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Affective Calculus: The Construction of Affect Through Information Integration Over Time

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Humans receive a constant stream of input that potentially influence their affective experience. Despite intensive research on affect, it is still largely unknown how various sources of information are integrated into the single, unified affective features that accompany consciousness. Here, we aimed to investigate how a stream of evocative input we receive is dynamically represented in self-reported affect. In 4 experiments, participants viewed a number of sequentially presented images and reported their momentary affective experience on valence and arousal scales. The number and duration of images in a trial varied across studies. In Study 4, we also measured participants' physiological responses while they viewed images. We formulated and compared several models with respect to their capacity to predict self-reported affect based on normative image ratings, physiological measurements, and prior affective experience (measured in the previous trial). Our data best supported a model incorporating a temporally sensitive averaging mechanism for affective integration that assigns higher weights to affectively more potent and recently represented stimuli. Crucially, affective averaging of sensory information and prior affect accounted for distinct contributions to currently experienced affect. Taken together, the current study provides evidence that prior affect and integrated affective impact of stimuli partly shape currently experienced affect.

Keywords: affect, information integration, affective fluctuations, momentary affect

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Affect constitutes a fundamental aspect of mental life (Barrett & Bliss-Moreau, 2009) and is a primary property of other psychological phenomena, such as emotion (Barrett, 2006; Russell, 2003), motivation (Lang & Bradley, 2010), personality (Mesquita, De Leersnyder, & Boiger, 2016), preferences (Zajonc, 1980), and judgment and decision making (Slovic, Finucane, Peters, & MacGregor, 2002). It is widely hypothesized that affect is linked to ongoing sensory changes within the body (Craig, 2015) that result from changes in the body's physiological systems (e.g., autonomic nervous system, immune system, and neuroendocrine system). This occurs because of both natural bodily fluctuations and the changes that are prompted by sensory information from the surrounding world (for a discussion, see Barrett, 2017; Lindquist, Satpute, Wager, Weber, & Barrett, 2016). Previous research has shown reliably that low-dimensional affective sensations have features of feeling pleasure to displeasure, referred to as valence, accompanied by a certain degree of arousal (Barrett & Russell, 1999; Russell & Barrett, 1999). In addition, these affective sensations fluctuate in a moment-to-moment fashion as the brain represents sensory input (e.g., Bradley, Codispoti, Cuthbert, & Lang, 2001; Bradley & Lang, 2000; Satpute et al., 2015). However, the question of how a stream of evocative stimuli is dynamically represented in affect remains unanswered. The fundamental question of how affect dynamically evolves over time in the face of

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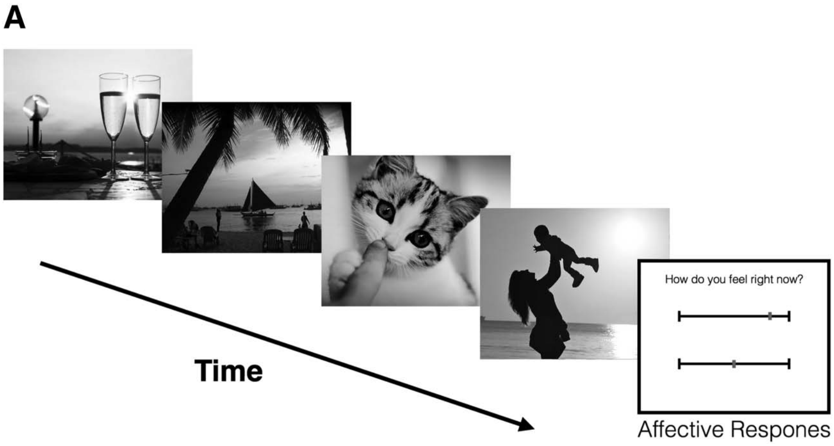
ongoing sensory stimulation and bodily fluctuations is arguably critical in understanding the role of affect in adaptive and maladaptive behaviors. Here, we investigate changes in momentary affective experience as a function of sensory input in the form of visual images using a novel experimental paradigm. Approaching affect as a dynamical system, we posit that experienced affect at any given time should reflect the affective impact of the given sensory input and previously experienced affect.

