

Measuring Intuition: Nonconscious Emotional Information Boosts Decision Accuracy and Confidence

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Abstract

The long-held popular notion of intuition has garnered much attention both academically and popularly. Although most people agree that there is such a phenomenon as intuition, involving emotionally charged, rapid, unconscious processes, little compelling evidence supports this notion. Here, we introduce a technique in which subliminal emotional information is presented to subjects while they make fully conscious sensory decisions. Our behavioral and physiological data, along with evidence-accumulator models, show that nonconscious emotional information can boost accuracy and confidence in a concurrent emotion-free decision task, while also speeding up response times. Moreover, these effects were contingent on the specific predictive arrangement of the nonconscious emotional valence and motion direction in the decisional stimulus. A model that simultaneously accumulates evidence from both physiological skin conductance and conscious decisional information provides an accurate description of the data. These findings support the notion that nonconscious emotions can bias concurrent nonemotional behavior—a process of intuition.

Keywords

intuition, decision making, unconscious, emotion, diffusion decision model

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From the times of ancient Greece, philosophers, psychologists, and, increasingly, the general populace have been attracted to the seductive proposition that individuals can make successful decisions without rational, analytical thought or inference, a process that has become known as intuition. Despite the widespread acceptance of this idea and everyday use of the term *intuition* to describe the feeling of certain sensations, little scientific evidence supports the existence of such a phenomenon.

The topic of intuition has become popular in applied sciences. For example, in management, intuition is investigated with survey-based techniques (e.g., Khatri & Ng, 2000; Sinclair, Ashkanasy, & Chattopadhyay, 2010) or interviews (Klein, Calderwood, & Clinton-Cirocco, 1986). These techniques tend to target an individual's perception or feeling of intuition, rather than the actual existence of a testable mechanism involving emotionally charged, rapid, unconscious processes. Accordingly, results of such studies can be inconsistent (for a review,

see Shirley & Langan-Fox, 1996; Westcott, 1968) and provide little insight into the mechanisms that might underlie the ability to utilize nonconscious emotional information for conscious decisions.

Cross-species studies of simple perceptual decisions have provided much insight into the neurobiological and computational mechanisms responsible for conscious decision making (Gold & Shadlen, 2007; Liu & Pleskac, 2011; Shadlen & Newsome, 2001). Behavioral and neural data strongly support simple accumulation models, which propose that a decision is made once enough noisy evidence has accumulated to reach a particular criterion level (Newsome, 1997; Ratcliff & McKoon, 2008). A

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recent study found that an accumulation model can describe how nonconscious sensory information is accumulated to boost decision accuracy (Vlassova, Donkin, & Pearson, 2014). It remains unknown, however, whether such accumulation and integration could occur for categorically different nonconscious information, such as emotional valence—the core ingredient of intuition.

We devised a novel psychophysical paradigm to investigate such notions of intuition. In the absence of a concise scientific definition of intuition, we define it as the productive influence of nonconscious emotional information on an otherwise unrelated decision or judgment. Our paradigm involves a random-dot-motion (RDM) task, in which subjects are asked to report the global motion direction of many moving dots. RDM has been widely used to study sensory decision making (Shadlen & Newsome, 1996). We chose to use an RDM task because it allows almost full control of the decision variables. Further, neural evidence shows that RDM tasks not only activate motion detectors, but also can be utilized to study the gradual accumulation of decisional evidence in post-sensory brain areas (Gold & Shadlen, 2007).

The moving-dot stimuli were presented concurrently with emotional images that were rendered nonconscious using continuous flash suppression (CFS). CFS has been applied in an extensive number of studies investigating nonconscious processing of visual stimuli (e.g., Tsuchiya & Koch, 2004) and can achieve long suppression periods (more than several seconds).

We conducted four main experiments and two control experiments to see if we would find evidence of an unconscious, emotionally based, rapid process that might correspond with the popular notion of intuition. Using behavioral data, physiological measures, and computational modeling, we tested the hypothesis that nonconscious emotional information can boost accuracy in an unrelated categorical decision task.

Experiment 1

Method

Subjects. Twenty-four healthy first-year university students participated in this experiment in exchange for a course credit.¹ Informed written consent was obtained according to procedures approved by the ethics committee of the School of Psychology at the University of New South Wales.

We excluded from analyses all subjects whose data did not show a monotonic or nearly monotonic increase in accuracy in the RDM task as a function of motion coherence in both of our experimental conditions (i.e., intact and phase-scrambled emotional images; see Procedure). The exclusion of these subjects was based on

previous studies, which consistently showed that accuracy in RDM tasks increased monotonically with motion coherence. Further, there is robust evidence that neural activity increases monotonically with motion coherence (Gold & Shadlen, 2007).

In our study, RDM decisions became easier as motion coherence increased, so if subjects did not show this simple relationship between motion coherence and accuracy, one could surmise that they could not or did not perform the task on the basis of the percentage of coherent motion (decisional evidence). In such cases, the data should not be used to investigate decision making, as the relationship between the decisional evidence and accuracy is inconsistent. Accordingly, we excluded 8 (33%) of the original subjects from analyses, for a final sample size of 16 (7 males and 9 females).

To ensure that the pattern of data we observed was not specific to undergraduate students, we ran a control experiment in which we tested 10 subjects (5 males and 5 females) who all had prior psychophysical experience in a lab setting. The data of only 1 of those subjects (10%) did not show a monotonic relation between accuracy and motion coherence; this subject was excluded from analyses.

Visual stimuli. All stimuli were presented on a 20-in. Sony Multiscan G520 CRT monitor (resolution = 1,024 × 768 pixels, refresh rate = 75 Hz). Subjects' heads were stabilized by a chin rest and positioned 57 cm away from the monitor. Stimuli were presented using the Psychophysics Toolbox, Version 3, for MATLAB (Kleiner, Brainard, & Pelli, 2007) on a Macintosh MacPro running Mac OS X.

Each RDM stimulus consisted of 60 white dots, each a 2- × 2-pixel square moving inside a circular black aperture with diameter of 3.98°. On each trial, the motion coherence was pseudorandomly selected from a pool of six coherence levels (6%, 11%, 17%, 24%, 32%, and 39%), and the motion direction was chosen from an equal number of left and right motion directions. This range of coherences was chosen on the basis of pilot testing, which indicated that it would allow us to discriminate different levels of behavioral performance in our specific setup, while keeping mean accuracy within the range of approximately 50% to 75%.

