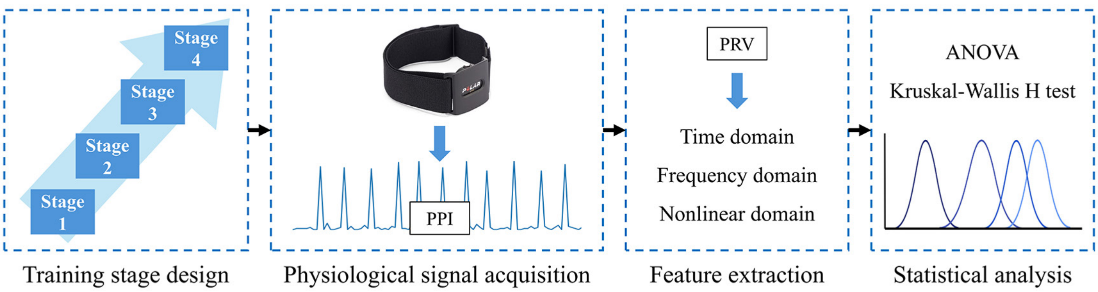

Figure 1. Framework of PRV-based training evaluation approach

2.1. Participants

Given that the aim of this study was to capture physiological changes and the process of flight skill acquisition during the initial stage of flight training, participants were required to have no prior exposure to flight-related activities. This was to avoid potential confounding effects arising from pre-existing operational habits or knowledge transfer associated with prior flight experience (Atasoy & Ekici, 2020). This sampling strategy minimized variability due to prior skill differences and enabled a clearer observation of physiological and cognitive changes during the training process.

Fourteen students (8 males and 6 females) from Southwest Jiaotong University participated in the experiment, with a mean age of 22.36 years old (standard deviation = 2.55, range = 18–26). All participants had normal vision or corrected-to-normal vision, normal hearing, no color blindness or color weakness, no history of smoking or cardiovascular disease, and were right-handed. None of the participants had consumed alcohol or coffee, taken medication, or used any substances within 24 hours prior to the experiment. Before the start of the experiment, all participants read and signed an informed consent form and were informed of their right to withdraw from the study at any time without penalty. The study was conducted in accordance with the Helsinki Declaration and was approved by the Medical Ethics Committee of Southwest Jiaotong University.

2.2. Flight simulator

This experiment was conducted at the Xinjin Flight College of the Civil Aviation Flight University of China. The flight simulator used in this experiment was an R66 flight training device, as shown in Figure 2, which has been certified by the Flight Standards Department of the Civil Aviation Administration of China (CAAC). This flight simulator features a 1:1 scale replica of the R66 real cockpit, equipped with a wrap-around curved screen in front of the field of view, forming a visual system with a field of view exceeding 180 degrees, which can cover most of the trainee's visual range. In addition, the simulator is equipped with a G1000 avionics system and professional flight training software, which has enhanced training efficiency.

Figure 2. R66 flight simulator

2.3. Wearable sensor

In this experiment, the Polar Verity Sense optical heart rate sensor was selected as a wearable physiological sensor to collect participants' photoplethysmography (PPG) signals, as shown in Figure 3. The device provides continuous PPG measurements with a sampling frequency of up to 135 Hz, which is sufficient for extracting PPI and deriving PRV features.

Figure 3. Polar Verity Sense used in the experiment

PPG technology utilizes a light source and a photodetector placed on the skin surface to achieve real-time and continuous monitoring of blood volume changes associated with the circulatory system (Castaneda et al., 2018). The Polar Sensor Logger software, which is compatible with the sensor, was used to obtain PPI data from the participants in .txt file format. PPI refers to the interval between two consecutive peak points in the PPG waveform. Specifically, each cycle in the PPG waveform corresponds to blood volume changes caused by a single cardiac contraction. PPI, as a time-domain parameter derived from the PPG waveform, is calculated by determining the time difference between the current peak and the preceding peak in the PPG signal (Georgieva-Tsaneva et al., 2022).