The main task of the brain is to manage resources in physiological systems to ensure the organism's survival. Hence, the brain, depending on biological functions and environmental circumstances, produces physiological adaptations to meet future demands (i.e., allostasis; Ganzel, Morris, & Wethington, 2010; Sterling, 2012). Affect is a basic property of this process because the brain continually represents physiological adaptations in connection with changing environmental circumstances (Barrett, 2017). Hence, affect is a constant stream of fluctuations in an organism's neurophysiological state that represents its ongoing relation to the environment (Barrett, 2006; Barrett & Bliss-Moreau, 2009; Russell, 2003). In other words, the dynamic, momentary affective state of an organism depends on how events influence its capacity to maintain allostasis. To study affect, researchers typically expose participants to stimuli or thought scenarios that will be experienced as threatening (or rewarding), such as coming across a bear or a snake in the forest. Ample research shows that the brain builds internal models of the causes of sensations based on prior knowledge (Clark, 2013; Friston, 2009). Coming across a bear in the forest—assuming the organism's priors represent that bears in wild may be dangerous (e.g., the outcome will be very different in a zoo)—will evoke an intense change in affect, which is experienced as unpleasant. Using the same analogy, consider the case of coming across a snake and a bear. Does one experience even stronger negative affect? Will the resulting affect intensity be twice that of the intensity when exposed to a single stimulus? While artificial, this scenario illustrates the first central question of the present research: How are multiple, independent stimuli integrated to influence an individual's affective experience? Even though bear–snake combinations may be rare, we receive an ever-flowing stream of evocative stimuli in our daily lives. The sensory information flow from our surroundings prompts fluctuations in our momentary affective experience, and, importantly, this information flow is continuous. Hence, changes in sensory information flow over time should partly be responsible for fluctuations in momentary affect. Nevertheless, we do not know how this dynamic information flow influences similarly dynamic patterns of affect. We argue here that the stream of sensory input is integrated over time in some way to influence the construction of momentary affective experience. Thus, we set out to investigate the mental calculus behind the integration of recent sensory information to influence currently experienced affect. In our studies, we tested various models such as averaging and weighted averaging describing how affective impact of the incoming stimuli is integrated over time (see The Present Research section for details).

Affect is a dynamical system that fluctuates as a function of changes in input variables and prior information represented in the system. This point illustrates the second central question of the present research. In typical studies of affect, researchers present stimuli in consecutive trials and treat these as independent stimuli presented in isolation from one another. In the current study, however, we approached affect as a temporally dependent process that carries information about sensory input in addition to the individual's prior affective experience. Thus, we argue that incoming sensory information may prompt a change in experienced affect, but the resulting affective experience will also be a function of previously experienced affect. Researchers have attempted to model affective dynamics based on moment-to-moment sensory and internal state changes (e.g., Carver, 2015; Cunningham, Dunfield, & Stillman, 2013). For instance, Cunningham and colleagues (2013) proposed that an individual's affective state at a given time is partially determined by what is occurring in the environment in addition to the individual's affective trajectory. These models, however, currently lack strong empirical support. The current studies explicitly test the hypothesis that affective integration of sensory input in the form of visual images together with prior affective experience shapes currently experienced affect. To achieve this, we designed a novel paradigm in which participants viewed sequentially presented images and subsequently reported their affective experience (Figure 1A) using two descriptive features: hedonic valence and arousal. Then, we formulated predictive models of self-reported affect based on the given images' normatively estimated propensity to evoke affective changes (normative valence and arousal ratings acquired from Kurdi, Lozano, & Banaji, 2017). We also included a term corresponding to prior affective experience (as measured in the previous trial) as a potential predictor of self-reported affect in all models. In Study 4, we introduced physiological reactions to these models. In all studies, images that are normatively associated with pleasant affect (referred to here as *pleasant images*) and those known to be associated with unpleasant affect (i.e., *unpleasant images*) were presented in separate blocks. Moreover, because we approach affect as a temporally dependent process that reflects the affective impact of sensory stimuli and previous affective experience, it is worthwhile to investigate the role of the temporal variables of the current paradigm such as viewing time and trial length on fluctuations of momentary affect. Therefore, we varied the number of stimuli per trial and duration of images in separate studies (see Figure 1B).

The Present Research

In the current research, we used three different types of factors in the predictive models of experienced valence and arousal: (a) normative valence and arousal ratings of the viewed images, (b) previously reported valence and arousal, and (c) physiological reactions. First, the normative ratings of an image were taken as a proxy for how an individual might feel in response to looking at a given image. This, therefore, represents the normative affective impact prompted by an image. Because we are interested in the question of how the affective impact of a stream of evocative stimuli is integrated over time, we tested different integration mechanisms. Psychophysical and behavioral experiments from a variety of domains have shown that humans are sensitive to statistical properties of stimuli. For instance, when individuals made likability judgments based on personality traits of a hypothetical person, simple averaging, in which each instance of a given trait has similar weight, accounted for their judgments (Anderson, 1981). Averaging could also account for individuals' affective assessments of their past experiences (Miron-Shatz, 2009).



