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Article

Bayesian Analysis of Pilot Physiology in a Simulated Flight Environment

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Abstract

Monitoring pilot cognitive state in real time is becoming increasingly important as automation plays a larger role in aviation. Traditional workload assessments, such as questionnaires or task-based performance metrics, provide useful insights but can be limited in rapidly changing flight environments. Physiological measures including heart rate, respiration, and electroencephalogram (EEG) offer continuous data streams, yet their variability and complexity present challenges for analysis. This study explores the use of a hierarchical Bayesian framework to quantify patterns from physiological signals recorded during high-fidelity flight simulations. Five certified pilots flew scenarios that varied in automation level and working memory demand while heart rate, respiration rate, and EEG-derived workload estimates were monitored. The model generated individualized and condition-specific estimates, quantified uncertainty, and remained stable with a small participant pool. Heart rate appeared to be the most consistent indicator, followed by EEG-derived workload, while respiration rate was less reliable across conditions. These results suggest that Bayesian inference may provide a promising way to interpret physiological data in aviation settings and could support the development of adaptive automation that responds to pilot workload. The approach emphasizes transparency and efficiency, offering complementary value to existing modeling techniques for aerospace human factors and flight deck applications.

Keywords: Bayesian modeling; physiological measurements; human-automation interaction; aviation human factors; adaptive systems

1. Introduction

In modern technological systems, humans are exposed to more information than ever before, shifting system limitations from computational power to human capacity [1]. Research in human factors has shown that task-induced workload can substantially impair performance and cognitive resource allocation [2–4]. Automation is often introduced in these information-heavy systems to reduce workload, but ironically it often ends up generating more complex technical challenges than the ones it was intended to solve [2,4–6]. With the shift from whether to how much automation to implement, careful consideration of human factors has become more crucial than ever for system designers [7].

Aviation exemplifies a domain where technological advancements have expanded the operator's access to information, yet this abundance more often leads to information overload than to information dominance [8]. Automation has been implemented in 5th gen aircraft that reduces information overload through information fusion and automated sensor management, which allows the pilot to focus on tactical decision-making. However, automating tasks previously performed by humans has been shown to have negative effects such as reducing the situational awareness of the

operator [9–11]. The implications of transitioning between autonomous and manual systems introduce the potential for degraded operator states either in cognitive overload (e.g., fully manual operations) or cognitive underload (e.g., fully autonomous operations), and it is important to design systems such that human agents and automated agents can collaborate optimally to achieve decision making superiority [7,12]. Since neither full automation nor full manual control is universally practical, the path toward adaptive hybrid systems begins with understanding and quantifying the operator's cognitive state.

Traditional methods of assessing cognitive workload often rely on subjective self-report tools such as the NASA-TLX [13], which capture an individual's perceived workload during specific experimental periods. However, these active assessments are not only time-consuming and intrusive for participants but also pose challenges for experimental validity, particularly in studies with small sample sizes. Subjective measures are prone to bias, as workload ratings have been shown to increase non-linearly with actual cognitive demand [14]. Although some other performance-based measures have been used (e.g. reaction time, response time, task completion time, time to transition between operating modes or between tasks, etc.), these measures lack in validity when performance is shared by the operator and automation.

Physiological measures such as heart rate, respiration, and brain activity provide continuous, objective insights into workload and arousal [15–17]. Unlike subjective ratings or task-based measures, they capture high-frequency dynamics but are noisy and individualized, posing statistical challenges. Physiological monitoring is a promising approach to gathering more data in real time for human factors studies, especially in specialized environments such as aviation where access to qualified participants is limited and simulations are resource intensive. Recent research has examined the relationships between physiological indicators and traditional subjective measures, such as correlations between NASA-TLX scores and heart rate variability. These studies have revealed complex, nonlinear patterns [18] and strong inter-correlations among subjective scales, yet often report weak or no associations with physiological measures [19], highlighting the nuanced challenges in aligning self-reported and physiological data.

Deterministic approaches often fall short in complex man-made systems, where intra- and inter-individual differences render behavioral data fundamentally statistical in nature [20,21]. Traditional frequentist approaches commonly assume that repeated observations across individuals follow the same distribution, often removing outliers to preserve population-level assumptions. However, in the context of physiological data where responses are highly individualized and inherently complex, this “one-size-fits-all” strategy loses power. What looks like noise at the population level may reflect meaningful signal. To produce robust and reliable predictions, statistical methods must account for individual variability rather than obscure and smooth it away. Rather, statistical methods used to analyze physiological data should be tailored to the individual to ensure robust and reliable predictions. Bayesian statistics offer a compelling alternative, providing a more ecologically valid framework for analyzing physiological data.

Unlike frequentist approaches, which focus on point estimates and often overlook uncertainty, Bayesian methods explicitly model uncertainty and differ in conceptualization, calculations, and functionality from traditional statistical approaches [22]. By incorporating prior knowledge and updating beliefs as new data becomes available, Bayesian inference naturally accommodates both intra- and inter-subject variability [23]. Epistemic uncertainty is quantified and reduced through posterior distributions as more evidence accumulates [24]. This probabilistic foundation enables researchers to analyze complex, individualized, and often sparse psychophysiological datasets without overfitting or oversimplifying the underlying patterns. Recent publications in human factors have used Bayesian analyses for modeling driver response times during automated vehicle takeovers [25–27], the effects of distraction and vigilance [28,29], and human automation interaction [30–32]. Bayesian analyses of small-sample-size factorial design has been explored in applications involving pilot incapacitation and flight trajectory predictions, and Bayesian methods were shown to increase the reliability and validity of results [33,34].

Despite growing interest in using physiology to assess cognitive states, most studies either treat psychophysiological signals as windowed features for classification or simple regression or apply Bayesian methods to discrete outcomes or small factorial designs. What is largely missing are probabilistic, time-sensitive models that operate directly on continuous multivariate physiological streams and capture both inter- and intra-subject variability. This gap is especially apparent in aviation contexts where sample sizes are small, performance is shared with automation, and subjective ratings are sparse and biased. Methods that exploit longitudinal, continuous time series per participant while borrowing strength across subjects are rare. As a result, current approaches provide limited individualized inference, weak uncertainty quantification, and little guidance for closing the loop between physiology and system design.