The emotional images, which measured 3.54° × 3.86°, were taken from the International Affective Picture System (IAPS; Lang, Bradley, & Cuthbert, 1999). We selected nine positive images (e.g., baby, puppy) and nine negative ones (e.g., gun, snake). In the IAPS norms, the mean pleasure ratings for these positive and negative images were 7.12 and 3.77, respectively, and the mean arousal ratings were 4.82 and 6.13, respectively (Lang et al., 1999). Three images of each valence were used in the

first block of trials, and a different set of three images of each valence was used in each subsequent block; therefore, we minimized any effect of image-specific learning. On some trials, the emotional images were distorted using a spatial phase-scrambling technique that removed high-level identification and semantic information without changing low-level image characteristics, such as contrast and spatial frequency. The original colors of all the emotional images were transformed to sepia, so that subjects could easily discriminate these images from the CFS stream (discussed in the next paragraph).

As noted earlier, we used CFS to suppress the emotional images from subjects' awareness. By means of a mirror stereoscope, the CFS stream was presented to one eye, and the emotional images were presented to the other, so that they overlapped at a single spatial location. The CFS stream comprised mosaics of shapes in six bright colors; sepia was excluded. The shapes were rectangles, triangles, and circles, which changed at a frequency of 10 Hz. The CFS stimuli subtended $4.37^\circ \times 4.77^\circ$ of visual angle. Thus, they were slightly bigger than the emotional images, so that they covered the whole area of the images, including the edges.

Procedure. Subjects were instructed to decide whether the global motion direction in each RDM stimulus (presented binocularly) was to the left or to the right and to report their decision by pressing the left or right arrow key on the computer keyboard. Concurrently, an emotional image was presented to one eye and rendered

nonconscious by the CFS stream presented to the other eye (see Fig. 1). The binary emotional valence of the images (positive or negative) was 100% concordant with the direction of the motion in the RDM stimuli across all six levels of motion coherence. On each trial, the stimuli were presented for 400 ms, and subjects had up to 2,000 ms to respond. The intertrial interval was 1,000 ms. Subjects completed three blocks of 144 trials. Within each block, 72 intact emotional images and 72 phase-scrambled images were intermixed; in each of these conditions, the numbers of positive and negative images were equal (i.e., 36 positive and 36 negative). The trials were presented in a different pseudorandom shuffled order for each subject.

Subjects were also asked to indicate when they saw a break in the CFS stream. Specifically, they pressed the space bar whenever they saw any sepia color within the stream. A trial in which suppression was reported broken was immediately stopped, and the subject moved on to the next trial; the aborted trial was then randomly reintroduced among future trials, so that all subjects completed an equal number of trials in each condition, and they could not shorten the total experimental time significantly by reporting a large number of suppression breaks. We did not give an explicit incentive to report awareness because we were afraid that such an incentive might attenuate performance on the RDM task; that is, an incentive might motivate subjects to pay too much attention to the CFS stream and not enough attention to the decision stimulus.

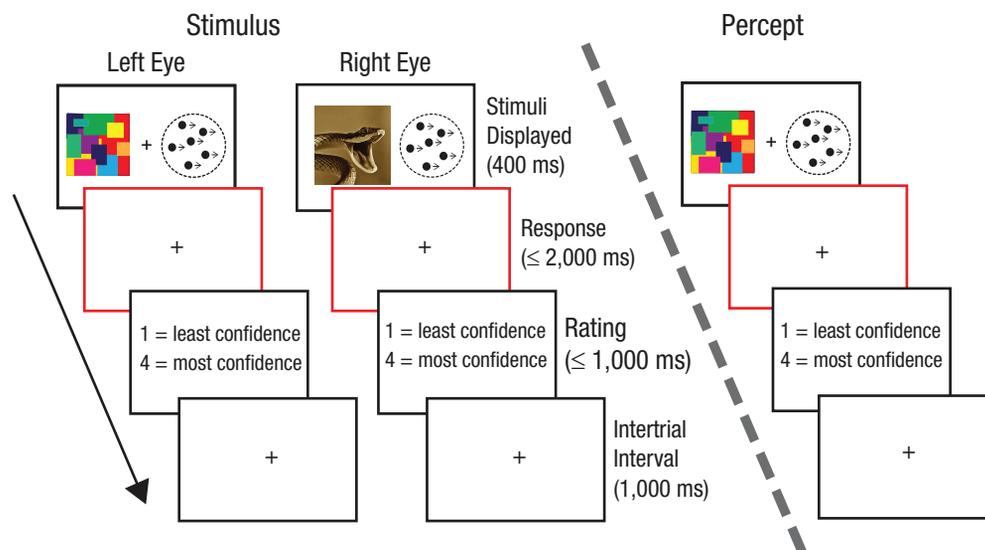


Fig. 1. Illustration of the trial sequence and subjects' percepts of the displays. Subjects were presented with a binocular random-dot-motion (RDM) stimulus, along with an emotional image (or neutral image, in one of the control experiments) that was rendered nonconscious by a continuous flash suppression stream. Subjects then reported whether the global motion of the RDM stimulus was to the left or right. In Experiments 2 and 3 only, subjects also indicated their confidence in their decision, using a 4-point rating scale.

Prior to the main experiment, each subject performed a detection task with a set of neutral images depicting single objects (i.e., book, hammer, and clock) so that we could determine an appropriate contrast level for the emotional images that would allow the CFS stream to render them unconscious.

Results

We found that decision accuracy was higher when the RDM stimuli were accompanied by suppressed intact emotional images ($M = 59.16\%$, $SD = 9.05$) than when they were accompanied by otherwise identical suppressed phase-scrambled images ($M = 56.53\%$, $SD = 8.74$), $F(1, 15) = 11.91$, $p = .003$, $\eta_p^2 = .467$ (Fig. 2a). This effect was largely driven by the trials with the lower levels of motion coherence. Note that this difference could not have been driven by low-level image characteristics, such as contrast, color, and spatial frequency, as they were not changed by the phase scrambling.

To ensure that our strict criterion for excluding subjects had not driven the pattern of our results, we analyzed the data after applying a more relaxed exclusion criterion. For this analysis, we excluded subjects whose data did not show a monotonic increase in accuracy as a function of motion coherence across only the 6%, 17%, and 32% levels of coherence (as opposed to all levels of coherence). This criterion resulted in inclusion of 21 of the total 24 subjects. We obtained the same significant effect of image condition on accuracy, $F(1, 20) = 17.574$, $p = .001$, $\eta_p^2 = .468$ (see Fig. S1 in the Supplemental Material available online), as we did using the stricter criterion. Note that we also found an interaction between coherence level and image condition, $F(5, 16) = 3.077$, $p = .039$, $\eta_p^2 = .490$. In addition, when we applied no exclusion criterion and analyzed the data from all 24 subjects, we obtained the same significant main effect of image condition, $F(1, 23) = 16.336$, $p = .001$, $\eta_p^2 = .415$ (Fig. S1), with a significant interaction between coherence level and image condition, $F(5, 19) = 3.869$, $p = .014$, $\eta_p^2 = .505$.

