Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Wearable EEG-Based Kansei Monitoring of Cognitive–Emotional States During a Standardized Simulation Task on a Robotic Surgical System: An Exploratory Feasibility Study

Yusuke Watanabe

ywatanabe328@gmail.com

Fujita Health University: Fujita Ika Daigaku https://orcid.org/0000-0002-2537-7053

Susumu Shibasaki

Fujita Health University: Fujita Ika Daigaku

Yasue Mitsukura

Keio University: Keio Gijuku Daigaku

Shutaro Hori

Keio University: Keio Gijuku Daigaku

Daiki Kimura

Fujita Health University: Fujita Ika Daigaku

Sota Hoshino

Keio University: Keio Gijuku Daigaku

Masaya Nakauchi

Fujita Health University: Fujita Ika Daigaku

Tsuyoshi Tanaka

Fujita Health University: Fujita Ika Daigaku

Koki Otsuka

Fujita Health University: Fujita Ika Daigaku

Takeshi Takahara

Fujita Health University: Fujita Ika Daigaku

Tetsuya Toma

Keio University: Keio Gijuku Daigaku

Ichiro Uyama

Fujita Health University: Fujita Ika Daigaku

Koichi Suda

Fujita Health University: Fujita Ika Daigaku

Research Article

Keywords: Electroencephalography, Robotic Surgical Procedures, Simulation Training, Cognitive Load, Emotions, Human Engineering

Posted Date: November 13th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11505102/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Abstract:

Purpose: This exploratory feasibility study examined whether a wearable electroencephalography (EEG)-based Kansei analyzer could provide continuous time-series cognitive–emotional data during simulation tasks on a robotic surgical system, and characterized preliminary experience-related patterns, action-specific variations, and temporal relationships among EEG-derived Kansei parameters.

Methods: Twelve surgeons (novice, intermediate, expert; n = 4 per group) performed six repetitions of the Advanced Training in Laparoscopic Suturing (ATLAS) needle handling task on the da Vinci Xi Surgical System while wearing a single-channel EEG-based Kansei analyzer. Five EEG-derived Kansei parameters (Stress, Like, Interest, Concentration, and Calmness) were recorded at 1 Hz. Experience-related patterns, action-specific Stress patterns, lagged relationships among selected parameters, and associations with task score were examined descriptively.

Results: All 12 surgeons completed all repetitions without signal acquisition failure, missing data, or task interruption. Across 72 trials, higher task scores were associated with lower 95th-percentile Stress Z-scores ($\rho = -0.34$), including within participants (repeated-measures $r = -0.25$), although attenuated after further adjustment. The expert group showed the highest median Stress value but fewer extreme Stress elevations. Median Stress was highest during Manipulation and lowest during Extraction. Lagged Stress–Concentration correlations were small, positive in experts and predominantly negative in intermediates.

Conclusions: Continuous wearable EEG-based Kansei monitoring was achieved during simulation tasks using a robotic surgical system without interfering with task execution, indicating that intraoperative monitoring is highly feasible. In exploratory analyses, better-performing trials involved fewer excessive transient Stress elevations, even within individual surgeons, supporting further validation of EEG-derived Kansei metrics against established workload and physiological measures.

Keywords: Electroencephalography, Robotic Surgical Procedures, Simulation Training, Cognitive Load, Emotions, Human Engineering

Introduction

Surgical performance depends not only on technical proficiency but also on the surgeon's ability to allocate cognitive resources, maintain attention, regulate arousal, and respond appropriately to changing task demands. During surgery, particularly in minimally invasive and robot-assisted procedures, surgeons must integrate visual information, instrument manipulation, spatial orientation, decision-making, and error recovery under time-sensitive conditions. When task demands exceed available cognitive resources, excessive cognitive load or mental workload may impair psychomotor performance, decision-making, learning, and error recovery [1, 2]. Conversely, the ability to maintain an appropriate balance between task demands and cognitive resources is regarded as an important feature of surgical expertise. Accordingly, assessment of cognitive load has become increasingly relevant to patient safety, surgical education, simulation-based training, and competency assessment.

In surgical education, assessment of cognitive load may provide information that is not captured by conventional performance metrics alone. Although task completion time, error counts, motion metrics, and global rating scores are useful for evaluating observable performance, they do not directly indicate the cognitive effort required to complete a task, the timing of workload escalation, or the operator's capacity to maintain cognitive reserve during technically demanding steps [1]. This distinction is particularly important because trainees may complete a task with acceptable observable performance while still requiring substantially greater cognitive effort than experienced surgeons. In contrast, expert surgeons may process information more efficiently during complex or high-demand phases of surgery.

Traditionally, surgeons' cognitive load and mental workload have been evaluated using retrospective self-report instruments such as the National Aeronautics and Space Administration Task Load Index (NASA-TLX) and the Surgery Task Load Index (SURG-TLX) [3]. Although these tools are easy to administer and

widely used in surgical research, they are typically completed after task performance and therefore cannot capture second-by-second fluctuations in workload during specific procedural steps. They are also susceptible to recall bias, individual differences in self-perception, and emotional or contextual influences. Interrupting a surgical task to obtain real-time subjective ratings is generally impractical and may itself interfere with performance.

For these reasons, increasing attention has been directed toward objective and continuous measures of cognitive load, including heart rate variability, eye tracking, skin conductance, functional near-infrared spectroscopy, and electroencephalography (EEG) [3–5]. Physiological and neurophysiological metrics may allow assessment of workload variation during task execution and may be particularly useful for identifying high-demand moments that are not apparent from summary performance scores alone. Recent studies have demonstrated the feasibility of using EEG and other physiological measures to assess cognitive workload, expertise development, learning processes, and performance during laparoscopic, neurosurgical, and robot-assisted simulation and surgery [2, 6–8]. EEG-derived metrics have been associated with mental workload, simulator performance, learning progression, and surgical expertise, supporting the potential value of neurophysiological monitoring in surgical education and human factors research. However, most previous studies have focused primarily on cognitive workload or performance-related measures rather than broader cognitive–emotional states.

Although cognitive workload is an important component of surgical performance, responses to operative and simulation tasks also involve affective and motivational dimensions, including stress, engagement, interest, preference, attentional focus, and emotional regulation. These factors may influence learning, performance adaptation, resilience, and human–technology interaction, yet they have received less attention than cognitive workload alone. Approaches capable of continuously monitoring both cognitive and affective

aspects of task performance may therefore provide complementary information beyond conventional workload assessment.

The Kansei analyzer is a wearable EEG-based system originally developed for real-time estimation of affective and cognitive states rather than specifically for surgical applications [9–11]. Kansei is a Japanese concept closely related to Kansei (affective) engineering, affective design, and emotional engineering, which seek to capture subjective impressions and multidimensional responses to stimuli, including affective reactions, sensory impressions, cognitive appraisal, preference, and engagement. The Kansei analyzer applies this framework to EEG-based estimation of moment-to-moment cognitive–emotional states. However, because the Kansei analyzer was not originally designed for surgeons or surgical training, its application to surgical task performance requires feasibility assessment before it can be used as a research tool for surgical education or cognitive–emotional monitoring. Accordingly, the present study was designed as a proof-of-concept feasibility study rather than a definitive validation study.

We therefore conducted an exploratory feasibility study to determine whether a wearable EEG-based Kansei analyzer could provide stable time-series cognitive–emotional data during simulation tasks on a robotic surgical system and to characterize preliminary experience-related patterns, action-specific variations, and temporal relationships among EEG-derived Kansei parameters. Specifically, we focused on the feasibility of continuous signal acquisition, experience-related patterns in Stress and other Kansei parameters, action-specific variations during surgical task execution, and temporal relationships among selected Kansei parameter pairs (Stress–Concentration, Stress–Like, and Concentration–Calmness). In addition, task performance data were analyzed as supplementary information to provide a behavioral context for interpreting the Kansei outputs.

Methods

Participants and study protocol

This exploratory feasibility study included surgeons with varying levels of robotic surgical experience (senior faculty, junior faculty, and surgical trainees), who were classified as novice, intermediate, or expert surgeons as described below. Each participant performed the Advanced Training in Laparoscopic Suturing (ATLAS) needle handling task six consecutive times using the da Vinci Xi Surgical System (Intuitive Surgical, Sunnyvale, CA, USA) while wearing the EEG-based Kansei analyzer. After the analyzer was attached to the participant's head, a 15-second calibration was performed with the participant in a relaxed state with eyes closed. Participants were then allowed a warm-up period of up to 3 minutes before the first trial only. Successive trials were separated by a brief interval of approximately 1 minute for task reset and EEG recording preparation; no additional rest period was scheduled. This study was conducted as part of a research project approved by the institutional review board [12]. Participation was voluntary, and informed consent was obtained from all participants.

ATLAS needle handling task

The ATLAS needle handling task was used as the standardized simulation task performed on a robotic surgical system in this study [13]. The ATLAS program was developed in response to the recognized need for an advanced laparoscopic skills curriculum beyond basic laparoscopic training, particularly for complex suturing-related skills (https://atlas.surgicaleducation.com/) [14, 15]. The ATLAS tasks were subsequently introduced as structured models for advanced laparoscopic suturing [13], and further studies established proficiency benchmarks and structured formative feedback tools, supporting their use as standardized and educationally valid simulation tasks [16, 17]. The ATLAS needle handling task consisted of passing a needle through six standardized holes positioned at different angles on a circular task platform using robotic

instruments. Participants were required to repeatedly adjust the needle orientation and grasping position to achieve an appropriate insertion angle for each target hole. The task score was calculated as the cutoff time (300 s) minus the completion time minus a penalty score based on the number of needle drops [13, 16].

For action-specific analyses, the task was divided into three phases: Manipulation, Insertion, and Extraction. Manipulation was defined as the period during which the participant adjusted and grasped the needle before insertion or after extraction. Insertion was defined as the period from initial needle penetration until the needle exited the task platform. Extraction was defined as the period required to pull the needle completely out of the hole.

