When Wearables Distort Time: Unintended Effects of Haptic Heartbeat Biofeedback on Temporal Cognition and Motor Performance

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Wearable haptic heartbeat biofeedback is increasingly deployed in research systems for stress regulation and cognitive enhancement, yet designers lack guidance on how feedback frequency affects users' temporal cognition and motor performance, two processes that shape user experience in time-sensitive interactive systems. We present a study examining how a wearable haptic device delivering heartbeat feedback at 50 BPM and 100 BPM influences time estimation and reaction time. Slower feedback leads to time *underestimation*, while faster feedback causes *overestimation* and *decreased* heart rate variability. Both frequencies improved reaction times. Rhythmic feedback may also reduce natural cardiac-phase effects on motor performance, though we report this as preliminary. We evaluate these findings against three explanatory frameworks (interoceptive illusions, physiological modulation, and neural entrainment) to derive design knowledge for wearable haptic systems, establishing feedback frequency as a key parameter for ubiquitous applications sensitive to temporal perception and motor readiness.

CCS Concepts: • **Human-centered computing** → **Haptic devices**; *Empirical studies in HCI*.

Additional Key Words and Phrases: Physiological computing, haptic, biofeedback, interception, interoceptive illusion, heartbeat, false feedback

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1 Introduction

Wearable haptic biofeedback systems are becoming a cornerstone of ubiquitous computing, deployed across application domains including stress management [1, 9, 49, 85], cognitive performance enhancement [70, 75], health monitoring [3, 60], and rehabilitation [82]. These systems convert physiological signals like heart rate [60, 70], skin conductance [24, 48], or breathing [3, 82] into rhythmic sensory feedback delivered through on-body actuators, improving self-regulation [12, 33, 54] and influencing bodily perception through artificial feedback the brain accepts as genuine [7, 45, 63], operating through non-conscious pathways that bypass explicit attentional demands [32]. Many of these deployments target contexts where temporal cognition and motor readiness shape user experience and safety, including driving [1, 39, 49], sustained attention tasks [75], public speaking [64], and time-pressured cognitive performance [10].

However, most wearable biofeedback designers overlook a critical side effect, that rhythmic haptic feedback distorts users' temporal processing [9, 14, 70]. This is a design gap, since interfaces delivering physiological

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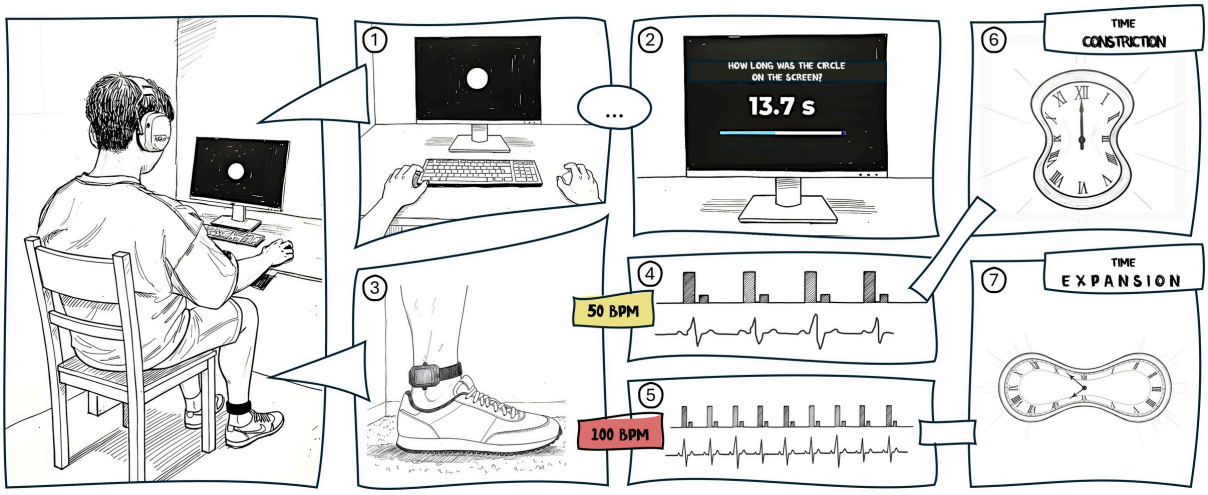


Fig. 1. Experiment 1 setup: participant observes (1) circle stimulus on screen, then (2) estimates its duration while wearing (3) ankle-mounted haptic device delivering heartbeat-like vibrations at (4) 50 BPM or (5) 100 BPM. Results show (6) slower rhythm produces time constriction (underestimation) while (7) faster rhythm causes time expansion (overestimation).

rhythms can alter perceived time and affect task performance and user experience. For example, slow heartbeat feedback for calm driving [1, 49] may compress a driver's sense of elapsed time and affect braking, while fast feedback for sustained attention [75] could expand perceived duration and alter pacing in time-critical tasks. These unintended consequences could enhance or undermine biofeedback interventions and may confound existing research, a pattern seen across haptic modalities where passive interventions produce subjective-physiological dissociations that go undetected without instrumentation [84]. Prior research identifies three mechanisms that may explain these effects: *(1) interoceptive illusions:* external stimuli creating false perceptions of internal states, *(2) physiological modulation:* changes in bodily functions, and *(3) neural entrainment:* synchronization of brain oscillations with external rhythms. Yet previous studies consider these mechanisms in isolation, leaving designers without clear guidance on how feedback frequency affects temporal cognition and motor performance.

This paper studies how a wearable haptic heartbeat device delivering feedback at two frequencies (50 and 100 BPM) influences time estimation and reaction time. We also examine whether synchronization between the artificial rhythm and the user's cardiac cycle modulates these effects. Rather than testing each framework in isolation, we evaluate all three within the same participants by identifying conditions where their predictions diverge, with interoceptive illusions predicting frequency-specific effects without physiological change, physiological modulation predicting coupled behavioral and autonomic shifts, and neural entrainment predicting rhythm-regularity benefits independent of frequency. By measuring behavioral outcomes (time estimation, reaction time) alongside physiological responses (heart rate, HRV), we identify which mechanism best accounts for each effect and derive design knowledge for wearable haptic systems.

Our results show that wearable haptic feedback frequency shifts time perception in both directions, consistent with interoceptive illusion accounts. 50 BPM feedback led to systematic underestimation of time intervals without accompanying physiological changes, consistent with a primarily perceptual account, while 100 BPM feedback produced overestimation alongside decreased heart rate variability, consistent with convergent interoceptive and physiological modulation. Both frequencies improved reaction times compared to no feedback, a frequency-independent benefit consistent with neural entrainment rather than arousal-based accounts. Rhythmic wearable

feedback might also reduce the natural cardiac phase constraint on reaction time, where responses tend to be slower during systole, though this pattern was not robust and we treat it as preliminary.

Our main contribution is cautionary. Wearable haptic heartbeat feedback, now widely deployed for stress regulation and performance support, can unintentionally distort users' sense of time and shift their motor readiness, so designers should anticipate and evaluate these side effects rather than assume the signal is neutral. Feedback frequency is the primary lever, and the motor-timing effects are preliminary. Our contributions are: (1) empirical design knowledge on how feedback frequency bidirectionally shifts time perception and enhances reaction time, evaluated against three frameworks (interoceptive illusions, physiological modulation, and neural entrainment) to identify which mechanisms inform design; (2) a preliminary observation we call *cardiac-phase attenuation*, where rhythmic feedback may reduce the natural cardiac-cognitive constraint on motor performance; and (3) design implications establishing feedback frequency as a key parameter for ubiquitous applications sensitive to temporal cognition and motor readiness. Table 1 lists each finding's novelty and level of evidence.

2 Background

Wearable haptic heartbeat biofeedback can influence temporal processing through three mechanisms, **interoceptive illusions** [11], **physiological modulation** [10, 70], and **neural entrainment** [65], which shape users' perception of elapsed time and coordination of motor responses [16, 23, 42]. Understanding these effects requires distinguishing the cognitive and motor components of timing [40]. The Wing-Kristofferson model [77, 78] separates a central timekeeper that generates internal representations of intervals, with variability increasing proportionally to duration [76], from a motor component that executes movements based on that timing. This distinction is critical for wearable designers because feedback that benefits one component may disrupt the other. Temporal processing is understood as:

Temporal Estimation. This is the brain's ability to perceive and judge durations [35]. The Wing-Kristofferson model attributes it to the central timekeeper, which tracks time through accumulated pulses, continuously monitoring elapsed time and forming an internal representation of duration even when external stimuli are unpredictable. Distortions here, whether from wearable biofeedback or internal factors, can cause overestimation (premature responses) or underestimation (delayed reactions) [36, 61].

Temporal Anticipation. This involves predicting and preparing for future stimuli or actions [30, 44]. Unlike estimation, it spans both the central timekeeper and motor implementation in the Wing-Kristofferson model [77, 78]. Even when stimulus timing is unpredictable, the brain dynamically modulates attentional and motor readiness [56], maintaining preparedness that balances speed and accuracy. Distortions in anticipation can lead to mistimed responses where inaccurate expectations cause premature or delayed actions [30].

Temporal Estimation versus Anticipation. The key difference is directional. Estimation evaluates past or current durations, while anticipation is prospective and action oriented. Wearable designers who fail to distinguish these processes risk creating devices that work against human cognitive architecture. In competitive archery training, slow feedback might help archers perceive shorter aiming periods, which correlates with higher performance [6]. However, it could disrupt the precise anticipatory timing needed for shot release, causing execution to drift relative to breathing cycles and target prediction. The consequences extend beyond inefficiency to wearable interfaces that create conflicts between the central timekeeper and motor components, impairing performance when timing precision matters most.

3 Related Work

Having established the theoretical foundations of temporal processing in Section 2, we now review how wearable rhythmic biofeedback systems influence temporal cognition through three mechanisms that prior work usually

studies in isolation, leaving designers without a clear sense of their relative contributions. A central question drives our work, *which of these mechanisms, or what combination of them, best accounts for the effects of wearable rhythmic biofeedback on temporal processing?* For each mechanism we present formal hypotheses in grey boxes that articulate testable predictions, establishing a structured approach to derive design-relevant knowledge.