This study develops a hierarchical Bayesian model to analyze continuous physiological data from pilots in a flight simulator, addressing small-sample challenges and individual variability. By modeling heart rate, respiration, and EEG-derived workload, we evaluate the potential of Bayesian methods for real-time cognitive state estimation in aviation. Despite the conceptual alignment between Bayesian inference and biological signal variability, there is limited work in applying Bayesian techniques to continuous physiological time series data in human factors research. To address this gap, physiological data was collected from experienced pilots performing flight tasks under varying levels of automation and task difficulty within a high-fidelity flight simulator. A hierarchical Bayesian model was constructed to examine the psychophysiological correlates of these dynamic flight environments and to evaluate the utility of Bayesian methods in an applied small-sample aviation use case. This work explicitly models individual differences, reducing the need to discard “outliers” that may be meaningful signal. Ultimately, this work seeks to advance real-time physiological state estimation by evaluating continuous physiological variables well-suited for Bayesian modeling, and developing an adaptable, data-efficient framework capable of producing robust and generalizable predictions across shifting environmental demands, limited sample sizes, and varying cognitive states.

2. Materials and Methods

Five pilots participated in the study approved by Oklahoma State University’s IRB (IRB-24-229-ATRC), and the inclusion criteria were pilot certification, a current instrument rating, and experience in a Cessna 172 or similar aircraft. All five participants were male with ages ranging from 21 to 39 years ($M = 27.60$, $SD = 9.10$) and experience ranging from 253 and 1,450 flight hours ($M = 706$, $SD = 572$). An auditory n-back task was used to manipulate workload throughout the experiment with $n = 1$ corresponding to low workload and $n = 2$ for high workload. In an n-back task, temporal sequences of stimuli are presented, and participants must decide if the stimulus is the same as the stimuli they heard “n” steps ago. A total of four 15-minute flight task scenarios were flown per participant, creating a 2 (Automation on or off) $\times$ 2 (Workload high or low) within-subjects factorial design.

Figure 1 displays the flight path for one participant. The outbound portion from KSWO RWY 17 to ACOKO did not include n-back activity. After completion of the turn-around maneuver the n-back task was started and consequently concluded after landing back at KSWO. Boxcar functions were generated for automation status and workload level throughout the continuous physiological data recordings and used to segment the data into conditions based on the experimental context.

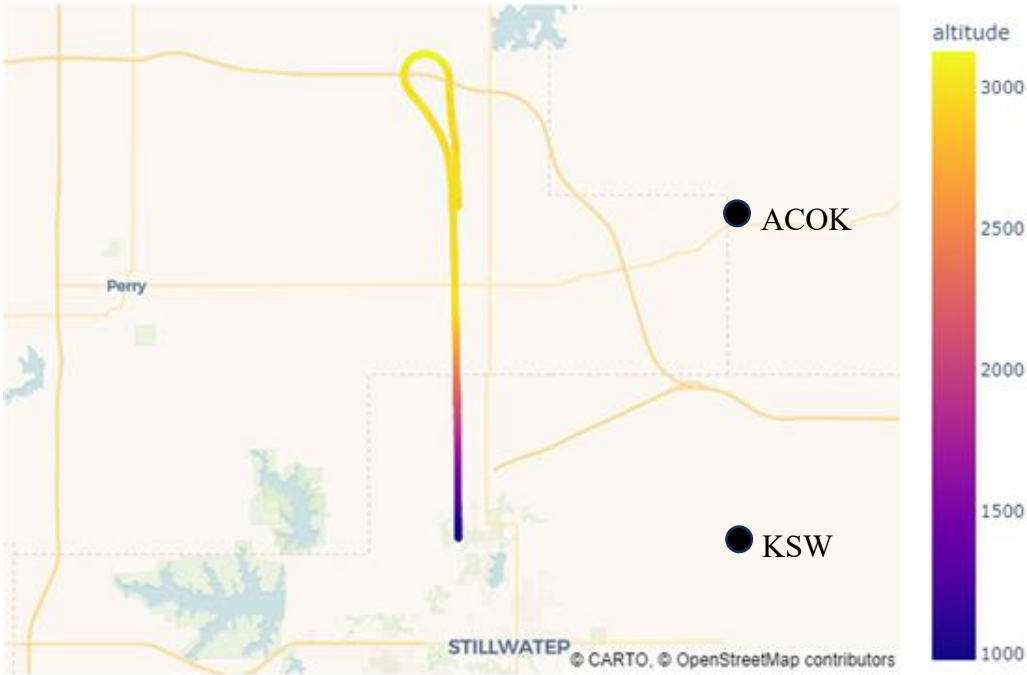


Figure 1. Participant flight path.

Physiological sensor hardware included an Advanced Brain Monitoring (ABM) B-Alert X10 EEG headset and an Equivital eq02+ Lifemonitor. The EEG headset collected raw brain activity at 256 Hz which was cleaned using 50, 60, 100, and 120 Hz notch filters as well as a 0.05 Hz high pass filter and median filter of order 56. Raw EEG signals were further processed using the headset’s proprietary artifact decontamination algorithm. After signal processing, probabilistic cognitive state estimates were generated at 1 Hz using the manufacturer’s classification algorithm [35–37]. The Lifemonitor collected ECG signals at 256 Hz which was used to calculate heart rate using R wave detection with a 30 second rolling average and was reported every 5 seconds [38,39]. Heart rate values were cleaned by removing extreme outliers less than 30 BPM or greater than 200 BPM and removing values outside of 3 standard deviations from an individual’s average heart rate [38]. Respiration rate was collected using the Lifemonitor’s expansion sensor which recorded values every 15 seconds. The final dataset was up sampled via linear interpolation into 1 second epochs which included heart rate (HR; beats per minute), respiration rate (RR; breaths per minute) and workload brain state estimates (WL; percent probability). While ECG-based signals are more practical for real-time analysis in aviation contexts, an EEG-based metric was included alongside ECG-derived measures to address the initial objective of identifying the most promising physiological indicators. In total, over 64 million database records of raw physiological time series data were collected from the sensors, and the final data frame used for analysis was a 19571 x 3 matrix.

2.1. Bayesian Modeling Methodology

We analyzed the physiological data at two levels: the group (experimental condition) level and the participant level. This hierarchical structure is warranted as physiological responses exhibit substantial between-subjects heterogeneity, are sampled at high frequencies (small-N, large-T), and partial pooling allows for the borrowing of strength across participants and conditions to stabilize individual estimates while preserving person-specific effects. The hierarchy also yields calibrated uncertainty at both levels, which is essential for aviation studies with noisy, autocorrelated signals and limited sample sizes.

A univariate approach was used as the foundation for the overall Bayesian modeling, and the HR, RR, and WL data were subset to illustrate the univariate Bayesian approach for each variable of

interest separately. Using heart rate as an example, it was assumed that the observed heart rate data is described in discrete observations. HR was sampled at 0.2 Hz throughout an experiment and is well approximated as a continuous variable that typically follows a bell-shaped distribution in healthy populations [40]. The normal distribution often appears in physiological measurements due to the Central Limit Theorem, which states that the sum of many small, independent factors tends to form a normal distribution [41]. Therefore, the heart rate data can be quantitatively described by a normal distribution where μ represents the sample mean HR and σ the sample standard deviation.