Although only a single wearable sensor was used in this study, this configuration is sufficient for the research objective. PRV is derived from inter-beat intervals and does not require multi-channel physiological measurements, making it suitable for wearable-based data acquisition in dynamic training environments. In addition, wearable PPG-based sensors have been validated in previous studies for assessing cognitive states in transportation-related dynamic environments, demonstrating their applicability and reliability (Yuan et al., 2025; Zhang et al., 2025).

2.4. Experimental design

Due to the difficulty of continuously tracking pilots throughout an entire training cycle, this study adopted a simplified experimental design in which participants acquired the skills for executing the Traffic Pattern maneuver through four simulator-based training stages (T1–T4), starting from a novice level.

Prior to each training stage, all participants received a unified 15-minute briefing on theoretical flight knowledge from the instructor. Then, one instructor and one participant entered the R66 flight simulation training device. The instructor delivered approximately 10 minutes of instruction on operational procedures, utilizing the simulator's instruments and control devices. To ensure consistency across participants, the instructor followed a standardized training protocol with predefined instructional content and procedures. Following the instruction, the participant was equipped with the Polar Verity Sense, and the training stage was performed. Each training stage lasted no longer than 15 minutes. Upon completion, the Polar Verity Sense sensor was removed, and the participant underwent a 1-hour rest period to minimize interference with subsequent training stages. During this rest period, the participant engaged in autonomous reflection and comprehension of the training stage, thereby facilitating knowledge internalization and consolidation.

The difficulty of the training stages progressively increased. During the first three training stages, participants performed the flights under the assistance of the instructor, whereas in the fourth training stage they were required to operate independently and complete the rectangular traffic pattern. The training objectives and contents for these four training stages are shown in Table 1. The first stage focuses on basic cognition, with an emphasis on understanding the causal relationship between the operating system and helicopter responses. The second stage moves into instrument reading and basic maneuvering, starting

Table 1. The training objectives and contents of the four training stages

Training stage	Training objective	Training content
T1	Understand the function of the helicopter operating system, recognize helicopter states, and learn the correspondence between control actions and helicopter states.	Use the operating system to change helicopter states; Understand the priority of state maintenance; Familiarize with the relationship between control inputs and helicopter inertia through quantitative state transitions.
T2	Recognize attitude instruments and performance instruments, and achieve changes and maintenance of flight data.	Maintain straight and level flight; Perform level turns with constant bank angle; Transition from climb to level flight, and from level flight to descent; Execute horizontal speed changes; Familiarize with the relationship between control inputs and helicopter inertia through quantitative state transitions.
T3	Achieve control of altitude, speed, and heading, understand and build the Traffic Pattern.	Familiarize with the relationship between control inputs and helicopter inertia through quantitative state transitions; Establish connections between different phases of the Traffic Pattern; Complete the Traffic Pattern under the instructor's guidance.
T4	Independently practice and complete the Traffic Pattern.	Control position and heading at low speeds; Perform corrections during the approach; Adjust deviations to ensure accurate flight data across all phases of the Traffic Pattern.

Table 2. Operational requirements for each phase of the helicopter Traffic Pattern procedure

Phase	Operational requirement
Takeoff	Apply takeoff power at 70% torque; Maintain runway heading 020°; Climb at a target airspeed of 60 knots; Continue climb through 1800 ft.
Upwind Leg	Maintain heading 020°; Continue climb.
Crosswind Leg	Set cruise power at 60% torque and enter level flight; Turn left to heading 290° (90° offset from runway heading); Increase airspeed to 80 knots; Continue climb to 2500 ft.
Downwind Leg	Maintain heading 290°, airspeed 80 knots, altitude 2500 ft; After 30 seconds of level flight, turn right to heading 200° (abeam touchdown point); Initiate 45-second timer.
Base Leg	Set descent power at 45% torque; Reduce airspeed to 60 knots; Descend to 2100 ft; Acquire visual reference with the runway and determine the final turn point (extended runway centreline).
Final Approach	Turn to heading 290°; Maintain 60 knots while aligning with runway centreline; Continue descent.
Landing	Establish an approximately 3-degree glide path; Progressively reduce airspeed; Execute the flare maneuver and terminate with touchdown.

quantitative practice related to helicopter inertia. The third stage establishes the overall flight process, practicing the complete the Traffic Pattern under instructor guidance. The fourth stage requires independent completion of the Traffic Pattern.