Finally, the control experiment revealed that the effect of the intact emotional images generalized beyond psychophysically naive undergraduates. In our sample of 9 experienced psychophysical observers, we saw the same boost in accuracy in the intact-images condition, $F(1, 8) = 9.37$, $p = .014$, $\eta_p^2 = .510$ (see Fig. S4 in the Supplemental Material).

Experiment 2

In Experiment 2, we extended the procedure from Experiment 1 to include measures of decision confidence and response time, as confidence and response times are typically thought to be based on the amount of

accumulated decision evidence (Kiani & Shadlen, 2009). Hence, if nonconscious emotional information increased confidence and sped up response times, this would constitute evidence that subjects might have combined the nonconscious emotional information with conscious decisional information.

Method

Twenty-one undergraduate students participated in this experiment in exchange for a course credit. Three (16%) were excluded from analyses because their data did not show a monotonic increase in accuracy in the RDM task as a function of motion coherence.

The procedure was similar to that of Experiment 1, with the following exceptions. First, response times for decisions on the RDM task were recorded. Second, after reporting the global motion direction of each RDM stimulus, subjects reported their confidence for their decision, using their left hand to press the appropriate key on the computer keyboard. Pressing “4” indicated the most confidence, and pressing “1” indicated the least confidence.

In addition, we intermixed catch trials with the experimental trials. In the catch trials (10% of the trials in each block), we set the contrast of the CFS stream to be very low, so that the sepia images always broke suppression. The suppressed images used in the catch trials were novel neutral images, not used in any experimental trials. We included in analyses only the subjects who reported the break in suppression on more than 93% of the catch trials across the three blocks. (We permitted an incorrect response on one trial per block, to allow for incidental human error, such as pressing the wrong button.) This filter, which resulted in the exclusion of 2 (10%) additional subjects, ensured that we could rely on the included subjects' criteria for reporting incidental suppression breaks in the actual experimental trials. Thus, the final sample size was 16 (6 males and 10 females).

At the end of the main experiment, each subject was given a suppression test as a measure of objective awareness. All images used in the main experiment were again presented, with the CFS stream but not the moving-dot stimuli. Subjects were asked to indicate whether each image contained an object (intact image) or an abstract pattern (scrambled image). We intentionally simplified the suppression test by including only the images and CFS stream, without the decision task, to obtain a stricter, or more conservative, measure of awareness; if anything, applying full attention to the CFS stream should have increased the number of suppression breaks. Previous work suggests that brain activity induced by suppressed stimuli can be altered when they are presented simultaneously with an additional cognitively demanding task (Bahrami, Lavie, & Rees, 2007).

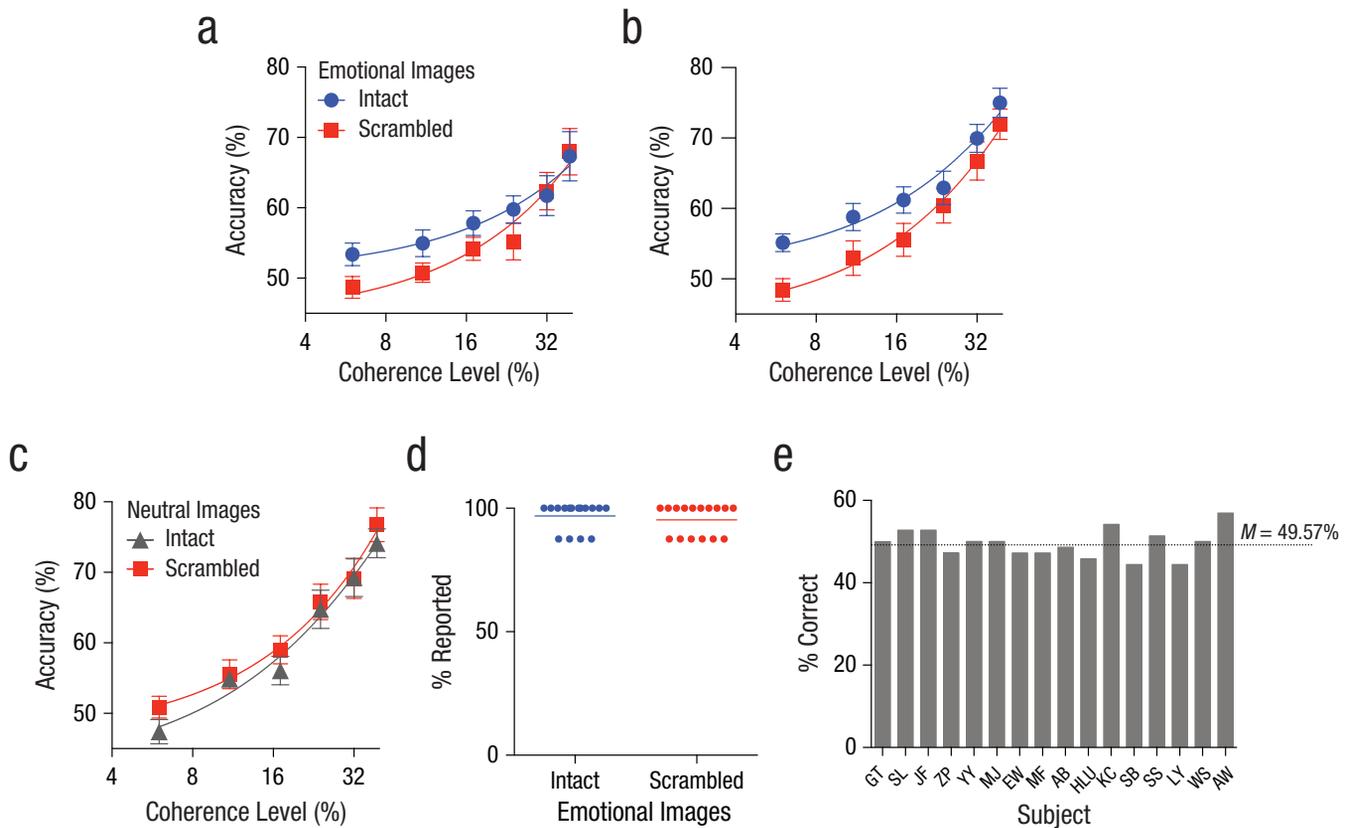


Fig. 2. Results from Experiments 1 and 2. The graphs in (a) and (b) show accuracy on the random-dot-motion (RDM) task in Experiments 1 and 2, respectively, as a function of motion coherence, separately for trials with intact and phase-scrambled emotional images. The graph in (c) shows accuracy on the RDM task in the control experiment for Experiment 2 as a function of motion coherence, separately for trials with intact and scrambled neutral images. Error bars represent ± 1 SEM. The graph in (d) shows the percentage of catch trials reported by subjects in the intact-images and scrambled-images conditions of Experiment 2; the data points show results for individual subjects, and the lines show means across subjects. The graph in (e) presents each subject's mean percentage correct in the suppression test.