When applying a Bayesian approach, the goal is ultimately to obtain a posterior distribution of the parameter of interest [42]. Although normality assumptions must be statistically verified in frequentist statistics, Bayesian statistical approaches do not require strict adherence to distributional assumptions such as normality for valid inference. This is because Bayesian inference is grounded in the likelihood function and the prior distribution, rather than relying on sampling distributions or asymptotic properties of estimators. As a result, the posterior distribution inherently reflects the observed data and the specified functional model, regardless of whether the data conforms to a standard normal distribution. This flexibility allows Bayesian models to accommodate skewed, heavy-tailed, or otherwise non-normal data, making them particularly well-suited for analyzing physiological time series.

In Bayesian statistics, conjugacy refers to a model where the prior and posterior distributions belong to the same family of probability distributions. For example, both the prior knowledge and observed likelihoods for heart rate data follow a normal distribution; therefore, the posterior is also a normal distribution due to conjugacy. The posterior probability is given by Bayes' theorem, in which the posterior distribution is proportional to the prior distribution multiplied by the likelihood function of the data. Since both are normal, the product of the two normal densities is proportional to another normal density [43]. This allows us to identify the posterior distribution that updates from the observed data by combining it with the prior distribution. More information about conjugacy derivations used in the work can be found in the Appendix (A1).

The Bayesian model was constructed hierarchically to account for both within- and between-subject variability in physiological responses arising from changes in primary and secondary task demands. This hierarchical framework supports robust inference at both group and individual levels, accommodates sparse or unbalanced datasets, and removes the need for manual transformation of physiological time series, making it especially well-suited for cognitive workload research in dynamic environments [45]. More information about the hierarchical form and mathematics can be found in the Appendix (A2).

To visualize the results of a Bayesian approach to analyzing physiological data, 95% credible intervals were constructed by calculating a highest posterior density (HPD) interval that captures 95% of the posterior probability density function. These credible intervals were plotted alongside the posterior means over the observed physiological density curve for each participant and condition. To evaluate the fit of the model, several diagnostics were compared for each participant. Predictive performance is assessed with an 80/20 train-test split (Automation On/Workload Low scenario for comparability). We report the Coverage Probability Index (CPI), Mean Absolute Percentage Error (MAPE), and Concordance Correlation Coefficient (CCC) on held-out data. The CPI was estimated by calculating the probability that the observed heart rate values fall within the predicted 95% credible interval [46]. The MAPE was calculated for the results of the overall prediction error [47]. CCC was found for each set of predictions using the epiR package in R [48].

The hierarchical Bayesian model was developed in R (Version 2023.12.1+402) that uses each physiological time series with associated contextual characteristics to model the pilot's behavior throughout the experiment. HR, RR, and WL were modeled separately with the same hierarchical structure; differences lay only in their priors and measurement models (e.g. WL bounded in [0,1]). Prior knowledge from biomedical literature can inform the selection of appropriate prior distributions for physiological variables. For instance, studies have shown that heart rate in healthy adult males typically follows a normal distribution centered around 75 beats per minute (bpm) with

a standard deviation of approximately 7.7 bpm [49]. This prior information can be further refined using individual-specific data, such as baseline resting heart rates, to create more informative and personalized priors. However, to preserve generalizability and facilitate comparisons across individuals, noninformative (or weakly informative) priors were applied uniformly in this study.

To assess the robustness of the model to prior assumptions, a prior sensitivity analysis was conducted. This involved re-running the model with a range of alternative priors—varying in both informativeness and distributional form—to evaluate the impact on posterior estimates. The goal was to ensure that key inferences were driven by the data rather than overly influenced by the choice of prior. Results of this analysis supported the stability of model outcomes, indicating that the primary conclusions held consistently across different prior specifications. The probabilistic nature of ABM’s brain state estimates quantifies workload between 0 and 1; thus, a weakly uninformative prior belief was set to 0.50 probability with a standard deviation of 0.1. Therefore, the prior distributions used for each variable of interest were:

$$\mu_{HR} \sim N(75, 7.7^2)$$
$$\mu_{RR} \sim N(15, 4^2)$$
$$\mu_{WL} \sim N(0.5, 0.1^2)$$

3. Results

The group level results of this hierarchical Bayesian model for HR, RR, and WL brain state estimates can be seen in Table 1. The hierarchical nature of the model allows for between-subjects comparisons in mean and standard deviations of each physiological variable. Participants exhibited the highest HR in the condition where Automation was on and workload was high (i.e., 2-back task). RR was the lowest in the Automation On/Workload High condition and highest in the Automation Off/Workload Low condition. WL estimates were higher while the n-back level was high, which reflects the efficacy of the secondary task working memory manipulation. In Table 1, n indicates the number of observations for the experimental condition, which may vary due to the participant variability in completing the simulated flight.

Table 1. Bayesian Modeling Group Level Results.

Automation Status	Workload	n	HR	HR	RR	RR	WL	WL
			Posterior Mean	Posterior SD	Posterior Mean	Posterior SD	Posterior Mean	Posterior SD
Off	Low	4776	88.3	0.112	15.0	0.040	0.544	0.002
Off	High	4948	89.8	0.152	14.9	0.055	0.579	0.003
On	Low	4819	89.6	0.112	12.3	0.040	0.560	0.002
On	High	5027	92.1	0.109	12.8	0.039	0.588	0.002

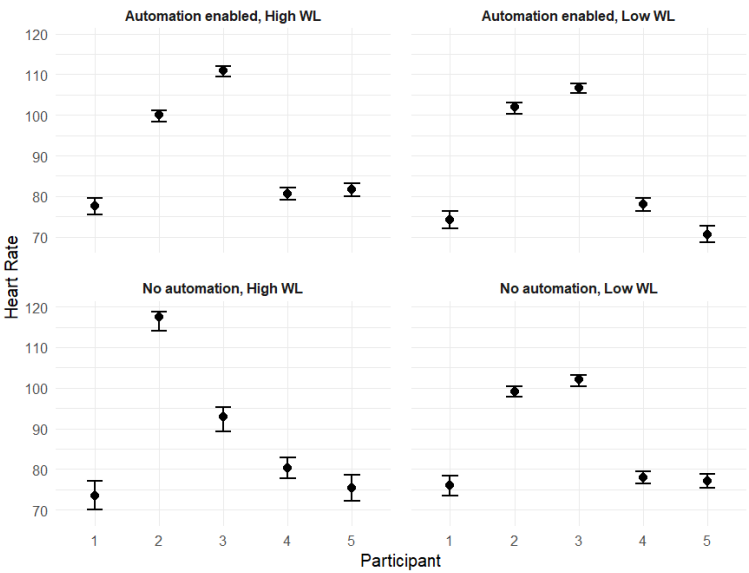
The participant level results for heart rate can be seen below in Table 2. The number of per-trial observations across participants ranges from 623 to 1433. The posterior means and standard deviations are reasonable for each physiological variable. In general, participants 2 and 3 have a higher heart rate than average. Participant 2 also exhibits the highest respiration rate on average. WL estimates from participant 5 are observed to be higher than the other participants. These results highlight the vast individual differences in physiology present in the data collected.

