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Abstract

We recorded head motion with one wireless marker attached to the back of the head during quiet stance as participants visually inspected a sloped ramp in order to perceive whether they might be able to stand on the surface. Participants responded with "yes" or "no" without attempting to stand on the ramp. As has been found in dynamic touch (Palatinus, Kelty-Stephen, Kinsella-Shaw, Carello, & Turvey, 2014), we hypothesized that multiscale fluctuation patterns in bodily movement during visual observation would predict perceptual judgments. Mixed-effects logistic regression predicted binary affordance judgments as a function of geographical slant angle, head-motion standard deviation, and multifractal spectrum width (Ihlen, 2012). Multifractal spectrum width was the strongest predictor of affordance judgments. Specifically, increased spectrum width predicted decreased odds of a "yes" answer. Interestingly, standard deviation was not a significant predictor, reinforcing our prediction that traditional measures of variability fail to account for what fractal measures of multiscale interactions can predict about information pickup in perception-action systems.

Keywords: *perception, action, fractal, affordance, confidence judgment*

Public Significance Statement:
Perception of action possibilities informs everyday action such as judging whether a sloped ground surface affords standing upright. This study demonstrated that the link between perception and action is established through subtle postural movement patterns that predict perceptual responses. This is evidence that perception and action are part of the same integrated system that guides behavior.

The interweaving of perception and action extends from the current, short-range adjustments to new information from, say, tripping over a crack in the pavement, into the longer range of anticipating what actions will later be possible, say, guessing whether it is safe to cross the street beyond the edge of the sidewalk or judging how steep the upcoming incline will be. Response to mechanical irregularities in the ground surface is a short reaction moderated by mechanoreceptors and the vestibular system, but for longer view of the path ahead, visual information creeps into the slower aspects of movement where we might find motor planning to press onward, safely across the street and briskly up the hill before us. Beyond the individual neurons' brief action potentials, the movement system as an aggregate of tissues neural and otherwise is hard at work exploring potential actions. Exploratory movements stopping short of actual performance might contain predictive information bridging the neural activity with the later cognitive processing.

The continuous onslaught of preparatory actions serves the purpose of uncovering new information that enables

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the perception-action system to home in on a candidate for possible performatory action. The goal of the current project is to describe the connection between the dynamics of preparatory actions and decisions about performatory actions. However, the effects of said dynamics need not stop with the perceptual response. In order to test this idea, we followed up each response by soliciting confidence judgments (Fitzpatrick, Carello, Schmidt, & Corey, 1994). Our hypothesis was that the exploratory dynamics of preparatory actions affect both perception and confidence as they co-implicate performatory behavior in terms of possibility and likelihood of occurrence, respectively.

Possibilities for action are what Gibson (1966; 1979) meant when he coined the term "affordance." They depend on an interaction across time scales and to entail a poise towards future action. Standing is never still but always poised for change in posture, and the fluctuations in standing carry a clear signature of the very interactions across time scale (Ihlen, Skjæret, & Vereijken, 2013). This signature—called "multifractal" structure—indicates the type and degree of attention to mechanical information about unseen loads on the back (Palatinus, Dixon, & Kelty-Stephen, 2013; Palatinus et al., 2014). Multifractality is a generic index of across-scale interactions in many animate biological systems (e.g. slime molds; Dixon & Kelty-Stephen, 2012), as well as nonanimate physical systems (e.g. turbulent flow dynamics of wind; Milan, Wächter, & Peinke, 2013), thus serving as an important way to connect psychological research with various fields' approach to the behavior of complex systems.

We take stand-on-ability of slopes as the affordance test case. Merely looking at a slope while standing on horizontal ground can increase postural stability (Hajnal, Rumble, Shelley-Tremblay, & Liu, 2014), even without asking participants to judge whether they might be able to stand on the slope. Multifractality of head sway serves to predict quantitative visual judgments of spatial extent across multiple tasks (Kelty-Stephen, & Dixon, 2014). We now test the hypothesis that the multifractality of head sway might contribute to affordance judgments by standing participants above and beyond known stimulus effects. Specifically, we predict that head sway multifractality will contribute to logistic models of whether or not participants judge a slope is stand-on-able or not, to ordinal models of confidence ratings, and to linear models of stimulus as a way to recover the slope's actual angle from postural sway.