Statistical analysis of the recorded time data indicates that the durations of all four training stages were generally stable. Across all participants, the mean durations ± standard deviations for T1, T2, T3, and T4 were 8.9 ± 2.8 min., 10.2 ± 3.6 min., 7.7 ± 1.6 min., and 7.1 ± 1.2 min., respectively. Kruskal–Wallis H test revealed no statistically significant differences in stage duration across the four training stages (H = 5.10, p = 0.164), suggesting that the overall time spent in each stage did not introduce significant bias. Therefore, the observed differences can be primarily attributed to variations in task demands and skill acquisition, rather than time-related confounding factors.

The training simulated flight scenario was conducted at Xinjin Airport, Chengdu, Sichuan Province, China. Participants were required to execute a standard helicopter Traffic Pattern procedure, which consisted of multiple phases. The operational requirements of each phase are summarized in Table 2.

2.5. Date processing

2.5.1. Date preprocessing

During the experimental procedure, vigorous movements by participants could cause slight displacements at the interface between the sensor and the skin, resulting in signal noise. Additionally, electromagnetic interference from nearby electronic devices may introduce outliers and artifacts into the PPI data. In this study, PPI values falling outside the range of [280 ms, 1500 ms] were defined as outliers, while data points where the difference between the current PPI and the preceding PPI exceeded 20% were defined as artifacts (Sun et al., 2023). During preprocessing, outliers and outliers are removed first, and then they are replaced using the method of linear interpolation.

2.5.2. PRV feature

In this study, a time window of 60 seconds with a 50% overlap rate was selected as the parameter configuration for PRV analysis. A total of 26 PRV features were extracted, encompassing time domain, frequency domain, and nonlinear features (Zhu et al., 2025). Specifically, 16 time domain features, 7 frequency domain features, and 3 nonlinear features were included, as detailed in Table 3.

Table 3. The definition of PRV features

Feature type	Feature	Definition
Time domain	mean_NNI	Mean PPI
	SDNN	Standard deviation of PPIs
	SDSD	Standard deviation of differences between adjacent PPIs
	NNI50	Number of adjacent PPIs with a difference greater than 50 ms
	PNNI50	Ratio of NNI50 to the number of PPIs
	NNI20	Number of adjacent PPIs with a difference greater than 20 ms
	PNNI20	Ratio of NNI20 to the number of PPIs
	RMSSD	Square root of the mean of the sum of squared differences of adjacent PPIs
	Median	Median of the absolute differences between consecutive PPIs
	std_HR	Standard deviation of heart rate
	Range	The difference between the maximum and minimum values of PPIs
	CVSD	Ratio of SDSD to mean_NNI
	mean_HR	Mean heart rate
	CVNNI	Ratio of SDNN to mean_NNI
	max_HR	Highest heart rate recorded during the test
	min_HR	Lowest heart rate recorded during the test
Frequency domain	LF	Power of the low frequency band (0.04–0.15 Hz)
	HF	Power of the high frequency band (0.15–0.40 Hz)
	LF/HF	Ratio of LF to HF
	Lfnu	Normalized low-frequency power
	Hfnu	Normalized high-frequency power
	TP	Total power of the frequency band
	VLF	Power of the very low frequency band (0.003–0.04 Hz)
Nonlinear domain	SD1	Standard deviation of the short-term PRV in the Poincaré plot
	SD2	Standard deviation of the long-term PRV in the Poincaré plot
	SD2/SD1	Ratio of SD2 to SD1

2.5.3. Statistical analysis

In this study, statistical analyses were conducted using SPSS Statistics 27, with a significance level set at 0.05. The Kolmogorov-Smirnov (K-S) test was first employed to assess the normality of the data. If the assumption of normal distribution was met, a one-way repeated measures Analysis of Variance (ANOVA) was performed. If the normality assumption was not satisfied, the Kruskal-Wallis H test was employed to analyze differences across conditions.