B

Sequence and trial information for the studies

	Sequence length	Duration	Number of trials
Study1	4 images	2 sec/image	64
Study2	4 images	2 sec/image	42
	4 images	4 sec/image	42
Study3	6 images	2 sec/image	60
Study4	4 images	4 sec/image	60

Figure 1. (A) Trial structure for the present studies. Participants viewed images in a sequence and then reported their affective states on valence and arousal scales. (B) Sequence information for each of the four studies. For each study, the number of trials, the number of images, and the view-time durations are listed together. Images are from the Open Affective Standardized Image Set (Kurdi et al., 2017).

Anderson (1981) also reported a primacy effect where the influence of a bad (or good) personality trait intermixed with good (or bad) ones on likability judgments decreased linearly with its ordinal position in the trait set. Further, Kahneman and colleagues (Fredrickson, 2000; Kahneman, Fredrickson, Schreiber, & Redelmeier, 1993) found that people's evaluations of affective episodes could be predicted by the affect experienced at moments of peak affect intensity and at the conclusion of the episode; that is, the peak-end rule. In the context of the current studies, in which participants viewed sequentially presented images, the effects described above provide explicit and unique predictions. An averaging effect posits that average normative valence and arousal of all images in a trial would provide the best prediction for the resulting affective experience. A peak effect, on the other hand, suggests that the best predictor would be the image with the most intense affective ratings. An end and a primacy effects predict that higher weights would be given to the last and first seen images.

Second, we included prior affective experience (valence and arousal reported in the previous trial) as a predictor of currently experienced valence and arousal in all models to test our hypothesis that affect is a dynamical system and the current state of such a system (i.e., currently experienced affect) carries information about its own prior state (i.e., previously experienced affect).

Finally, because physiological activity fluctuates with affective changes, assessing physiological reactions together with self-reported affect increases the information represented in our models. Therefore, in Study 4, we recorded participants' facial electromyography (EMG), electrodermal activity (EDA), pulse, and respiration rate during image viewing; and used this data to predict momentary affect. We recorded facial EMG over corrugator supercillii (CS) and zygomatic major (ZM) muscles. These muscle sites are widely used in studies of affect and, on average, increased activity in CS and ZM are correlated with increased unpleasant and pleasant affect (e.g., Bradley & Lang, 2000; Cacioppo, Petty, Losch, & Kim, 1986; Lang, Greenwald, Bradley, & Hamm, 1993; Larsen, Norris, & Cacioppo, 2003). EDA reflects ongoing sympathetic activity and correlates with sympathetic arousal (e.g., Critchley, 2002). Pulse rate (e.g., Bradley & Lang, 2000; Lang et al., 1993) and respiration rate (e.g., Boiten, Frijda, & Wientjes, 1994) were also used in several studies of affect and sudden changes in them can be prompted by intense affective fluctuations.

Study 1

The first study set out to test our hypothesis that currently experienced affect is partly shaped by affective integration of visually presented images and prior affective experience.

Method

Participants. Forty-four (22 women; M age = 25.2, SD = 6.27) individuals participated in the study. Informed consent was received prior to inclusion in the experiment and participants were compensated after the study. The study was conducted in accordance with the ethical standards in the Declaration of Helsinki and it was carried out in a university computer laboratory. Participants were admitted to the room in groups (maximum 12 participants per session). The data collection was open for 3 weeks, after which we stopped the experiment and analyzed the results.

Experimental design and procedure. In each trial, participants viewed a sequence of four images presented at a 2-s per image rate. After presentation of the last image, participants were asked to report their momentary affective experience ("How do you feel right now?") using visual analog scales of valence (pleasant–unpleasant) and arousal (low arousal–high arousal). Participants were explicitly instructed that they should assess how they currently feel in each trial. They were instructed to "look inward" and assess how they felt at that moment. Next trial started 3 s after participants responded. Images within any given sequence were either all pleasant or all unpleasant, as determined by normative ratings (acquired from Kurdi et al., 2017). Participants were instructed that images presented in a trial were selected randomly, and there were no meaningful connections between them. After reading the instructions, participants completed three practice trials in which they viewed only neutral images. Each experimental session consisted of two pleasant and two unpleasant image blocks. The two blocks with the same valence always followed each other but the order of the pleasant and unpleasant blocks was counterbalanced among participants.