Method

Participants

Twelve undergraduate students with normal or corrected-to-normal vision participated in fulfillment of extra credit option in their psychology courses after providing informed consent according to University of Southern Mississippi's Institutional Review Board. The average age was 24.0 years (SD = 10.9 years). Kelty-Stephen and Dixon (2014) indicate Cohen's d=.84 for significant effects of head-sway multifractality. Based on this precedent N = 12 in the current study gives us power of 82%.

Materials

A metal crossbar supported one end of a plywood ramp (243.84cm x 121.92cm) in notches cut into two support bars (153.67 cm tall). Crossbar placements into any of the nine corresponding pairs of notches in the support bars allowed changing surface angles from 12˚ to 48˚ in increments of 3˚ and 6˚ (*Figure 1*). The ramp's other end rested on the floor. Uniformly textured, green carpeting covered the ramp and the surrounding areas. Black felt curtain occluded the top half of the ramp area, including crossbar, support bars, and experimenters who set ramp angle for each trial.

Motion-tracking cameras (Vicon Inc., Nexus Software) tracked participants' head movements in three dimensions with sub-millimeter precision at 200Hz from behind. A cloth headband affixed a small reflective marker to the back of the participant's head.

Procedure

Participants stood 5cm in front of the bottom of the ramp for 15 seconds, at which time, experimenters prompted them to respond with yes/no judgments of "stand-on-ability," i.e., with both feet, without bending their limbs or shifting weight (cf. Malek & Wagman, 2008). Following each affordance judgment, participants rated confidence in their judgment on a scale from 1 (not confident at all) to 7 (extremely confident). Three repetitions for nine inclinations (12, 18, 24, 27, 30, 33, 36, 42, and 48 degrees) resulted in 27 randomized trials per session. Intermediary stimuli angles (from 24˚ to 36˚) appeared in 3˚ increments to provide finer sampling around typical action boundaries of 30˚ (Hajnal, Wagman, Doyon, & Clark, 2016). The relatively long duration of trials (15 seconds) was necessary due to the fact that multifractal analyses require that the time series contain at least 1500 data points. With our sampling rate, we met and exceeded this criterion to provide for stable and reliable computed values of movement parameters.

After all 27 trials, experimenters assessed maximal geographic slant affording each participant's upright stance. Experimenters set ramp angle to 12º. Participants attempted to stand on the ramp's surface without bending limbs or shifting weight. If they could stand stably on the ramp for 5 seconds, they stepped down, and the experimenters raised the surface to the next steeper angle, and they repeated the task. Experimenters recorded the angle at which participants could no longer stand for 5 seconds and repeated this task 3 additional times in double-staircase fashion (Cornsweet, 1962) alternating in ascending and descending angle settings. Experimenters obtained the individual's action boundary, that is, the maximal geographic slant angle affording upright stance, as the average of angles at which the participant could no longer stand (ascending trials) and angles at which they could stand (descending trials). This action boundary task always followed the affordance-judgment task to prevent effects of feedback on perception.

Data Analysis

We computed the mean magnitude of head movement, and the coefficient of variation (CV) defined as the ratio between standard deviation and the mean. Multifractality is a complexity measure often used to quantify movement variability (Kelty-Stephen et al., 2013). We computed the Multifractal Spectrum Width (MFW) as the variable that characterizes the postural sway time series on each trial using Multifractal Detrended Fluctuation Analysis (MF-DFA) following Kantelhardt et al.'s (2002) algorithm as implemented by Ihlen (2012). A brief summary of the MF-DFA algorithm is provided in the Appendix. Whereas standard deviation (SD) is a relatively intuitive measure of variability, SD portrays variability exhaustively only under the assumption that all fluctuations are independent and identically distributed. Heterogeneity of movement variability entails that SD of measured movements change with different time scales of measurement. According to the assumptions of the linear model, this time-scale dependence of SD should entail a growth of SD with time *t* according to an exponent *H* = .5, i.e., SD ~ $t^{H=.5}$. When H assumes the same value at all time scales, the time series is considered monofractal. However, this exponent *H* can vary with time and with different-sized values, in which case, we can denote local exponents *h*. MF-DFA provides a way to quantify the spectrum of observed values of *h* in a single measurement. The width of the multifractal spectrum (MFW) increases as variability becomes more heterogeneous across timescales.