We also conducted an experiment to see if the boost in decision accuracy remained when emotional content did not differentiate the two categories of images. This experiment was identical to the main experiment except that we used nonemotional images instead of the emotional images. Specifically, we used two categories of nonemotional images, animate and inanimate, to stand in for the positive and negative images. Twenty first-year university students participated in this control experiment in exchange for a course credit. Four (20%) were excluded because their accuracy in the RDM task did not increase monotonically with the dots' motion coherence. Thus, the final sample consisted of 16 subjects (7 males and 9 females).

The neutral images were taken from sources on the Internet, rather than the IAPS. Most of the neutral images in the IAPS show heterogeneous natural scenes (e.g., mountains, landscapes), which are spatially diffuse and not centered on a single object, and we wanted to use neutral images that depicted a single dominant object, as the emotional images did.

One potential concern arising from our use of images from different sources is that the characteristics of the images might be notably different. Therefore, for each image, we determined the Michelson contrast, which compares the highest and lowest luminance. The average contrast values of the 18 emotional images from the IAPS and the 18 neutral images from the Internet were 0.56 ($SD = 0.07$) and 0.54 ($SD = 0.10$), respectively. These contrast values did not differ significantly, $t(17) = -1.057$, $p > .250$, which indicates that at least the contrast of the images taken from the different sources was comparable.

Results

All subjects reported more than 90% of the catch trials (intact images: $M = 96.88\%$; scrambled images: $M = 95.31\%$; Fig. 2d) and performed at chance level in the final suppression test that served as our measure of objective awareness ($M = 49.57\%$; Fig. 2e). Despite these strict tests of subjects' awareness of the emotional images and their criteria for reporting breaks in suppression, we

replicated the effect of the intact emotional images on accuracy in the RDM task (intact images: $M = 63.83\%$, $SD = 7.68$; scrambled images: $M = 59.34\%$, $SD = 9.17$), $F(1, 15) = 14.98$, $p = .002$, $\eta_p^2 = .500$ (Fig. 2b). Further, accuracy did not differ significantly between RDM trials accompanied by negative images and those accompanied by positive images, $F(1, 15) = 0.12$, $p > .250$ (see Fig. S2 in the Supplemental Material). This suggests that there was no valence-specific effect or bias.

We also calculated incidental suppression breaks during the experimental trials. Overall, subjects reported suppression breaks on fewer than 5% of the trials (see Fig. S3 in the Supplemental Material), and there was no correlation between the number of reported suppression breaks and decision accuracy either in the intact-images condition ($r = .21$, $p > .250$) or in the scrambled-images condition ($r = -.27$, $p > .250$). Therefore, we conclude that the boost in accuracy associated with the intact emotional images was not generated by conscious perception of these stimuli.

The results for the control experiment using nonemotional animate and inanimate images were opposite to those observed with the emotional stimuli. Decision accuracy was lower in the intact-images condition ($M = 61.08$, $SD = 8.09$) compared with the scrambled-images condition ($M = 62.85$, $SD = 8.89$), though this difference was not significant, $F(1, 15) = 3.44$, $p = .084$, $\eta_p^2 = .186$ (Fig. 2c). These results suggest that it was the emotional content and not the specific categories of the images that caused the boost in accuracy in the main experiment.

Note that the RDM stimulus was always presented for 400 ms (regardless of response time). Thus, longer response times were not associated with longer stimulus-presentation times, which otherwise might lead to a higher probability of suppression breaks on the trials with lower motion coherence, which are more difficult and typically have longer response times than trials with higher levels of coherence.

Further analysis showed that the higher accuracy for decisions paired with intact emotional stimuli, compared with those paired with scrambled emotional stimuli, was accompanied by faster response times across all coherence levels, $F(1, 15) = 30.43$, $p > .001$, $\eta_p^2 = .670$ (Fig. 3a). In contrast, response times in the intact- and scrambled-images conditions of the control experiment did not differ reliably, $F(1, 15) = 0.02$, $p > .250$ (Fig. 3b).

The pattern of results for the confidence ratings mirrored that for accuracy: Decisions accompanied by intact emotional images were given significantly higher confidence ratings ($M = 3.04$, $SD = 0.32$) compared with those accompanied by phase-scrambled emotional images ($M = 2.92$, $SD = 0.41$), $F(1, 15) = 8.64$, $p = .010$, $\eta_p^2 = .366$ (Fig. 3c). However, decision confidence in the

nonemotional control experiment did not differ reliably between the intact- and scrambled-images conditions (intact images: $M = 2.77$, $SD = 0.32$; scrambled images: $M = 2.75$, $SD = 0.27$, $F(1, 15) = 0.63$, $p > .250$ (Fig. 3d).

Next, we considered how a decisional evidence accumulator might adapt to use unconscious emotional information to help discriminate the two directions of motion. Might the boost in accuracy observed with intact emotional images be immediate, or might it require learning (even though our subjects did not receive any trial-by-trial accuracy feedback)? We fit the data from Experiment 2 with linear regressions and found that there was a positive trend for accuracy to increase over time for the lower motion coherences, but not for all the motion coherences combined (see Figs. S6a and S6b in the Supplemental Material). In addition, we compared mean accuracy between the first and the last blocks of the main experiment. Accuracy across all levels of coherence did not change significantly, $t(15) = -1.67$, $p = .116$ (Fig. S6c). However, there was learning across blocks for the lower coherence levels, $t(15) = -2.28$, $p = .037$ (Fig. S6d), but not for the higher coherence levels, $t(15) = -1.57$, $p = .138$ (Fig. S6e).

Experiment 3

In the previous experiments, the contingency between emotional valence of the image and motion direction of the RDM stimulus was always constant. Therefore, it was unclear whether the boosts in decision accuracy and confidence were merely due to general arousal from the presence of the emotional images, rather than the specific alignment between an emotion and motion direction. In Experiment 3, we explicitly tested whether subjects had learned the contingency between emotional valence and motion direction.