Table 2. Summary of Bayesian posterior means and standard deviations for HR, RR, and WL participant level results.

Participant	Automation Status	N-Back Level	n	HR Post	HR Post	RR Post	RR Post	WL Post	WL Post
				Mean	SD	Mean	SD	Mean	SD
1	Off	Low	623	76.0	3.10	13.4	1.89	0.519	0.057
		High	714	73.6	3.81	14.0	1.36	0.617	0.041

	On	Low	709	74.2	2.91	12.5	1.45	0.545	0.044
		High	756	77.5	2.81	13.8	1.49	0.561	0.045
2	Off	Low	1209	99.2	2.23	18.2	1.59	0.511	0.048
		High	1433	118	3.11	18.1	2.32	0.532	0.070
	On	Low	1124	102	2.31	17.3	1.89	0.554	0.057
		High	1072	99.6	2.36	18.4	2.11	0.527	0.064
3	Off	Low	1066	102	2.37	12.1	1.94	0.524	0.059
		High	942	92.4	3.47	14.8	2.21	0.572	0.067
	On	Low	1292	106	2.15	6.17	1.77	0.559	0.053
		High	1252	111	2.19	6.84	1.41	0.599	0.043
4	Off	Low	998	77.9	2.45	15.5	1.31	0.467	0.040
		High	1007	80.3	3.18	14.8	1.52	0.474	0.046
	On	Low	958	77.9	2.50	14.5	1.74	0.466	0.053
		High	967	80.6	2.49	13.8	1.72	0.478	0.052
5	Off	Low	881	77.1	2.61	14.8	1.44	0.720	0.044
		High	852	75.5	3.62	11.6	1.33	0.751	0.040
	On	Low	736	70.7	2.85	12.3	1.52	0.704	0.046
		High	980	81.6	2.47	12.5	1.51	0.770	0.046

The HR, RR, and WL estimates are shown visually with 95% credible intervals in Figure 2. The participants’ physiological responses varied noticeably throughout the experiment. Some participants demonstrated substantial differences across conditions, for instance participant 5’s WL estimates, while others showed more minimal changes, such as in participant 1’s HR across conditions. Overall, there was more variation present for all three physiological variables during the Automation Off/Workload High condition, as shown in the bottom left plot in each set of plots.



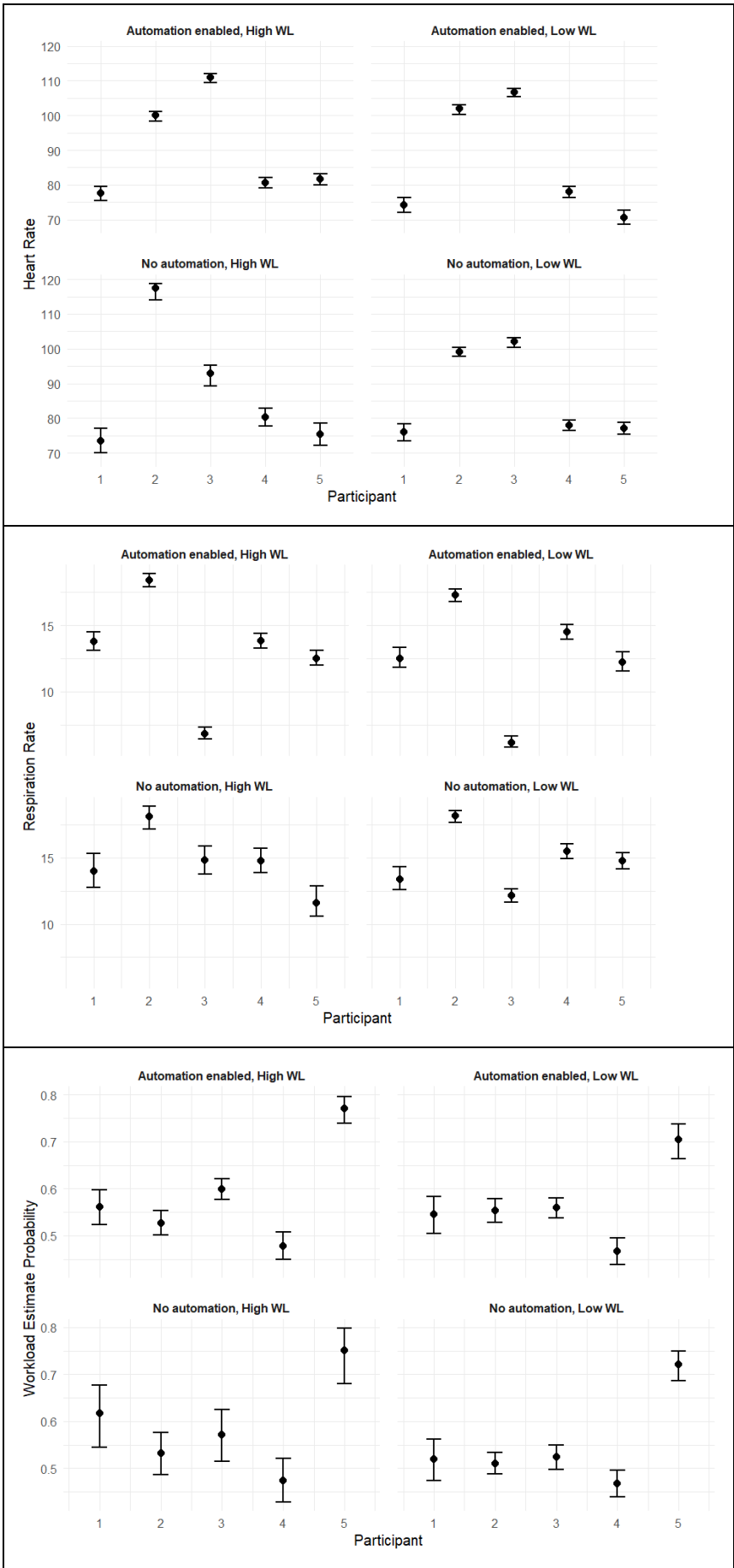


Figure 2. Posterior credible intervals for HR (Top), RR (Middle), and WL (Bottom).