Wearable EEG-based Kansei analyzer

Participants' cognitive–emotional states during task performance were continuously measured using a wearable EEG-based Kansei analyzer (a research-grade unit equivalent to the commercially available system manufactured by IKI JAPAN, Tokyo, Japan) equipped with two consumer-grade dry electrodes (Fig. 1). The device estimated five Kansei-related affective and cognitive parameters: Stress, Like, Interest, Concentration, and Calmness. Each parameter was expressed on a 0–100 scale and recorded at a sampling frequency of 1 Hz. The Kansei outputs were not visible to participants during task performance, and no real-time feedback was provided.

The Kansei analyzer is a lightweight, single-channel EEG system designed to estimate Kansei-related affective and cognitive states in real time from scalp EEG signals. EEG signals were acquired noninvasively using an exploring electrode placed on the prefrontal region and a reference electrode clipped to one earlobe, which was also used for artifact reduction. The acquired EEG signals were processed every second using frequency-domain analysis, preprocessing, noise reduction, calibration, and pattern-recognition procedures.

The conceptual and algorithmic framework for Kansei estimation has been developed through prior studies

by Mitsukura and colleagues [9–11]. In this framework, Kansei is regarded as a multidimensional construct reflecting subjective impressions, affective reactions, sensory impressions, cognitive engagement, preference, and task-related mental states. The device estimates Kansei-related states from EEG-derived features using algorithms informed by prior studies examining associations between EEG signal patterns, subjective evaluations, task-evoked affective or cognitive states, and neuroendocrine responses. The device does not directly measure neuroendocrine markers during task performance; rather, the output values represent EEG-derived algorithmic estimates of Kansei-related affective and cognitive states. In surgical simulation, Kansei parameters have also been associated with subjective workload assessed using the NASA-TLX and with eye-tracking metrics reflecting visual attention and cognitive workload in a dual-task laparoscopic setting (Hori et al., Association for Surgical Education Annual Meeting, 2025). These findings suggest that Kansei-derived parameters may capture aspects of cognitive and emotional responses relevant to surgical task performance.

For interpretation, the capitalized terms Stress, Like, Interest, Concentration, and Calmness were used as EEG-derived Kansei output labels. Stress was interpreted as an algorithm-derived estimate related to psychological stress or task-related strain; Like as an estimate related to positive preference, affinity, or favorable emotional appraisal; Interest as an estimate related to momentary engagement or motivation to know, observe, or continue the task; Concentration as an estimate related to task-focused immersion; and Calmness as an estimate related to a relaxed or stable affective state. These parameters were analyzed as exploratory EEG-derived digital metrics reflecting temporal changes in cognitive–emotional responses during standardized simulation tasks on a robotic surgical system, rather than as diagnostic measures, direct measurements of discrete psychological states, or direct measures of neuroendocrine activity.

Data Analysis

Task performance analysis

Task performance metrics included task score, time to completion, number of errors, needle driving time, and needle manipulation time. Each participant completed the task six times. To avoid treating repeated trials within the same participant as independent observations, participant-level median values across the six repetitions were calculated for each task performance metric and used for subsequent analyses.

Participants were categorized into three experience groups: novice, intermediate, and expert surgeons. Expert surgeons were operationally defined as surgeons who held robot-assisted surgery proctor certification and were qualified under the Endoscopic Surgical Skill Qualification System (ESSQS) of the Japan Society for Endoscopic Surgery. Novice surgeons were defined as those who had performed 25 or fewer robot-assisted surgical procedures as console surgeon, and intermediate surgeons as those who had performed more than 25 such procedures but did not meet the expert criteria. For the analysis of task performance metrics, participants were further dichotomized into novice and experienced groups, with the experienced group comprising intermediate and expert surgeons. This grouping was used because the needle handling task, when performed on a robotic platform, was expected primarily to distinguish participants without or with limited robotic surgical experience from those with prior robotic surgical experience.

Data are presented as median [interquartile range]. Between-group comparisons using the Mann–Whitney U test were performed only as supplementary analyses for task performance metrics. Cliff's delta was calculated as an effect size to quantify the magnitude and direction of differences between novice and experienced participants. Cliff's delta is shown as the estimate with 95% confidence interval, with positive values indicating higher values in the novice group than in the experienced group.

Exploratory trial-level association analysis

As a supplementary analysis to provide a behavioral context for interpreting the Kansei outputs, exploratory trial-level analyses were performed to examine descriptive associations between Kansei-derived metrics and

task performance. For each trial and each Kansei parameter, several summary metrics were calculated to characterize different aspects of the time-series data. The median value was used as an index of the overall level of each parameter during task performance. The coefficient of variation (CV), calculated as the standard deviation divided by the mean, was used as an index of relative temporal variability. The mean absolute difference (MAD), defined as the mean absolute difference between consecutive observations, was used as an index of moment-to-moment fluctuation. To characterize transient high-intensity responses relative to each trial's distribution, values were standardized using the mean and standard deviation of the same trial; Z-score P95 was calculated as the 95th percentile of the standardized values, and Z-score >1.5 rate and Z-score >2.0 rate were calculated as the proportions of observations exceeding Z-scores of 1.5 and 2.0, respectively. These trial-level Kansei-derived metrics were correlated with task score using Spearman's rank correlation coefficient as descriptive exploratory analyses. Because each participant contributed multiple trials, these analyses were not treated as confirmatory inferential analyses and were interpreted as hypothesis-generating observations. Because these analyses were exploratory, no adjustment for multiple comparisons was applied across the 30 parameter–metric combinations examined (five parameters and six metrics); p values are therefore presented for descriptive purposes only, and some associations may have arisen by chance. To distinguish within-participant associations from between-participant differences, such as those related to surgical experience, repeated-measures correlation coefficients (r_{rm}; df = 59) were additionally calculated [18], with Benjamini–Hochberg false discovery rate adjustment. Sensitivity analyses for Stress Z-score P95 accounting for trial order and error-related events were also performed. These analyses were performed using the pingouin package in Python.

Kansei parameter analysis according to experience

For the Kansei analysis according to experience, five EEG-derived Kansei parameters were analyzed:

Stress, Like, Interest, Concentration, and Calmness. Time-series data for each parameter were summarized at the participant level to avoid treating repeated 1-Hz observations from the same participant as independent data points. For each participant and each Kansei parameter, median, CV, MAD, Z-score P95, Z-score >1.5 rate, and Z-score >2.0 rate were calculated from the 1-Hz time series concatenated across the six trials; for these participant-level metrics, Z-scores were standardized using the mean and standard deviation of each participant's concatenated series. Participant-level Kansei metrics were then summarized according to the three experience groups and presented as median [interquartile range]. Kansei parameters were analyzed descriptively, and no formal hypothesis testing was performed for these exploratory analyses.

Action-specific Stress analysis

For action-specific analyses, phase boundaries for Manipulation, Insertion, and Extraction were retrospectively annotated from task video recordings by a trained research assistant who was blinded to participants' experience groups, and all annotations were verified by one of the authors, a robotic surgeon. Metrics were first calculated across all segments of each action within each participant and were then summarized across participants as median [interquartile range]. For action-specific Z-score–based metrics, Stress values were standardized using the mean and standard deviation of each participant's concatenated time series across the six trials before being assigned to each action. Error-related events were recorded separately and excluded from the primary action-specific analysis because of their low frequency and heterogeneous duration.

Lagged correlation analysis

Lagged correlation analyses were performed to explore temporal relationships among selected Kansei parameter pairs. For each participant and trial, one time series was shifted relative to the other across lags from −5 to +5 seconds, and Spearman's rank correlation coefficients were calculated at each lag. The ±5-s

window was chosen because each needle pass in this task lasted only several seconds, and longer lags would extend into subsequent task phases. Trial-level coefficients were averaged within each participant and then across participants within each experience group. Positive lag values indicated that changes in the first parameter preceded changes in the second parameter by the corresponding number of seconds (e.g., for Stress–Concentration, positive lags indicate that changes in Stress preceded changes in Concentration). These analyses were exploratory and were not intended to establish causal temporal relationships. For both the trial-level and lagged correlation analyses, correlation magnitudes were described as small, moderate, or large using conventional thresholds of $|\rho| = 0.10$, 0.30, and 0.50, respectively. Because lagged coefficients were averaged across trials and participants, group-mean values may underestimate the strength of relationships within individual trials when the direction of correlation varied.

All analyses were performed using JMP Student Edition (version 19; SAS Institute Inc., Cary, NC, USA) and Python (version 3.13; Anaconda distribution with JupyterLab, managed via Anaconda Navigator version 2.7). JMP was used for descriptive statistics, task performance comparisons, and exploratory visualization. Python was used for time-series processing, Z-score-based summaries, lagged correlation analysis, and visualization.

Use of generative artificial intelligence

During the preparation of this manuscript, the authors used Claude Opus 5.5 (Anthropic) to assist with drafting the manuscript and with English-language writing and editing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Results

A total of 12 participants (4 female and 8 male; 4 novice, 4 intermediate, and 4 expert surgeons) completed

six consecutive repetitions of the needle handling task. Wearable EEG-based Kansei monitoring was successfully performed in all participants. No participant had unsuccessful measurement, device malfunction, signal acquisition failure, or missing time-series data during the simulation protocol. The device could be worn throughout the simulation tasks without preventing task execution or requiring interruption of the protocol. Time-series data for the five Kansei parameters (Stress, Like, Interest, Concentration, and Calmness) were exported at 1-Hz resolution and were available for exploratory analysis (Online Resource 1). The median task duration per trial was 77 s (interquartile range, 64–108 s; range, 40–237 s), yielding a total of 6,524 1-Hz data points per Kansei parameter across the 72 trials.

Task performance

Task performance metrics are summarized in Table 1. Compared with experienced participants, novice participants tended to have lower task scores, more errors, and longer completion and needle driving times. The largest effect size was observed for error count (Cliff's delta, 0.50; 95% confidence interval [CI], −0.22 to 0.87), followed by time to completion and needle driving time (both 0.38) and task score (−0.31); however, all 95% CIs included zero. Needle manipulation time showed little difference between groups (0.09).