3. Results and discussion

The results of the K-S normality tests indicated that, at a significance level of 0.05, all 26 PRV features significantly deviated from a normal distribution. Some time-domain measures and certain frequency-domain power indices frequently display non-normal distribution characteristics across various populations and conditions. This phenomenon arises from the inherent nonlinear dynamics underlying the complex fluctuations of a healthy heart, with short-term measurements (less than 5 minutes) being especially prone to deviations from normality (Shaffer & Ginsberg, 2017). Therefore, this finding is, to a considerable extent, consistent with observations reported in existing literature. It indicates that the non-normality of these indices is not attributable to systematic biases in data acquisition or processing but rather reflects intrinsic variability patterns inherent to physiological signals.

Based on the results of the normality tests, the Kruskal-Wallis H test was applied to assess the statistical significance of differences across all 26 PRV features. The results showed that there were 21 PRV features with significant differences, including 11 time domain features, 7 frequency domain features, and 3 nonlinear features, while the five features of mean_NNI, NNI20, PNNI20, Median, and mean_HR had no significant differences among different task stages. Most of the features with significant differences in this study have also been proven to be associated with workload in the previous literature. Zhou et al. (2024) found that CVSD, RMSDD, SDSD, and min_HR showed significant differences at different flight stages and could be used as key indicators of workload. Alaimo et al. (2022) found SDNN, LF/HF, and SD2 could differentiate low, medium, and high workload levels during flights. Mohanavelu et al. (2020) reported that SDNN, TP, VLF, and SD2 were significant indicators of workload across different task-load conditions. These studies support the present finding that different training stages impose varying workload levels on novice flight trainees, thereby confirming the validity of the four-stage training design adopted in this study. This finding highlights the sensitivity of PRV features to early-stage increases in task complexity, suggesting their potential as objective indicators for detecting workload escalation during initial skill acquisition.

Figure 4 illustrates the results of mean comparisons for the 21 significant PRV features across different task phases. The asterisks indicate significance levels following Bonferroni multiple comparison testing. In Figure 4, the sign * indicates $p < 0.05$, the sign ** indicates $p < 0.01$, and the sign *** indicates $p < 0.001$. Except for the time domain feature max_HR and four frequency domain features HF, LF/HF, Lfnu, and Hfnu, the remaining 16 PRV features exhibited significant differences between the T1-T2. Notably, the features Range, CVNNI, and SD2 showed highly significant differences between T1-T2, with $p < 0.001$. In addition, with the exception of min_HR, the remaining 15 PRV features in T2 were significantly lower than those in the T1 stage. Workload during flight tasks often induces changes in autonomic nervous system activity, typically characterized by increased sympathetic activation and reduced parasympathetic activity, which results in elevated heart rate and significantly decreased PRV (Koskelo et al., 2024). In this study, the T1 stage involved only helicopter attitude control training, while the T2 stage introduced additional instrument navigation operations. This indicates that after incorporating instrument operations, the increased task complexity or workload led to an overall reduction in PRV. In other words, the transition from T1 to T2, with its higher level of difficulty, triggered heightened sympathetic nervous system activity and decreased parasympathetic activity, ensuring sufficient cognitive resources were allocated for information processing and learning during the task. This pattern reflects a typical learning-related adaptation process, in which physiological responses transition from high-load states to more efficient regulation as skill proficiency improves. It suggests that PRV can serve not only as a workload indicator but also as a marker of training progression and skill acquisition.