Method

Twenty-one first-year university students participated in this experiment in exchange for a course credit. Five (24%) were excluded from analyses because their accuracy on the RDM task did not increase monotonically with motion coherence. Thus, the final sample size was 16 (5 males and 11 females). The procedure for this experiment was identical to that for Experiment 1 except that the contingency between emotional valence and motion direction was reversed in the last block of trials (i.e., the third block). For example, if leftward motion was always presented with negative emotional images in the first two blocks, leftward motion was then always presented with positive emotional images in the third block (Fig. 4a).

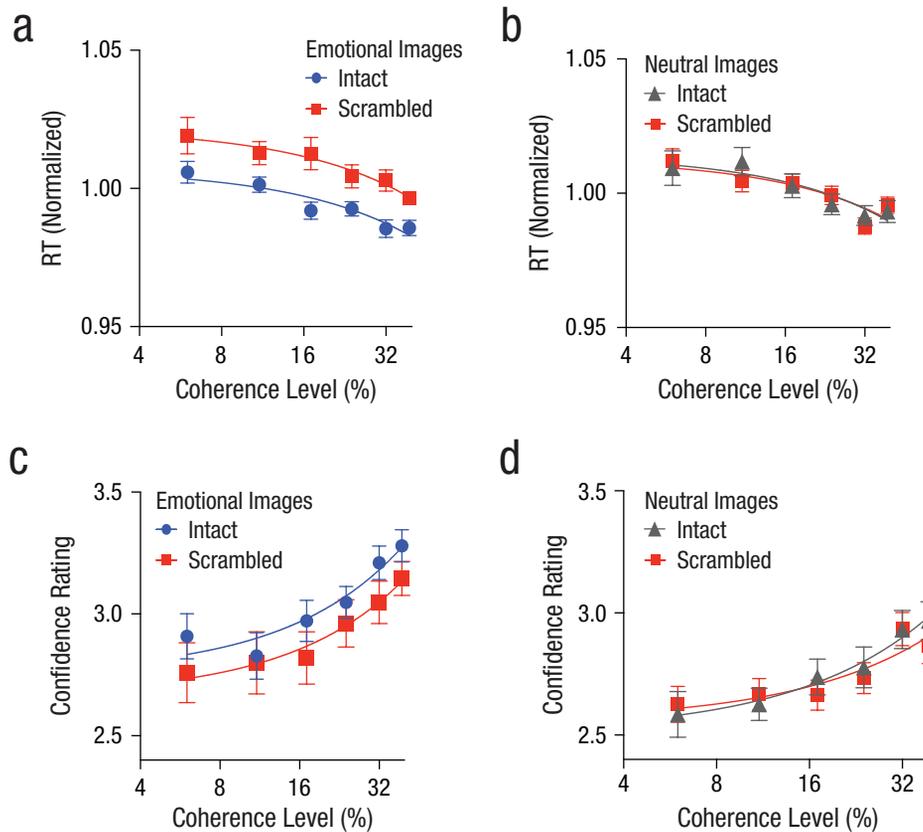


Fig. 3. Response times (RTs) and confidence ratings in Experiment 2. The top row shows normalized RT in the random-dot-motion task of (a) the main experiment and (b) the control experiment as a function of the dots' motion coherence. (For raw RTs, see Fig. S5 in the Supplemental Material.) The bottom row shows confidence level in (c) the main experiment and (d) the control experiment as a function of the dots' motion coherence. In each graph, results are shown separately for the intact- and scrambled-images conditions. Error bars represent ± 1 SEM.

Results

Across the first two blocks, we replicated the boost in accuracy in the intact-images condition ($M = 62.54$, $SD = 8.84$) compared with the scrambled-images condition ($M = 59.07$, $SD = 9.54$), $F(1, 15) = 13.45$, $p = .002$, $\eta_p^2 = .473$ (Fig. 4b); however, when the association was flipped in the final block, the difference between the two conditions disappeared (intact images: $M = 62.85$, $SD = 12.20$; scrambled images: $M = 62.07$, $SD = 11.42$), $F(1, 15) = 0.19$, $p > .250$ (Fig. 4c).

Experiment 4

Our data thus far suggest that suppressed intact emotional images boost decision accuracy and confidence, and speed response times. However, it remained unknown if this nonconscious information is somehow bound, or mixed, with the consciously available decisional information. To test for a physiological marker of the nonconscious influence of emotional information on

decisions and to probe for an interaction between the nonconscious and conscious information, we measured the skin conductance response (SCR) on a trial-by-trial basis during the task.

Method

Twenty-seven first-year university students participated in this experiment in exchange for a course credit. Five (19%) were excluded because their accuracy in the RDM task did not increase monotonically with motion coherence. This left a final sample of 22 (9 males, 13 females). As in the previous experiments, subjects performed the RDM task while being exposed to suppressed emotional images. However, the number of trials was reduced by 20%, and we used only six positive and six negative IAPS images, to reduce the experiment's duration. Two images of each valence were used in the first block, and a different set of two images of each valence was used in each subsequent block, to minimize image-specific learning. In addition, we recorded the SCR from each subject