Exploratory analyses of 72 trials showed small-to-moderate associations between selected Kansei-derived metrics and task score (Online Resource 2). Higher task scores were associated with higher median Stress values ($\rho = 0.316$), lower Stress Z-score P95 values ($\rho = -0.342$), lower Like MAD ($\rho = -0.395$), and lower Concentration Z-score >2.0 rates ($\rho = -0.323$). Small associations were also observed for Concentration Z-score P95 ($\rho = -0.293$), Calmness Z-score P95 ($\rho = -0.240$), and Like Z-score >2.0 rate ($\rho = -0.237$). In repeated-measures correlation analyses, the association with Stress Z-score P95 remained within participants ($r_{rm} = -0.25$; 95% CI, -0.48 to -0.00), persisted after adjustment for trial order, and was of similar magnitude in error-free trials, whereas the association with median Stress was not observed within

participants (r_{rm} = −0.19) (Online Resource 2). The association with Stress Z-score P95 was attenuated after additional adjustment for the error penalty, which is itself a component of the task score, and after exclusion of seconds annotated as error-related events. Within-participant associations in the same direction were also observed for Concentration Z-score >2.0 rate and Z-score P95, but none remained after false discovery rate adjustment.

Kansei parameters according to experience

Preliminary descriptive patterns were observed across the Kansei parameters (Fig. 2a–e), most consistently for Stress. The median Stress value was higher in the expert group (58.0 [52.5–66.5]) than in the novice (53.8 [50.4–62.0]) and intermediate (51.5 [41.2–55.4]) groups. In the expert group, the proportion of time points with Z-score >1.5 was also higher, whereas the proportion with Z-score >2.0 was lower. Stress MAD was also greatest in the expert group. Like showed a lower median value with a wider interquartile range in the intermediate group (49.0 [45.0–56.8]), together with a higher CV. For Concentration, median values were similar across groups, whereas the expert group showed a higher Z-score >2.0 rate, CV, and MAD. Interest and Calmness showed broadly similar distributions across groups, with no consistent descriptive pattern across the summary metrics examined.

Kansei parameters according to surgical action

Stress-related Kansei metrics according to surgical action are summarized in Table 2. The median Stress value was highest during Manipulation (55.5 [51.3–58.0]) and lowest during Extraction (50.5 [46.6–54.8]), whereas MAD was higher during Insertion (9.36 [7.82–10.84]) and Extraction (9.40 [7.14–11.85]) than during Manipulation (8.53 [7.37–9.29]). Z-score–based metrics showed broadly similar values across surgical actions, with Z-score P95 values of 1.87 [1.74–2.04], 1.80 [1.62–1.93], and 1.77 [1.58–1.86] during Manipulation, Insertion, and Extraction, respectively. When stratified by experience level, the expert group

showed higher Stress MAD and Z-score >1.5 rates than the other groups across all three actions (Online Resource 3).

Lagged correlation analysis of Kansei parameters

Lagged correlation analyses showed different temporal patterns among the experience groups, although all mean correlation coefficients were small in magnitude ($|\rho| \leq 0.27$; Fig. 3a–c). For Stress–Concentration, the expert group showed positive correlations at most lags, increasing from approximately 0.07 at lag 0 to 0.16 at lag +5, whereas the intermediate group showed negative correlations at negative lags (−0.27 at lag −5) that approached zero at positive lags. The novice group showed correlations close to zero overall (−0.10 to 0.03). For Stress–Like, correlation coefficients were generally small in all groups, although the expert group showed small negative correlations at negative lags (approximately −0.09 to −0.11). For Concentration–Calmness, correlations increased at lag 0 in all groups; this increase persisted at positive lags in the novice and expert groups (approximately 0.10–0.15) but declined toward zero in the intermediate group.

Discussion

In this exploratory feasibility study, wearable EEG-based Kansei monitoring was successfully implemented during a standardized needle-handling task performed using a robotic surgical system. Stable time-series data were obtained from all participants without measurement failure, device malfunction, interruption of task performance, or missing time-series data, supporting the feasibility of continuous EEG-derived Kansei monitoring during simulation tasks on a robotic surgical system. Exploratory analyses further suggested preliminary experience-related patterns in several Kansei-derived metrics, action-specific variation in Stress-related parameters, and temporal relationships among selected Kansei parameters. In addition, the trial-level associations with task score, the experience-group comparisons, and the lagged correlation analysis yielded

patterns that were consistent with existing concepts of adaptive arousal and cognitive load: better-performing trials tended to involve fewer excessive transient Stress elevations, whereas experienced surgeons showed higher overall Stress levels. These findings provide an initial, hypothesis-generating characterization of cognitive–emotional dynamics during surgical simulation task performance.

To our knowledge, this is one of the first studies to explore real-time cognitive–emotional dynamics during simulation task performance on a robotic surgical system using a wearable EEG-based system capable of estimating interpretable cognitive–emotional indicators continuously and in real time. Previous studies have demonstrated the feasibility of EEG-based monitoring during surgical simulation and operative performance, primarily focusing on cognitive workload, mental load, expertise, and skill acquisition, often through retrospective analysis of recorded physiological data [2, 6–8]. In contrast, the present system provides continuously updated Kansei output labels, including Stress, Like, Interest, Concentration, and Calmness, which may offer a practical framework for examining time-resolved cognitive–emotional responses during task performance. Because the system was not originally developed for surgical applications, the present study evaluated its feasibility in a simulation environment using a robotic surgical system as an initial step before further validation in more complex simulation or operative settings.

The successful acquisition of continuous EEG-derived Kansei data throughout task execution is an important feasibility finding. Previous studies evaluating physiological workload monitoring in surgery have highlighted practical challenges related to signal quality, motion artifacts, workflow integration, and user acceptance of wearable devices [3, 5]. In the present study, the wearable EEG-based Kansei analyzer could be used throughout simulation tasks on a robotic surgical system without preventing task execution or requiring interruption of the protocol. No apparent noise-related signal disturbance was observed, even with the head positioned in the console viewer. Importantly, measurements were obtained while participants operated the

surgeon console of a robotic surgical system, using the same hardware, viewer, and head position as in actual robot-assisted surgery, rather than a virtual-reality simulator. Because the main practical barriers to wearable EEG monitoring at the console were therefore not encountered, these findings indicate that intraoperative Kansei monitoring during robot-assisted surgery is highly feasible, with remaining considerations mainly related to longer procedure durations and the operating room environment.

The most consistent pattern across the exploratory analyses concerned transient Stress elevations. In the trial-level analyses, higher task scores were associated with lower Stress Z-score P95 values, and this association remained within participants, suggesting that, even within the same surgeon, better-performing trials tended to involve fewer excessive transient Stress elevations. In contrast, the association between higher median Stress and higher task score was not observed within participants and therefore appears to reflect between-participant differences, such as surgical experience. Consistent with this interpretation, the expert group showed the highest median Stress value but a lower rate of extreme elevations (Z-score >2.0) than the other groups. These observations should be interpreted with caution because the within-participant associations were small, each experience group included only four participants, and no association remained after adjustment for multiple comparisons.

Several explanations may account for these patterns. Learning across repetitions is unlikely to be the sole explanation, because the within-participant association persisted after adjustment for trial order. Alternatively, smoothly progressing trials may leave sufficient technical reserve to meet task demands without abrupt strain. Because a similar association was observed in error-free trials, such transient peaks may reflect not only overt errors but also less visible difficulties, such as repeated regrasping or adjustment of the needle angle. From a cognitive load perspective, poorer-performing trials, which likely involved greater technical difficulty, may have imposed transient increases in cognitive demand that were reflected as excessive Stress elevations.

Together with previous observations of associations between Kansei parameters and NASA-TLX scores, this suggests that transient Stress outputs may also serve as a potential indicator of moment-to-moment cognitive load, although validation against established workload measures is required. Finally, experienced surgeons may maintain a higher level of task-related engagement throughout the task, while their technical proficiency may make situations that provoke extreme responses less likely to arise. Compared with novices, experienced surgeons have generally performed more procedures independently and encountered postoperative complications, and this clinical experience may foster habitual attentiveness to tissue handling and surgical outcomes that carries over into simulation tasks. Their higher overall Stress levels may also reflect higher self-imposed performance standards, such as aiming for precise and efficient needle handling rather than mere task completion, or greater awareness of being observed by colleagues during the simulation. Longitudinal studies of the same surgeons with detailed event-level annotation will be required to distinguish among these explanations.

The lagged correlation analysis provided additional, albeit weaker, support for this interpretation, suggesting predominantly positive Stress–Concentration correlations in expert surgeons, whereas intermediate participants showed predominantly negative correlations and novice participants showed correlations close to zero. Although these findings should be interpreted cautiously because of the small magnitude of the correlations, the exploratory nature of the study, the small number of participants in each group, and the algorithm-derived nature of the Kansei outputs, they may suggest that the relationship between task-related strain and attentional engagement differs according to surgical experience. These observations are broadly consistent with the concept of adaptive arousal in performance psychology. Moderate levels of stress or arousal are often considered compatible with effective attention and task engagement, whereas excessive arousal may impair performance and cognitive control, consistent with contemporary interpretations of the

Yerkes–Dodson relationship between arousal and performance [19]. The positive Stress–Concentration relationship observed in expert surgeons may therefore be interpreted as a hypothesis-generating pattern in which increased task-related strain was accompanied by maintained or enhanced attentional engagement, rather than as evidence of a validated neurocognitive mechanism. Importantly, stress in surgical practice should not necessarily be viewed as a purely negative phenomenon. In a recent multicenter cohort study of real-world surgical procedures, increased surgeon physiological stress at the beginning of surgery was associated with fewer major postoperative complications, illustrating the complex relationship between stress and performance [20]. The present findings are consistent with the possibility that the relationship between stress-related responses and surgical performance may depend not only on the magnitude of stress itself but also on how that response is associated with task-focused attention.