The diagnostic results of the Bayesian models for each participant can be seen in Table 3 for HR, RR, and WL. Prediction diagnostics revealed clear differences in model accuracy across physiological measures. HR predictions were consistently accurate across participants, with low MAPE values (ranging from 8.15% to 10.1%) and strong agreement between predicted and observed values, as reflected in relatively high CCCs (0.766–0.904) and moderate to high CPIs (0.660–0.853). In contrast, RR predictions showed greater variability and generally poorer performance. MAPE values for RR were markedly higher (10.9% to 50.8%), and CCCs were notably lower (0.181–0.681), suggesting weaker concordance. CPIs for RR were also inconsistent, with values ranging from 0.363 to 0.853. WL predictions exhibited the highest overall MAPE (24.5% to 37.7%), yet CCCs ranged more favorably (0.610–0.853), indicating moderate agreement for some participants. CPI values for WL also varied widely (0.323–0.807), pointing to mixed coverage quality. These results suggest that predictive models performed best for HR, followed by WL, and were least reliable for RR.

Table 3. Bayesian Model Diagnostics.

	Participant	MAPE	CCC	CPI
HR	1	8.24	0.766	0.660
	2	8.15	0.897	0.853
	3	9.11	0.820	0.733
	4	9.25	0.904	0.806
	5	10.1	0.801	0.710
RR	1	28.1	0.354	0.707
	2	18.0	0.681	0.533
	3	10.9	0.181	0.853
	4	50.8	0.196	0.763
	5	28.4	0.651	0.363
WL	1	37.4	0.648	0.807
	2	24.5	0.610	0.323
	3	33.6	0.817	0.663
	4	37.7	0.853	0.567
	5	28.4	0.676	0.747

To understand the implications of this Bayesian approach, the results of this model in the form of posterior estimates for mean and standard deviation can be visualized in conjunction with the observed physiological data collected throughout the experiment. Posterior density plots with corresponding 95% credible intervals (CIs) were generated for each participant for HR, RR, and WL to assess model calibration and predictive uncertainty. Figures 3–5 demonstrate the distribution of physiological data by participant. The colored bars on the plots correspond to the experimental conditions (Red represents the Automation Off/Workload Low condition, Green represents the Automation Off/Workload High condition, Orange represents Automation On/Workload Low condition, and Blue represents Automation On/Workload High condition).

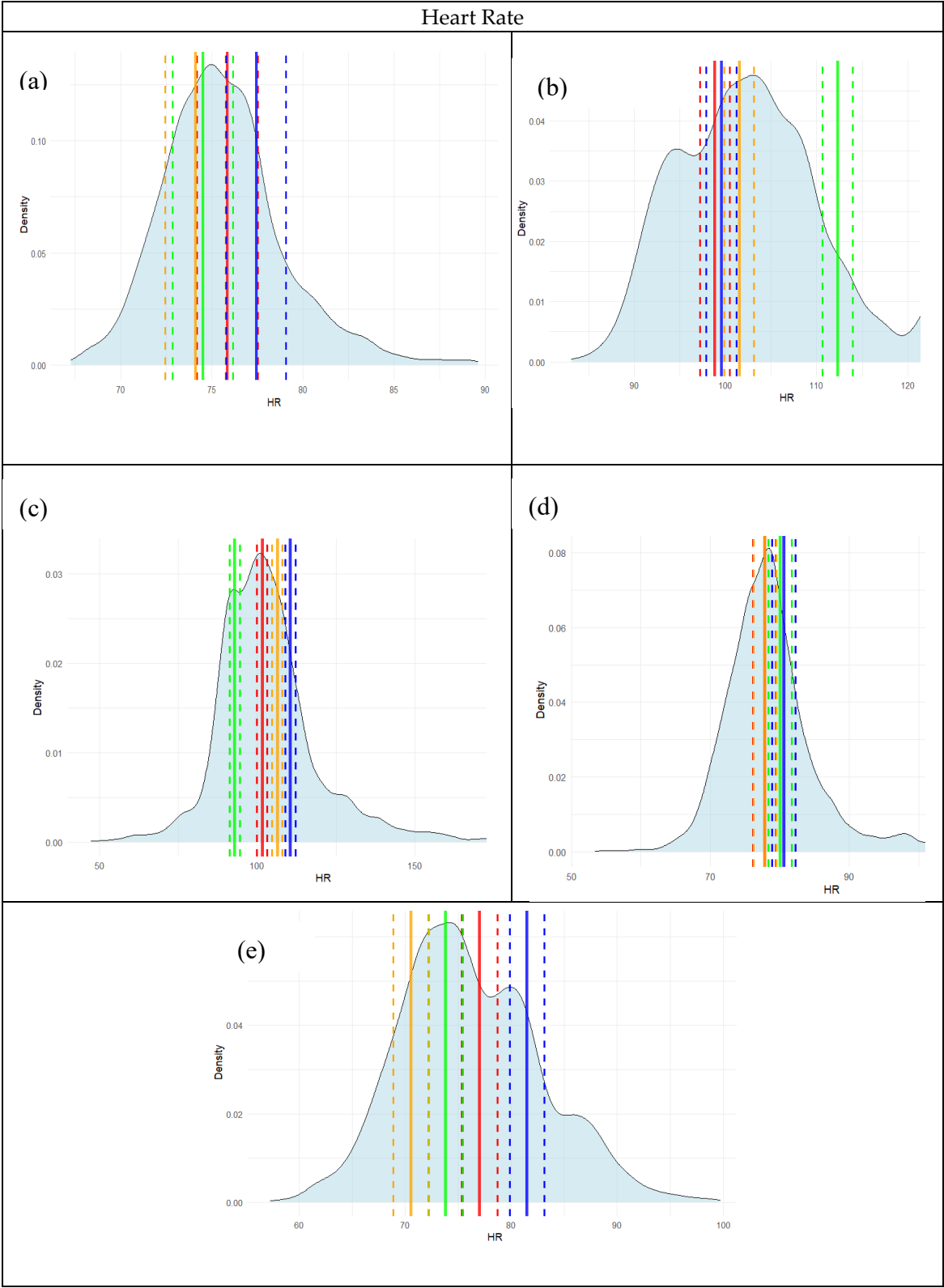


Figure 3. Stacked Density Plots with Posterior Estimates for HR. (a) Participant 1, (b) Participant 2, (c) Participant 3, (d) Participant 4, (e) Participant 5.