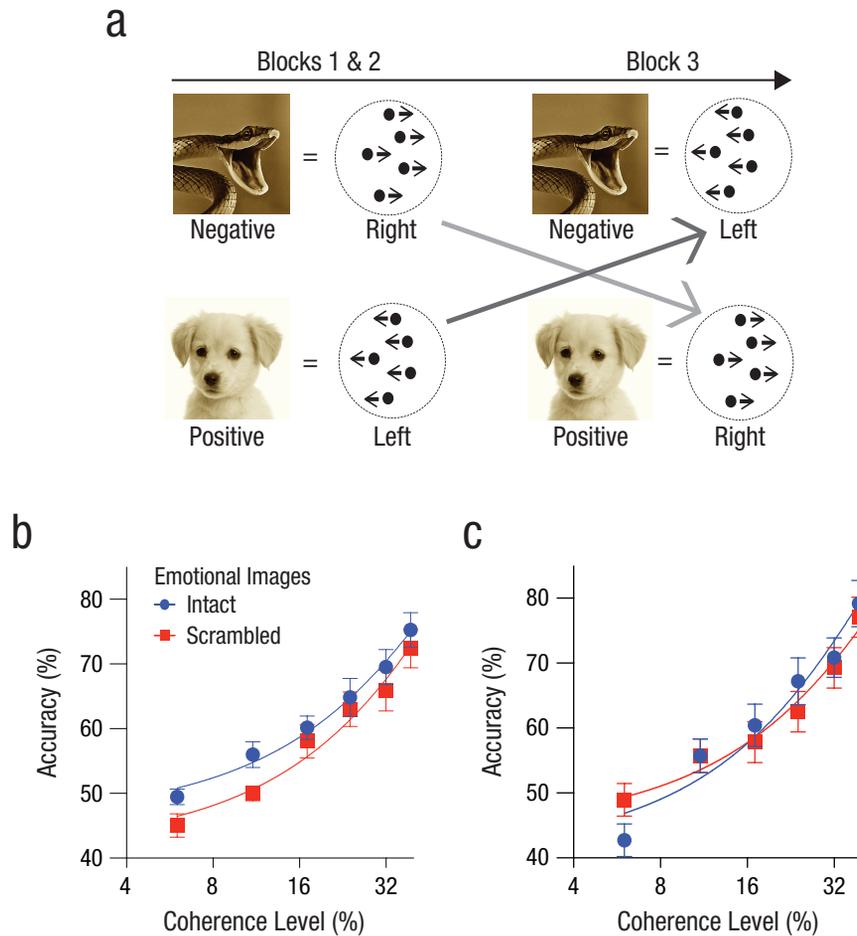


Fig. 4. Design and results of Experiment 3. In this experiment, the contingency between the valence of the emotional stimulus (i.e., negative or positive valence) and the direction of motion was reversed in the last block (a) to test whether the particular alignment of valence with motion drove the effects observed in Experiments 1 and 2. The graphs show accuracy in the random-dot-motion task as a function of the coherence of the dots' motion in (b) Blocks 1 and 2 and (c) Block 3, separately for the intact- and scrambled-images conditions. Error bars represent ± 1 SEM.

during this task. SCR is considered to be a bodily marker of emotion during an ambiguous decision task (Bechara, Damasio, Tranel, & Damasio, 1997).

SCR was recorded using the ADInstruments PowerLab 16/30 system, following the standardized published guidelines (ADInstruments, 2009). Electrodes were placed on the middle phalanges of the index and second fingers of the nondominant hand (i.e., the hand not used to report the direction of motion). Before each block, the signal was stabilized and calibrated.

We computed the mean SCR value on each trial, from the onset of the stimuli up to 6,000 ms after the response, to capture the entire dynamics of the SCR. Previous work using various types of stimuli (e.g., visual, auditory) has suggested that SCR values reach peak amplitude between 4,000 and 6,000 ms following stimulus offset (Bach, Flandin, Friston, & Dolan, 2010). We binned the individual

SCR values in 400-ms windows, separately for each level of motion coherence, and removed outlier values (i.e., those more than 2.5 SD from the mean), which we assumed were due to confounding events (e.g., random musculoskeletal response). Finally, we averaged the SCR across the entire 6-s window, separately for each coherence level.

Results

Experiment 4 again replicated the previous behavioral data. Accuracy was higher in the intact-images condition ($M = 72.37\%$, $SD = 7.98$) than in the scrambled-images condition ($M = 69.40\%$, $SD = 9.04$), $F(1, 21) = 25.77$, $p < .001$, $\eta_p^2 = .551$. In addition, the interaction between image condition and motion coherence was significant, $F(5, 17) = 4.30$, $p = .010$, $\eta_p^2 = .558$.

SCR was significantly higher in the intact-images condition ($M_{\text{normalized}} = 1.11$, $SD = 0.10$) than in the scrambled-images condition ($M_{\text{normalized}} = 0.89$, $SD = 0.01$), $F(1, 21) = 12.99$, $p = .002$, $\eta_p^2 = .382$ (Fig. 5a). Also, SCR in the intact-images condition decreased as motion coherence increased, $F(5, 17) = 2.56$, $p = .067$, $\eta_p^2 = .429$, but SCR in the scrambled-images condition did not, $F(5, 17) = 0.95$, $p > .250$. These results suggest that SCR might reflect utilization of suppressed emotional information during decision making. The finding that the SCR, largely driven by the nonconscious stimuli, was modulated by consciously perceived motion coherence suggests that the

nonconscious emotional information likely interacted, or mixed, with the conscious decisional information to boost performance.

Across all the behavioral and SCR data (not including the behavioral data from the control experiments and third block of Experiment 3), the largest differences between the intact- and scrambled-images conditions were observed at the lowest levels of motion coherence (i.e., the most difficult decisions), and we found a significant interaction between motion coherence and image condition. Accordingly, if SCR was indeed a proxy for a source of decisional evidence, then the gap between the