Action-specific analyses further suggested that Stress-related outputs varied within a single task. Median Stress was highest during Manipulation, when participants repeatedly adjusted the needle orientation and grasping position to achieve an appropriate insertion angle, and lowest during Extraction, whereas moment-to-moment fluctuation, as indicated by MAD, was greater during Insertion and Extraction. These observations may indicate that needle orientation and regrasping, rather than needle passage itself, imposed the greatest sustained demand in this task. This is consistent with the design of the ATLAS needle handling task, in which adjusting needle orientation and grasping position to achieve an appropriate insertion angle for each target hole constitutes one of the core skills being trained. The expert group showed higher Stress MAD across all three actions, consistent with the greater temporal variability in Stress observed in the participant-level analysis. These phase-specific patterns were consistent with the expectation that Kansei outputs would change during task segments likely to impose greater cognitive demand, supporting the potential of time-resolved monitoring to identify such segments during surgical training.

The temporal relationship between Stress and Like also provides a useful exploratory perspective on the interpretation of Kansei outputs. Correlations between these parameters were generally small, with only a small negative tendency at negative lags in the expert group, and did not show a strong inverse relationship, which might have been expected if Stress simply reflected negative emotional experience. In the context of surgical simulation and operative performance, challenge, engagement, and task satisfaction may coexist with stress-related responses. Therefore, the small Stress–Like relationship observed in this study may suggest that the Stress output should not be interpreted solely as a marker of negative affect, but rather as a task-related Kansei response that may interact with motivational or affective states in a more complex manner. This interpretation remains preliminary and requires validation using concurrent subjective and physiological measures.

The Concentration–Calmness relationship also showed a tendency toward positive correlations around lag 0 across all experience groups. This pattern may suggest that increases in the Concentration output were often accompanied by increases in the Calmness output during standardized simulation task performance on a robotic surgical system. Although the magnitude of these correlations was small, this observation is compatible with the possibility that task-focused engagement and affective stability may coexist during structured simulation tasks. However, because the present study did not include concurrent subjective assessments or physiological comparators, this finding should not be interpreted as evidence of a validated focused or flow-like psychological state. Moreover, cognitive–emotional responses during actual surgical procedures may differ substantially because of patient responsibility, operative uncertainty, time pressure, and intraoperative decision-making.

The Kansei estimation framework is grounded in previous foundational studies that linked EEG signal patterns with subjective evaluations, task-evoked affective and cognitive states, and neuroendocrine responses

[9–11]. The present study extends this framework to surgical task performance on a robotic surgical system, and several of the observed patterns were broadly consistent with established concepts from cognitive workload research, performance psychology, and surgical education. Because the Kansei outputs represent EEG-derived estimates, the next important step is to establish how they relate to established measures in the surgical context. Concurrent comparisons with subjective workload instruments such as NASA-TLX, eye-tracking and pupillometry metrics, and heart rate variability would clarify the construct validity of each Kansei parameter and strengthen the interpretability of Stress, Like, Interest, Concentration, and Calmness outputs during surgical performance. Such multimodal comparisons would provide the basis for applying EEG-derived Kansei metrics in surgical simulation and, eventually, operative settings.

If further validated, Kansei-based EEG monitoring may have potential applications beyond feasibility assessment. Recent work in surgical sabermetrics and technology-enhanced assessment has emphasized the value of objective, continuous, and multimodal measurements for understanding surgical performance [1, 5]. Time-resolved cognitive–emotional data may provide complementary information that is not captured by conventional performance metrics alone. For example, trainees with similar task scores may show different trajectories of Stress, Concentration, Calmness, or Like outputs during task performance. Furthermore, the within-participant association between fewer excessive transient Stress elevations and better performance suggests that monitoring transient Stress responses, rather than overall Stress levels alone, may provide performance-relevant information. Such information could help identify learning bottlenecks, task segments associated with increased cognitive or affective demand, or opportunities for individualized feedback. In addition, these approaches may contribute to human factors evaluation and usability assessment of surgical technologies by providing complementary information regarding user interaction with complex devices and interfaces.

Several limitations should be acknowledged. First, this was a small exploratory study involving only 12 participants (four per experience group), and the observed patterns should not be interpreted as definitive evidence of group differences. Second, the Kansei parameters represent algorithm-derived estimates whose validity in surgical settings remains incompletely established. The present study did not include concurrent subjective workload instruments, such as NASA-TLX or SURG-TLX, or physiological comparators, such as heart rate variability, eye-tracking metrics, or skin conductance. Therefore, construct validity and criterion validity could not be directly assessed. Third, the device-specific algorithm and calibration procedures are not fully transparent, which may limit reproducibility and mechanistic interpretation. Fourth, single-channel prefrontal EEG is susceptible to ocular and facial muscle artifacts, which may be relevant when the surgeon's head is positioned in the console viewer, although no apparent noise-related disturbance was observed in the present study. Fifth, synchronization between task video recordings and physiological measurements was performed retrospectively, and minor temporal misalignment may have affected phase-specific and lagged correlation analyses. Sixth, several analytic choices warrant caution: Z-score–based metrics were standardized within each trial for the trial-level analyses and within each participant for the experience-group comparisons, and therefore reflect the shape of the corresponding distribution rather than absolute intensity; lagged correlations were calculated on autocorrelated 1-Hz time series without prewhitening; and multiple summary metrics were examined without adjustment for multiplicity. Seventh, the study was conducted using a single standardized simulation task on a single robotic platform. Cognitive–emotional responses during actual surgical procedures may differ substantially because real operations involve greater clinical complexity, patient-related responsibility, uncertainty, time pressure, intraoperative decision-making, and unexpected events. Therefore, the present findings cannot be directly generalized to other tasks, platforms, or actual operating room settings. Finally, repeated task performance may have introduced learning or fatigue effects

across the six repetitions, which could have influenced Kansei time-series patterns.

In conclusion, this exploratory feasibility study showed that a wearable EEG-based system capable of continuously estimating interpretable cognitive–emotional indicators could be successfully applied during operation of a robotic surgical system in a standardized simulation task. Stable time-series data were obtained without interfering with task execution, enabling exploratory characterization of cognitive–emotional dynamics during performance. Because measurements were obtained at the surgeon console under the same conditions as in actual robot-assisted surgery, intraoperative Kansei monitoring appears highly feasible. Preliminary experience-related patterns, action-specific Stress variations, and temporal relationships among selected Kansei parameters were observed. In particular, better-performing trials tended to involve fewer excessive transient Stress elevations, even within individual surgeons, whereas higher overall Stress levels characterized experienced surgeons. Such transient Stress outputs may also serve as a potential indicator of moment-to-moment cognitive load. Because these findings were obtained in a simulation setting, comparison with Kansei dynamics during actual robot-assisted surgery represents an important next step. These findings support further validation of EEG-derived Kansei metrics as potential tools for studying human performance, surgical simulation, and human–technology interaction in surgical settings.

Statements and Declarations

Funding: This work was supported in part by JSPS KAKENHI Grant-in-Aid for Scientific Research (C).

Competing interests: One of the authors is the chief executive officer of IKI JAPAN, the manufacturer of the EEG-based Kansei analyzer used in this study. The other authors have no competing interests to declare that are relevant to the content of this article.

Ethics approval: This study was approved by the institutional review board and was conducted in accordance

with the principles of the Declaration of Helsinki.

Consent to participate: Informed consent was obtained from all individual participants included in the study.

Data availability: The datasets generated and analysed during the current study are not publicly available. De-identified data are available from the corresponding author on reasonable request, subject to approval by the relevant institutional ethics committee and a data use agreement.

Author contributions: Author contributions are provided on the title page to maintain anonymity during peer review.

References

1. Howie EE, Dharanikota H, Gunn E, Ambler O, Dias R, Wigmore SJ, Skipworth RJE, Yule S. Cognitive load management: an invaluable tool for safe and effective surgical training. J Surg Educ. 2023;80(3):311–322. https://doi.org/10.1016/j.jsurg.2022.12.010
2. Maimon NB, Bez M, Drobot D, Molcho L, Intrator N, Kakiashvilli E, Bickel A. Continuous monitoring of mental load during virtual simulator training for laparoscopic surgery reflects laparoscopic dexterity: a comparative study using a novel wireless device. Front Neurosci. 2022;15:694010. https://doi.org/10.3389/fnins.2021.694010
3. Dias RD, Ngo-Howard MC, Boskovski MT, Zenati MA, Yule SJ. Systematic review of measurement tools to assess surgeons' intraoperative cognitive workload. Br J Surg. 2018;105(5):491–501. https://doi.org/10.1002/bjs.10795
4. Modi HN, Singh H, Yang GZ, Darzi A, Leff DR. A decade of imaging surgeons' brain function (part I): terminology, techniques, and clinical translation. Surgery. 2017;162(5):1121–1130. https://doi.org/10.1016/j.surg.2017.05.021
5. Almukhtar A, Caddick V, Naik R, Goble M, Mylonas G, Darzi A, Orihuela-Espina F, Leff DR. Objective assessment of cognitive workload in surgery: a systematic review. Ann Surg. 2025;281(6):942–951. https://doi.org/10.1097/SLA.0000000000006370
6. Natheir S, Christie S, Yilmaz R, Winkler-Schwartz A, Bajunaid K, Sabbagh AJ, Werthner P, Fares J, Azarnoush H, Del Maestro R. Utilizing artificial intelligence and electroencephalography to assess expertise on a simulated neurosurgical task. Comput Biol Med. 2023;152:106286. https://doi.org/10.1016/j.compbiomed.2022.106286
7. Shafiei SB, Shadpour S, Mohler JL, Kauffman EC, Holden M, Gutierrez C. Classification of subtask types and skill levels in robot-assisted surgery using EEG, eye-tracking, and machine learning. Surg Endosc. 2024;38(9):5137–5147. https://doi.org/10.1007/s00464-024-11049-6
8. Lim C, Obuseh M, Cha J, Steward J, Sundaram C, Yu D. Neural insights on expert surgeons' mental workload during live robotic surgeries. Sci Rep. 2025;15(1):12073. https://doi.org/10.1038/s41598-025-96064-w
9. Mitsukura Y. EEG signal processing for real applications. J Signal Process. 2016;20:1–7. https://doi.org/10.2299/jsp.20.1
10. Ogino M, Mitsukura Y. Portable drowsiness detection through use of a prefrontal single-channel electroencephalogram. Sensors. 2018;18:4477. https://doi.org/10.3390/s18124477
11. Shima Y, Sato T, Mitsukura Y, Toma T. Psychological impressions and real-time KANSEI trajectory of music listeners resulting from differences in piano performance methods. In: Fukuda S, editor.