First we modeled the hypothesis that perception is predicted by multifractality of movement patterns. Mixed-effects logistic-regression from the *lme4* R package (Bates, Maechler, Bolker, & Walker, 2015; Version 3.3.2, R Core Team, 2015) modeled the dichotomous yes/no affordance judgments (*Afford*) as a dependent variable with fixed-effect predictors *Angle* (geographical slant of the visual stimulus), *Action boundary*, *Mean* and *coefficient of variation (CV)* of head displacement series, *Hurst exponent (H)* and *multifractal spectrum width (MFW)*. Random effects included *Participant* and *Trial* as random intercept and slope effects:

Afford ~ (Trial|Participant) + Angle + Action + Mean×CV + H×MFW.

The monofractal Hurst exponent and MFW both appear in the modeling to adjudicate whether task-relevant postural sway depends on a single autoregressive pattern defined over a range of potentially independent scales (i.e., according to the single power-law exponent of *H*) or whether task-relevant postural sway depends sooner on the variety of power-law exponents that characterize a cascade built upon interactions across scales. The former description addresses decay of the linear autocorrelation, and the latter description is a nonlinear estimate of how the autocorrelation varies (Kelty-Stephen & Wallot, in press). The statistical interaction HxMFW models the degree to which task-relevant postural sway depends on the linear autocorrelation but also on the nonlinear variability in autocorrelation.

To test whether multifractality of sway can recover the trial-by-trial visual stimulus, a cumulative link model (Agresti, 2002) tested the ranked but nonlinearly-spaced dependent measures of *Angle* for effects of perceived-affordance response (*Afford*) while also testing effects of movement parameters in a similar fashion as our logistic model:

Angle ~ Afford + Action + Mean×CV + H×MFW.

Action boundary was a subject variable, representing body-scaled differences among participants. The movement predictors were organized into two groups (mean and CV together, H and MFW together) to model the differential contribution of gross descriptors and multiscale descriptors of movement time series, respectively.

To test the hypothesis that multifractality predicts confidence judgments, another cumulative-link model of the dependent variable *Conf* (confidence judgments) was evaluated. The environmental stimulus variable of *Angle* was centered and squared to account for the quadratic shape that typically reflects confidence judgments being the lowest around the action boundary and the highest at low and high geographical slants:

$$\text{Conf} \sim \text{Afford} + \text{Action} + \text{Angle}\times\text{Mean}\times\text{CV} + \text{Angle}\times\text{H}\times\text{MFW} + \text{Angle}^2\times\text{Mean}\times\text{CV} + \text{Angle}^2\times\text{H}\times\text{MFW}.$$

Results

Perceptual and Action Boundaries

Percentages of "yes" (i.e., "the ramp is step-on-able") responses decreased with ramp angle (*Figure 2*). Perceptual boundaries (M=27.5°, SD=6.50°) did not differ from action boundaries (M=29.5°, SD=4.04°), dependent-samples $t(11)=1.05$, $p=.32$. Visual perception of stand-on-ability matched the steepest slope angle that one can actually stand on.

Confidence Judgments

Average confidence was smallest at 27° (M=5.03, SD=1.49; *Figure 3*), an angle not significantly different from the action boundary, one-sample $t(11) = 2.14$, $p = .06$. Mean angle at which minimum confidence occurred (M=29.8°, SD=7.70°) was also not significantly different from the action boundary (M = 29.5°, SD = 4.04°), $t(11) = 0.11$, $p = .92$. Confidence judgments were lowest at and closely matched the action boundary, replicating past results (Fitzpatrick et al., 1994).

Multifractality of Postural Sway Predicts Confidence Judgments

Table 1 shows the complete results with bolded effects outlined in subsequent remarks. Three classes of predictors (Angle, Afford, Action) predict confidence judgments about participants' own affordance judgments. Positive quadratic effects of Angle (*Angle²*) indicated that confidence was largest at extremely low and high angles and lowest around the action boundary. Affordance judgments (*Afford*) and action boundary (*Action*) each contributed negatively to confidence judgments. The positive *Angle²×Mean* interaction was significant, suggesting that more movement at extremely shallow and steep angles resulted in higher confidence. The three-way *Angle²×H×MFW* interaction qualified negative lower-order interactions with its own significant positive estimate, revealing that H and MFW balanced each others' effects across angles.

