



Pink noise promotes sooner state transitions during bimanual coordination

Kolby^{a,1}, Breiumkg^a, K^aqondokilmH^a, omPnoIrefnenida^b, Mmaaeaa^c, S taenrdg iAaur d¹ⁿ D. Likens

Affiliations are included on p. 7.

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The seemingly straightforward task of tying one's shoes requires a sophisticated interplay of joints, muscles, and neural pathways, posing a formidable challenge for researchers studying the intricacies of coordination. A widely accepted framework for measuring coordinated behavior is the Haken–Kelso–Bunz (HKB) model. However, a significant limitation of this model is its lack of accounting for the diverse variability structures inherent in the coordinated systems it frequently models. Variability is a pervasive phenomenon across various biological and physical systems, and it changes in healthy adults, older adults, and pathological populations. Here, we show, both empirically and with simulations, that manipulating the variability in coordinated movements significantly impacts the ability to change coordination patterns—a fundamental feature of the HKB model. Our results demonstrate that synchronized bimanual coordination, mirroring a state of healthy variability, instigates earlier transitions of coordinated movements compared to other variability conditions. This suggests a heightened adaptability when movements possess a healthy variability. We anticipate our study to show the necessity of adapting the HKB model to encompass variability, particularly in predictive applications such as neuroimaging, cognition, skill development, biomechanics, and beyond.

coordination | Haken–Kelso–Bunz model | variability

Coordination is a fundamental problem of movement that must be solved by all animals. “Solving” the act of coordination is to organize the available degrees of freedom in time and in sequence to produce a functional movement pattern (1). Squirrels solve this problem with every leap through the complex canopies to travel and avoid predators (2). Plummeting gannets have mastered a perfectly timed coordinated dive into the water from heights of up to 30 m (3). Kangaroos coordinate their muscular limbs and long tails to locomote in a peculiar “pentapedal” gait (4). Human movement is no less remarkable. Even the simple act of tying one's shoes requires the coordination of countless degrees of freedom (5–7). The investigation of movement coordination is largely guided by the Haken–Kelso–Bunz (HKB) model. This model is considered to be the most extensively used quantitative model for understanding coordinated behavior in living things.

Quantifying Coordination in Dynamical Systems. The HKB model quantifies the stability of coordinated movement patterns and predicts transitions between them (8). For example, when an individual taps their index fingers alternately, gradually increasing the tapping speed, they undergo an abrupt and involuntary shift to tapping their fingers in unison (8, 9). The HKB model captures this coordination shift with a collective variable that represents the system's global state. That collective variable, relative phase (ϕ) (8, 10–15), captures the phase difference between oscillating limbs. Kelso and many others show that evolving ϕ over time reveals coordination switching (see example above), where the human body automatically switches to a more preferred mode of coordination, depending on the constraints of the person, task, and environment (13, 14, 16–19). As such, bimanual movements (e.g., finger tapping, wrist rotations, arm swinging) automatically switch from a less stable antiphase coordination pattern (e.g., asymmetrical movement of oscillating limbs) to a more stable in-phase coordination pattern (e.g., symmetrical movement of oscillating limbs) after reaching a critical speed of oscillation (8, 12, 13, 20) (Fig. 1C). Other relationships have also been observed—usually with practice (21–23)—but in-phase and antiphase are pervasive in human movement (24). Phase transitions, however, are not the sole method used to assess the stability of biological movements. The stability and dynamics of coordinated biological movements are also evaluated through the examination of movement variability, with a particular focus on whether variability exhibits a pink noise structure (25–27).

Significance

From microscopic to macroscopic scales, intricate coordination processes define biological systems. The Haken–Kelso–Bunz model, a widely adopted framework predicting coordinated movements, overlooks the crucial influence of temporal variability—an inherent feature of coordination that changes with age and pathology. This study quantifies the influence of variability on coordination transitions, particularly in healthy and aging populations. Experimental observations and simulations show that coordination synchronized to a healthy variability exhibits enhanced adaptability, efficiently navigating increasingly unstable movement states. Furthermore, our research elucidates the relationship between coordination, variability, and brain activity, showing how their interconnectivity shapes movement. Our revised models, based on experimental findings, improve our comprehension of coordinated behavior.

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¹To whom correspondence may be addressed. alikens@unomaha.edu.