Emotional engineering. Vol. 9. Cham: Springer; 2023. pp. 79–89. https://doi.org/10.1007/978-3-031-05867-7_8

12. Kimura D, Shibasaki S, Watanabe Y, Harada T, Nakano Y, Akimoto S, Nakauchi M, Tanaka T, Inaba K, Takahara T, Otsuka K, Uyama I, Suda K. Handling performance of the novel Bi-curve and G-curve suture needle designs: an exploratory study. Surg Today. 2026;56(9):1914–1923. https://doi.org/10.1007/s00595-026-03312-1
13. Watanabe Y, McKendy KM, Bilgic E, Enani G, Madani A, Munshi A, Feldman LS, Fried GM, Vassiliou MC. New models for advanced laparoscopic suturing: taking it to the next level. Surg Endosc. 2016;30(2):581–587. https://doi.org/10.1007/s00464-015-4242-6
14. Nepomnayshy D, Alseidi AA, Fitzgibbons SC, Stefanidis D. Identifying the need for and content of an advanced laparoscopic skills curriculum: results of a national survey. Am J Surg. 2016;211(2):421–425. https://doi.org/10.1016/j.amjsurg.2015.10.009
15. Enani G, Watanabe Y, McKendy KM, Bilgic E, Feldman LS, Fried GM, Vassiliou MC. What are the training gaps for acquiring laparoscopic suturing skills? J Surg Educ. 2017;74(4):656–662. https://doi.org/10.1016/j.jsurg.2016.12.004
16. Bilgic E, Watanabe Y, Nepomnayshy D, Gardner A, Fitzgibbons S, Ghaderi I, Alseidi A, Stefanidis D, Paige J, Seymour N, McKendy KM, Birkett R, Whitledge J, Kane E, Anton NE, Vassiliou MC. Multicenter proficiency benchmarks for advanced laparoscopic suturing tasks. Am J Surg. 2017;213(2):217–221. https://doi.org/10.1016/j.amjsurg.2016.07.033
17. McKendy KM, Watanabe Y, Bilgic E, Enani G, Munshi A, Lee L, Feldman LS, Fried GM, Vassiliou MC. Establishing meaningful benchmarks: the development of a formative feedback tool for advanced laparoscopic suturing. Surg Endosc. 2017;31(12):5057–5065. https://doi.org/10.1007/s00464-017-5569-y
18. Bakdash JZ, Marusich LR. Repeated measures correlation. Front Psychol. 2017;8:456. https://doi.org/10.3389/fpsyg.2017.00456
19. Beerendonk L, Mejías JF, Nuiten SA, de Gee JW, Zantvoord JB, Fahrenfort JJ, van Gaal S. Adaptive arousal regulation: pharmacologically shifting the peak of the Yerkes-Dodson curve by catecholaminergic enhancement of arousal. Proc Natl Acad Sci U S A. 2025;122(28):e2419733122. https://doi.org/10.1073/pnas.2419733122
20. Awtry J, Skinner S, Polazzi S, Lifante JC, Dey T, Duclos A; TopSurgeons Study Group. Association between surgeon stress and major surgical complications. JAMA Surg. 2025;160(3):332–340. https://doi.org/10.1001/jamasurg.2024.6072

Fig. 1 Wearable EEG-based Kansei analyzer used in this study. The system consists of a headband with a prefrontal dry electrode, an earlobe reference electrode, and a tablet application displaying the five Kansei outputs in real time

Fig. 2 EEG-derived Kansei parameters during robotic needle handling task performance
(a) Median values of Stress, Like, Interest, Concentration, and Calmness according to experience level (novice, intermediate, and expert surgeons). **(b)** Z-score P95 values of each Kansei parameter according to experience level, representing the upper range of within-task fluctuations. **(c)** Rates of observations exceeding Z-score thresholds (>1.5 and >2.0) for each Kansei parameter, reflecting the frequency of transient elevations relative to each participant's distribution (gray boxes, Z-score >1.5; white boxes, Z-score >2.0). **(d)** Coefficients of variation (CV) of each Kansei parameter according to experience level, representing relative temporal variability during task performance. **(e)** Mean absolute differences (MAD) of each Kansei parameter according to experience level, reflecting second-to-second temporal fluctuations. Boxes indicate the median and interquartile range, and each dot represents one participant. Z-score–based metrics were calculated using values standardized within each participant's concatenated time series. Tables below each panel show the corresponding values as median (interquartile range). CV, coefficient of variation; MAD, mean absolute difference.

Fig. 3 Lagged temporal relationships among Kansei parameters according to experience level. Values are group means of participant-level Spearman correlation coefficients at lags from −5 to +5 s; positive lags indicate that changes in the first parameter preceded changes in the second
(a) Lagged Stress–Concentration correlations
(b) Lagged Stress–Like correlations
(c) Lagged Concentration–Calmness correlations

Online Resource 1 Representative surgical performance video with real-time Kansei analyzer values

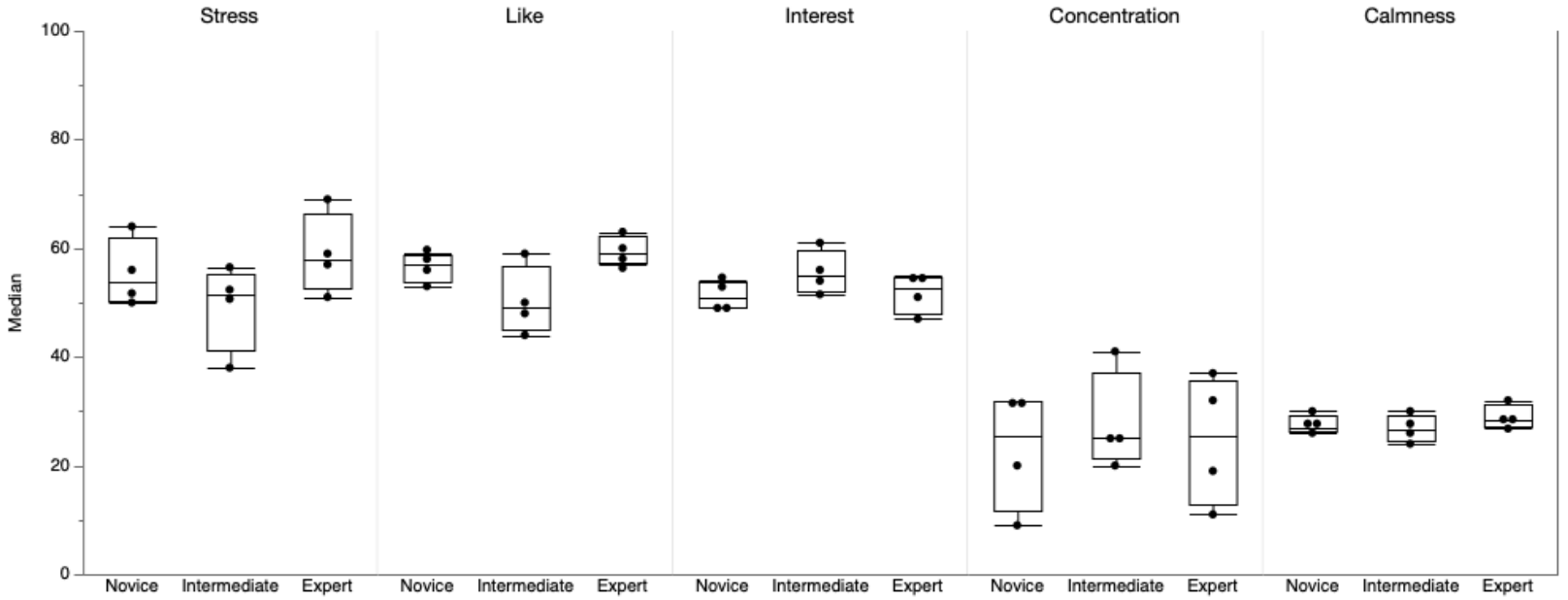
Online Resource 2 Exploratory associations between Kansei-derived metrics and task score

Online Resource 3 Action-specific Stress metrics according to experience level
(a) Median, coefficient of variation (CV), and mean absolute difference (MAD) of Stress during Manipulation, Insertion, and Extraction
(b) Z-score P95 and rates of observations exceeding Z-scores of 1.5 (left box) and 2.0 (right box) during each