3.1 Is it Interoception?

Interoception, the perception of internal bodily signals such as heartbeat or breathing, significantly affects temporal processing. Droit et al. [16] show that perceived arousal influences subjective time, with higher arousal typically making time feel slower and lower arousal producing the opposite effect [62].

3.1.1 Effect of Rhythms on Interoception. Several studies show how wearable biofeedback creates interoceptive illusions affecting perception and performance. External rhythms that mimic physiological patterns can distort perception of internal bodily signals [9, 14, 70, 71] and alter time perception. Costa et al. [9] showed this with "EmotionCheck", a wrist-worn vibrotactile system delivering slow heartbeat vibrations during simulated interviews, which reduced self-reported anxiety despite unchanged heart activity. Their "BoostMeUp" system [10] showed slow-rhythm feedback decreased anxiety and affected math test performance. Iodice et al. [31] used false heartbeat acoustic feedback during cycling, where faster feedback increased perceived effort.

These interoceptive illusion systems have largely overlooked effects beyond emotional regulation. While BoostMeUp confirmed that interoceptive illusions can alter self-perceived anxiety, feedback frequency also unexpectedly affected task accuracy and response time. Slow feedback improved accuracy, while higher frequency feedback increased speed. Without a no-feedback control condition, the authors could not determine whether these effects stemmed from interoceptive illusions or from neural entrainment triggered by rhythmic stimulation. Users tend to accept system interpretations of physiological signals as revealing genuine internal states, sometimes overriding their own subjective experience in favor of system outputs [28, 32], suggesting that the brain's acceptance of artificial feedback as genuine extends beyond the laboratory stimuli studied in interoceptive illusion research. This matters for HCI because wearable biofeedback systems are interactive technologies that can shape not only how users feel, but also how they time actions, respond to stimuli, and perform tasks while relying on the system. More broadly, the wearable biofeedback literature lacks frameworks to explain how haptic feedback shapes temporal processing beyond emotional regulation.

H1: Interoception Framework

If biofeedback affects temporal processing primarily through perceived arousal changes (interoceptive illusions) rather than actual physiological modulation, we would expect:

- **H1.a** Faster feedback (100 BPM) to be associated with overestimation, consistent with perceived high arousal.
- **H1.b** Slower feedback (50 BPM) to be associated with underestimation, consistent with perceived low arousal.
- **H1.c** Faster feedback to be associated with decreased reaction times, consistent with perceived higher arousal.
- **H1.d** Slower feedback to be associated with increased reaction times, consistent with perceived lower arousal.

3.2 Is it Physiological Modulation?

Physiological modulation is the process by which external stimuli directly influence bodily states. In wearable biofeedback, rhythmic stimulation can cause measurable changes in parameters such as heart rate and heart rate variability (HRV). It connects to temporal processing through autonomic mechanisms [8], where higher arousal often causes time overestimation and restorative states underestimation [51]. Cardiac phase also shapes timing precision and motor responses, as McIntyre et al. [41] found that during systole increased baroreceptor activity suppresses neural processing while diastole enhances sensitivity, and Pfeifer et al. [50] showed feedback during systole enhanced the emotional impact of fearful faces. Heart rate fluctuations also influence motor actions, with higher HRV linked to better time anticipation [46].

3.2.1 Effects of Rhythms on Physiological Modulation. Wearable rhythmic feedback can induce physiological changes that affect temporal processing. Zhou et al. [85] found that haptic heartbeat feedback increased HRV and reduced heart rate in relaxed states, effects absent with auditory feedback, suggesting tactile stimulation has privileged access to autonomic regulation. Dey et al. [13] showed that manipulated heart rate feedback, increased by 20%, affected participants' actual physiological responses, and Valente et al. [70] observed that high-frequency haptic heartbeat feedback increased heart rate, decreased HRV, and reduced answer time. The "MoodWings" wearable [39], a butterfly device mirroring real-time stress through wing movements, unexpectedly increased physiological stress yet improved driving performance and safety behaviors.

A critical limitation persists in understanding the directionality of these relationships. "MoodWings" showed improved driving performance despite increased stress, while Valente et al. observed decreased response times with high-frequency feedback, yet neither disentangled whether physiological changes cause alterations in time perception or vice versa. By isolating the two fundamental components of temporal processing (estimation and anticipation), our work aims to start disentangling these relationships for wearable design.

H2: Physiological Modulation Framework

If biofeedback affects temporal processing through measurable physiological change, we would expect:

- **H2.a** Faster feedback (100 BPM) to produce both increased physiological arousal (elevated HR, reduced HRV) and temporal overestimation, consistent with established links between sympathetic activation and internal pacemaker acceleration.
- **H2.b** Slower feedback (50 BPM) to produce reduced arousal (decreased HR, increased HRV) and temporal underestimation, consistent with restorative states decelerating the internal clock.
- **H2.c** Faster feedback to produce both increased physiological arousal and decreased reaction times, consistent with heightened sympathetic activation facilitating motor readiness.
- **H2.d** Slower feedback to produce both relaxation (decreased HR, increased HRV) and increased reaction times, consistent with parasympathetic dominance slowing motor preparation.

3.3 Is it Neural Entrainment?

Neural entrainment occurs when brain oscillations synchronize with external rhythmic stimuli [66], aligning neural activity with environmental patterns. External rhythms shape temporal abilities, affecting sensory perception and cognitive tasks [17, 26, 34, 67]. Aligning brain oscillations with consistent rhythms enhances neural representation within temporal intervals, improving time estimation [29, 59] and creating expectations about future event timing that result in faster reaction times and better motor preparation [23, 58].

3.3.1 Effects of Rhythms on Neural Entrainment. External rhythmic feedback creates neural entrainment that affects perception and performance across sensory modalities [59], including touch, where vibrations alter brain activity [73]. Zhang et al. [83] showed that 15 Hz skin vibrations enhance movement-related brain rhythms and improve attention. Hashimoto and Yotsumoto [25] found flickering visual stimuli caused systematic time overestimation consistent with neural entrainment, and Pranjić et al. [53] showed rhythmic auditory cues establish predictive timing frameworks that enable movement anticipation.

Despite this potential, designers of wearable rhythmic biofeedback systems often overlook how their interventions affect timing perception. Whitmore et al. [75] present wearable rhythmic feedback for improved attention and propose ubiquitous applications but do not consider effects on temporal processing. For example, low-frequency rhythmic feedback in classrooms might improve student attention but compress subjective time, potentially creating negative learning effects [80]. This tradeoff between attentional benefits and temporal distortion lacks empirical foundation.

H3: Neural Entrainment Framework

If biofeedback affects temporal processing through neural entrainment (synchronization of brain activity with external rhythms), we would expect:

- **H3.a** Both 50 BPM and 100 BPM rhythmic feedback to show enhanced temporal estimation precision (lower CV) compared to baseline, regardless of frequency-specific effects on accuracy.
- **H3.b** Baseline (no rhythmic feedback) to show reduced temporal estimation precision (higher CV) compared to rhythmic conditions.
- **H3.c** Both 50 BPM and 100 BPM rhythmic feedback to show reduced reaction times compared to baseline, as rhythmic patterns provide temporal frameworks for motor preparation.
- **H3.d** Baseline (no rhythmic feedback) to show increased reaction times compared to rhythmic conditions due to absence of temporal cues.

3.4 Integrated Research Approach

Wearable heartbeat biofeedback [9, 10, 64, 70] uniquely intersects the three mechanisms modulating temporal processing reviewed above. Our study examines how this type of wearable feedback influences both temporal estimation and anticipation, distinct yet related processes within the Wing-Kristofferson model [78]. Our approach simultaneously tests predictions from all three mechanisms rather than examining them in isolation. We measure both behavioral outcomes (time estimation and reaction time) and physiological responses (heart rate and HRV) across different feedback frequencies (50 BPM and 100 BPM). This allows us to compare observed patterns against each framework's predictions and assess their relative explanatory power for informing wearable design.

We do not assume these mechanisms are mutually exclusive. They may operate simultaneously, with their relative contributions varying by task demands and feedback parameters, and our design tests conditions where the frameworks make divergent predictions. Understanding these frameworks and their interactions provides a foundation for wearable systems that strategically affect performance in time-sensitive ubiquitous applications.

4 User Study: Time Estimation and Reaction Time

We examined how a wearable haptic heartbeat device delivering feedback at different frequencies affects temporal perception and motor performance. The study comprised **two experiments** with the same participants, a *time estimation task* and a *No-Go reaction time task*, counterbalanced with a Balanced Latin Square.

4.1 Wearable Haptic System

We built a wearable system that delivers rhythmic haptic heartbeat feedback while measuring users' cardiac responses. The haptic device used an Eccentric Rotating Mass (ERM) motor in a small 3D-printed enclosure, driven to produce a "lub-dub" heartbeat cadence at the specified BPM; the device components and the lub-dub timing formula are reported in Appendix A. Heart rate was captured using a BITalino board with three ECG electrodes in a lead-II configuration, sampled at 1000Hz, with game events synchronized to the physiological recording. The wearable haptic device was secured to the inside of the participant's ankle using a velcro strap, following Valente et al. [70], who compared chest, wrist, neck, and ankle placements and found that the ankle produced measurable physiological effects while resulting in lower reported awareness than other locations, a property that reduces conscious attention to the feedback and better isolates unintended perceptual consequences. All cardiac-haptic synchronization analyses used latency-corrected haptic timing; the motor's activation latency (mean 119.8 ms) and its measurement are reported in Appendix A.