Visual stimuli. Visual stimuli were selected from Open Affective Standardized Image Set (OASIS) database (Kurdi et al., 2017) that provided normative valence and arousal ratings (measured on seven-point scales, ranging from 1 = very negative or very low arousal to 7 = very positive or very high arousal). We first removed all neutral images (normative valence ratings between 3.5 and 4.5). The remaining pleasant and unpleasant images were assigned to three different arousal categories based on their normative arousal ratings: low- (below 3.5), middle- (between 3.5 and 4.5), and high-arousal (above 4.5). With six groups of images so defined, we selected for use in the present Study 30 images from each group. In this way, we ensured that the selected images covered a wide range of arousal in both valence groups.

In the first study, image sequences were formed depending on the arousal grouping. An example of a temporal order of arousal groups for a four-image sequence could be as follows: middle–low–high–middle (MLHM). For the first experiment, we included 17 unique sequences (see the online supplemental material for details) that were repeated twice for positive and negative blocks. Our primary goal while forming the sequences was to place a highly arousing image at distinct temporal positions to ensure that highly evocative images would not occur at the same temporal position or only within the same trial. Then, images were assigned randomly to sequences for each individual. Hence, all participants viewed the same stimuli in different combinations.

Data analyses and modeling. Participants' affective responses were investigated, and their mean responses and variances were computed for each scale (i.e., valence and arousal) and block (i.e., positive and negative). Seven individuals with log variances lower than two standard deviations below the group mean were removed prior to running the predictive models. Responses from these individuals did not appear to depend on the presented stimuli, instead they responded at the lower end or midpoint of each scale at each measurement point.

Our primary analysis strategy was to predict self-reported valence and arousal at a given trial using the normative valence and arousal of the given images using generalized linear mixed models (GLMMs). First, we centered the normative image ratings around zero (-3 to $+3$ range) and scaled experienced valence and arousal between -3 and $+3$. We then tested two models to predict valence and arousal. A number of parameters (peak, end, primacy, and average, see the following text for details) derived from the normative ratings were tested in the first set of models (Single parameter models). In the second set of models, we predicted self-reported valence and arousal using the normative ratings in the presentation order in each trial (Temporal order models). In addition, we introduced valence and arousal as measured in the previous trial (i.e., prior affective experience) as a predictor of currently experienced valence and arousal in all models. A dummy coded block variable (pleasant = 1; unpleasant = -1) was also included to control for the mean differences between blocks. In addition, all models contained random intercepts and slopes at the participant level.

The predictors in the single parameter models (i.e., peak, end, primacy, average, and prior affective experience) were entered in a hierarchical regression. The predictors were individually entered in the models in all possible orders. If the significance of the coefficient estimate of a predictor was above $p = .1$, then it was removed from the model. For arousal predictions, peak represented the highest normative arousal in a sequence. Primacy and end were represented by the normative arousal of the first and last image of a sequence, respectively. Average was the mean normative arousal of all the images in a sequence. Arousal measured in the previous trial was the final predictor. Predictive models of valence were similar except that peak-valence was the most negative normative valence in unpleasant blocks and the most positive normative valence in pleasant blocks. The predictors of the temporal order models were the normative image ratings in the presentation order, in addition to prior affective experience. These models allowed us to inspect temporal order effects on affective integration.

Results

Single parameter models. Hierarchical regressions predicting valence and arousal included fixed effects of extracted parameters (peak, end, primacy, and average) and prior affect. Valence prediction revealed that both prior valence (B = 0.18, 95% confidence interval [CI; 0.12, 0.23], $p < .001$) and average normative valence (B = 0.69, 95% CI [0.55, 0.83], $p < .001$) were positively associated with currently experienced valence (see Study 1 in Table 1). The other parameters did not reliably contribute to the model ($p > .1$). Similarly, the arousal model indicated that only prior arousal (B = 0.19, 95% CI [0.13, 0.25], $p < .001$) and average normative arousal of images (B = 0.56, 95% CI [0.42, 0.69], $p < .001$) were significant predictors of currently experienced arousal (see Study 1 at Table 1).