Multifractality of Postural Sway Predicts Perception

Table 2 shows increase in Angle contributed to the likelihood of switching from "yes" to "no" responses. Action boundary did not influence affordance perception. All other movement variables significantly contributed to the prediction of affordance judgments. Increases in *Mean* and *CV* increased the likelihood of transitioning from a "yes" to "no" answer. The opposite was true for *H* and *MFW*. Specifically, increases in both *H* and *MFW* resulted in higher likelihood of "yes" responses. Importantly, the Mean×CV interaction was significant with a positive estimate, suggesting that the overall magnitude and variability of postural sway amplified each other's effects. On the flipside, the H×MFW interaction was significant with a negative estimate, suggesting that fractality and multifractality mitigated each other's effects (Kelty-Stephen, Stirling, & Lipsitz, 2015).

Multifractality of Postural Sway Predicts the Stimulus

Next we considered whether movement variables were indicative of which ramp angle the participant was looking at (see *Table 3*). The main effect of *Afford* was significant with a negative estimate suggesting that lower probability of stand-on-ability revealed that the observer was looking at a larger geographical slant angle. Action boundary was not a significant predictor of the stimulus angle. As in the case of the logistic model of perception, H and MFW contributed significantly (both with positive estimates) to the specification of the stimulus angle: the visual inspection of larger angles was tied to increases in H and MFW of head movements. The significant negative HxMFW interaction suggested that the two movement parameters mitigated each other's effects. Notably absent were effects of gross measures of variability (mean and CV). Thus, we can conclude that multiscale interactions in the movement pattern and the perceptual response can be used to recover the visual stimulus on any given trial.

Discussion

We tested a hypothesis about multifractality's role in the interweaving of perception, action and the environment under three aspects: the production of a yes/no affordance judgment, the production of a confidence judgment, and the recovery of the original stimulus from postural sway. Fractality *H*, multifractality MFW, and their interaction during each trial significantly predicted the affordance judgment as well as the original stimulus, and the interaction of these terms with a quadratic effect of angle significantly predicted confidence about the judgments—all effects controlling for contribution of mean and CV of postural sway. These three aspects operationalized three interwoven time scales beyond the shortest timescales of pre-response postural sway: 1) the perceptual response, 2) the confidence judgment and 3) the stimulus and action-boundary. Action boundary represented the enduring and stable action capability of the organism standing within the longest time scale of a stable environment. For instance, subtleties of postural sway may have created correspondingly intricate patterns of optic flow patterns that richly specified the slant of the ramp surface. Future empirical work is needed to thoroughly describe the invariant structure of this optic flow pattern, potentially casting it as the information that specifies perception of the affordance of stand-on-ability. The common thread in all models was that multifractality of movement patterns moderated the constraints of the environment, action capability, perception, and confidence, mutually predicting complementary dimensions of performance at multiple time scales.

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Appendix

The goal of MFDFA (Kantelhardt et al., 2002) is to quantify fluctuations at multiple scales in nonstationary time series data. Movement trajectory time series are typically integrated and detrended by subtracting the mean from each sample. Next the time series is divided into bins. In each bin the local residual variance from a linear regression fit is computed. The variances are raised to the power of $q/2$. Larger values of q amplify the contribution of larger fluctuations, while smaller values of q emphasize smaller fluctuations:

$$F_q(s) = \left\{ \frac{1}{2N_s} \sum_{v=1}^{2N_s} \left[F^2(v,s)^{q/2} \right] \right\}^{1/q}$$

where F^2 is the variance in each bin, v indicates the number of bins, N is the total number of samples, and s is the bin size. For each value of q, the slope of the logF^2–log$s$ plot gives the scaling relationship between the variance and bin size, known as the Hurst exponent (H). For multifractal time series, each value of q specifies a different H. A Legendre transformation of the Hurst exponents and q values yields the multifractal spectrum containing all power-law exponent values (h) for any given q parameter values. The difference between the maximum and minimum values of h defines the multifractal spectrum width (MFW) which indicates the degree of heterogeneity of power-law relationships in the time series.