4.2 Participants and Procedure

We recruited 24 participants (11 identified as women, 13 as men), between 20 and 50 years of age (M = 30.1, SD = 6.7). A post-hoc power analysis using the observed effect size for the primary reaction time outcome ($F(2, 46) = 5.642$, partial $\eta^2 = 0.197$, $f = 0.495$) indicated a minimum required sample of 9 participants for a one-way repeated measures ANOVA ($\alpha = .05$, power = .80, $r = .50$), confirming our sample of 24 is well-powered for primary outcomes. All participants confirmed having no cardiac problems. Participants volunteered for the study without compensation and were informed they would complete two experiments while wearing our haptic device. This study was approved by the University of Auckland Human Participants Ethics Committee (UAHPEC, reference UAHPEC26829). All participants gave informed consent before taking part.

We calibrated vibration intensity following prior work [70], setting amplitude halfway between each participant's perception and discomfort thresholds. After calibration, all participants reported interpreting the vibration as a heartbeat sensation when prompted, though we did not specify whether it corresponded to their actual heartbeat. More generally, we did not tell participants whether the vibration was a heartbeat, genuine biofeedback, or linked to their own cardiac activity. We left this ambiguous and used no deception, never stating that the feedback reflected their own heart, so any interoceptive illusion arises from the signal itself rather than an induced belief. Participants self-placed three electrodes using a provided lead-II diagram.

4.3 Experiment #1: Time Estimation

Participants completed a time perception task where they estimated how long a visual stimulus (a white circle against a black background) was presented while wearing the haptic device at two different feedback frequencies (Figure 1). This visual stimulus was based on Droit et al. [15], with the intention of minimizing perceptual processing demands. By employing a visual stimulus rather than a simple counting task, we aimed to reduce participants' direct focus on the haptic feedback, minimizing self-focus and interoceptive attention that could confound our results. After the circle disappeared, participants reported their estimate using an on-screen slider ranging from 0 to 30 seconds, with a precision of 0.1 seconds, allowing unconstrained adjustment before confirming their response (illustrated in Figure 1). Before the first trial of each condition block, participants received 10 seconds of continuous haptic feedback, the minimum epoch duration for assessing neural entrainment

[68]. This feedback continued uninterrupted throughout all trials within that condition. The ECG recording began on this initial pre-exposure period and continued throughout the block. We chose duration estimation over temporal comparison tasks because it isolates temporal accumulation processes without working memory confounds, allowing us to examine how wearable rhythmic feedback impacts continuous time perception in a naturalistic attention-sharing context.

4.3.1 Experimental Design. This experiment included three conditions. These were baseline with no haptic feedback, low frequency feedback at 50 BPM, and high frequency feedback at 100 BPM. We selected 50 BPM and 100 BPM based on prior work [9, 10, 70] and because they approximate the lower and upper bounds of typical resting heart rates. This supports interoceptive interpretation as slow and fast heartbeats. The 2 to 1 frequency ratio also helps control potential beat counting effects. At 50 BPM, beats occur every 1.2 seconds and are easy to distinguish, while at 100 BPM beats are more likely to be perceptually grouped in pairs. If participants used beat counting as a timing strategy, they could count individual beats at 50 BPM or beat pairs at 100 BPM, which could keep counting rates similar across conditions.

The wearable haptic device was attached to the participant's ankle throughout all conditions, including baseline. Nine different durations were used (0.5, 2, 3, 7, 10, 12, 14, 20, and 25 seconds), each presented twice per condition, following the protocol by Pollatos et al. [52]. Condition order was counterbalanced using a Latin square design, and durations within each condition were randomized. Participants completed training trials of 5, 8, and 2 seconds for each condition before the main task. Between conditions, participants rested for two minutes to ensure physiological measures returned to baseline. The complete experiment lasted approximately 14 minutes (57 trials: 3 training + nine durations × two × three conditions).

4.3.2 Metrics. We calculated the following time-estimation metrics:

- **Accuracy Index (AI)**: The ratio between estimated and actual duration

$$AI = \frac{\text{Estimated Duration}}{\text{Actual Duration}} \tag{1}$$

- **Absolute Error (AE)**: The absolute difference between estimated and actual duration

$$AE = |\text{Estimated Duration} - \text{Actual Duration}| \tag{2}$$

- **Constant Error (CE)**: The signed difference between estimated and actual duration, indicating directional bias

$$CE = \text{Estimated Duration} - \text{Actual Duration} \tag{3}$$

- **Coefficient of Variation (CV)**: A normalized measure of estimate variability that enables comparison across different time scales

$$CV = \frac{\text{Standard Deviation of Estimates}}{\text{Mean of Estimates}} \tag{4}$$

The Accuracy Index (AI) is relative, where 1 indicates perfect estimation, above 1 *overestimation*, and below 1 *underestimation*. Constant Error (CE) captures the direction and magnitude of bias, and Absolute Error (AE) its magnitude regardless of direction. The Coefficient of Variation (CV) measures timing consistency relative to the mean, normalizing for variability at longer durations. We computed CV per participant and condition, separately for each duration and averaged across durations, preserving the scalar property of temporal variability.

4.4 Experiment #2: No-Go Reaction Time

The reaction time experiment employed a No-Go task [18] to assess participants' response inhibition and reaction time while wearing the haptic device. The No-Go paradigm requires participants to maintain sustained attention

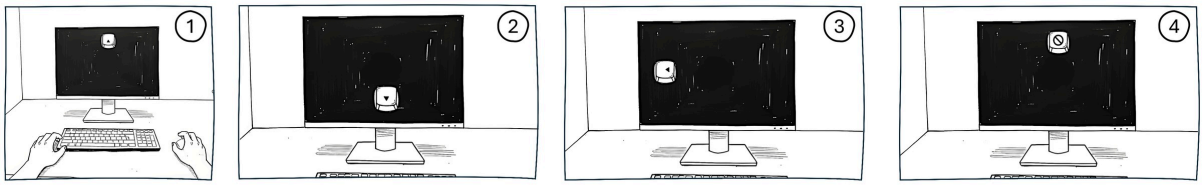


Fig. 2. No-Go task setup and stimulus examples. (1) Participant setup at the monitor, (2) a 'Go' trial with a downward arrow (↓), (3) a 'Go' trial with a leftward arrow (←), and (4) a 'No-Go' trial requiring response inhibition.

while occasionally inhibiting prepared motor responses, providing a more comprehensive assessment of cognitive control compared to simple reaction time tasks [43].

The task presented participants with arrow symbols (←, →, ↑, ↓) arranged in a keyboard-like configuration on the screen, as seen in Figure 2. Each stimulus appeared for 200ms, with inter-stimulus intervals randomly varying between 700ms and 4000ms. In 80% of trials ("Go" trials), participants pressed the corresponding arrow key. The remaining 20% were "No-Go" trials, where a circle-backslash symbol appeared over one of the arrows, requiring response inhibition. The system provided no feedback for correct or incorrect responses to mitigate physiological reactions to performance. Before each block, participants received 10 seconds of continuous haptic feedback [68], which continued uninterrupted throughout all 45 stimuli. The ECG recording began with this pre-exposure period and continued throughout the block.

4.4.1 Experimental Design. The experiment followed three conditions: baseline (no haptic feedback), high-frequency feedback (100 BPM), and low-frequency feedback (50 BPM). Each condition was performed twice, resulting in six experimental blocks counterbalanced using a Latin square design. Each block consisted of 45 stimuli, of which nine were No-Go trials. Participants completed three training blocks of five stimuli each before the main task. A two-minute rest period between blocks ensured physiological measures returned to baseline. The complete experiment lasted approximately 24 minutes (9 blocks: 3 training + 2 × three conditions).

4.4.2 Metrics. We calculated the following reaction-time metrics:

- **Mean Reaction Time (RT)**: on correct Go trials, the time in milliseconds between stimulus onset and the participant pressing the corresponding key
- **Commission Error Rate (CER)**: commission errors (false alarms) occur when participants incorrectly respond during No-Go trials, indicating failures of response inhibition

$$\text{CER} = \frac{\text{Incorrect Responses to No-Go Trials}}{\text{Total No-Go Trials}} \times 100 \tag{5}$$

- **Omission Error Rate (OER)**: omission errors (misses) occur when participants fail to respond during Go trials, potentially indicating attention lapses or an overcautious response strategy

$$\text{OER} = \frac{\text{Missed Responses to Go Trials}}{\text{Total Go Trials}} \times 100 \tag{6}$$

4.5 Heart Activity Metrics

In both experiments, we recorded electrocardiogram (ECG) to analyze heart rate variation across feedback conditions. We processed ECG using NeuroKit 2.0[1]. To reduce motion artifacts and noise, we applied a third order Butterworth band pass filter from 2 to 45 Hz [5]. We detected QRS complexes using the Pan Tompkins

[1]NeuroKit 2.0: https://neuropsychology.github.io/NeuroKit/

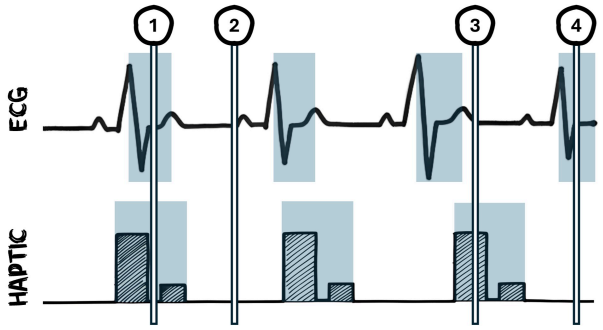


Fig. 3. The blue-shaded regions mark ventricular systole in the cardiac (top) and haptic (bottom) signals. Reaction time is measured when (1) cardiac (ECG) and haptic signals are both in systole, (2) both are in diastole, (3) the heart is in diastole while haptic stimulation is in systole, and (4) the heart is in systole while haptic stimulation is in diastole.

algorithm [47] and analyzed heart rate and Root Mean Square of Successive Differences (RMSSD) to examine links between wearable haptic feedback, physiological arousal, and task performance. RMSSD was computed over a 2-minute epoch drawn from the trial block duration, excluding the initial 10-second pre-exposure period, applied consistently across both experiments.