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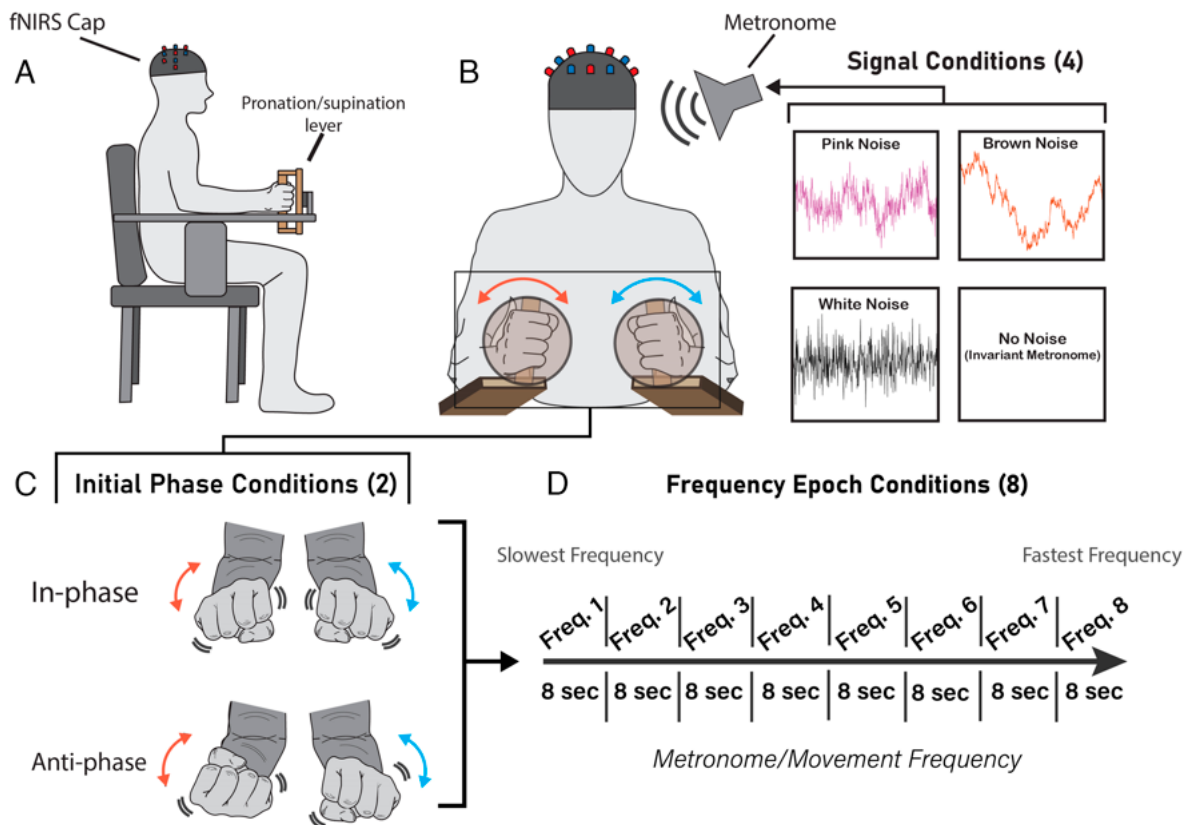


Fig. 1. Bimanual coordination test setup and conditions. (A) Subject wearing fNIRS cap and holding device with pronation/supination lever. (B) Subject wearing fNIRS cap and listening to metronome. (C) Initial phase conditions: In-phase and Anti-phase. (D) Frequency epoch conditions: Slowest Frequency to Fastest Frequency, with 8 epochs of 8 seconds each, labeled Freq. 1 through Freq. 8. Signal conditions include Pink Noise, Brown Noise, White Noise, and No Noise (Invariant Metronome).

Variability's Association with Health. Pink noise is an intersystem phenomenon ubiquitous in biology and physiology. A nonexhaustive list of observations includes heart rate (26, 28, 29), respiratory rate (30–32), postural sway (33, 34), gait strides (25, 35), and relevant for the current study, bimanual coordination (13, 15, 20, 36) and brain dynamics (37–41). Fascinatingly, pink noise is pervasive in nature, being present in fluctuations of tide and river heights (42), climate (43), and song production in zebra finches (44). Many theoretical explanations have been proposed for the origin and function of pink noise in physiology and behavior (45–49). The Optimal Movement Variability Hypothesis (OMVH) (25) posits that the widespread presence of pink noise results from the interaction of physiological systems, leading to the emergence of variable movement patterns that, when observed over time, exhibit stability and adaptability typical of well-coordinated and healthy systems. Deviations from optimal pink noise can happen in two ways: 1) movement patterns exhibit variability that is uncorrelated over time and thus random, as in white noise, and 2) movement patterns exhibit temporal variability that is overly determined, as in Brown noise. Both result in a lack of stability and adaptability (35, 50–52) and altered brain dynamics (37–41).

Inspired by the presence of pink noise in complex coordinated processes, we investigated the influence of differently timed variable metronomes on the human capacity to transition from anti-phase to in-phase coordination. We hypothesized that altering the interbeat interval in the metronome to reflect certain statistical noise types would affect how soon phase transitions occur. Specifically, we

hypothesized that the inclusion of pink noise in the metronome's interbeat intervals would lead to earlier phase transitions (i.e., anti-phase to in-phase) in comparison to all other metronome conditions in the same context. Secondly, we investigated how variable metronomes influence brain dynamics, given that brain dynamics change with variations in temporal movement variability (37).