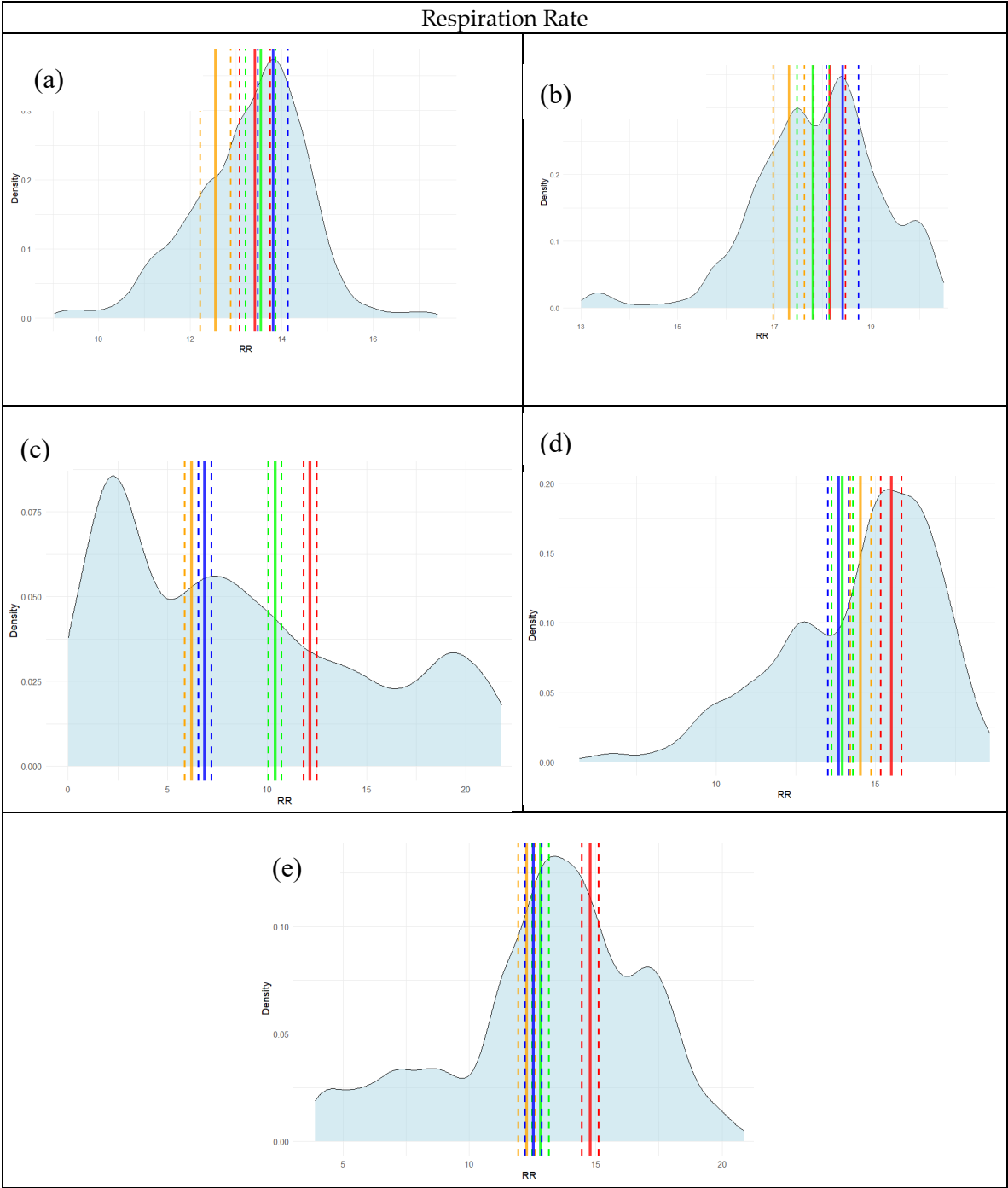


Figure 4. Stacked Density Plots with Posterior Estimates for RR. (a) Participant 1, (b) Participant 2, (c) Participant 3, (d) Participant 4, (e) Participant 5.