Temporal order models. The second set of regressions included terms accounting for normative ratings in temporal presentation order as well as prior affect to predict self-reported valence and arousal. Prior affect made significant contributions to predictive models of both valence and arousal with the same coefficient estimates as in the single parameter models (see Study 1, Tables 1 and 2). Each image contributed to both valence and arousal predictions with positive and significant coefficient estimates (see Study 1, Table 2). As a general trend, the relative contribution of a given image increased as it appeared later in a sequence in both valence and arousal models (see Table 2). This point supports a weighted-averaging account of affective integration, in which later stimuli are given higher weights compared with earlier stimuli.

Discussion

We investigated how a stream of evocative images are represented affectively and tested different models for predicting self-reported affect as a function of the viewed images' normative tendency to evoke affective changes. The results showed that an affective averaging mechanism provides the best account of integration over time. Further, previously experienced affect was a reliable predictor of the current affective experience. In addition, changes in current affective experience was slightly more sensitive for later stimuli. In Study 2, we investigated whether a change in presentation rate would yield the same pattern of findings.

Table 1
Results of the Single Parameter Models Predicting Self-Reported Valence and Arousal

Model parameters	Study 1	Study 2		Study 3	Study 4
	Four images, 2 s per image	Four images, 2 s per image	Four images, 4 s per image	Six images, 2 s per image	Four images, 4 s per image
Valence models					
Predictors and coefficient estimates	V_0: .18 (.03)**	V_0: .25 (.03)**	V_0: .19 (.03)**	V_0: .16 (.03)**	V_0: .17 (.03)**
	Av: .69 (.07)**	Av: .56 (.08)**	Av: .31 (.11)**	Av: .32 (.1)**	Av: .3 (.11)*
			Pk: .35 (.08)**	Pk: .40 (.07)**	Pk: .31 (.09)**
R^2	.71	.76	.75	.77	.72
AIC	6,120	3,653	3,763	5,806	3,232
Arousal models					
Predictors and coefficient estimates	A_0: .19 (.03)**	A_0: .19 (.04)**	A_0: .23 (.03)**	A_0: .19 (.03)**	A_0: .27 (.04)**
	Av: .56 (.07)**	Av: .52 (.1)**	Av: .54 (.09)**	Av: .6 (.11)**	Av: .53 (.1)**
R^2	.43	.5	.47	.48	.39
AIC	7,219	4,944	5,050	7,692	3,963

Note. Numbers in parentheses represent standard errors. V_0 = prior valence; A_0 = prior arousal; Av = average normative rating; Pk = peak normative rating; AIC = Akaike information criterion.
* $p < .05$. ** $p < .005$.

Study 2

In Study 2, we aimed to replicate the findings from Study 1 and to investigate whether an increase in stimulus duration would affect affective integration of evocative stimuli over time. Hence, participants viewed four images in each sequence presented at a 2-s per image or a 4-s per image rate.

Method

Participants. Forty-five (13 women; *M* age = 23.4, *SD* = 3.73) individuals participated in the study. Recruitment procedures and the stopping rule for data collection were the same as in Study 1.

Experimental design, procedure, and materials. In each trial, participants viewed four images presented at either a 2-s per image or 4-s per image rate. Subsequently, participants were asked to report their momentary affective experience. The instructions, measurement scales, and visual stimuli were the same as in Study 1. We formed image sequences depending on the arousal grouping. The same 17 sequences from Study 1 and an additional four sequences were used to balance the appearance of images from different arousal levels at different temporal positions (see the

Table 2
Results of Temporal Order Models Predicting Self-Reported Valence and Arousal