To address these aims, we used the fNIRS brain imaging equipment and a bimanual wrist rotation device (Fig. 1A). Twenty healthy adults rotated both hands in synchrony with metronomes of increasing speed and a variable (i.e., pink, white, or Brown noise) or invariable (i.e., a traditional metronome such as the one used in the original HKB studies) beat interval (Fig. 1B, Table 2). We hypothesized movements entrained to a pink noise metronome would phase transition at a slower frequency (i.e., at an earlier movement epoch; Fig. 1D) than in other conditions. Pink noise enhances movement stability and adaptability (25, 53, 54). Therefore, we reasoned that employing a metronome with a pink noise structure would enhance the ability to efficiently switch coordination states. Compared with other conditions, we hypothesized that coordination patterns synchronized with pink noise would exhibit transitions that align more closely with the 0° attractor (ϕ observed in in-phase movements). Considering brain dynamics, we hypothesized that the more difficult coordination pattern (i.e., anti-phase) would result in a higher hemodynamic activity across all conditions, replicating previous findings (55). We further posited that entraining movements to a white noise metronome would lead to heightened hemodynamic activity. This

is attributed to the increased effort necessary to coordinate with a random pattern.

Results

Variability Affects Coordination. To test these hypotheses, we calculated the mean relative phase ($\bar{\phi}$) per epoch of increasing average frequency. *SI Appendix, Table S2* contains statistics for all possible pairwise comparisons. Here, we only compare pink noise and all other conditions during the first epoch that revealed a difference among conditions. Subjects transitioned from anti-phase to in-phase at a lower movement frequency when pacing their movements to the pink noise variable metronome relative to the white noise [N = 15; Pairwise comparison; Epoch 4; Estimated Difference (ED) = -0.3559, (~0.4 SDs), $P = 0.0358$], the Brown noise, [Pairwise comparison; Epoch 4; ED = -0.3526, (~0.4 SDs), $P = 0.0384$], and the invariant metronome [Pairwise comparison; Epoch 3; ED = -0.4760, (~0.3 SDs), $P = 0.0111$; Fig. 2*A*]. After the transition, $\bar{\phi}$ was closer to zero (i.e., in-phase) in the pink noise than all other conditions at the fastest movement speeds (Epochs 7 to 8) [Pairwise comparison; ED > -0.7000, (>0.5 SDs), $P < 0.0100$].

We asked subjects to perform the same task prepared in an in-phase coordination pattern (Fig. 1*C*). According to the HKB model, we hypothesized that no phase transition would occur, regardless of noise implementation. Multiple studies have shown that in-phase patterns are performed with greater accuracy and consistency at higher frequencies than antiphase patterns (8, 9, 13, 14, 20, 56, 57). Therefore, we did not expect changes in noise signals to influence this strong coordination state. As expected, no phase transitions occurred during the in-phase prepared conditions, suggesting that in-phase is a stable coordination pattern regardless of noise implementation (Fig. 2*B*). To determine the stability of ϕ , we calculated its standard deviation (ϕ_{SD}) at each frequency epoch (Fig. 2*C* and *D* and *SI Appendix, Table S3*). The ϕ_{SD} in the Brown noise condition was significantly lower than pink [N = 15; Pairwise comparison; ED = -0.1152, (~0.3 SDs), $P = 0.0234$] and white noise [Pairwise comparison; ED = -0.1644, (~0.4 SDs), $P = 0.0003$; *SI Appendix, Table S4*] conditions but not significantly different than in the invariant condition. Also, ϕ_{SD} increases and later decreases during antiphase pink noise movements (Fig. 2*C*), likely due to the earlier onset of the phase transition (14) (Fig. 2*A*). The other noise conditions produced no such decrease, as the phase transition appeared