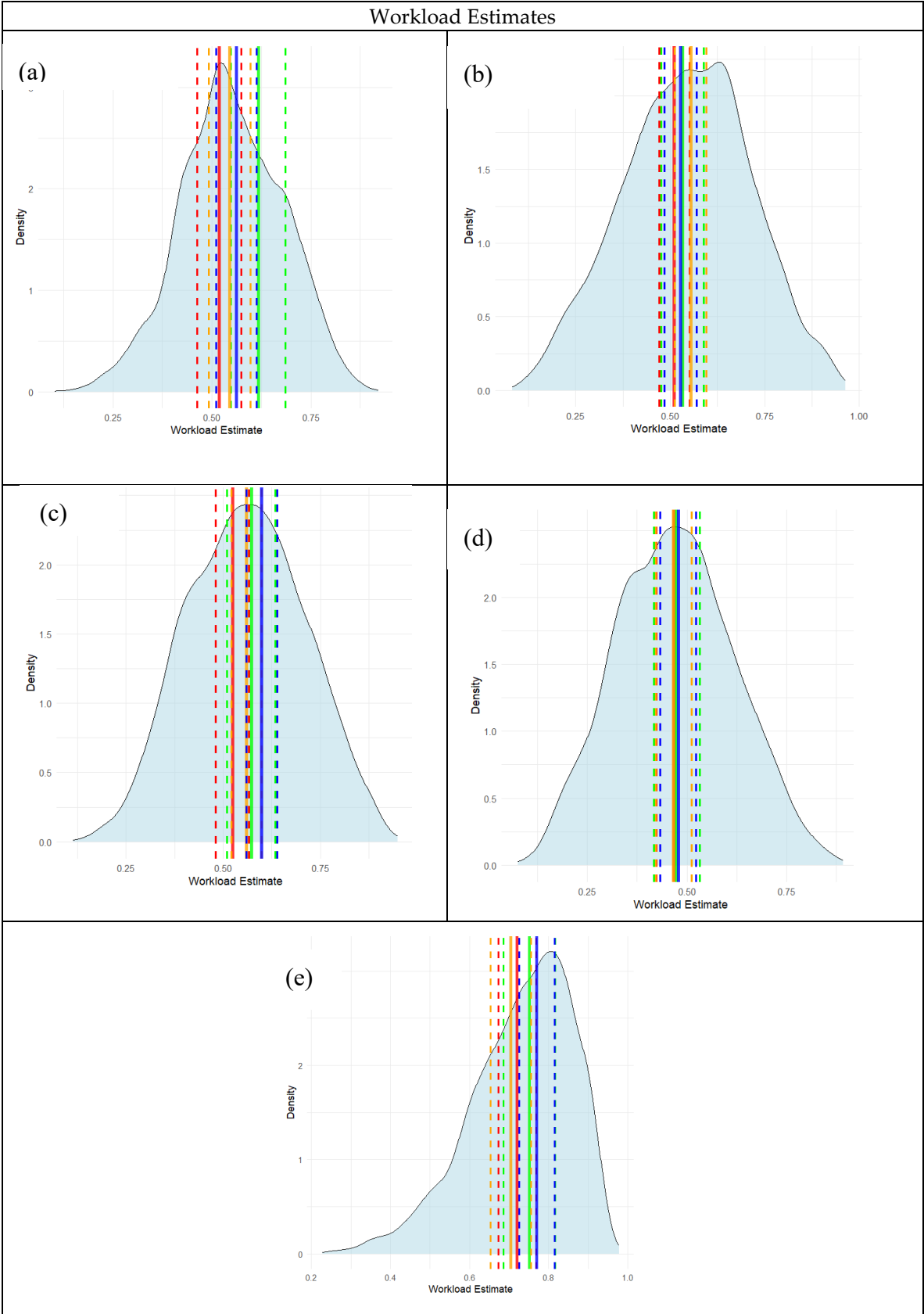


Figure 5. Stacked Density Plots with Posterior Estimates for WL. (a) Participant 1, (b) Participant 2, (c) Participant 3, (d) Participant 4, (e) Participant 5.

With the complete posterior distribution over all experimental conditions, several pieces of information can be gathered from the model. For HR, observed values for all participants generally fell within the high-density regions of the posterior distributions and were encompassed by the 95%

CIs, suggesting well-calibrated and reliable estimates. Participants 1 and 5 exhibited particularly tight HR posterior distributions with close alignment between predicted and observed values. In contrast, RR predictions showed greater variability across participants. Several posterior distributions—most notably for participants 3, 4, and 5—were skewed or multimodal, and observed values occasionally fell near the tails of the distributions, indicating increased uncertainty and reduced precision for RR. Workload predictions showed more consistent performance. The posterior distributions for WL were relatively symmetric and narrow, with observed values frequently aligning with the posterior modes for all participants. WL posterior credible intervals were more centered in the observed distributions, failing to capture densities on the tails of the workload estimate distributions. Overall, model performance appeared strongest for HR and WL, with greater variability and lower confidence in RR estimates—consistent with trends observed in the quantitative prediction diagnostics.

4. Discussion

A Bayesian approach was adopted to quantify and predict participants' physiological states in a flight simulator study examining the effects of automation level and task workload. The model successfully captured variation in physiological responses across experimental conditions by leveraging contextual information to segment and interpret the continuous time series data. This enabled meaningful comparisons between levels of automation and cognitive demand. A hierarchical modeling structure facilitated both within- and between-subject analyses. At the group level, heart rate was consistently elevated under high workload conditions with automation. While most participants followed this trend, one outlier underscored the value of individualized modeling, highlighting how Bayesian methods accommodate variability without discarding data as “noise.”

Heart rate was the most reliable measure, followed by workload estimates from EEG, while respiration rate proved least consistent. As anticipated, EEG-based WL estimates were higher during the 2-back task compared to the 1-back task, confirming the effectiveness of the working memory manipulation. Additionally, respiration rates were generally lower when automation was disengaged, potentially reflecting the increased cognitive and physical demands associated with manual flight control. These findings highlight the promise of Bayesian approaches for interpreting small-sample, high-frequency physiological data in aviation.

A key advantage of this framework is its ability to accommodate individual variability without discarding it as statistical noise. For example, while most participants showed elevated heart rate under high workload with automation, one deviated from this trend: an effect that traditional averaging methods would obscure. By modeling posterior distributions rather than single point estimates, the Bayesian approach offers nuanced, data-efficient predictions. For instance, participant 5 exhibited a distinct local heart rate maximum near 82 BPM under the Automation On/Workload High condition, yet their overall mean heart rate more closely aligned with the Automation Off/Workload High condition, which produced a global maximum near 75 BPM. These observations suggest the presence of semi-stationary elevated workload states that manifest differently across task contexts, with extended periods of physiologically distinct responses.

This individualized modeling approach enables the comparison of overall trends without compromising data integrity or inflating Type I error due to repeated measures. As additional data becomes available, the model naturally converges toward more precise estimates, improving both robustness and predictive accuracy. Notably, posterior estimates from one iteration of the model can be reused as informed priors in subsequent analyses, enabling longitudinal or within-subject modeling across multiple experimental sessions. Repeated sessions from a single participant could be analyzed using their personalized posterior distribution as a prior, yielding more accurate and context-specific predictions of physiological state. This iterative capability offers broad applicability across experimental designs and time-varying datasets, underscoring the flexibility and power of Bayesian inference in psychophysiological research.

Collectively, these findings highlight the utility of Bayesian modeling in capturing individual-specific and context-dependent physiological patterns, offering a powerful tool for real-time

assessment of cognitive workload in complex, dynamic environments. Bayesian approaches allow researchers to explicitly model uncertainty and tailor likelihoods to the characteristics of the data, improving robustness and ecological validity in real-world applications. Physiological signals are influenced by multiple intrinsic and extrinsic factors and often shift over time, making them non-stationary. Bayesian approaches are well suited for such data because they quantify uncertainty and adapt as evidence accumulates. This combination provides the repetition and granularity needed for highly confident, data-efficient predictions.

While recent advances in noninvasive physiological and neurological sensing have significantly improved our ability to observe the human state in real time, there remains a considerable gap in understanding the complex dynamics, interdependencies, and feedback mechanisms within these signals—particularly in the context of brain activity. Although physiological metrics such as heart rate, respiration, and EEG have been quantitatively linked to constructs like workload, fatigue, and engagement [50–52], the majority of existing work analyzes these signals in isolated snapshots. Very little research has focused on modeling physiological data longitudinally, limiting our understanding of how these metrics evolve over time and interact with cognitive processes. Without temporally sensitive models, researchers risk drawing incomplete or misleading conclusions from highly individualized, non-stationary data. Furthermore, while multimodal sensing approaches have shown promise for workload prediction in simulation and surgical settings [53,54], these methods typically rely on machine learning classifiers that require large training datasets and offer limited transparency.

These results carry important implications for aviation. Real-time Bayesian monitoring could inform adaptive automation, enabling systems to respond dynamically to operator state by adjusting task allocation or interface complexity. Unlike black-box machine learning classifiers, Bayesian models are lightweight, interpretable, and provide quantified uncertainty – qualities essential for aerospace applications where transparency and robustness are critical. Given its relatively non-invasive nature compared to EEG-based metrics, heart rate demonstrates strong potential for future modeling efforts in similar contexts. The current model provides discrete, condition-specific predictions for heart rate using a hierarchical Bayesian structure, yet its framework can be extended to incorporate time as an explicit variable allowing for true time-series prediction rather than random posterior sampling on static conditions. Future work should also explore posterior updating using segmented time windows of varying lengths to evaluate signal stability, noise sensitivity, and time-dependent patterns in physiological state.