A fundamental design consideration for wearable biofeedback is whether feedback should be temporally synchronized with cardiac events. We assessed this by examining reaction time when ventricular systole detected via ECG coincides with tactile stimulation (hereafter "haptic systole"), illustrated in Figure 3.

Cardiac phase was determined on a per-beat basis using NeuroKit 2.0's ECG delineation algorithm. Systole was defined as the interval from each R-peak to the corresponding T-wave peak, with diastole spanning from T-wave peak to the subsequent R-peak. This approach produces heart-rate-adaptive windows that scale naturally with each participant's cardiac cycle. Haptic phase was defined using the latency-corrected timestamps: haptic systole spanned from the corrected lub onset through the dub beat (the first third of the haptic cycle, per Equation 1), with haptic diastole covering the remaining two-thirds. Reaction time events were assigned to the cardiac and haptic phase in which stimulus onset occurred. Trials where stimulus onset fell within 10.9 ms of a phase boundary were excluded from phase analyses to avoid ambiguous classification. The fixed latency correction of 119.8 ms introduces temporal jitter of ±10.9 ms (1 SD), which is negligible relative to typical cardiac cycle durations (600–1200 ms at resting heart rates).

5 Results

We present findings for the time estimation task (Figure 4) then the No-Go reaction time task (Figure 7). Each dependent variable addresses a distinct theoretical prediction from our framework, so corrections for multiple comparisons were applied within each analysis (Bonferroni-adjusted post hoc tests) rather than across the full set of dependent variables. We also separate confirmatory analyses, planned in advance, from exploratory ones. The condition effects on the time estimation measures, reaction time, and error rates are confirmatory. The cardiac phase, haptic phase, and synchrony analyses are exploratory, rest on small or incidental trial subsets, and are reported with participant and trial counts. Normality was assessed for each measure with the Shapiro-Wilk test, and the full normality and pairwise statistics appear in Appendix B. We used repeated measures ANOVA and paired t-tests where normality held and Friedman and Wilcoxon tests where it was violated.

Table 1. Summary of findings, their novelty relative to prior work, supported design implications, and level of evidence, developed in the Discussion.

Phenomenon tested	Prior work?	Our result	Design implication	Evidence
Feedback frequency				
Frequency → time-estimation direction	Partial [9, 70]	50 BPM underestimation, 100 BPM overestimation (24/24 and 22/24 participants)	Frequency sets the direction of perceived-time distortion	Confirmatory
Frequency → estimation accuracy	No	50 BPM raises absolute error; precision (CV) unchanged	Slow feedback carries an accuracy cost	Confirmatory
Frequency → heart rate and HRV	Yes [70]	100 BPM lowers HRV in pairwise tests (omnibus n.s.); HR effects small and task-dependent	Watch for possible reduced HRV at 100 BPM	Suggestive
Rhythmic feedback → reaction time	Yes [70, 75]	Both 50 and 100 BPM faster than baseline	Rhythmic feedback supports motor readiness	Confirmatory
Rhythmicity vs frequency for reaction time	No	50 and 100 BPM statistically equivalent (within 15 ms)	Within the range tested, either frequency aids reaction time; choose frequency for perception	Confirmatory
Heart-rate to feedback mismatch	No	No effect on reaction time or errors	Adapting feedback to the user's real-time heart rate may be unnecessary for these effects	Null
Cardiac and haptic timing				
Cardiac-phase attenuation	No (constraint known [41])	Systole slowdown appears reduced under feedback, not robust to modelling	Possible readiness lever, needs confirmation	Exploratory
Haptic-cardiac synchrony	No	Possible reaction-time gain at 100 BPM, sparse incidental trials	Motivates a study that manipulates synchrony	Preliminary
General contributions				
Integrated mechanism evaluation	Studied in isolation	Interoception, physiology, and entrainment compared jointly; dominant mechanism differs by task	Match feedback parameter to the target process	Framework
Physiological measurement	Often subjective only	HRV and phase effects are invisible to behaviour alone	Include cardiac monitoring in evaluation	Method

5.1 Experiment #1: Time Estimation

5.1.1 Accuracy Index (AI). A repeated measures ANOVA showed AI differed across conditions ($F(1.547, 35.575) = 44.045$, $p < .001$, partial $\eta^2 = .657$). AI was lower at 50 BPM than baseline (0.104, 95% CI 0.063 to 0.145, $p < .001$) and higher at 100 BPM than baseline (0.110, 95% CI 0.040 to 0.179, $p = .001$) and 50 BPM (0.214, 95% CI 0.151 to 0.276, $p < .001$). Feedback frequency thus biases temporal perception bidirectionally, with slower rhythms compressing subjective time and faster rhythms expanding it.

5.1.2 Absolute Error (AE). A repeated measures ANOVA showed mean AE differed across conditions ($F(1.200, 27.607) = 8.879$, $p = .004$, partial $\eta^2 = .278$). AE was higher at 50 BPM than baseline (0.512, 95% CI 0.104 to 0.921, $p = .011$) and than 100 BPM (0.919, 95% CI 0.159 to 1.679, $p = .014$), while baseline and 100 BPM did not differ (0.407, $p = .096$). Overall, slow rhythmic feedback at 50 BPM disrupted temporal processing more than fast feedback or no feedback, reducing estimation accuracy beyond directional bias.

5.1.3 Constant Error (CE). A repeated measures ANOVA determined that mean CE differed significantly between conditions ($F(2, 46) = 94.080$, $p < .001$, partial $\eta^2 = .804$). CE was significantly lower at 50 BPM than baseline (-1.037, 95% CI -1.369 to -0.705, $p < .001$) and than 100 BPM (-1.960, 95% CI -2.400 to -1.520, $p < .001$), and higher at 100 BPM than baseline (0.923, 95% CI 0.599 to 1.247, $p < .001$). These results indicate that the wearable haptic rhythm produces reliable directional biases of approximately 1 second magnitude, with 50 BPM consistently causing underestimation and 100 BPM consistently causing overestimation. This bias was consistent across individuals.

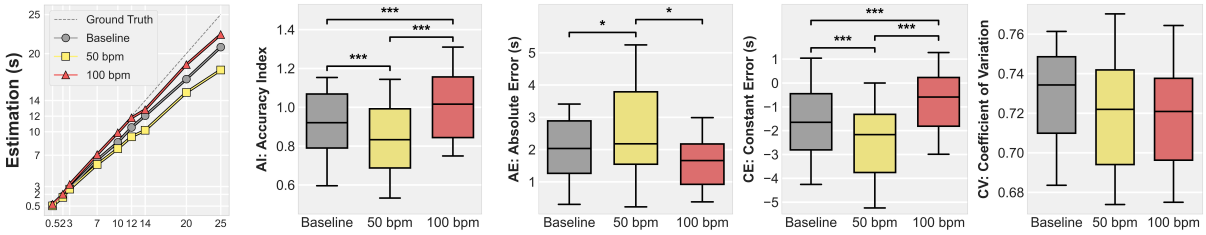


Fig. 4. Time estimation results across baseline, 50 BPM, and 100 BPM conditions showing, from left to right, estimated vs. actual duration, Accuracy Index, Absolute Error, Constant Error, and Coefficient of Variation (* p<.05, ** p<.01, *** p<.001).

All 24 participants showed lower Constant Error at 50 BPM than baseline (mean change -1.04 s, within-subject d = 1.65) and 22 of 24 showed higher Constant Error at 100 BPM (mean change 0.92 s, d = 1.50).

5.1.4 Coefficient of Variation (CV). A repeated measures ANOVA showed that mean CV did not differ significantly between conditions (F(2, 46) = 0.865, p = .428, partial η^2 = .036), with no significant pairwise differences across baseline (M = 0.728, SD = 0.035), 50 BPM (M = 0.719, SD = 0.038), and 100 BPM (M = 0.719, SD = 0.039). These results indicate that wearable rhythmic feedback influences temporal estimation accuracy without affecting timing precision, suggesting effects on the internal clock's calibration rather than its stability.

5.1.5 Heart Rate (HR). A Friedman test showed no significant HR differences between conditions ($\chi^2(2)$ = 5.250, p = .072, Figure 5, left), and no pairwise comparison was significant. Temporal perception biases thus occurred without corresponding heart rate changes, so the wearable feedback's perceptual effects operate independently of measurable physiological change in this task.

5.1.6 Heart Rate Variability (HRV). The results regarding HRV can be seen in Figure 5 (right). A Friedman test showed no significant differences in HRV between conditions ($\chi^2(2)$ = 5.083, p = .079); in pairwise comparisons baseline had significantly higher variability than 100 BPM (Z = -2.200, p = .028, r = -.449), with no other significant difference. These results indicate that fast wearable rhythmic feedback (100 BPM) was associated with subtle autonomic changes (reduced HRV), suggesting that physiological responses to the wearable feedback contribute to time overestimation alongside perceptual effects.

5.2 Experiment #2: No-Go Reaction Time

5.2.1 Mean reaction time (RT). A repeated measures ANOVA showed significant RT differences between conditions (F(2, 46) = 5.642, p = .006, partial η^2 = .197). Reaction times were significantly slower in baseline than 50 BPM (13.40 ms, 95% CI 2.39 to 24.41, p = .014) and than 100 BPM (10.74 ms, 95% CI 0.14 to 21.34, p = .046). A two one-sided tests procedure confirmed the two frequencies were statistically equivalent within a 15 ms margin (p = .004; direct comparison 2.7 ms, $t(23)$ = 0.62, p = .542, d = 0.05). The benefit held at the individual level, with faster reaction time than baseline in 21 of 24 participants at 50 BPM (mean -13.4 ms, d = 0.64) and 16 of 24 at 100 BPM (mean -10.7 ms, d = 0.53). These results indicate that wearable rhythmic feedback enhances motor preparation regardless of frequency, suggesting that rhythm regularity rather than specific frequency facilitates temporal anticipation and response execution.