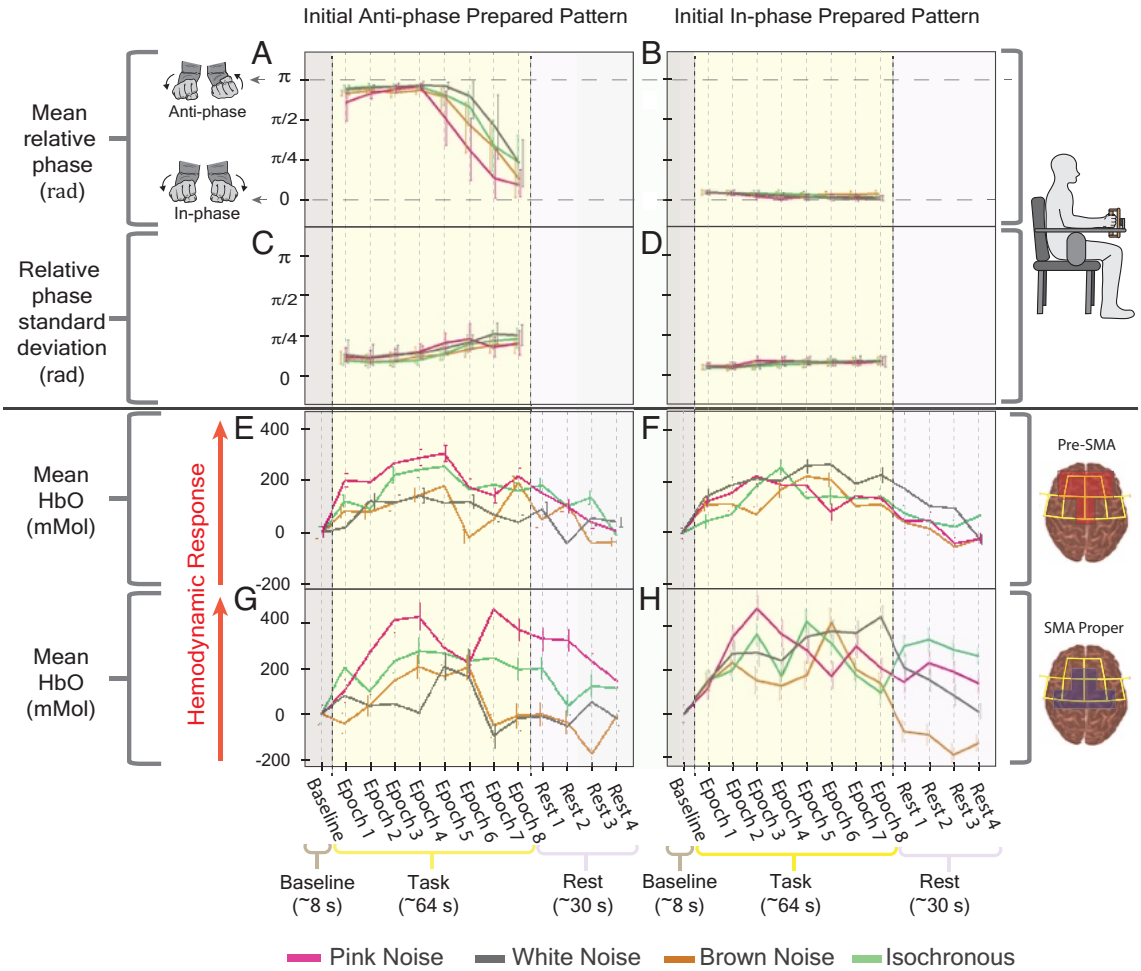


Fig. 2. Metronome temporal structure modulates both coordination and hemodynamic response during antiphase movements, respectively. Error bars depict confidence intervals condition. Values axes depict mean relative phase and standard deviation of the metronome. The pink noise variable metronome represents a random pattern of frequency changes during antiphase movements, respectively. Baseline represents ~8 s of baseline hemodynamic activity prior to the trial starting. The average baseline was then subtracted from the mean HbO (represent posterior supplementary motor area) and HbO response

to occur during the fastest frequency on average. Additionally, no significant differences in ϕ_{SD} were found comparing the noise variable metronome conditions for the in-phase condition, bolstering in-phase as a stable coordination pattern, regardless of noise implementation (Pairwise comparisons; $P > 0.0500$; Fig. 2D).

Hemodynamics of Noise-Driven Phases. To determine whether brain activation changed due to the noise signal, we observed the rate of change in HbO₂ in the anterior supplementary motor area (pre-SMA; *SI Appendix, Table S5*) and the posterior supplementary motor area (SMA Proper; *SI Appendix, Fig. S1 and Table S7*). During the antiphase condition, pink noise movements invoked greater changes in HbO₂ compared to Brown [ED = 91.47, (~ 0.4 SDs), $P = 0.0017$] and white noise conditions [ED = 94.60, (~ 0.4 SDs), $P = 0.0010$] in the pre-SMA (Fig. 2E) as well as SMA Proper (Fig. 2G). Notably, HbO₂ during antiphase in the pink noise condition yielded larger activity than all other conditions during the phase transition period (Epochs 6 to 8) in the SMA proper (Fig. 2G). For the in-phase conditions, HbO₂ during the Brown noise variable metronome was lower than white noise in the pre-SMA [ED = -72.27, (~ 0.3 SDs), $P = 0.0219$; Fig. 2F] and was significantly lower than all other conditions during Epoch 5 through Rest 4 in the SMA proper (Fig. 2H). In-phase movements did not yield as notable differences in hemodynamic response as antiphase prepared patterns. Perhaps, this is because in-phase movements are not as physically challenging as antiphase movements. The stability of in-phase movements may “mask” any profound influence the metronomes exert on hemodynamic response.

As subjects transitioned from an antiphase to an in-phase state in the antiphase prepared trials, it's possible that changes in hemodynamics were primarily driven by the specific coordination phase rather than being solely attributed to noise (58). To strictly isolate the impact of noise on HbO₂ in the antiphase condition, we focused on the epochs when all subjects remained in the same phase (i.e., antiphase), ensuring that no subjects had yet transitioned to an in-phase state. To accomplish this, we isolated the baseline and epochs 1 to 4 during the antiphase prepared trials. We found that while phase did not improve a model of the hemodynamic response, the inclusion of noise explained significant variance not explained by phase alone (*SI Appendix, Table S10*).

Discussion

The current findings reveal an intimate connection between relative phase dynamics and movements exhibiting pink noise variability. Altering the structural properties of variability quantitatively changed the timing from which antiphase movements transitioned to in-phase movements. Specifically, pink noise-driven coordination transitioned from an antiphase to an in-phase pattern at a significantly lower frequency than all other pacing conditions. Further evidence that movement variability influences coordination was observed following phase transitions. Pink noise-entrained movements dwelled closer to the expected 0° (i.e., in-phase) attractor, indicating greater stability after transition. Also, the different pacing signals similarly affected in-phase prepared movements, consistent with the stability of the in-phase coordination pattern (9, 13, 59). That is, the coordination pattern strength seems to determine one's sensitivity/vulnerability to pacing signals, explaining why antiphase movements, characterized by a weaker attractor, seemed more susceptible to being influenced by all pacing signals.