In addition, a key direction for future research is the integration of multiple physiological signals within a unified Bayesian framework. While this study used a parallel univariate approach via Normal-Normal conjugacy, future modeling efforts could explore multivariate extensions, such as the Multivariate Normal-Wishart conjugate structure, to jointly model heart rate, respiration, and other physiological variables. Prior work has successfully applied classifiers, including neural networks and multiresolution fusion frameworks, to multivariate physiological data for real-time emotion recognition and mental workload assessment [55,56]. However, these approaches often prioritize prediction accuracy over interpretability and lack mechanisms for uncertainty quantification or integration of prior knowledge—limitations that the Bayesian modeling framework used in the present study is designed to address.

5. Conclusions

This study applied a hierarchical Bayesian modeling framework to physiological data collected from experienced pilots in a flight simulator—an environment that by nature presents challenges in terms of small sample sizes. Within the aviation research community, concerns about generalizability and statistical power are common, particularly when using traditional frequentist approaches that rely heavily on large samples and repeated trials. Bayesian statistics offer a compelling alternative: they naturally accommodate small-n, high-resolution datasets through the integration of prior knowledge and the probabilistic modeling of uncertainty. This makes Bayesian inference particularly

well-suited for flight-based human factors research, where within-subjects data are rich but participant pools are often limited.

As flight systems become increasingly automated, physiological monitoring has gained importance as a real-time source of insight into pilot cognitive state. Bayesian models provide a principled framework for interpreting such data by contextualizing it within prior knowledge such as normative resting heart rates or baseline workload levels, and by treating individual variability as meaningful information rather than noise. Unlike point-estimate methods that oversimplify complex human states, Bayesian approaches quantify uncertainty directly, offering a more nuanced and transparent interpretation of operator state across changing task demands and environments.

Looking ahead, the continued development of this Bayesian framework may enable implementation directly within flight systems. A real-time Bayesian model could continuously update posterior beliefs about a pilot’s physiological condition and adapt automated systems accordingly, allowing the level of automation to be dynamically calibrated to cognitive state. Compared to computationally intensive models such as neural networks or black-box classification algorithms, the Bayesian approach is lightweight, interpretable, and data-efficient, making it more feasible for real-time deployment in operational settings. Finally, by enabling continuous, individualized modeling of cognition and physiology, this method offers a more ecologically valid alternative to standardized questionnaires and discrete behavioral metrics. It represents a promising paradigm for advancing human-automation interaction and suggests that Bayesian inference may be the key analytical lens through which to understand and model the dynamic, complex nature of human physiological data in high-stakes environments.

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Abbreviations

The following abbreviations are used in this manuscript:

- HR Heart rate
- RR Respiration rate
- HRV Heart rate variability
- EEG-WLElectroencephalogram based workload estimates

Appendix A

Appendix A.1: Normal-Normal Conjugacy Derivations

Consider a segment with n observations and sample mean $\bar{y}$. With known measurement variance σ^2 and a Normal prior $\mu \sim \mathcal{N}(\mu_0, \sigma_0^2)$, the posterior distribution can be described as:

$$p(\mu \mid \bar{y}) \propto \exp\left(-\frac{(\bar{y}-\mu)^2}{2(\sigma^2/n)} - \frac{(\mu-\mu_0)^2}{2\sigma_0^2}\right) \tag{1}$$

To find the posterior distribution form, we expand the quadratic in μ and complete the square in Equation (1) to expose the Normal kernel. This allows us to identify the posterior distribution that “learns” from the observed data $\bar{y}$ by combining it with the prior belief μ , weighted by their

respective precisions. Thus, the Normal-Normal conjugate update is for the posterior mean and posterior variance is quantified respectively in Equations (2) and (3):

$$\sigma_{post}^2 = \left(\frac{n}{\sigma^2} + \frac{1}{\sigma_0^2}\right)^{-1} \tag{2}$$

$$\mu_{post} = \sigma_{post}^2 \left(\frac{n\bar{y}}{\sigma^2} + \frac{\mu_0}{\sigma_0^2}\right) \tag{3}$$

Appendix A.2: Hierarchical Pooling Methodology

Let n_p denote the number of samples for participant p and n_g the number of samples for condition group g , with $\bar{y}_p$ and $\bar{y}_g$ their respective means. Each group-level mean is assigned a Normal prior and updated to a Normal posterior $\mu_{g,post}$, as described in the previous section. These group-level estimates are then used to inform individual participant-level posteriors, enabling the model to borrow strength across conditions and individuals. The explicit partial pooling equations can be found in Table A1.

A prior variance regularization parameter τ governs the relative influence of the prior group mean versus the observed data. Larger values of τ yield more conservative posteriors (i.e., less sensitive to new data), whereas smaller values allow the model to adapt more readily to incoming observations. As data accumulates—either within a participant (increasing n_p) or across participants (increasing n_g)—the influence of τ diminishes, allowing the posterior to become increasingly data-driven. Additionally, a hyperparameter δ is introduced to capture between-group variability, facilitating flexible modeling of condition-level effects.

Table A1. Formulas used for Group Level and Individual Level Posterior Estimates.

Parameter	Group Level Posterior Estimates	Individual Level Posterior Estimates
Posterior form	$\mu_g \bar{y}_p = \mathcal{N}(\mu_{g,post}, \sigma_{g,post}^2)$	$\mu_p \mu_g = \mathcal{N}(\mu_{p,post}, \sigma_{p,post}^2)$
Mean	$\mu_{g,post} = \frac{\frac{\mu_0}{\sigma_0^2} + \frac{n_g\bar{y}_g}{\sigma^2}}{\frac{1}{\sigma_0^2} + \frac{n_g}{\sigma^2}}$	$\mu_{p,post} = \frac{\tau\mu_g + \frac{n_p\bar{y}_p}{\delta^2}}{\tau + \frac{n_p}{\delta^2}}$
Variance	$\sigma_{g,post}^2 = \frac{1}{\frac{1}{\sigma_0^2} + \frac{n_g}{\sigma^2}}$	$\sigma_{p,post}^2 = \frac{1}{\tau + \frac{n_p}{\delta^2}}$
Hyperparameter for between-group variability		$\delta = \sqrt{\frac{\sum_{i=1}^{n_p} \frac{\sum_{j=1}^{n_g} (\mu_j - \mu_i)^2}{n_g}}{n_p}}$
Hyperparameter for within-group variability		$\tau = \frac{\sum_{i=1}^{n_p} \frac{\sum_{j=1}^{n_g} \sigma_{i,j}}{n_g}}{n_p}$

Notation key: p participant, g condition, t time index; μ_0, σ_0^2 prior mean/variance; σ_p^2 within-person variance; σ_g^2 between-person variance.

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