action

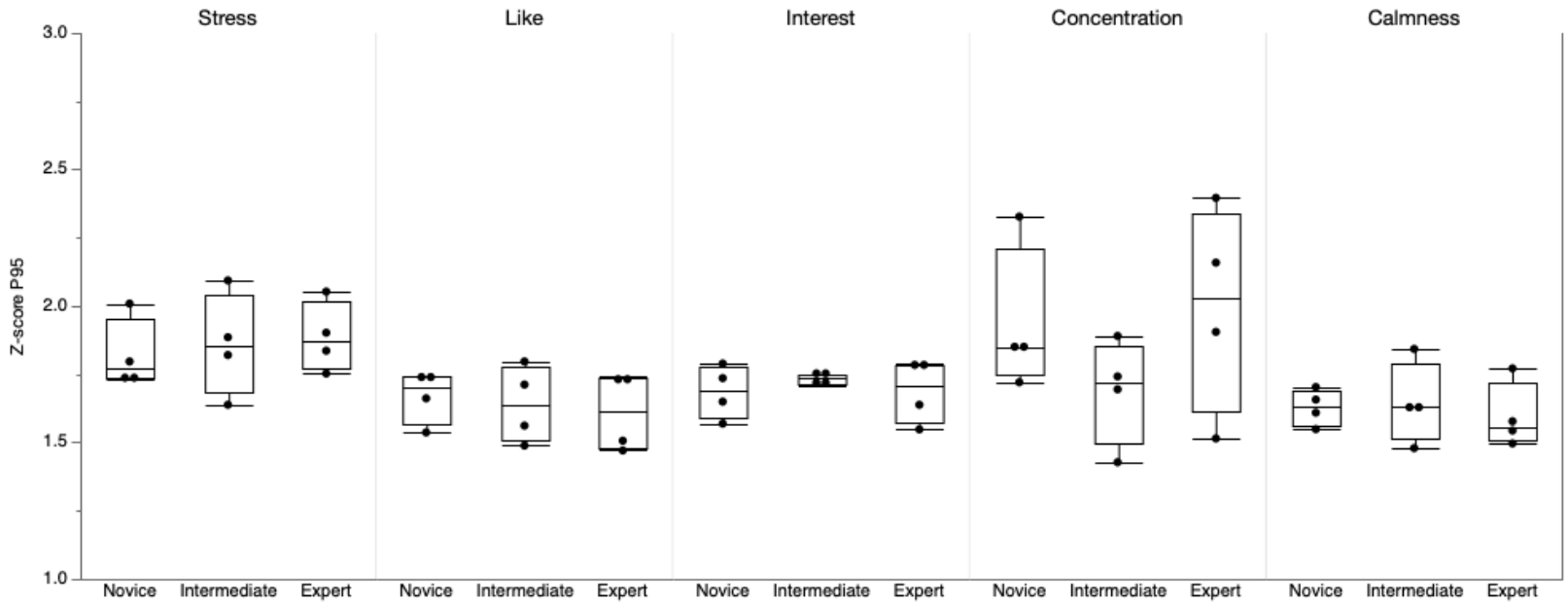

HUAWEI
COMPARISON
比較
20220202_152250_g
ESTIMATION RESULT
EXPRESSION
INTEREST
LIKE
CONCENTRATION
集中度
STRESS
ストレス度
CALMNESS
60sec
30sec
TIME
22
sec

2a



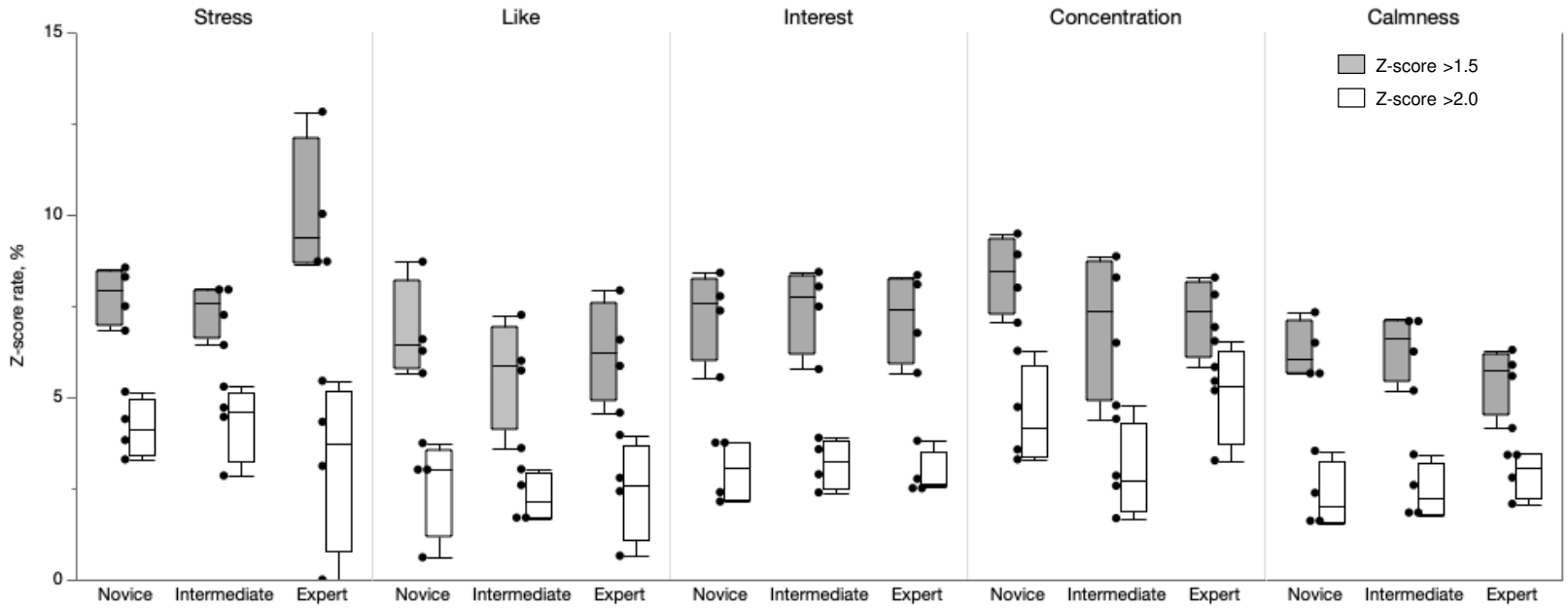
	Novice n = 4	Intermediate n = 4	Expert n = 4
Stress	53.8 (50.4–62.0)	51.5 (41.2–55.4)	58.0 (52.5–66.5)
Like	57.0 (53.8–58.8)	49.0 (45.0–56.8)	59.0 (57.2–62.2)
Interest	51.0 (49.0–53.8)	55.0 (52.1–59.8)	52.5 (48.0–54.8)
Concentration	25.5 (11.8–31.8)	25.0 (21.2–37.0)	25.5 (13.0–35.8)
Calmness	27.0 (26.2–29.2)	26.5 (24.5–29.2)	28.5 (27.2–31.2)

2b



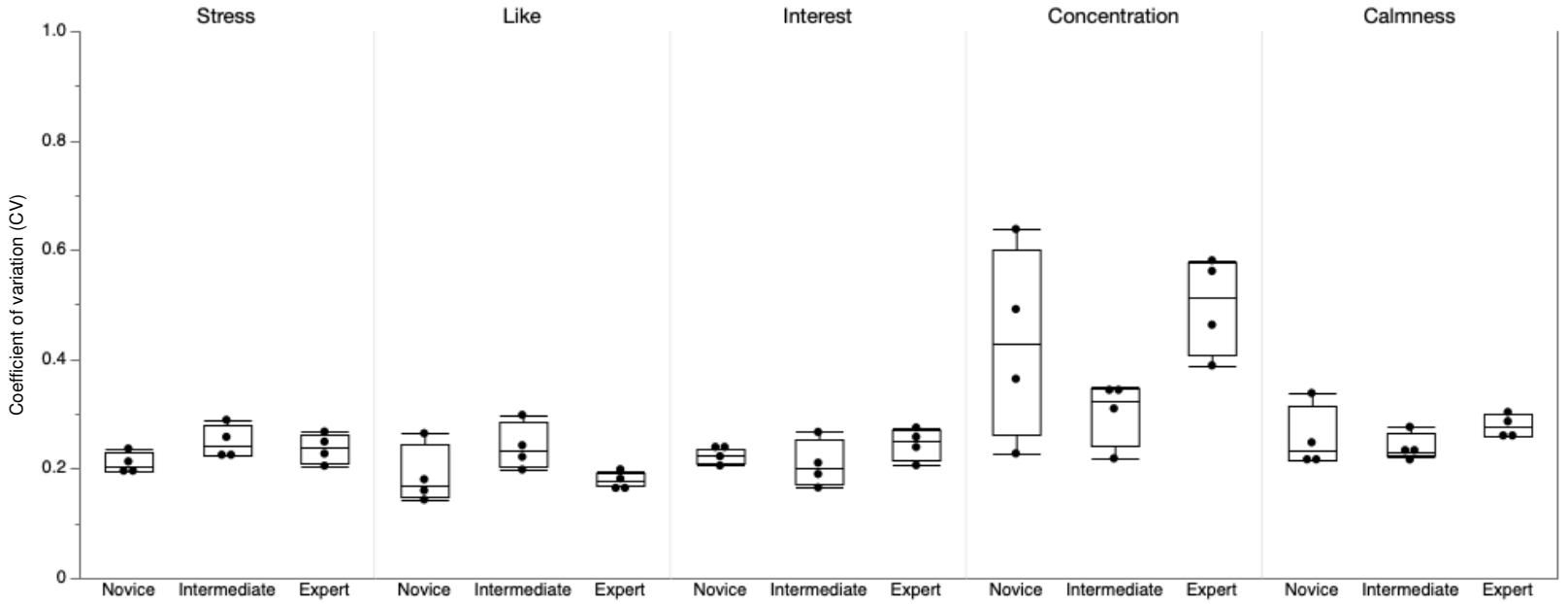
	Novice n = 4	Intermediate n = 4	Expert n = 4
Stress	1.8 (1.7–2.0)	1.9 (1.7–2.0)	1.9 (1.8–2.0)
Like	1.7 (1.6–1.7)	1.6 (1.5–1.8)	1.6 (1.5–1.7)
Interest	1.7 (1.6–1.8)	1.7 (1.7–1.8)	1.7 (1.6–1.8)
Concentration	1.9 (1.8–2.2)	1.7 (1.5–1.9)	2.0 (1.6–2.3)
Calmness	1.6 (1.6–1.7)	1.6 (1.5–1.8)	1.6 (1.5–1.7)