The simulations reported below bolster our experimental findings. A modified HKB model with a pink noise term transitions

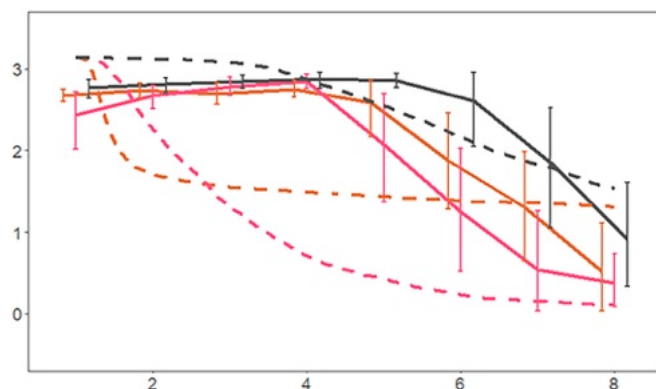


Fig. 3. Pink noise induces faster phase transitions simulated and experimental results. Line patterns of upper limb bimanual movement conditions. The plot depicts six distinct phase values and transitions attaining to 0. Experimental data, shown by solid lines, show the average relative phase values for pink, brown, and gray noise conditions. These phase transitions. Simulated data, presented by dashed lines, show the average relative phase values for pink, brown, and gray noise conditions. Notably, both experimental and simulated data show quicker transitions to 0 relative phase than the original HKB model.

from anti-phase to in-phase sooner than the HKB model with (typically modeled) white noise (Fig. 3). In contrast to white noise, which is inherently stationary, this modified HKB model allows flexibility to define the characteristics of the noise component. This modification allows exploration of not only stationary noise (e.g., white, pink noise) but also nonstationary signals, such as Brown noise. In addition, the HKB model can be modified with one of several noise terms to provide further insight into the effects of noise on coordination. Among three modifications to the HKB model—altering the original noise term, introducing noise to the collective frequency term, and adding noise to the relative phase term—the version with noise added to the collective frequency term most closely mirrored our experimental data. This aligns logically with our experiment, where we intentionally manipulated the variability at the level of each oscillator (i.e., the hand rotation intervals). Thus, incorporating noise into the oscillations, rather than the output relative phase signal (as in the traditional model), allowed us to closely match observed experimental outcomes. Fig. 3 juxtaposes simulation and experimental data, highlighting agreement between shifts in ϕ obtained from simulations and the noise-induced shifts in human movements. The simulations and experimental data align regarding the order of phase transitions for each noise condition; however, disparities exist in the degree at which the transition occurred (e.g., gradually vs rapidly). Consequently, while our adjustments to the HKB model improve the prediction of when phase transitions might occur, there remains a need for additional research to model the grade of these transitions with greater accuracy.

As a theoretical summary, our findings demonstrate that variability structure is a key component in coordination described by the HKB framework. We show timing of phase transitions (from anti- to in-phase) is heavily influenced by the temporal structuring of the person's recurring movements. Pink noise appears to poise the system for optimal self-organization. Theoretical and conceptual implications are 1) variability in movement and dynamical hallmarks of coordination circularly influence one another; 2) movement variability impacts the ability to adapt to external constraints; and 3) incorporating the temporal structure of noise into the HKB model could improve its representation of complex

coordinative processes in future research and applications. An important caveat to these points is that we did not employ traditional methods such as detrended fluctuation analysis or spectral analysis to measure movement variability in wrist oscillations, as this was no part of the hypothesis under consideration. Techniques like these necessitate numerous coordination cycles for reliable results which was not the case in our experiment. Several other experiments involving auditory and visual metronomes with pink noise and white noise have consistently shown that participants reliably synchronize with such metronome cues (60–64). Thus, based on the broader literature, we can reasonably assume that participants in our experiment were matching the statistical properties consistent with the respective conditions.

The presence of pink noise in various healthy biological processes has been widely documented (29, 39, 65–67), supporting the idea that faster transitions to an in-phase pattern during pink noise movements indicate a more adaptable system, thus aligning the OMVH. However, the behavioral explanations for Brown, invariant, and white noise signals do not necessarily follow the progression suggested by the OMVH. One might anticipate that the white noise would induce greater instability in the antiphase pattern, leading to a faster transition to the stable in-phase attractor (12). Similarly, Brown noise might result in greater rigidity, causing delayed transition (53). Both rigidity and randomness can similarly influence coordination attractor dynamics by constraining the system's capacity to explore and adapt to diverse behavioral patterns (50). When a system becomes excessively rigid, it locks into a particular pattern, reducing its flexibility to transition to alternative states. Similarly, when randomness or excessive randomness (as seen in white noise) dominates the system, it disrupts the stability and consistency necessary for coordinated behavior, hindering the system's ability to settle into specific attractor states. We argue that in both cases, the system is constrained in its exploration of different coordination patterns. Rigidity restricts the system's ability to move beyond a specific attractor, while excessive randomness prevents the system from settling into a stable attractor state. This limitation can impede the system's adaptability and reduce the behavioral options available to individuals. Therefore, despite their seemingly opposite nature, both rigidity and randomness can negatively impact coordination attractor dynamics by constraining the system's capacity to explore and transition between different behavioral patterns. Torre and colleagues have concluded similar interpretations when investigating the variability of relative phase at critical frequencies. Their conclusions, in line with our current interpretation, is that the presence of pink noise characterizes the adaptive capability of the system (68).