Figures

Figure 1. The experimental apparatus showing the ramp from a side view. The angle (β) between the horizontal floor and the ramp was set to one of nine angles ranging between 12˚ to 48˚. The participant stood in front of the ramp. A black felt curtain (not shown here) occluded the top portion of the ramp surface. A single marker attached to the back of the head was tracked by the motion capture system.

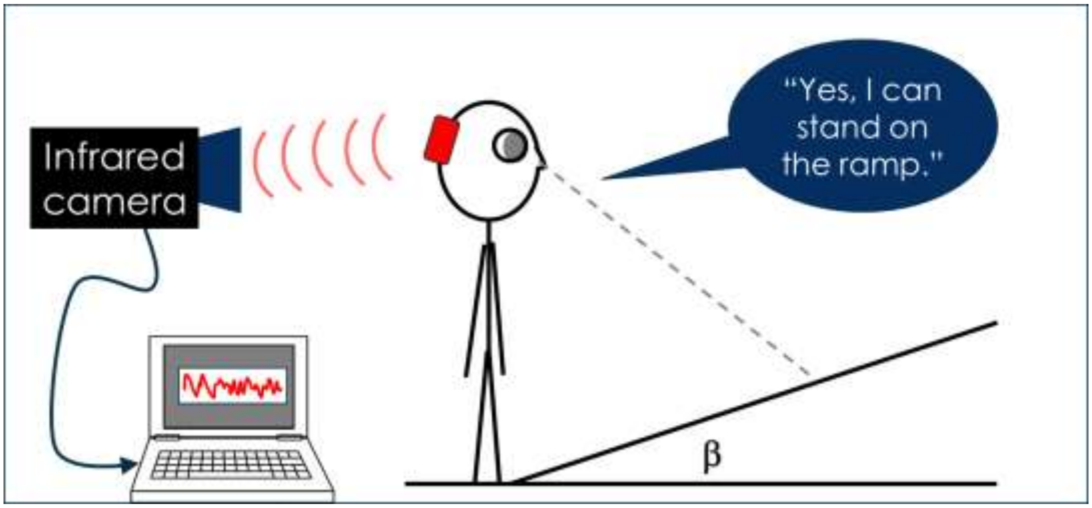

Figure 2. The percentage of "YES" responses as a function of geographical slant angle. Error bars indicate ±1 standard error of the mean.