2c



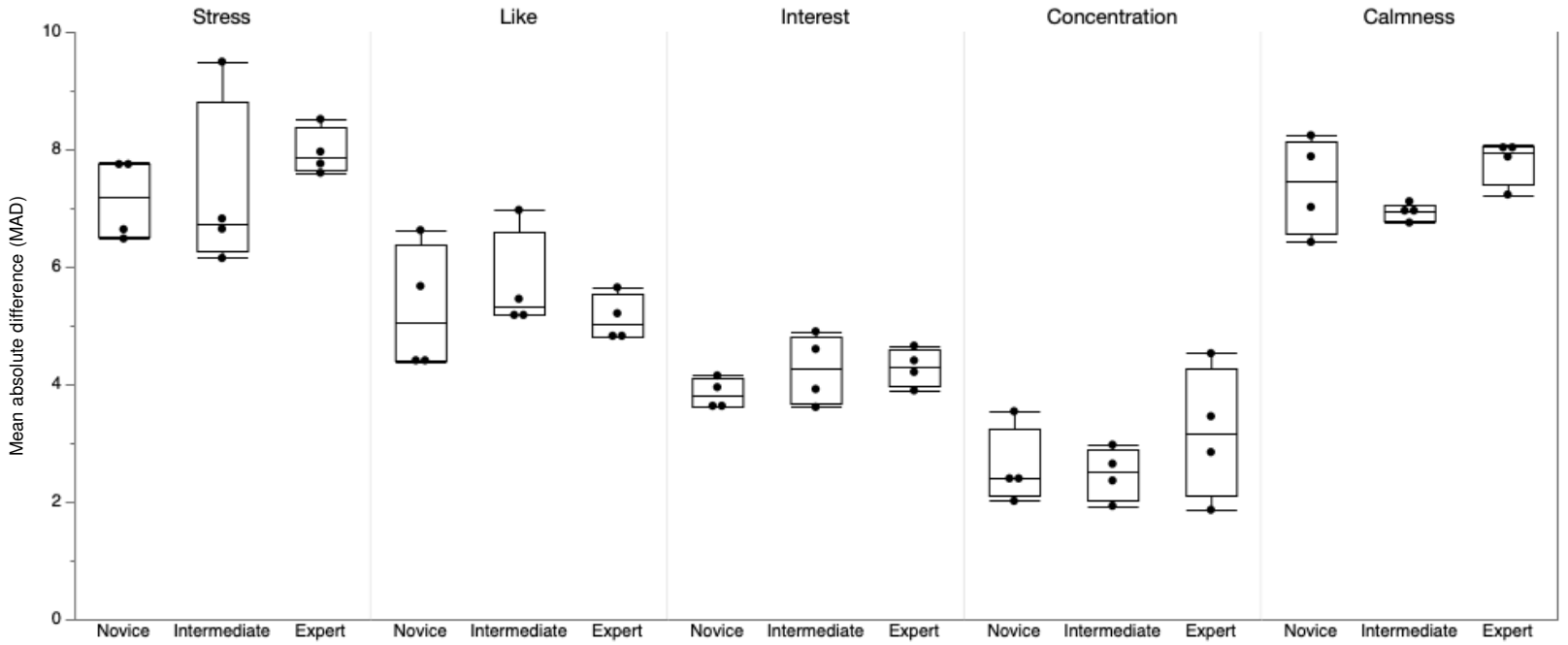
	Novice (n = 4)		Intermediate (n = 4)		Expert (n = 4)	
	Z-score > 1.5 rate, %	Z-score > 2.0 rate, %	Z-score > 1.5 rate, %	Z-score > 2.0 rate, %	Z-score > 1.5 rate, %	Z-score > 2.0 rate, %
Stress	7.93 (6.99–8.48)	4.11 (3.43–4.96)	7.59 (6.63–7.95)	4.59 (3.25–5.14)	9.4 (8.68–12.12)	3.72 (0.78–5.17)
Like	6.43 (5.81–8.18)	3.01 (1.2–3.57)	5.87 (4.14–6.94)	2.15 (1.69–2.92)	6.22 (4.9–7.59)	2.61 (1.1–3.67)
Interest	7.57 (6–8.25)	3.06 (2.2–3.76)	7.76 (6.2–8.33)	3.23 (2.51–3.81)	7.42 (5.94–8.25)	2.63 (2.58–3.52)
Concentration	8.46 (7.28–9.34)	4.15 (3.36–5.88)	7.39 (4.93–8.71)	2.71 (1.9–4.3)	7.37 (6.1–8.16)	5.31 (3.75–6.26)
Calmness	6.07 (5.65–7.12)	2.03 (1.58–3.24)	6.62 (5.45–7.12)	2.26 (1.79–3.22)	5.73 (4.51–6.19)	3.07 (2.26–3.45)

2d



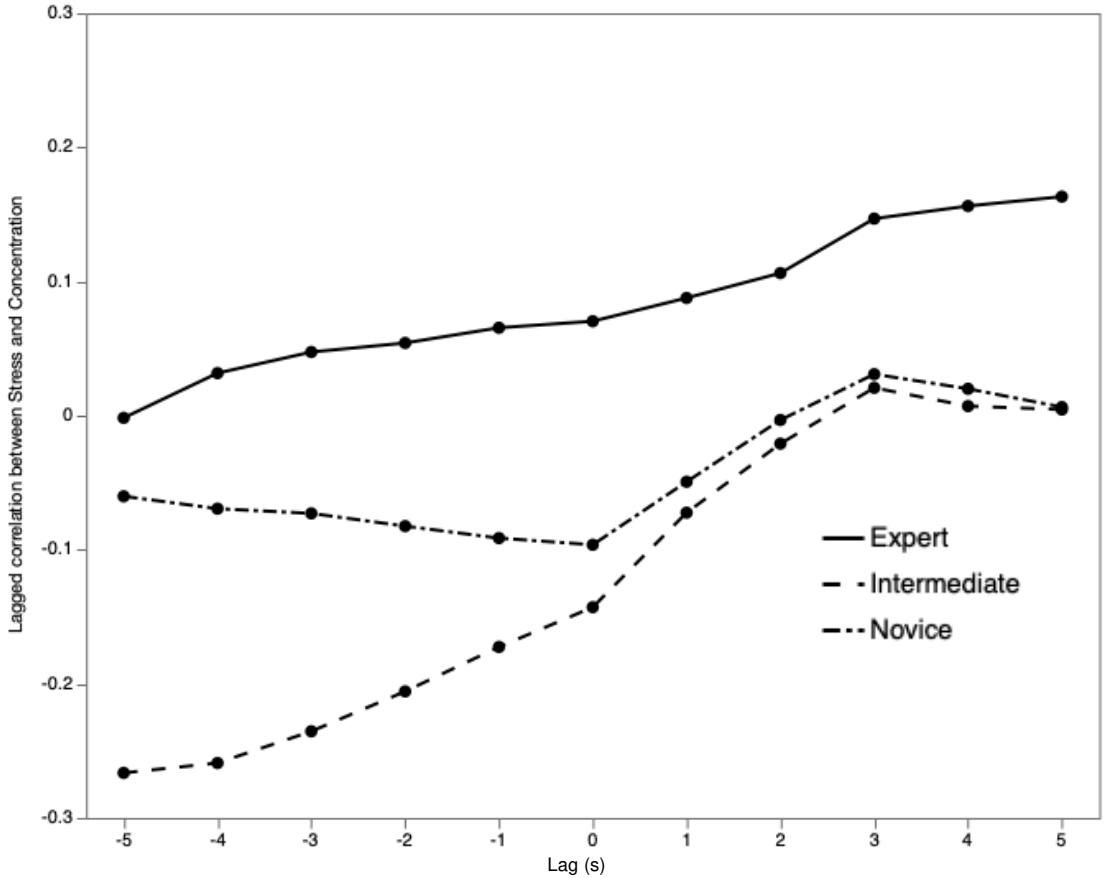
	Novice n = 4	Intermediate n = 4	Expert n = 4
Stress	0.2 (0.2–0.23)	0.24 (0.23–0.28)	0.24 (0.21–0.26)
Like	0.17 (0.15–0.24)	0.23 (0.2–0.28)	0.18 (0.17–0.19)
Interest	0.22 (0.21–0.24)	0.2 (0.17–0.25)	0.25 (0.21–0.27)
Concentration	0.43 (0.26–0.6)	0.32 (0.24–0.35)	0.51 (0.41–0.58)
Calmness	0.23 (0.22–0.32)	0.23 (0.22–0.27)	0.28 (0.26–0.3)