In this paper, we have interpreted the early transition as indicative of optimal variability facilitating efficient shifts toward a more stable state. An alternative explanation, considering that white noise was the last to transition, could be that pink noise potentially disrupts the coordination process while white noise facilitates it. While this hypothesis is certainly a possibility, we find it improbable for the following reasons:

First, pink noise is pervasive in numerous healthy natural behaviors such as gait, heartbeat, respiratory cycles, cognition, tapping, and wrist oscillations, which degrade during pathology and aging (63–69). This suggests that pink noise is associated with healthy, adaptive states, aligning with our interpretation of the results. Moreover, previous research has demonstrated that synchronizing to pink noise enhances resilience and adaptability during tripping (70). Nevertheless, this experiment alone cannot conclusively rule out the possibility the above alternative hypothesis. Hence, future experiments incorporating instructions to resist coordination switching are warranted and would significantly contribute to this discourse.

The interaction between coordination stability and movement variability concerning brain activity has been previously, yet separately, explored (37, 55, 71). One potential theory that describes the hemodynamic response is *information processing load*. Information processing load, in this context, attributes the increased brain activity to the increased effort required to maintain a given motor coordination state. Thus, the difficulty of maintaining a given coordination pattern (e.g., the relative phase of limbs) is suggested to directly and lawfully relate to the amount of energy used by the brain (55).

Our findings support that account but not in its entirety. Presumably, performing a relatively less stable pattern (i.e., antiphase) requires more effort than performing a relatively more stable pattern (i.e., in-phase). Pursuant to that logic (58, 71, 72), hemodynamic activity decreased in the pre-SMA when transitioning from antiphase to in-phase, simultaneously supporting the idea that information processing load is reduced. Furthermore, antiphase movements in other conditions followed a similar hemodynamic trend in the pre-SMA. However, while hemodynamic activity during in-phase prepared movements was similar regardless of signal condition, the overall hemodynamic response appeared to depend on signal condition. Antiphase movements in the pink noise condition resulted in the greatest hemodynamic response. Additionally, movements paced in other conditions (i.e., white noise, Brown noise, and invariant signals) presented with diminished hemodynamic activation. It is possible that synchronizing to pink noise is more difficult, particularly during antiphase prepared movements, resulting in a higher hemodynamic response. However, that explanation has two challenges: First, synchronizing to white noise is putatively more difficult because it is completely random and provides no information about future states. Yet, white noise during antiphase movements demonstrated a lower hemodynamic response. Second, no such differences emerged during movements prepared in-phase. Information processing load alone, driven by task difficulty, cannot be the causal force behind the hemodynamic response. Instead, the hemodynamic response may reflect the level of engagement in the activity itself. When individuals perform a relatively less stable pattern, such as antiphase coordination, it is plausible that they engage more actively and effortfully to maintain the desired motor coordination state. Increased engagement and effort could lead to a greater hemodynamic response.

In the larger context, our work offers insights for researchers aiming to model neurological activity. It is well established that the brain exhibits a diverse range of oscillatory activities across different frequencies, markedly influencing cognitive, emotional, and motor processes (73). Our findings highlight the significance of considering the structure of these oscillations, opening different possibilities for future investigations of neuronal activity utilizing the HKB model.

In conclusion, our investigation focused on the interplay between coordination dynamics, represented by the HKB model, and the temporal structure of upper limb bimanual movement speed. By incorporating pink, white, and Brown noise variability, we explored phase transitions, a key characteristic of the HKB model, through simulations and experimental observations. Our study also examined how these experimental conditions influenced changes in brain dynamics. We contend that bimanual coordination entrained to pink noise, as observed in healthy movements, adapts quicker to stabilize increasingly unstable movement patterns. Additionally, hemodynamic response is influenced by both the relative phase and temporal structure of the variability of upper limb movements. These findings contribute to our understanding of coordinated behavior in living organisms and enrich the HKB model with a different dimension that can impact its applications

in various domains, including neuroimaging, cognition, skill development, and biomechanics. By elucidating the intricate relationship between coordination stability, movement variability, and brain activity, we advance our knowledge of motor coordination and open avenues for further exploration in this field.