5.2.2 Commission Error Rate (CER). A Friedman test showed no significant differences in CER between conditions ($\chi^2(2)$ = 0.400, p = .819), and no pairwise comparison was significant. These results indicate that reaction time improvements with the wearable haptic feedback occurred without compromising response inhibition, suggesting genuine processing enhancement rather than impulsive responding.

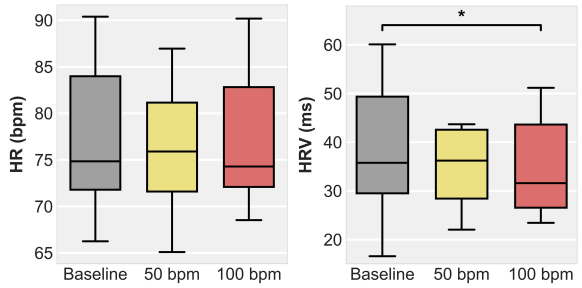


Fig. 5. Time estimation task physiological results. **Left:** Heart rate. **Right:** Heart rate variability across baseline, 50 BPM, and 100 BPM conditions (* p<.05).

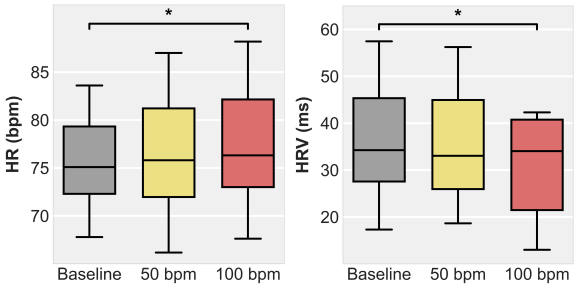


Fig. 6. No-Go reaction time task physiological results. **Left:** Heart rate. **Right:** Heart rate variability across baseline, 50 BPM, and 100 BPM conditions (* p<.05).

5.2.3 Omission Error Rate (OER). A Friedman test showed no significant differences in OER between conditions ($\chi^2(2) = 1.600$, $p = .449$), and no pairwise comparison was significant. These results indicate that attention levels remained consistent across conditions, confirming that reaction time improvements reflect enhanced motor preparation rather than motivational or attentional changes.

5.2.4 Heart Rate (HR). The results regarding HR can be seen in Figure 6 (left). A Friedman test showed no significant differences in HR between conditions ($\chi^2(2) = 1.750$, $p = .417$); in pairwise comparisons HR was significantly higher at 100 BPM than baseline (Z = -2.057, $p = .040$, $r = -.420$), with no other significant difference. These results indicate that fast wearable rhythmic feedback (100 BPM) was associated with physiological arousal, while slow rhythms (50 BPM) showed no comparable autonomic effects.

5.2.5 Heart Rate Variability (HRV). The results regarding HRV can be seen in Figure 6 (right). A Friedman test showed no significant differences in HRV between conditions ($\chi^2(2) = 2.333$, $p = .311$); in pairwise comparisons HRV was significantly lower at 100 BPM than baseline (Z = -2.057, $p = .040$, $r = -.420$), with no other significant difference. These results indicate that fast wearable rhythmic feedback was associated with reduced cardiac flexibility and a shift in autonomic balance toward sympathetic dominance, suggesting that physiological arousal from the wearable may contribute to performance enhancement effects.

5.2.6 Heart Rate to Feedback Mismatch. Because heart rate drifts, the gap between a participant's heart rate and the feedback frequency varies within a block. We recovered a heart rate at each stimulus onset from the ECG and defined mismatch as its absolute difference from the feedback frequency. In trial-level mixed models, mismatch did not predict reaction time (50 BPM $b = 0.27$ ms per BPM, $p = .62$; 100 BPM $b = 0.37$, $p = .68$; mismatch by frequency $p = .73$) or commission errors (100 BPM odds ratio 1.07, $p = .09$; 50 BPM 1.03, $p = .32$), and omissions were at floor. A block-level check using mean heart rate per half block agreed. The feedback's behavioural effects thus do not appear to depend on moment to moment cardiac alignment.

5.2.7 Mean reaction time (RT) per Cardiac Phase. We compared reaction times during cardiac systole (positions (1) and (4) in Figure 3) with cardiac diastole (positions (2) and (3)), shown in Figure 7.

Aggregated across conditions, mean RT was normal during systole (W = .931, $p = .160$) but not diastole (W = .900, $p = .041$), at 483.05 ms (SD = 55.69) during systole versus 460.19 ms (SD = 58.98) during diastole. A Wilcoxon signed-rank test showed no significant difference between cardiac phases (Z = -1.456, $p = .145$, $r = -.297$).

At baseline, mean RT was normal during systole (W = .948, $p = .361$) but not diastole (W = .861, $p = .010$), at 500.39 ms (SD = 55.74) in systole and 467.72 ms (SD = 62.92) in diastole. A Wilcoxon signed-rank test showed a significant phase difference (Z = -2.012, $p = .044$, $r = -.411$), with faster RT in diastole.

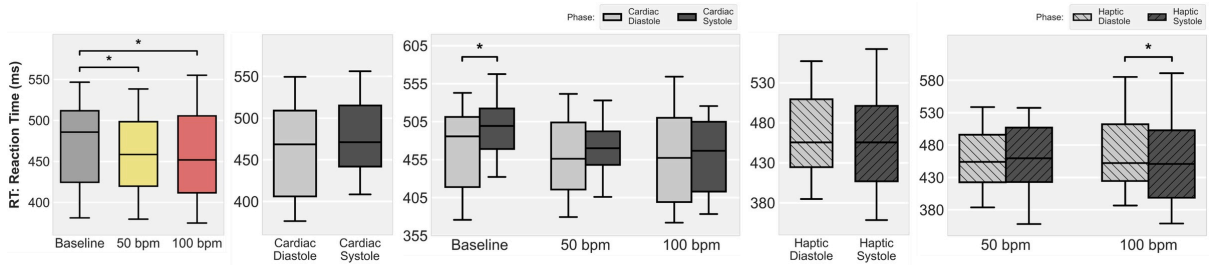


Fig. 7. Reaction times per feedback condition and cardiac/haptic phase alignment (* p<.05).

For the low-frequency condition, mean RT violated normality during systole (W = .862, p = .013) but met it during diastole (W = .932, p = .210). Mean RT was higher during systole (M = 480.77 ms, SD = 76.82) than diastole (M = 459.83 ms, SD = 52.17), and a Wilcoxon test showed no phase difference (Z = -.283, p = .777, r = -.058). In the high-frequency condition, mean RT deviated from normality during both systole (W = .849, p = .005) and diastole (W = .888, p = .025), and was higher during systole (M = 486.25 ms, SD = 101.12) than diastole (M = 457.49 ms, SD = 68.00), though a Wilcoxon test found this difference non-significant (Z = -.784, p = .433, r = -.160).

To formally test whether the cardiac phase effect differed across feedback conditions (Figure 9, left), we conducted a linear mixed-effects model on trial-level RT data (N = 24, 4,699 trials) with Condition (baseline, 50 BPM, 100 BPM) and ECG Phase (systole, diastole) as fixed factors and participant as a random intercept. The **Condition × ECG Phase interaction** was significant (F(2, 4677.70) = 3.089, p = .046), confirming that the cardiac phase effect on RT differed across feedback conditions. Bonferroni-corrected simple effects showed a significant systole-diastole difference at baseline (28.8 ms, p = .001) and a reduced but still significant difference at 100 BPM (18.0 ms, p = .010), while 50 BPM feedback eliminated the difference entirely (1.6 ms, p = .860). This interaction was significant only in the random-intercept model. It became non-significant once by-participant random slopes were added (p = .23 with a phase slope, p = .17 with condition and phase slopes) and in a participant-level repeated measures ANOVA on the cell means (F(2, 34) = 0.09, p = .913). We therefore treat the cardiac phase attenuation as exploratory rather than established.

5.2.8 Mean reaction time (RT) per Haptic Phase. We compared reaction times during haptic systole (positions (1) and (3) in Figure 3) with haptic diastole (positions (2) and (4)), shown in Figure 7.

Across conditions, mean RT met normality for both haptic systole (W = .966, p = .560) and diastole (W = .957, p = .377), at 456.14 ms (SD = 58.42) and 462.29 ms (SD = 49.47) respectively. A repeated measures ANOVA (F(1, 23) = 2.503, p = .127, partial η^2 = .098) showed no significant difference between the two phases.

For the low-frequency condition, the Shapiro-Wilk test indicated that reaction time data satisfied normality assumptions for both haptic systole (W = .955, p = .351) and haptic diastole (W = .954, p = .326). Mean RT during haptic systole was 458.80 ms (SD = 54.26 ms) compared to haptic diastole at 459.42 ms (SD = 45.91 ms). A repeated measures ANOVA showed no significant difference between haptic phases (F(1, 23) = .010, p = .920, partial η^2 = .000, f = 0.021). For the high-frequency condition, the Shapiro-Wilk test revealed that reaction time data satisfied normality assumptions for both haptic systole (W = .958, p = .397) and haptic diastole (W = .951, p = .288). Mean reaction time during haptic systole was 454.96 ms (SD = 63.85 ms) compared to haptic diastole at 466.16 ms (SD = 56.51 ms). A repeated measures ANOVA revealed a significant difference between haptic phases (F(1, 23) = 4.806, p = .039, partial η^2 = .173, f = 0.457), with faster reaction times during haptic systole than during haptic diastole.

A linear mixed-effects model on trial-level RT data (N = 24, 3,134 trials) with Condition (50 BPM, 100 BPM) and Haptic Phase (systole, diastole) as fixed factors and participant as a random intercept showed no significant

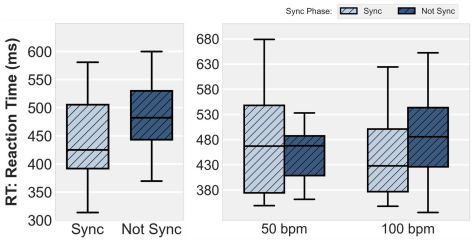


Fig. 8. Reaction times per haptic-cardiac synchronization. **Left:** Synchronized vs. non-synchronized conditions. **Right:** Synchronization effects across 50 BPM and 100 BPM conditions (* p<.05).