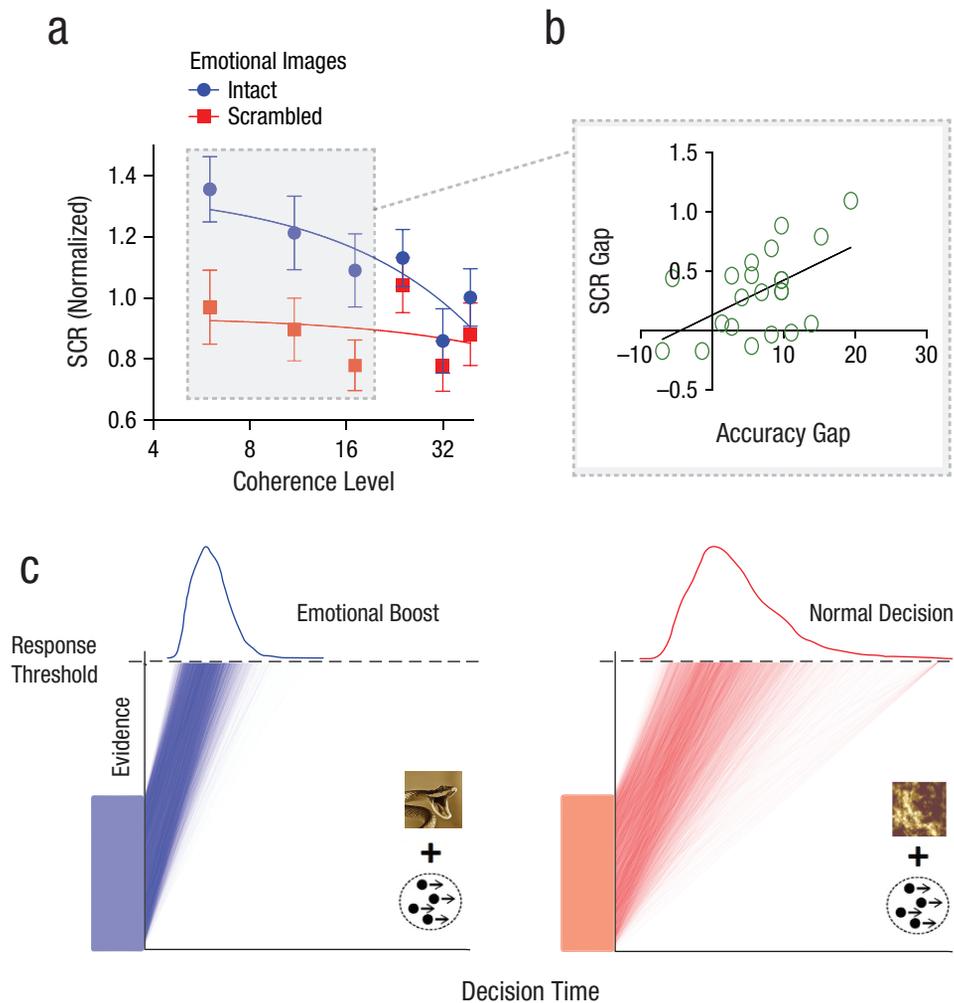


Fig. 5. Skin conductance response (SCR) in Experiment 4 and modeling results. The graph in (a) shows normalized SCR as a function of motion coherence, separately for the intact- and scrambled-images conditions. Error bars represent ± 1 SEM. The graph in (b) shows the relationship between the SCR gap between the two image conditions (intact images minus scrambled images) and the accuracy gap between the two image conditions (intact images minus scrambled images), collapsed across the three lowest motion coherences, highlighted by the shaded rectangle in (a). The graphs in (c) depict decision models for the intact-images condition (left) and scrambled-images condition (right) in Experiments 2 through 4. Model results for individual trials are indicated by lines from the origin to the response threshold. The colored block at the corner of each graph shows the range of the starting points of evidence accumulation. The curves at the tops of the graphs show the distributions of drift rates in the two conditions.

SCR values for the two image conditions at the lowest coherences might predict the mean accuracy gap between the conditions. Further analysis showed that the SCR difference score (intact minus scrambled images), collapsed across the three lowest coherence levels predicted the analogous difference score for accuracy ($r = .53, p = .012$; Fig. 5b).

Computational models

Method

We fit a linear ballistic accumulator model (LBA; Brown & Heathcote, 2008) to subjects' full set of choices and response times (excluding Experiment 1). In an LBA model, each potential response is assigned an evidence accumulator. The evidence in each accumulator at the start of a trial is a random draw from between 0 and A . A response is triggered when one of those accumulators reaches a threshold amount of evidence, b . For computational simplicity, evidence for each response is assumed to accumulate linearly and without within-trial noise. The rate of accumulation and starting point of evidence in each accumulator can vary from trial to trial.

We assumed that subjects would have an accumulator for the "left" response and an accumulator for the "right" response. For simplicity, we assumed that they did not have a bias for either response, so that, we could collapse across trials with left and right motion and consider accumulators for correct and incorrect responses. Further, we assumed that the mean rate of evidence accumulation would be a function of both the coherence of the motion stimuli and whether the suppressed stimulus was an intact or scrambled image.

In particular, we assumed that motion coherence and accumulation rate were linearly related, so the average rate of evidence accumulation for the correct response was calculated as follows: $v = \alpha_i + \beta_i \times \text{coherence}$, where i is 1 when the emotional stimulus was intact and 0 when it was scrambled; α_1 and α_0 represent the accumulation rates in the scrambled- and intact-images conditions, respectively; and β represents the increase in accumulation rate due to an increase in coherence of 1%.

The model had eight free parameters: the maximum starting point, A ; the standard deviation of the distribution of the between-trials accumulation rate, s ; the response threshold, b ; the non-decision-time parameter, t_0 ; and the accumulation-rate parameters, α_0 , α_1 , β_0 , and β_1 . The mean accumulation rate for incorrect responses was assumed to be 1 minus the rate for correct responses (as is standard; see Donkin, Heathcote, & Brown, 2009).

The simplifying assumptions of the LBA model mean that there is a closed-form analytic likelihood expression (Brown & Heathcote, 2008). We fit the model to each

subject's choices and response times from all trials using maximum likelihood estimation. Best-fitting parameters were obtained using a combination of differential-evolution and simplex search algorithms (Price, Storn, & Lampinen, 2006).

We were unable to fit the model to the data from Experiment 1 because no response time data were collected. We fit the model to the data from all trials in Experiments 2 and 4, and to the data from only the first two blocks in Experiment 3 (i.e., before the mapping between emotional valence and motion direction was reversed).

We fit an additional model to the data from Experiment 4, making use of the SCR data. This model was identical to the model described thus far, with one critical exception. The mean accumulation rate for correct responses in the scrambled-images condition was given by $v = \alpha_0 + \beta_0 \times \text{coherence}$, and the mean accumulation rate for correct responses in the intact-images condition was calculated by taking the accumulation rate from the scrambled-images condition and adding $k \times \Delta\text{SCR}$, where k was a free parameter, and ΔSCR was the individual's mean difference in SCR response between the scrambled- and intact-images conditions. Note that the k parameter effectively replaced the α_1 and β_1 parameters in the alternative model.

Results

We found that an LBA model accounted for the influence of suppressed emotional stimuli on both the accuracy and the speed of responses. The diagonal plots in Figure 5c show estimates for accumulation rates on individual trials in the intact-images condition (left) and scrambled-images condition (right) of Experiments 2 through 4. The spread of these line plots indicates the variability in these estimated accumulation rates. When the decisions were accompanied by suppressed intact emotional images, rather than scrambled emotional images, the variability in these rates was lower and their distribution was centered on an earlier time point. These results suggest that the presence of emotional content increased the rate at which evidence accumulated.

Figures S7 through S9 in the Supplemental Material compare the observed data and model predictions averaged over subjects, given each individual's best-fitting parameters. The graphs show the cumulative probability of both correct and incorrect responses as a function of response time. The models and the observed data were very consistent, with the exception that some incorrect responses at the high motion-coherence levels were much slower than predicted.

The parameter estimates of the models suggest that the nonconscious emotional images led to an overall

boost in the rate of evidence accumulation, as reflected in differences between α_0 and α_1 —Experiment 2: $\alpha_0 = .48$, $\alpha_1 = .496$, $t(15) = 1.72$, $p = .1$; Experiment 3: $\alpha_0 = .450$, $\alpha_1 = .476$, $t(14) = 2.69$, $p = .02$; Experiment 4: $\alpha_0 = .482$, $\alpha_1 = .575$, $t(21) = 2.98$, $p = .007$; aggregate: $\alpha_0 = .474$, $\alpha_1 = .521$, $t(53) = 3.18$, $p = .002$. The differences between β s, which may reflect the interaction between coherence level and the emotionality of the suppressed images, were less consistent—Experiment 2: $\beta_0 = 0.003$, $\beta_1 = 0.003$, $t(15) = 1.10$, $p = .29$; Experiment 3: $\beta_0 = 0.0047$, $\beta_1 = 0.0045$, $t(14) = 0.4$, $p = .70$;² Experiment 4: $\beta_0 = 0.008$, $\beta_1 = 0.004$, $t(21) = 2.89$, $p = .008$; aggregate: $\beta_0 = 0.0058$, $\beta_1 = 0.0046$, $t(53) = 2.08$, $p = .042$.