Materials and Methods

Subjects. We conducted a power analysis by referencing effect sizes reported in relevant literature, following similar study designs (56). Utilizing a Cohen's *f* effect size of 0.62, a type I error rate set at 0.05, and a statistical power of 0.80, we calculated that a minimum of *N* = 15 subjects would be necessary (74). To mitigate potential data loss or participant attrition, we recruited an additional five subjects. Thus, a total of twenty healthy adults (12 males, 8 females; mean age = 25.1 ± 2.52 years; mean body mass = 71.9 ± 13.8 kg; mean height = 1.72 ± 0.12 m; 15 right-handed, 5 left-handed) with normal or corrected-to-normal hearing were enrolled in the study. Participants were excluded if diagnosed with musculoskeletal pathologies such as rheumatoid arthritis, neuropathy, myopathy, vertigo, joint replacement, diabetes, stroke, scoliosis, inability to hear the auditory stimulus, pulmonary diseases, recent major surgery, acute illness, or history of pulmonary, cardiac, or locomotor disorders (including unexplained falls within the past year). Five participants were excluded due to noncompliance during the study, specifically for failing to maintain pace with the metronome at faster frequencies. Demographic details of included participants are provided in Table 1. Participants were blinded to the testing condition. The study received approval from the Institutional Review Board at the University of Nebraska Medical Center, and all participants provided written informed consent before participation.

Experiment Design. The study employed a 2 × 4 × 8 repeated measures design featuring three independent variables (Table 2). The first independent variable, termed "initial phase," involved subjects initiating either an in-phase or antiphase coordination pattern. The second independent variable, termed "signal type" pertained to the temporal structure of metronomic timing intervals, encompassing pink, white, brown, and invariant signal types. These signal types were selected based on their prevalence in previous literature examining movement behavior (52, 75). The third independent variable, termed "frequency" denoted the incremental increase of the metronome by 0.25 Hz every 8 s over eight total epochs. These parameters were chosen to mirror a prior study utilizing the same bimanual movement pattern while observing relative phase changes (56). All signal types followed the frequency increase pattern described above.

Custom MATLAB code was developed for variant metronomes requiring frequency increase and proper scaling structure. This involved generating time series comprising eight seconds of eight incrementally increasing frequencies (as specified), embedded with the appropriate scaling structure (e.g., pink), and concatenating these frequencies into one time series. Consequently, each trial lasted approximately 64 s, a duration determined suitable based on pilot data assessing subjects' fatigue and the likelihood of phase transitioning.

The dependent variables for assessing bimanual coordination included mean relative phase ($\bar{\phi}$) and standard deviation of relative phase. Additionally, the dependent variable for the fNIRS analysis was the mean ΔHbO_2 in the pre-SMA and SMA proper regions (SI Appendix, Fig. S1).

Apparatus. Participants were instructed to sit in a chair equipped with modified armrests featuring two levers positioned at the distal ends of the armrest platforms (Fig. 1A). With their arms positioned at approximately a 90° angle, participants grasped the levers, which were fixed solely to rotational movement

Table 1. Demographics and sample size	
<i>N</i> = 10, 5 females	
Demographics	
Age (y)	25.2 ± 2.6
Height (m)	1.73 ± 0.12
Body mass (kg)	71.9 ± 13.8
Data are presented group mean ± SD.	

Table 2. Conditions of initial phase				
Invariant (Pink, White, Brown) (B)				
In-phase (I)	IV	IP	IW	IB
Antiphase A	(IAV)	A-P	A-W	A-B

within the frontal plane. All movements remained within the participants' normal range of motion, and conditions were devised to minimize unnecessary fatigue (further details provided in Experimental Procedure). Kinematic data from pronation and supination movements were captured using a Phasespace Camera system (PhaseSpace Impulse X2, CA) sampling at 960 Hz. Active LED markers were affixed directly onto the rotating levers to track the oscillatory movements.

Experimental Procedure. Participants were seated and outfitted with the fNIRS cap, positioned on the head according to the 10 to 20 international system (76). They then engaged in a self-paced task involving pronation and supination wrist rotations without an auditory metronome. During this task, participants were instructed to perform an in-phase pattern at a comfortable pace for approximately 10 min, although the trial itself lasted only 1 min. The aim of this task was to gather the mean and standard deviation of movement relative to each participant, facilitating the structuring of subject-relative variability in each signal through a custom MATLAB script.

Following the acquisition of relative standard deviation, participants underwent a phase transition baseline (PTB) test. In this test, the auditory metronome frequency was adjusted relative to each participant. Initially, participants performed an antiphase pattern to an invariant metronome starting at 1 Hz and increasing by 0.25 Hz every 8 s. The trial concluded upon a phase transition occurrence. These frequencies were selected to replicate the incremental process of the experiment but commencing at a much slower frequency. Pilot testing established that 1 Hz was an appropriate starting point for this baseline test. The PTB test aimed to determine the frequency at which a phase transition occurred relative to each participant. Subsequently, epochs were scaled by 0.25 in both directions, positioning the phase transition epoch as the 6th of eight frequency epochs. For instance, if a participant phase-transitioned during the PTB test at 1.75 Hz, the corresponding epochs were set as 0.5, 0.75, 1.0, 1.25, 1.5, 1.75, 2.0, and 2.25 Hz. This method was employed to ensure a high likelihood of a phase transition occurring relative to each participant.

Upon establishing the relative metronome frequency and standard deviation, metronome timing intervals were generated using a custom MATLAB script. Time series for noise conditions (pink, white, and brown) were created utilizing the Fractional Brownian Motion Synthesis function (*wfbm()*) in MATLAB (77).