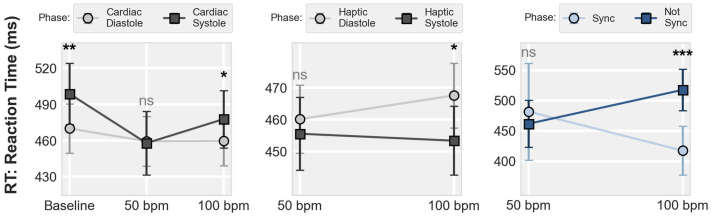


Fig. 9. Interaction plots showing estimated marginal means for reaction time. **Left:** Condition × ECG Cardiac Phase. **Middle:** Condition × Haptic Phase. **Right:** Condition × Haptic-Cardiac Synchrony. (* p<.05, ** p<.01, *** p<.001).

Condition × Haptic Phase interaction (F(1, 3110.73) = 1.832, p = .176; Figure 9, center). However, Bonferroni-corrected simple effects revealed a significant haptic phase difference at 100 BPM (11.8 ms, p = .013) but not at 50 BPM (1.4 ms, p = .819). These exploratory results suggest that high-frequency haptic pulses at 100 BPM may create temporal attention windows during haptic systole that enhance motor readiness, while 50 BPM does not, though the interaction test was non-significant and cannot confirm a difference between frequencies.

5.2.9 Mean reaction time (RT) per Haptic-Cardiac Synchrony. This subsection examines how reaction times during cardiac systoles differ based on whether they are synchronized with haptic stimulation. We compare reaction times when cardiac and haptic systoles occur simultaneously (synchronized condition), shown in Figure 3 as position (1), against reaction times when cardiac systole occurs while haptic stimulation is in diastole (non-synchronized condition), shown in Figure 3 as position (4). The results regarding mean RT per haptic-cardiac synchrony can be seen in Figure 8.

For all conditions aggregated, the Shapiro-Wilk test indicated that mean RT satisfied normality assumptions for both synchronized (W = .933, p = .193) and non-synchronized (W = .932, p = .192) conditions. Mean reaction time during synchronized cardiac-haptic periods was 455.97 ms (SD = 95.56 ms) compared to non-synchronized periods at 496.40 ms (SD = 74.55 ms). The repeated measures ANOVA (F(1, 18) = 3.108, p = .095, partial η^2 = .147, f = 0.416) showed no significant overall difference between the two synchrony conditions. However, this aggregate analysis collapses across frequencies and may obscure frequency-dependent synchrony patterns.

For the low-frequency condition, RT met normality for both synchronized (W = .889, p = .116) and non-synchronized (W = .947, p = .597) conditions. Mean RT during synchronized cardiac-haptic periods was 477.46 ms (SD = 117.01 ms) compared to non-synchronized periods at 439.58 ms (SD = 77.03 ms). A repeated measures ANOVA showed no significant difference between synchrony conditions (F(1, 11) = .967, p = .347, partial η^2 = .081, f = 0.296). For the high-frequency condition, RT met normality for both synchronized (W = .945, p = .329) and non-synchronized (W = .921, p = .117) conditions. Mean RT during synchronized periods was 450.00 ms (SD = 107.98 ms) compared to non-synchronized periods at 510.18 ms (SD = 140.67 ms). A repeated measures ANOVA revealed no significant difference between synchrony conditions (F(1, 18) = 3.041, p = .098, partial η^2 = .145, f = 0.411), though the effect size suggests it may warrant investigation with larger samples.

A linear mixed-effects model on trial-level RT data during cardiac systole (N = 20, 294 trials) with Condition (50 BPM, 100 BPM) and Synchrony (synchronized, non-synchronized) as fixed factors and participant as a random intercept revealed a significant **Condition × Synchrony interaction** (F(1, 292.11) = 5.506, p = .020; Figure 9, right). This was corroborated by a repeated-measures ANOVA on participant-level means (F(1, 11) = 6.910, p = .023, partial η^2 = .386). Bonferroni-corrected simple effects showed that at 100 BPM, synchronized trials were

100.1 ms faster than non-synchronized trials ($p < .001$), while at 50 BPM no synchrony effect was observed (20.1 ms, $p = .652$). We report this as a preliminary lead, because synchronization arose incidentally rather than by design. It rests on sparse trials, 294 in total from 20 participants, with a median of about one synchronized trial per participant per condition. A study that manipulates synchrony directly is needed to establish it.

6 Discussion

Feedback frequency is a critical and previously overlooked design parameter for haptic biofeedback, with systematic and divergent effects on users' temporal cognition and motor performance. Haptic heartbeat feedback bidirectionally shifts time perception, enhances reaction time regardless of frequency, and may reduce natural cardiac constraints on motor performance. We read these findings through three mechanisms (interoceptive illusions, physiological modulation, and neural entrainment) to derive design knowledge for haptic systems in ubiquitous computing. We frame the mechanisms as plausible interpretations rather than directly measured processes, and use arousal to mean physiological arousal inferred from heart rate and HRV, since we collected no subjective, interoceptive, or neural measures.

6.1 Feedback Frequency Bidirectionally Shifts Time Perception via Interoceptive Illusion

Designers should expect that their choice of feedback frequency will systematically distort users' time perception in opposite directions. 50 BPM produced significant underestimation and 100 BPM significant overestimation, with biases of about 1 second over mean 2-second intervals, roughly 50% modulation of subjective time. These results partially support both the interoception framework (**H1.a**, **H1.b**) and the physiological modulation framework.

The bidirectional nature of this effect rules out simpler alternative accounts, since attentional distraction [81] and motor interference [4] would produce symmetric disruption across both frequencies rather than the frequency-specific directional pattern we observed. Moreover, the 2:1 frequency ratio was chosen to control for conscious beat-counting strategies, and our inclusion of durations as short as 0.5 seconds, below the 1.18-second threshold where counting becomes beneficial [21, 22], further argues against counting as a primary driver. The constant *Coefficient of Variation* (CV) across conditions provides additional evidence, as counting strategies violate the scalar property of timing by reducing variability [27, 55], yet we observed preserved scalar timing throughout.

These two frequencies are not interchangeable design choices, because they differ in estimation accuracy. Slow rhythms (50 BPM) degraded accuracy, with Absolute Error 0.9 seconds higher than at 100 BPM ($p = .014$), a 45% increase in temporal variability, whereas fast rhythms (100 BPM) biased perception without comparable accuracy costs. This asymmetry has a mechanistic basis that informs design decisions.

At 50 BPM, the timing effect without HRV change points to interoceptive illusion over physiological modulation (**H1.b** over **H2.b**), consistent with Costa et al.'s [10] "BoostMeUp." The slow rhythm likely created a perception of low arousal sufficient to decelerate the internal pacemaker [20, 69] through top-down modulation, yet insufficient to trigger autonomic changes. This fits predictive coding frameworks where interoceptive perception can operate independently of peripheral signals [2], and models of wearable interfaces that work through non-conscious pathways without explicit user awareness [32]. Meanwhile, the 0.83 Hz stimulus falls below optimal cortical entrainment ranges (delta-theta, 1–8 Hz) [57], likely causing phase drift [38] and competitive interference rather than stable entrainment [72], which explains the elevated absolute errors. For designers, slow heartbeat feedback thus carries a dual cost, directional bias *plus* increased absolute error.

In contrast, at 100 BPM the effects were robust and stable. The 1.67 Hz stimulus falls within optimal cortical entrainment ranges [57], and the reduced HRV is consistent with convergent interoceptive and physiological mechanisms, where both perceptual arousal and sympathetic activation may have contributed to pacemaker acceleration [20, 37], consistent with **H2.a**. The decreased parasympathetic activity aligns with established links between sympathetic dominance and time overestimation [51, 79]. This convergence produced systematic

overestimation while preserving accuracy, making 100 BPM a more predictable design choice than 50 BPM. The accompanying HRV reduction is a physiological side effect that designers must weigh, particularly in relaxation or stress-management contexts, as illustrated by MoodWings [39], which unexpectedly increased physiological stress despite improving driving performance. The dissociation between accuracy and precision, where CV stayed constant even as accuracy shifted, fits the attentional pulse mechanism [38], where rhythmic feedback shifts the phase of internal oscillations (affecting accuracy) without altering their period variability (preserving precision), so directional biases stay predictable without degrading timing consistency.

6.2 Rhythmic Haptic Feedback Enhances Motor Readiness Regardless of Frequency

For applications involving motor performance, our results establish rhythm regularity, not specific frequency, as the primary design parameter. Both 50 BPM and 100 BPM feedback significantly decreased reaction times compared to baseline (13.40 ms and 10.74 ms respectively), with no significant difference between frequencies. This pattern is consistent with neural entrainment (**H3.c**) and contradicts predictions that slower rhythms would impair reaction time (**H1.d**, **H2.d**). Importantly, this improvement occurred without affecting Commission or Omission Error Rates, confirming genuine processing enhancement rather than a speed-accuracy trade-off. While the effect size was medium (partial η^2 = .197), its consistency across 21 of 24 participants suggests a robust underlying mechanism. Such magnitudes are characteristic of physiological interventions targeting highly optimized cognitive processes, comparable to McIntyre et al.'s [41] findings of approximately 6 ms cardiac-phase differences in reaction time. In applied contexts, a 10 ms reduction in brake reaction time at 100 km/h corresponds to approximately 28 cm of additional stopping distance [19], and such gains accumulate across repeated decisions in sustained vigilance tasks [74]. The brevity of exposure in our study also suggests potential for stronger effects with extended use, though habituation remains an open question.