For Experiment 4, we found that the model that used the SCR data to account for the difference between decisions accompanied by suppressed intact images and those accompanied by suppressed scrambled images provided a more parsimonious account of the data than the standard model, in which that difference was freely estimated. We measured model fit using the Bayesian information criterion (BIC) and found that the model with seven parameters outperformed the eight-parameter model for 20 of the 22 subjects. The probability that the SCR model generated the data, as derived from the BIC, ranged from .05 to .99, with a median value of .87. In other words, the SCR data had sufficient explanatory power that free parameters could be removed. Further, the aggregate estimated value of k (0.08) approached significance, according to a one-tailed test, $t(21) = 1.45$, $p = .08$.

Discussion

We aimed to test the popular belief in the existence of intuition using a model initially developed to account for fully conscious analytic decisions. We found that nonconscious emotional information can boost decision accuracy (Experiments 1–4) and increase confidence (Experiment 2), as well as speed response times (Experiment 2). Models of decision making typically link confidence in any given decision directly with the accumulated amount of discriminatory information relevant to the decision (Kiani & Shadlen, 2009). Accordingly, the increase in decision confidence on the trials with intact emotional images may reflect the combination of nonconscious emotional information with conscious decisional evidence (i.e., sensory evidence).

Contrary to the assumption that emotional information simply increases the gain, or the overall sensitivity, of the decision-making mechanism (Etkin, Egner, & Kalisch, 2011), our data suggest that the presence of emotion alone is not enough to boost decision accuracy significantly (Experiment 3). This interpretation is supported by the finding that decisions accompanied by

negative images were no more accurate than decisions accompanied by positive images, despite the known asymmetry in salience between positive and negative emotions. The specific and differential concordance between emotional valence and motion direction was seemingly required for individuals to utilize nonconscious emotional information in the otherwise unrelated decision task. Therefore, we demonstrated not simply emotion-based decision making (e.g., Mikels, Maglio, Reed, & Kaplowitz, 2011), but rather a type of decision making in which behavior is biased by a specific association and possibly interaction between nonconscious emotion and conscious sensory evidence. We further tested the interaction between these two categories of information using an evidence-accumulator model, which is commonly used in two-choice decision tasks (Brown & Heathcote, 2008).

We have also shown that SCR can be used as a proxy for the additional information provided by nonconscious emotional stimuli (Experiment 4). Further, the increase in accuracy provided by the intact emotional stimuli was proportional to the difference between the SCRs for the intact and phase-scrambled emotional images. This result supports the claim that the SCR signal taps into the utilization of nonconscious emotional information in a decision-making task (for a review, see Bechara, Damasio, & Damasio, 2000), and boosts confidence in the resulting decisions (Persaud, McLeod, & Cowey, 2007), as well as response times.

Across all the behavioral and SCR data, the largest differences between the intact- and scrambled-images conditions were at the lowest levels of motion coherence. The low-motion-coherence trials were more difficult than the others because there was less signal (coherent motion) among the noise (random motion). With less sensory information, decisions were more difficult and ambiguous; hence, the extra information from the emotional images had a greater impact. We suggest that nonconscious emotional information acts as additional evidence when the system is otherwise lacking task-related evidence. When there is plenty of conscious decisional information (e.g., when motion coherence in the RDM task is high), the decision threshold is easily reached without additional emotional information.

Our computational model indicated that nonconscious emotional information mixed with conscious motion information, despite their obvious categorical differences, thereby increasing the amount of overall evidence and its accumulation rate. By calculating decision parameters, we were able to estimate the value of the nonconscious emotional information in units of motion coherence. Across our data, the nonconscious emotional information was comparable to approximately a 10% increase in motion coherence.

The ability of emotional information, as opposed to nonemotional information, to boost decision outcomes might be due to the particular characteristics of emotion. In our experiment, we always presented stimuli for 400 ms because we were testing the popular belief in intuition as a rapid process. The architecture of the human brain allows emotional stimuli to be processed rapidly in the absence of conscious awareness (Almeida, Pajtas, Mahon, Nakayama, & Caramazza, 2013). Via the brainstem's arousal system, the retina can send a direct alarm-like signal to the pulvinar and amygdala that bypasses the primary visual cortex (Lidell et al., 2005; Tamietto & de Gelder, 2010; Vuilleumier et al., 2002). This pathway is a likely candidate for the transmission of nonconscious emotional information that boosts otherwise unrelated decisions.

Although the exact neural architecture responsible for the effects we observed is yet to be determined, our data show that under the right circumstances, something that resembles the general description of intuition does indeed exist, can be precisely and reliably measured and manipulated using our novel paradigm, and can be modeled using existing decision models. Note that the size of the decisional boost from unconscious emotion and the related SCR were proportional to the difficulty of the decision.

Previous studies have demonstrated that associative learning can occur nonconsciously (Almeida et al., 2013; Raio, Carmel, Carrasco, & Phelps, 2012). Therefore, it is likely that in our study, subjects established "intuition" from consistent pairings between the two sources of information, one of which was rendered nonconscious. The fact that the boost in accuracy improved over time without any performance feedback suggests that intuition might indeed be something that can be improved with practice.

Our data suggest that the brain is able to combine categorically different sources of information (e.g., emotion and direction of motion), even when one source is suppressed from awareness, to aid behavior. The capacity limits of this ability remain unknown. For example, could three or four different sources of information, such as temperature, pain, and taste, be simultaneously combined and then utilized as evidence to aid behavioral decisions? This new paradigm opens the door to novel investigations of the phenomenon popularly referred to as intuition.

Action Editor

Ralph Adolphs served as action editor for this article.

Author Contributions

J. Pearson and G. Lufityanto developed the study concept and methods. Testing and data collection were performed by

G. Lufityanto. C. Donkin provided the computational model and analysis. G. Lufityanto and J. Pearson wrote the manuscript, and C. Donkin provided critical revisions. All authors approved the final version of the manuscript for submission.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at <http://pss.sagepub.com/content/by/supplemental-data>

Notes

1. Our target sample sizes for the experiments reported here were based on previous studies using RDM tasks (e.g., Vlassova et al., 2014; Vlassova & Pearson, 2013).
2. We excluded 1 subject from the statistical test in Experiment 3 because this subject's estimated alpha value was 6 times that for the remainder of the subjects, and the effect was in the opposite direction. For completeness, it is worth noting that the test that included this subject's data was not significant, $t(15) = 0.85, p = .41$.

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