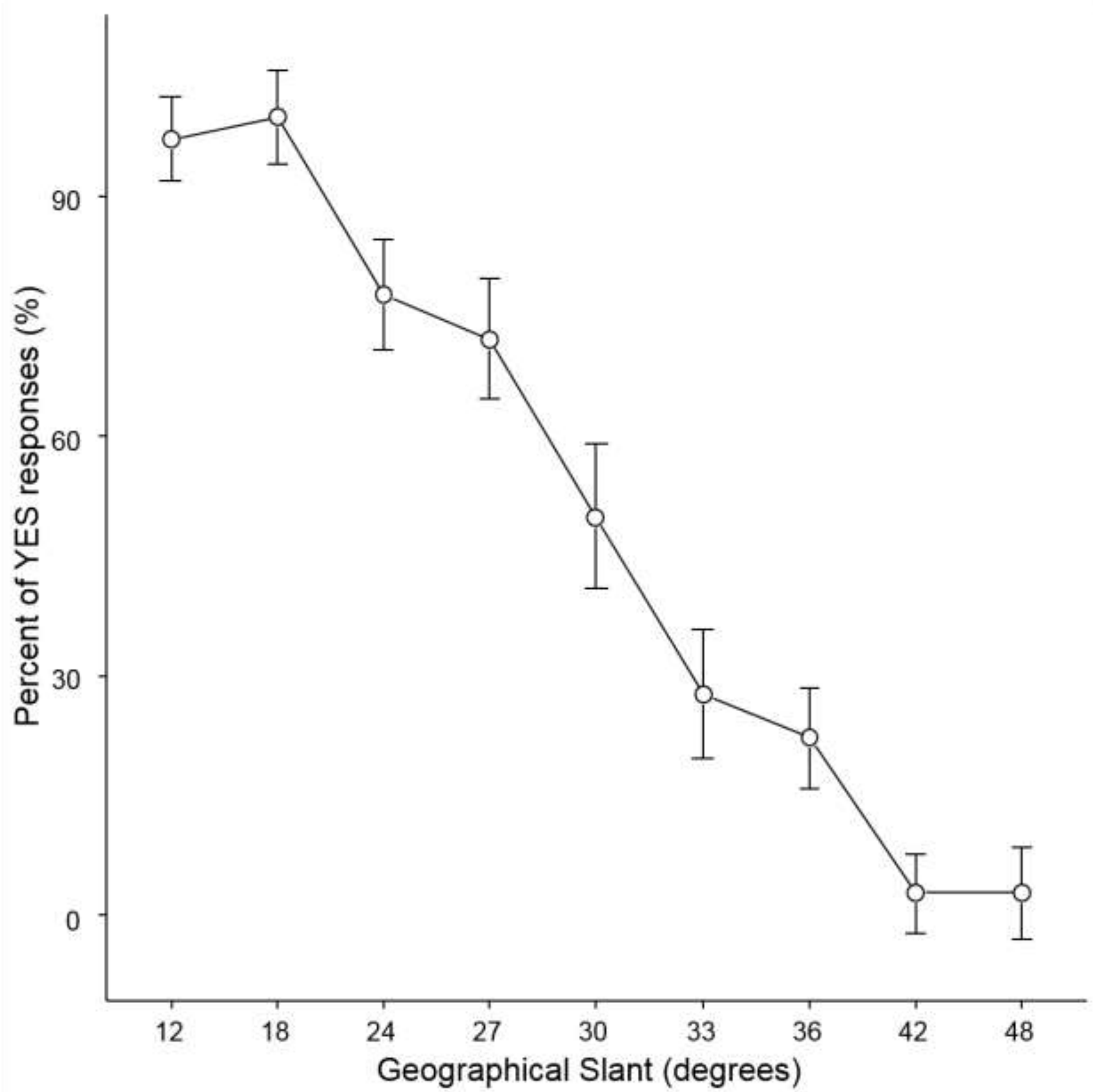

Figure 3. Confidence judgments as a function of geographical slant angle. Error bars indicate ±1 standard error of the mean.