The contrast with time perception is significant for design. Time estimation was sensitive to feedback *frequency* through arousal modulation, whereas reaction time was sensitive to feedback *regularity*, consistent with a neural entrainment account. This dissociation aligns with the Wing-Kristofferson model's [77, 78] separation of timing into central timekeeper and motor implementation components. Frequency biases the central timekeeper (shifting time perception) while rhythmicity enhances motor implementation (improving reaction time). Thus any rhythmic haptic feedback provides a temporal framework for predictive motor preparation, extending Whitmore et al. [75], who showed rhythmic benefits for attention but did not examine motor performance or temporal processing. The divergent physiological responses between tasks further underscore the context-dependent nature of biofeedback effects. Heart rate significantly increased during the 100 BPM condition in the reaction time task but not during time estimation, likely reflecting the motor task's greater cognitive demands and enhanced susceptibility to physiological modulation. Designers should therefore expect that the same feedback parameters produce different physiological profiles depending on the user's task context.

6.3 Rhythmic Feedback May Attenuate Natural Cardiac Constraints on Motor Performance

Rhythmic haptic feedback may also attenuate an inherent physiological limit on motor performance. In baseline, participants responded more slowly during cardiac systole than diastole (p = .044), consistent with baroreceptor work showing cardiac contraction suppresses neural processing [41]. This cardiac phase constraint on reaction time is established, but has not previously been shown to be modifiable through haptic intervention. A linear mixed-effects model on trial-level data indicated a Condition × Cardiac Phase interaction (F(2, 4677.70) = 3.089, p = .046), although, as Section 4 reports, this did not hold once individual variability was modelled.

Both haptic feedback conditions reduced the cardiac-phase RT advantage to non-significance. At 50 BPM, the systole-diastole difference disappeared (1.6 ms, p = .860), suggesting that external haptic sensations mask or compete with internal cardiac sensations, reducing baroreceptor-mediated inhibition of cognitive processing. At

100 BPM, the effect was attenuated but detectable (18.0 ms, $p = .010$), with reactions during systole becoming numerically closer to diastole. Furthermore, at 100 BPM we observed a significant haptic phase effect ($p = .013$), with reaction times faster during haptic systole than diastole, which may reflect the "lub" phase acting as an alerting signal, consistent with neural entrainment (**H3**), although the haptic-phase interaction was not significant. A Condition × Synchrony interaction ($F(1, 292.11) = 5.506$, $p = .020$) further indicated that at 100 BPM, synchronized haptic-cardiac trials were 100.1 ms faster than non-synchronized trials ($p < .001$), while no such effect occurred at 50 BPM ($p = .652$). However, synchronization arose incidentally and rests on very few trials, so a study that manipulates it directly is needed to confirm this.

This cardiac-phase attenuation could become a design resource. Cardiac-phase constraints on motor performance are well documented [41], yet no prior work has shown that haptic biofeedback can attenuate them. Rhythmic haptic feedback may offer a way to reduce this limitation, providing an alternative temporal framework that lessens dependence on variable internal cardiac cues and may stabilize motor performance across the cardiac cycle. Because these effects are exploratory and rest on limited data, we treat them as a promising direction rather than an established phenomenon, and their generalizability beyond the No-Go paradigm remains open.

6.4 Task Context Determines Which Feedback Parameter Matters for Haptic Biofeedback Design

Rather than supporting a single theoretical framework exclusively, our findings show that all three mechanisms contribute, but their relative importance varies systematically with task demands. This task-dependent mechanistic profile directly affects how designers should select feedback parameters. For applications involving perceptual-cognitive processes such as time estimation, duration judgment, or the subjective experience of waiting, interoceptive illusions emerged as the dominant mechanism. Here, the feedback's *frequency* determined whether users experienced time compression or expansion, with physiological modulation playing a secondary role only at higher frequencies. Designers must therefore select frequency based on the desired perceptual outcome, recognizing that frequency choice carries both intended directional effects and potential side effects such as reduced HRV at higher frequencies.

For motor performance, neural entrainment was the dominant mechanism, and rhythm *regularity* mattered more than specific frequency. Both frequencies improved reaction time equally, and may also reduce natural cardiac-phase constraints, an exploratory pattern. This simplifies design for motor-focused applications, since any rhythmic pattern in the range tested enhances motor readiness, letting designers choose frequency by other considerations such as comfort, physiological side effects, or perceptual goals. The multi-mechanism view also explains an apparent paradox. Contrary to predictions **H1.d** and **H2.d**, slow feedback improved rather than impaired reaction time, likely because entrainment benefits for motor preparation outweighed any arousal-reducing effects. This has broader implications for the biofeedback literature. Valente et al. [70] found high-frequency feedback decreased response times but, without a no-feedback control, could not tell whether this reflected interoceptive illusions or entrainment. Our controlled design suggests that entrainment underlies the motor benefit and interoception the temporal perception bias, a distinction previous biofeedback systems such as "BoostMeUp" [10] and "EmotionCheck" [9] could not make.

Physiological metrics are essential evaluation components for haptic biofeedback systems, not optional additions. Subjective reports alone would have missed the HRV reduction at 100 BPM, the exploratory cardiac-phase effects, and the task-dependent divergence in cardiac responses. This is not unique to us. Zhao et al. [84] found affective touch wearables reduced self-reported anxiety while leaving HRV unchanged, a dissociation invisible without instrumentation. Without physiological assessment, designers risk haptic patterns that produce unintended autonomic effects or disrupt beneficial natural rhythms. We advocate integrating cardiac monitoring into the design evaluation of any system delivering rhythmic haptic feedback, treating the body as an active participant rather than a passive receiver of stimulation.

6.5 Design Implications for Haptic Biofeedback

Our findings are primarily a caution for systems already in use. Because wearable haptic heartbeat feedback is increasingly deployed in time-sensitive contexts, designers should treat its effects on temporal cognition and motor readiness as consequences to anticipate and measure rather than as neutral. Table 1 summarises which effects are well supported and which are preliminary.

Several deployed system types are implicated. In-car calming and breathing wearables [1, 39, 49] deliver slow rhythmic feedback to relax drivers, which our results suggest could compress a driver's sense of elapsed time and reduce accuracy. Because braking and gap decisions depend on judging short durations, designers should weigh this cost against the rhythm's reaction-time benefit, favouring it when the vehicle is stationary. Attention-support wearables [75] could distort how long a work session feels, compressing it at slower frequencies and expanding it at faster ones. Because a session that feels longer or shorter than it is may prompt users to disengage early or misjudge breaks, designers should correct for this where the device drives a timer or pacing cue, or exploit it to make short focus intervals feel substantial. Pre-performance calming wearables for public speaking and cognitive performance under pressure [10, 64] use slow feedback that our results link to underestimation and lower accuracy, so a device meant to steady a user before a timed task may also make them misjudge pacing, arguing for delivering it before rather than during the performance. By contrast, contexts that mainly need motor readiness, such as cardiovascular or alerting interventions [60], can benefit from any rhythmic feedback in the range tested, since the reaction-time gain was frequency-independent, letting designers choose frequency for comfort or a perceptual effect without losing the motor benefit.

These implications are scoped to the conditions tested (50 and 100 BPM, ankle placement, healthy young adults, and short laboratory tasks), and the cardiac-timing effects remain exploratory. None of these application contexts was tested directly, so they should be read as cautions to evaluate rather than validated recommendations, and safety-critical uses in particular warrant direct testing before deployment.

7 Limitations

Our findings establish feedback frequency as a key design parameter but do not yet map the full parameter space designers will need. We examined only two frequencies (50 and 100 BPM), which cannot capture non-linear relationships between frequency and temporal processing, nor identify inflection points where effects flip from underestimation to overestimation or where reaction-time benefits peak. The parameter space was otherwise narrow, since we tested one haptic pattern at a single ankle placement, with short exposures and a healthy adult sample, so effects may differ with other patterns, body sites, longer use, or clinical and older populations. We scoped the design implications accordingly, as cautions rather than validated recommendations.

A central methodological limitation is the absence of a non-rhythmic haptic control condition (e.g., arrhythmic, noise, or tonic vibration). Without such a control, we cannot conclusively attribute the reaction time improvements to rhythmic entrainment rather than general tactile alerting. The pattern of results still favors rhythmicity as the operative mechanism. General tactile arousal would predict frequency-dependent RT effects, stronger at 100 BPM from more pulses per unit time, yet improvements were equivalent across both frequencies, and the bidirectional time estimation effects are difficult to explain through non-specific alerting alone. A non-rhythmic control nonetheless remains essential to isolate these contributions.

A related limitation is the absence of direct measures for interoception and neural entrainment. Our framework evaluation relies on conditions where the theories make divergent predictions rather than on neurophysiological evidence. Without subjective arousal measures, the interoceptive illusion account (H1) rests on behavioral inference rather than confirmed perceptual states, and without EEG, the entrainment account (H3) rests on behavioral signatures consistent with entrainment rather than direct evidence of neural synchronization. Future work should incorporate these measures to strengthen mechanistic claims. We also did not collect detailed

subjective ratings, such as whether participants noticed the frequency differences or judged the vibration to be their own heartbeat, though they did report interpreting it as a heartbeat sensation. This was deliberate, since prompting participants to attend to and compare the feedback would have encouraged the self-focus and interoceptive attention our tasks were designed to minimise and drawn attention from the primary tasks. We treat it as a limitation but believe it was the right trade-off for the study design.

Another limitation concerns how directly these findings translate to HCI contexts. Our tasks isolated temporal estimation and reaction time under controlled conditions, but real interactive systems involve richer goals, multitasking, interface feedback, social context, and longer-term use. As a result, our findings identify haptic feedback frequency as a design-relevant parameter, but they do not yet specify how these effects should be calibrated for applications such as mobile interaction, training systems, safety-critical interfaces, or stress-regulation tools. Future work should examine these effects in situated HCI scenarios to determine when temporal distortion is beneficial, disruptive, or problematic.

The phase-dependent effects remain exploratory, as the cardiac-phase attenuation reached significance only in a random-intercept model, not with random slopes or participant-level aggregation. The haptic phase interaction was non-significant, and synchronization rested on sparse, incidental trials. Direct manipulations of cardiac phase and synchrony are needed before treating these as reliable design resources.