Nine features showed significant differences between the T2-T4 task phases, and four features, SDNN, std_HR, CVNNI, and max_HR, exhibited highly significant differences with $p < 0.001$. All nine PRV features were significantly lower in T2 compared to the T4 stage, indicating a recovery of PRV during T4. This result may stem from the cumulative effects of learning and training: as the four training sessions progressed, participants' proficiency in performing the Traffic Pattern improved, leading to a reduction in workload during task execution. Previous research has demonstrated that experienced pilots exhibit lower physiological stress responses under identical tasks compared to novices (Durantin et al., 2014). In the present experiment, participants gradually acquired the skills necessary for the Traffic Pattern maneuver from T1 to T4. Their PRV features also began to approximate those typically observed in experienced individuals, with T4 characterized by reduced sympathetic activation and increased vagal tone, resulting in higher PRV values. This finding also aligns with Wang et al. (2024), indicating that greater task familiarity and improved skills reduce workload and consequently increase PRV. Hence, the changes in PRV features observed in this study correspond closely to both task complexity and training progression.

The findings of this study provide important implications for flight training and human factors research. First, PRV features can serve as objective physiological indicators for monitoring trainees' workload and adaptation

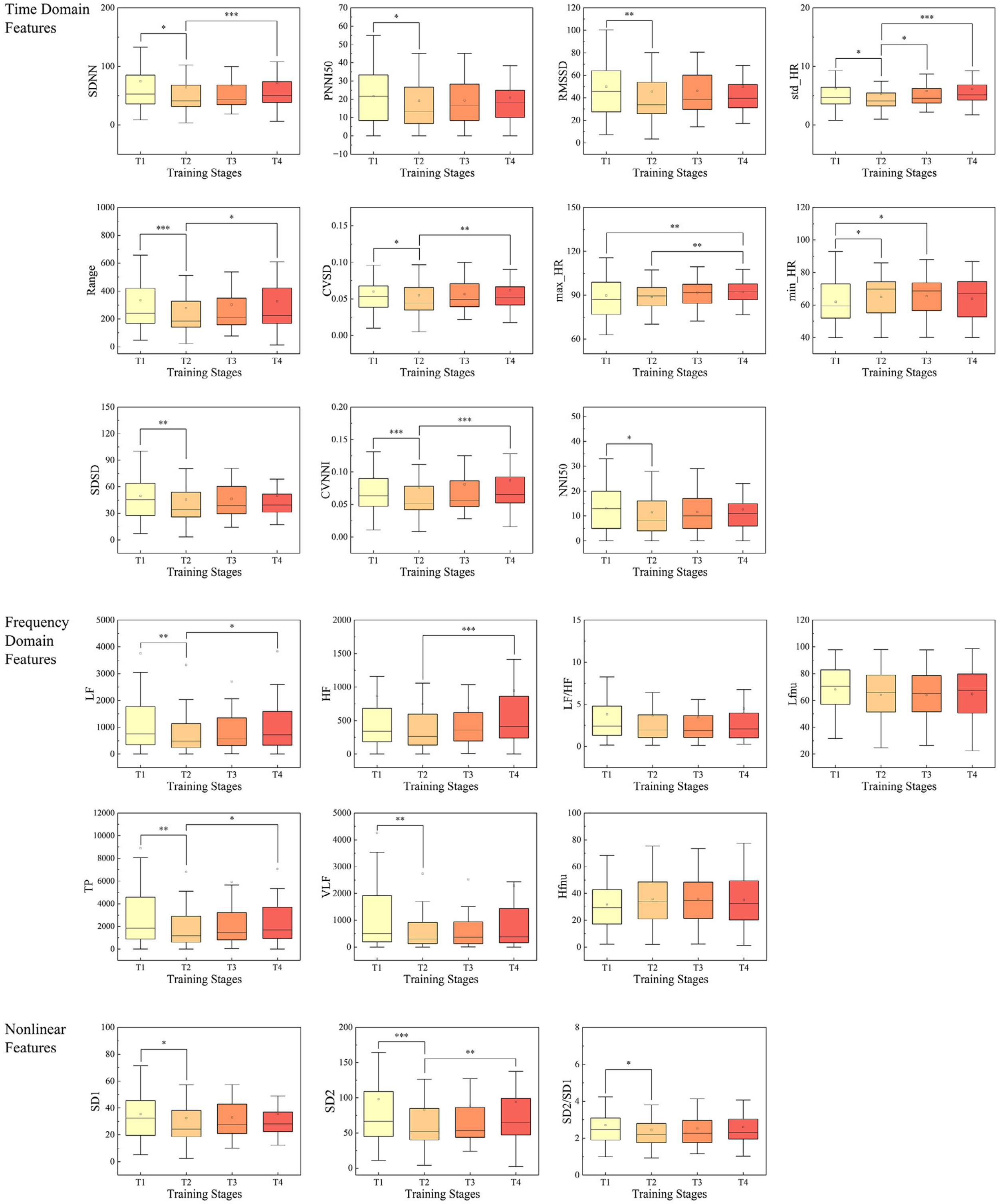

Figure 4. Multiple comparisons of 21 significant PRV features between training stages

across different training stages. This enables instructors to better understand trainees' internal mental states beyond observable performance. Second, the stage-dependent changes in PRV suggest the possibility of developing adaptive training strategies, in which training difficulty can be dynamically adjusted based on physiological feedback. Finally, the proposed approach offers a potential foundation for real-time monitoring systems to support training optimization and safety enhancement in aviation contexts.

Despite revealing the dynamic patterns of PRV features during the ab-initio flight training phase, this study has several limitations. First, the sample size was relatively small, which may limit the generalizability of the findings. Second, the analysis primarily focused on differences in PRV features and group comparisons, without integrating direct quantitative measures of cognitive performance during flight tasks (e.g., operational accuracy, error rate, task completion time). Third, body mass index (BMI) was not included as a factor in this study. Although all