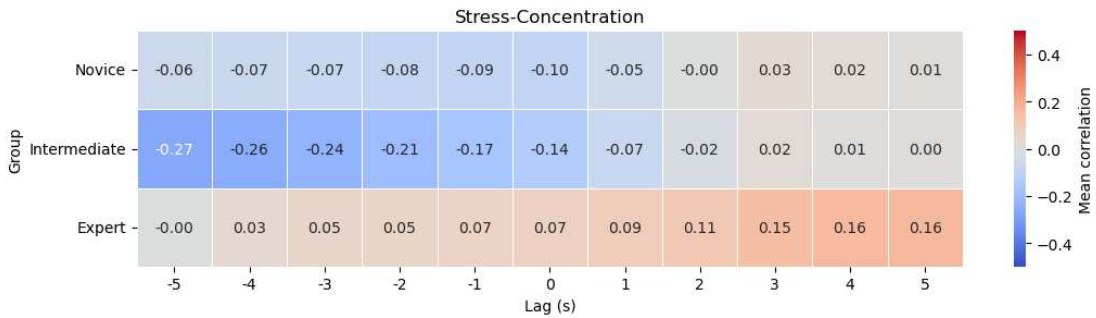
2e



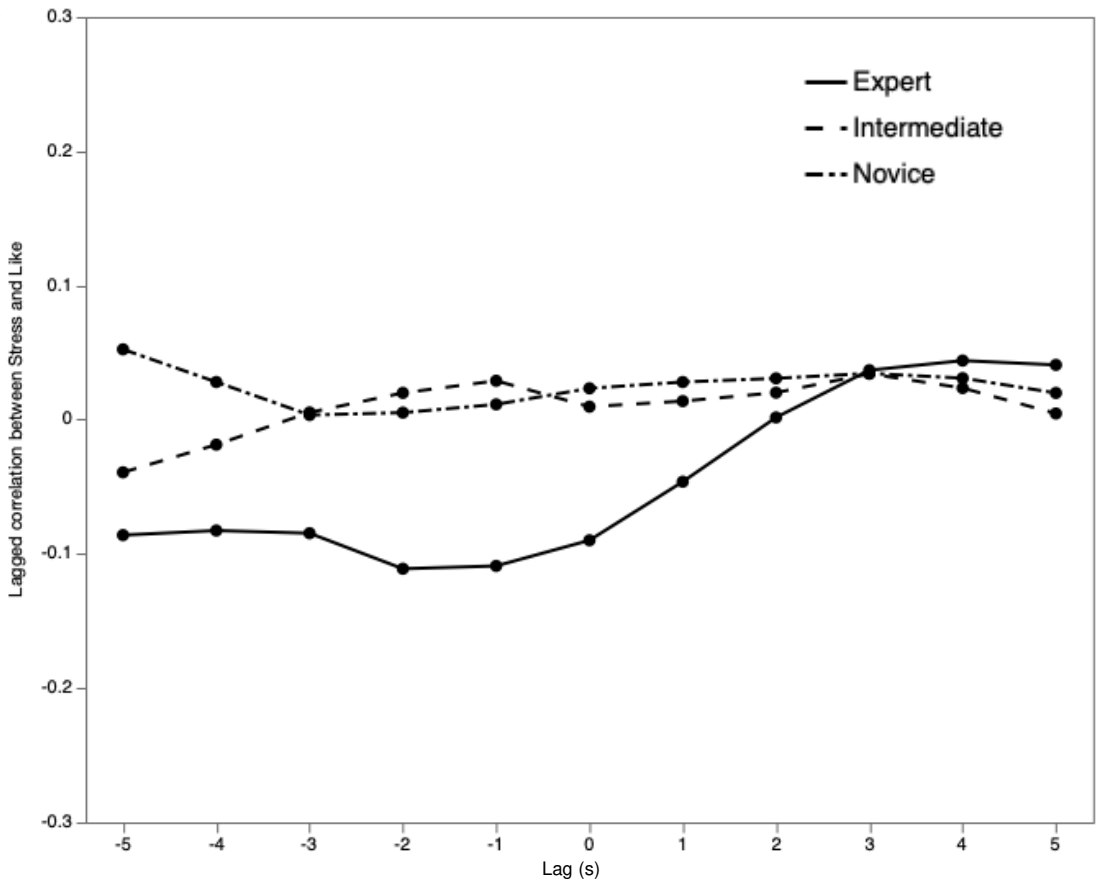
	Novice n = 4	Intermediate n = 4	Expert n = 4
Stress	7.2 (6.5–7.8)	6.7 (6.3–8.8)	7.9 (7.6–8.4)
Like	5.1 (4.4–6.4)	5.3 (5.2–6.6)	5.0 (4.8–5.5)
Interest	3.8 (3.6–4.1)	4.3 (3.7–4.8)	4.3 (4.0–4.6)
Concentration	2.4 (2.1–3.3)	2.5 (2.0–2.9)	3.2 (2.1–4.3)
Calmness	7.4 (6.6–8.1)	7.0 (6.8–7.1)	7.9 (7.4–8.1)

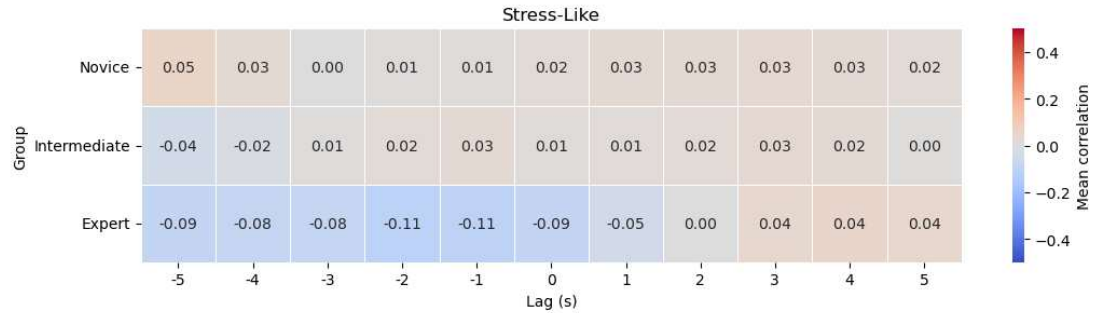
3a


Lagged correlation between Stress and Concentration
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5
-4
-3
-2
-1
0
1
2
3
4
5
Lag (s)
Expert
Intermediate
Novice

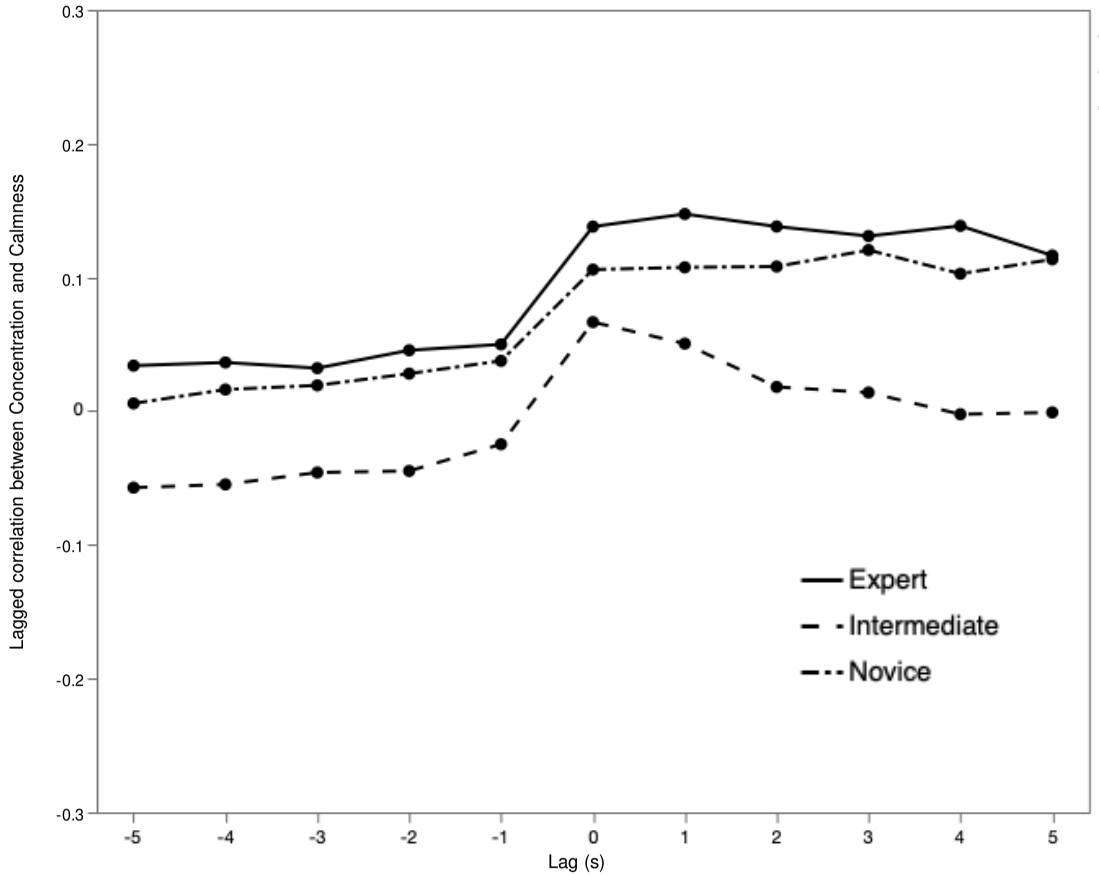

Stress-Concentration
Group
Novice
Intermediate
Expert
-0.06 -0.07 -0.07 -0.08 -0.09 -0.10 -0.05 -0.00 0.03 0.02 0.01
-0.27 -0.26 -0.24 -0.21 -0.17 -0.14 -0.07 -0.02 0.02 0.01 0.00
-0.00 0.03 0.05 0.05 0.07 0.07 0.09 0.11 0.15 0.16 0.16
-5 -4 -3 -2 -1 0 1 2 3 4 5
Lag (s)
Mean correlation
0.4
0.2
0.0
−0.2
−0.4

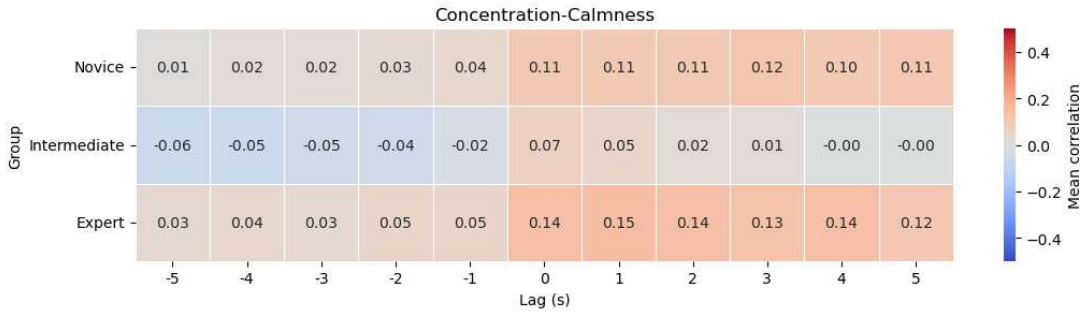
3b


Expert
Intermediate
Novice
Lagged correlation between Stress and Like
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5
-4
-3
-2
-1
0
1
2
3
4
5
Lag (s)


Stress-Like
Novice
Intermediate
Expert
Group
0.05 0.03 0.00 0.01 0.01 0.02 0.03 0.03 0.03 0.03 0.02
-0.04 -0.02 0.01 0.02 0.03 0.01 0.01 0.02 0.03 0.02 0.00
-0.09 -0.08 -0.08 -0.11 -0.11 -0.09 -0.05 0.00 0.04 0.04 0.04
-5 -4 -3 -2 -1 0 1 2 3 4 5
Lag (s)
0.4
0.2
0.0
−0.2
−0.4
Mean correlation

3c


Lagged correlation between Concentration and Calmness
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-5
-4
-3
-2
-1
0
1
2
3
4
5
Lag (s)
Expert
Intermediate
Novice


Concentration-Calmness
Group
Novice
Intermediate
Expert
0.01 0.02 0.02 0.03 0.04 0.11 0.11 0.11 0.12 0.10 0.11
-0.06 -0.05 -0.05 -0.04 -0.02 0.07 0.05 0.02 0.01 -0.00 -0.00
0.03 0.04 0.03 0.05 0.05 0.14 0.15 0.14 0.13 0.14 0.12
-5 -4 -3 -2 -1 0 1 2 3 4 5
Lag (s)
Mean correlation
0.4
0.2
0.0
−0.2
−0.4

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- OnlineResource2.docx
- OnlineResource3.pptx