8 Future Work

Future work should expand the parameter space of haptic heartbeat biofeedback beyond the two frequencies tested here. Researchers could explore dynamic feedback synchronized in real time with users' actual heartbeats at varying ratios, which may reveal more personalized effects than fixed-frequency stimulation. Systematically varying frequency, rhythm regularity, amplitude, body placement, and synchronization timing would identify relevant parameters for temporal estimation, motor readiness, and physiological modulation. Non-biological controls, such as metronomic pulses at matched frequencies without heartbeat cadence, and arrhythmic controls would isolate the contributions of rhythmicity, heartbeat-specific interoceptive framing, and tactile stimulation.

The explanatory frameworks also need more direct tests. Our study compared interoceptive illusion, physiological modulation, and neural entrainment through behavioral and physiological predictions, but each mechanism requires targeted measurement. Subjective arousal and interoceptive awareness measures could clarify when users perceive artificial feedback as bodily information, EEG could test whether rhythmic haptic feedback produces neural synchronization, and longer physiological recordings could determine whether frequency-dependent changes in heart rate and HRV persist, adapt, or disappear.

To better reflect real-world deployment, researchers should investigate these effects in divided-attention scenarios that approximate everyday multitasking, such as mobile interaction, driving or cycling simulations, training systems, collaborative work, and safety-critical interfaces where temporal distortion and reaction-time changes may differ. These contexts would show when haptic heartbeat feedback should support performance, when it should be avoided, and how designers should communicate or constrain its effects.

Cross-modal controls, such as auditory rhythmic feedback at matched frequencies, would also show whether the tactile modality has privileged access to the mechanisms studied here, as suggested by Zhou et al. [85]. Finally, individual differences in physiological responses suggest that adaptive systems adjusting feedback to real-time physiological profiles and task demands may outperform static frequency selection. These point toward ubiquitous biofeedback systems that treat haptic feedback frequency as an adaptive design parameter calibrated to the user, task, and interaction context.

9 Conclusion

This work established feedback frequency as a key design parameter for haptic heartbeat biofeedback by contributing the first empirical investigation of how rhythmic haptic feedback at different frequencies affects both temporal perception and motor performance within the same participants. Through systematic evaluation against three explanatory frameworks, we identified that different cognitive processes are governed by different mechanisms, meaning that designers must consider what their application primarily engages when selecting feedback parameters. We also report a preliminary cardiac-phase attenuation effect, where artificial rhythmic stimulation may reduce the natural cardiac-phase constraint on reaction time, a physiological limitation previously considered inherent and unmodifiable. We treat this as exploratory, because it was not robust once individual variability was modelled. These contributions move haptic biofeedback design beyond trial-and-error frequency selection toward a principled understanding of how feedback parameters interact with human temporal cognition and physiology. As rhythmic haptic feedback becomes more common in consumer and clinical devices, the design implications presented here offer a foundation for building systems that account for, rather than accidentally disrupt, the temporal and physiological processes that shape how people perceive and act in the world.

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A Appendix A: Wearable Device and Latency Calibration

The haptic device used a Seeed Studio XIAO ESP32C3 microcontroller connected to a DRV2605L haptic motor driver controlling an Eccentric Rotating Mass (ERM) motor (7×25 mm; rated voltage 3.7–5 V, rated current 0.09 A, rated speed 18,000 rpm), housed in a 3D-printed enclosure (33×33×19 mm). The device produced a "lub-dub" cadence at the specified BPM, with the time between the start of systole ("lub" beat) and the start of diastole ("dub" beat) set from the cardiac cycle duration:

$$\text{Lub-to-Dub Time} = \frac{1}{3} \times \frac{60}{\text{Heart Rate (BPM)}}$$

Heart rate was captured using a BITalino board[2] with three ECG electrodes in a lead-II configuration, sampled at 1000 Hz. Game events were synchronized with the physiological recording using the BITalino DAC block, which sent event markers to the acquisition stream.

To ensure accurate temporal alignment between commanded and delivered haptic stimulation, we measured the ERM motor's response latency using a piezoelectric ceramic disc mounted against the motor housing, with the sensor's voltage sampled at 10 kHz via the ESP32C3's analog-to-digital converter. Motor activation latency was defined as the time from command signal to the first piezoelectric voltage deflection exceeding three times the baseline noise level. Across 120 trials with randomized inter-trial intervals (200 ms–3 s) to control for thermal effects and prevent rhythmic artifacts, mean latency was 119.8 ± 10.9 ms (median 119.5 ms, range 90.6–149.3 ms, CV 9.1%). All cardiac-haptic synchronization analyses used latency-corrected haptic timing, with commanded haptic systole timestamps adjusted forward by 119.8 ms.

B Appendix B: Full Statistical Results

This appendix reports the complete statistics summarised in the main text. For each measure we report the omnibus test and all pairwise comparisons across the baseline, 50 BPM, and 100 BPM conditions.

Table 2. Time-estimation task omnibus tests and Bonferroni-corrected pairwise comparisons. Omnibus values are F for repeated-measures ANOVA and chi-square for Friedman, and pairwise values are the Bonferroni-adjusted mean difference for ANOVA measures and Z for Wilcoxon. AI is Accuracy Index, AE is Absolute Error, CE is Constant Error, CV is Coefficient of Variation, HR is heart rate, HRV is heart rate variability.

Measure	Omnibus	Base–50	Base–100	50–100
AI	$F(1.55, 35.58) = 44.05$ $\mathbf{p < .001}$	$\Delta = 0.104$ $\mathbf{p < .001}$	$\Delta = 0.110$ $\mathbf{p = .001}$	$\Delta = 0.214$ $\mathbf{p < .001}$
AE	$F(1.20, 27.61) = 8.88$ $\mathbf{p = .004}$	$\Delta = 0.512$ $\mathbf{p = .011}$	$\Delta = 0.407$ $p = .096$	$\Delta = 0.919$ $\mathbf{p = .014}$
CE	$F(2, 46) = 94.08$ $\mathbf{p < .001}$	$\Delta = 1.037$ $\mathbf{p < .001}$	$\Delta = 0.923$ $\mathbf{p < .001}$	$\Delta = 1.960$ $\mathbf{p < .001}$
CV	$F(2, 46) = 0.87$ $p = .428$	$\Delta = 0.009$ $p = 1.000$	$\Delta = 0.009$ $p = .669$	$\Delta = 0.001$ $p = 1.000$
HR	$\chi^2(2) = 5.25$ $p = .072$	$Z = -1.03$ $p = .304$	$Z = -0.26$ $p = .797$	$Z = -1.51$ $p = .130$
HRV	$\chi^2(2) = 5.08$ $p = .079$	$Z = -0.23$ $p = .819$	$Z = -2.20$ $\mathbf{p = .028}$	$Z = -1.69$ $p = .092$

[2]BITalino (r)evolution: https://bitalino.com/products/plugged-kit-dual-mode-ble-bt

Table 3. Reaction-time task omnibus tests and Bonferroni-corrected pairwise comparisons. Omnibus values are F for repeated-measures ANOVA and chi-square for Friedman, and pairwise values are the Bonferroni-adjusted mean difference for ANOVA measures and Z for Wilcoxon. RT is mean reaction time, CER is commission error rate, OER is omission error rate, HR is heart rate, HRV is heart rate variability.

Measure	Omnibus	Base–50	Base–100	50–100
RT	$F(2, 46) = 5.64$ **p = .006**	$\Delta = 13.40$ **p = .014**	$\Delta = 10.74$ **p = .046**	$\Delta = 2.66$ $p = 1.000$
CER	$\chi^2(2) = 0.40$ $p = .819$	$Z = -0.45$ $p = .651$	$Z = -0.41$ $p = .685$	$Z = -0.29$ $p = .774$
OER	$\chi^2(2) = 1.60$ $p = .449$	$Z = -1.00$ $p = .317$	$Z = -1.00$ $p = .317$	$Z = 0.00$ $p = 1.000$
HR	$\chi^2(2) = 1.75$ $p = .417$	$Z = -1.29$ $p = .199$	$Z = -2.06$ **p = .040**	$Z = -0.86$ $p = .391$
HRV	$\chi^2(2) = 2.33$ $p = .311$	$Z = -0.43$ $p = .668$	$Z = -2.06$ **p = .040**	$Z = -1.71$ $p = .086$

Table 4. Shapiro-Wilk normality tests per measure and condition. Bold p marks a violation of normality (p below .05), for which non-parametric tests were used. AI is Accuracy Index, AE is Absolute Error, CE is Constant Error, CV is Coefficient of Variation, RT is mean reaction time, CER is commission error rate, OER is omission error rate, HR is heart rate, HRV is heart rate variability.

Measure	Baseline	50 BPM	100 BPM
Time-estimation task			
AI	$W = .990$ $p = .996$	$W = .977$ $p = .824$	$W = .936$ $p = .135$
AE	$W = .953$ $p = .307$	$W = .950$ $p = .274$	$W = .939$ $p = .155$
CE	$W = .989$ $p = .995$	$W = .956$ $p = .364$	$W = .953$ $p = .319$
CV	$W = .976$ $p = .817$	$W = .980$ $p = .891$	$W = .976$ $p = .808$
HR	$W = .921$ $p = .060$	$W = .906$ **p = .029**	$W = .914$ **p = .044**
HRV	$W = .795$ **p < .001**	$W = .761$ **p < .001**	$W = .802$ **p < .001**
Reaction-time task			
RT	$W = .925$ $p = .076$	$W = .965$ $p = .552$	$W = .952$ $p = .305$
CER	$W = .723$ **p < .001**	$W = .733$ **p < .001**	$W = .665$ **p < .001**
OER	$W = .393$ **p < .001**	$W = .209$ **p < .001**	$W = .209$ **p < .001**
HR	$W = .888$ **p = .012**	$W = .903$ **p = .025**	$W = .916$ **p = .049**
HRV	$W = .583$ **p < .001**	$W = .869$ **p = .005**	$W = .789$ **p < .001**