participants were generally healthy, the potential confounding effect of BMI on PRV features cannot be entirely ruled out. Furthermore, the experimental design was restricted to a single-task scenario, which may not adequately capture the dynamic interactions between physiological responses and cognitive performance in more complex, multitask flight environments. Future research will aim to expand the sample size and include cadets with diverse backgrounds and BMI ranges to more systematically validate the role of PRV features in flight skill development and workload regulation. In addition, it is necessary to integrate PRV features with multidimensional task performance metrics to explore their coupling relationships across varying task difficulties and stages, thereby providing a more precise understanding of PRV as a potential physiological marker of pilots' workload and task performance. Further studies may also incorporate multimodal physiological measures such as EEG and eye-tracking to construct a comprehensive pilot cognitive state assessment model, offering a more scientific basis for flight training evaluation and personalized interventions.

4. Conclusions

In this study, a PRV-based physiological evaluation approach was developed to investigate the dynamic changes in physiological states during helicopter flight simulation training. A total of 26 PRV features, including time-domain, frequency-domain, and nonlinear indices, were extracted and analyzed across four progressive training stages. The results revealed significant stage-dependent variations in PRV features, particularly between T1 and T2, as well as between T2 and T4. A pronounced reduction in most PRV features was observed in the T2 stage, suggesting that this phase represents a critical transition point characterized by increased workload and cognitive demand. In contrast, the subsequent increase in PRV features in later stages reflects the adaptation process associated with skill acquisition and improved task proficiency. These findings demonstrate that PRV can effectively capture both workload variation and training-related physiological adaptation. Compared with traditional evaluation methods that rely on subjective assessment or behavioral performance, the proposed approach provides an objective and continuous measure of trainees' internal mental states. From a practical perspective, this study provides a physiological basis for optimizing flight training programs and supports the development of adaptive training strategies.

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Disclosure statement

All authors declare that they have not any competing financial, professional, or personal interests from other parties.

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