At the onset of each trial, participants remained motionless for approximately 5 to 8 s to establish a baseline brain activity. They then performed paced oscillatory wrist rotations to an auditory metronome played through a speaker. The metronome comprised an invariant stimulus or a variability embedded stimulus (i.e., noise). Bimanual pronation and supination began with either an in-phase or antiphase movement pattern, selected because prior research indicated that additional degrees of freedom are recruited when attempting to maintain antiphase movement patterns at higher frequencies (78). The current movement protocol and apparatus constrained movement to a single plane of rotation, preventing additional degrees of freedom recruitment. All potential conditions of metronome stimuli and initial phase preparation were randomized for each participant.

Participants were instructed to maintain the prepared pattern as accurately as possible, refraining from intervening should the coordination pattern change. That is, they were not to actively resist pattern alteration but establish the most comfortable pattern at the prevailing frequency (13). Immediately after the trial, participants remained still for 30 s to capture any delayed hemodynamic activity following wrist rotations. Subsequently, they were given a 2 to 5-min break to mitigate excessive fatigue, allowing sufficient time for hemodynamic activity to return to baseline values. Once four trials were completed, participants were queried about their need for a longer break and any discomfort they experienced.*

Simulation Procedure. To simulate the HKB model, we utilized MATLAB software (77). The HKB model is defined by the following equation:

$$\dot{\phi} = \Delta\omega - a \sin(\phi) - 2b \sin(2\phi) - \sqrt{Q}\zeta_t. \quad [1]$$

Relative phase, ϕ , represents the phase disparity between oscillating limbs (11). The term $\dot{\phi}$ denotes the rate of change of relative phase between oscillators over time. The "imperfection parameter", $\Delta\omega$ quantifies variations in natural periods between oscillators, predicting deviations in relative phase. The ratio, b/a , models the collective frequency of coordinated oscillation. The term $\sqrt{Q}\zeta_t$ accommodates noise within the model. Notably, ζ_t signifies a Gaussian white noise component with a strength of $\sqrt{Q}$. This component of the model addresses the multitude of subsystem interactions (i.e., the apparent "random noise" arising from underlying physiological functions), inducing stochastic fluctuations in the system's collective behavior, as elaborated below.

Aligned with our experimental approach, we aimed to modify the noise parameter in the HKB model to incorporate noises distinct from the original (random) Gaussian white noise. To achieve this, we parameterized the ζ_t term in the HKB model based on its autocorrelation and stationarity (see Eq. 2). We utilized five amplitudes of noise strength (Q), ranging from 0.001 to 1 in powers of 10, to explore the influence of noise magnitude and temporal structure on transitions (SI Appendix, Fig. S2).

$$\dot{\phi} = \Delta\omega - a \sin(\phi) - 2b \sin(2\phi) - \sqrt{Q}\zeta(H, I)_t. \quad [2]$$

In addition, we attempted to impose noise on parameters that are relevant to the overall outcome in the collective behavior of the system. To achieve this, we added the ζ_t term to the relative phase, ϕ (Eq. 3 and SI Appendix, Fig. S3) and the collective frequency, b/a (Eq. 4 and SI Appendix, Fig. S4).

$$\dot{\phi} = \Delta\omega - a \sin\left(\phi + \sqrt{P}\zeta_1(H, I)_t\right) - 2b \sin\left(2\left(\phi + \sqrt{P}\zeta_1(H, I)_t\right)\right) - \sqrt{Q}\zeta_2(H, I)_t, \quad [3]$$

$$\dot{\phi} = \Delta\omega - \sin(\phi) - 2(k + \sqrt{P}\zeta_1(H, I)_t)\sin(2\phi) - \sqrt{Q}\zeta_2(H, I)_t. \quad [4]$$

The k parameter in Eq. 4 is equivalent to b/a . The H parameter is the Hurst exponent. The original ζ_t parameter, implements white Gaussian noise only. That term was reparameterized with H to include blue ($H = 0.1$), white ($H = 0.5$), pink ($H = 0.99$), or brown ($H = 0.5$) noise as well. The integrated, I , term was used to signify whether the noise term is a stationary or nonstationary signal. The noise parameter was strengthened by multiple values of P and Q (0.0001, 0.001, 0.01, 0.1, and 1). The initial ϕ value, ϕ , was set to π . The b/a ratio was set to 0.25. Subsequently, 1000 simulations were conducted for both the original HKB model (with the white noise parameter) and the modified HKB models (with the pink noise parameter, with pink noise added to the relative phase, with pink noise added to collective frequency). The average trend of $\dot{\phi}$ for each condition was determined by calculating the mean values from those 1000 simulations.

Data, Materials, and Software Availability. Anonymized codes and datasets data have been deposited in figshare (10.6084/m9.figshare.24986436) (79). All other data are included in the manuscript and/or SI Appendix.

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*Subjects were asked whether they needed to any signs of discomfort or fatigue.

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Author affiliations: Department of Biomechanics, University of Nebraska Omaha, NE 68182; Department of Psychology, Arizona State University, Tempe, AZ 85287; Department of Physical Education and Sport Sciences, Thessaloniki, Thessaloniki 57001, Greece

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