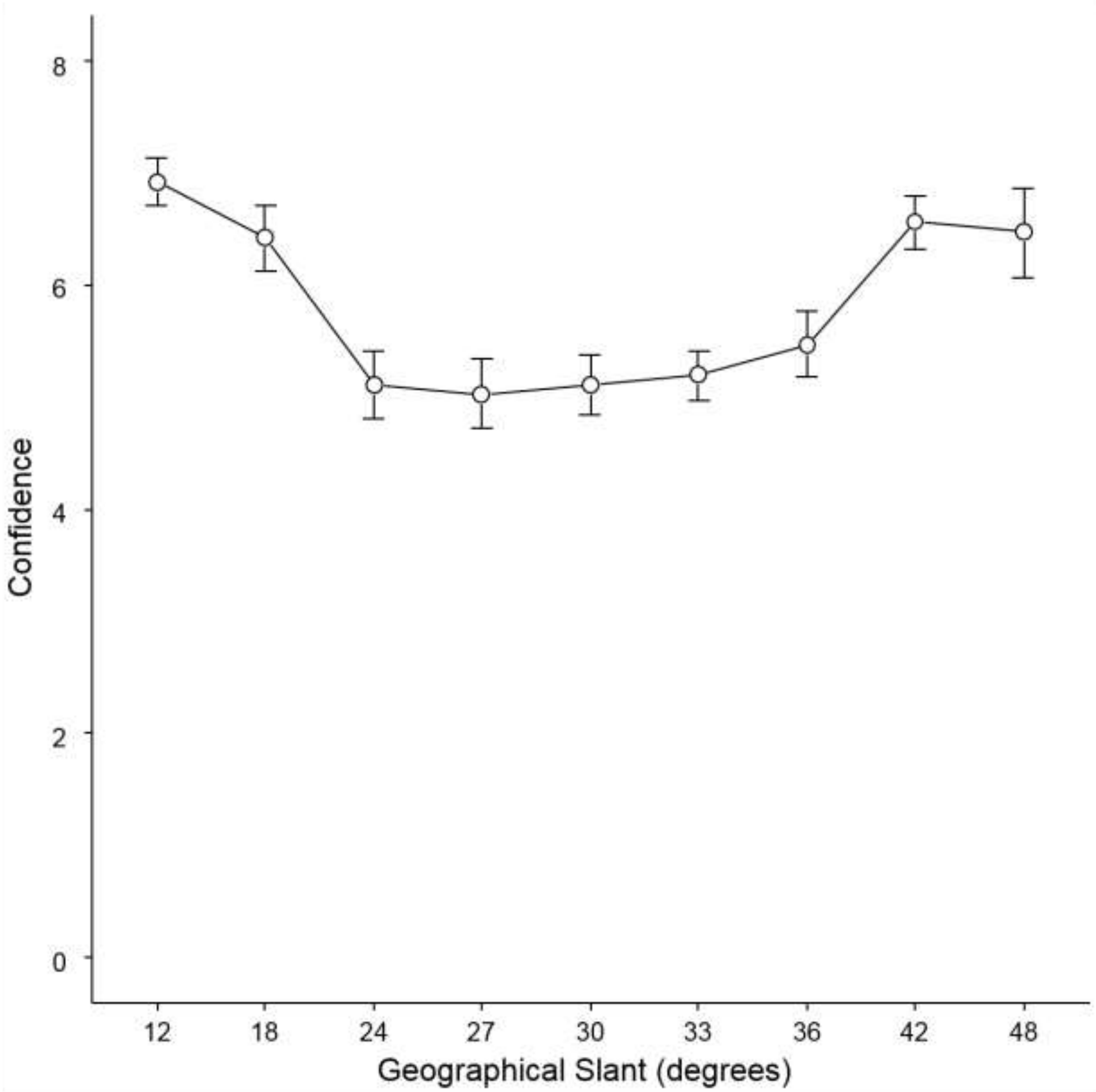

Table 1. *Coefficients from best-fitting cumulative link model of confidence judgments.*

Predictor	*B*	*SE*	*p*
Angle	0.01	0.02	.6131
Angle^2	**0.017**	**0.002**	**< .0001**
	Effects of Perception		
Afford	**-0.76**	**0.31**	**< .0147**
	Effects of Action System		
Action	**-0.11**	**0.03**	**< .0013**
Mean	-0.51	0.63	.4171
CV	-0.57	0.68	.4031
Mean×CV	-0.04	0.64	.9535
H	0.57	0.65	.3785
MFW	1.14	0.60	.0553
H×MFW	-0.42	0.55	.4460
Angle×Mean	0.0001	0.02	.9942
Angle×CV	0.029	0.023	.1939
Angle×Mean×CV	-0.004	0.018	.8313
Angle×H	-0.027	0.020	.1833
Angle×MFW	-0.031	0.019	.1037
Angle×H×MFW	0.004	0.018	.8313
Angle^2×Mean	**0.004**	**0.002**	**< .0243**
Angle^2×CV	0.003	0.002	.1267
Angle^2×Mean×CV	-0.0007	0.002	.7546
Angle^2×H	**-0.004**	**0.002**	**< .0368**
Angle^2×MFW	-0.003	0.002	.1488
Angle^2×H×MFW	**0.004**	**0.001**	**< .0100**

Table 2. *Regression coefficients from best-fitting logistic model of affordance judgments.*

Predictor	*B*	*SE*	*p*
Intercept	-1.41	14.84	0.9243
Angle	**-0.56**	**0.09**	**< .0001**
Effects of Action System			
Action	0.01	0.26	.9815
Mean	**-191.00**	**94.94**	**< .0442**
CV	**-17.22**	**8.18**	**< .0352**
Mean×CV	**272.60**	**134.60**	**< .0428**
H	**27.23**	**12.54**	**< .0299**
MFW	**29.65**	**13.99**	**< .034**
H×MFW	**-27.41**	**13.46**	**< .0417**

Table 3. *Coefficients from best-fitting cumulative link model of geographical slant angle.*

Predictor	*B*	*SE*	*p*
	Effects of Perception		
Afford	**-3.41**	**0.27**	**< .0001**
	Effects of Action System		
Action	0.02	0.03	.3575
Mean	-13.13	35.99	.7152
CV	-1.18	3.20	.7103
MeanxCV	14.37	55.85	.7970
H	**9.76**	**4.21**	**< .0203**
MFW	**10.16**	**4.64**	**< .0286**
HxMFW	**-9.18**	**4.41**	**< .0377**