Model parameters	Study 1	Study 2		Study 3	Study 4
	Four images, 2 s per image	Four images, 2 s per image	Four images, 4 s per image	Six images, 2 s per image	Four images, 4 s per image
Valence models					
Predictors and coefficient estimates	V_0: .18 (.03)**	V_0: .25 (.03)**	V_0: .19 (.03)**	V_0: .16 (.03)**	V_0: .17 (.03)**
	P1: .15 (.04)**	P1: .03 (.04)	P1: .11 (.04)*	P1: .15 (.03)**	P1: .12 (.04)*
	P2: .15 (.04)**	P2: .14 (.04)**	P2: .1 (.04)*	P2: .06 (.03)*	P2: .14 (.04)**
	P3: .17 (.04)**	P3: .13 (.04)**	P3: .21 (.04)**	P3: .07 (.03)*	P3: .13 (.04)**
	P4: .22 (.04)**	P4: .25 (.04)**	P4: .21 (.04)**	P4: .06 (.03)^{t}	P4: .21 (.04)**
				P5: .13 (.03)**	
				P6: .2 (.03)**	
R^2	.71	.76	.75	.76	.72
AIC	6,129	3,644	3,779	5,837	3,249
Arousal models					
Predictors and coefficient estimates	A_0: .19 (.03)**	A_0: .19 (.04)**	A_0: .23 (.03)**	A_0: .2 (.03)**	A_0: .27 (.04)**
	P1: .12 (.03)**	P1: .12 (.04)**	P1: .08 (.04)*	P1: .05 (.04)	P1: .11 (.03)**
	P2: .13 (.04)**	P2: .07 (.04)^{t}	P2: .16 (.04)**	P2: .07 (.03)*	P2: .09 (.03)*
	P3: .16 (.03)**	P3: .17 (.05)**	P3: .16 (.04)**	P3: .08 (.03)*	P3: .14 (.05)**
	P4: .19 (.04)**	P4: .16 (.04)**	P4: .14 (.04)**	P4: .08 (.04)*	P4: .18 (.04)**
				P5: .11 (.04)**	
				P6: .2 (.04)**	
R^2	.44	.51	.47	.48	.39
AIC	7,226	4,952	5,065	7,721	3,978

Note. Numbers in parentheses represent standard errors. V0 = prior valence; A0 = prior arousal; P1 = normative rating of the first image in a trial; AIC = Akaike information criterion.
^{t} $p < .10$. * $p < .05$. ** $p < .005$.

online supplemental material for details). Here, each of the 21 sequences were used twice for each valence block: once at 2-s per image and once at 4-s per image presentation rate in a random order. Images were randomly assigned to sequences for each individual.

Data analyses and modeling. The analysis and modeling strategy were the same as in Study 1. First, we inspected participants' mean responses and variances in each measurement scale and block. Six individuals with log variances lower than two standard deviations below the group mean were removed prior to running the predictive models. Similar to those in Study 1, these individuals responded at the lower end or midpoint of each scale at each measurement point.

We constructed single parameter models and temporal order models to predict valence and arousal based on the normative image ratings within each sequence and prior affect in the same manner as in Study 1. We tested separate models depending on the presentation rate.

Results

Single parameter models. Hierarchical regressions predicting valence and arousal included fixed effects of extracted parameters (peak, end, primacy, and average) and prior affect. Valence prediction revealed that only prior valence (B = 0.25, 95% CI [0.19, 0.31], $p < .001$) and average normative valence (B = 0.56, 95% CI [0.4, 0.71], $p < .001$) reliably entered in the model for the 2-s/image presentation rate. On the other hand, peak valence parameter emerged as a reliable predictor (B = 0.35, 95% CI [0.19, 0.51], $p < .005$) of current valence in longer sequences together with prior valence (B = 0.19, 95% CI [0.13, 0.24], $p < .001$) and average normative valence (B = 0.31, 95% CI [0.09, 0.52], $p = .004$; see Study 2 in Table 1).

In both presentation rates, only prior arousal and average normative arousal of images were significant predictors of currently experienced arousal (see Study 2 in Table 1). The coefficient estimates of the prior arousal parameter was 0.19 (95% CI [0.12, 0.26], $p < .001$) and 0.23 (95% CI [0.16, 0.3], $p < .001$) for 2-s and 4-s per image rates, respectively. The coefficient estimates of the average-arousal parameter was virtually the same during both presentation rates (B = 0.52, 95% CI [0.33, 0.71], $p < .001$ for 2-s per image; and B = 0.54, 95% CI [0.36, 0.72], $p < .001$ for 4-s per image). The other parameters did not reliably contribute to predicting arousal ($p > .1$).

Temporal order models. Temporal order models yielded similar results as in Study 1. First, prior affect made significant contributions with the same coefficient estimates as in the single parameter models (see Study 2 in Tables 1 and 2). In addition, the general trend of increasing coefficient estimates for later images were found (see Table 2). However, this trend seemed somewhat weaker in arousal predictions.

Discussion

First, we replicated the general findings of Study 1. The averaging mechanism was the best to account for affective integration when each image was presented for 2 s. The same pattern also emerged for arousal predictions in longer sequences (4-s per image). However, valence predictions for longer sequences showed that peak-valence parameter contributed to fluctuations in experienced valence beyond averaging. One possible explanation for this finding is that the effect of less potent stimuli on experienced valence may be limited in a longer time span, so that the reliable effect of the most potent stimuli could be observed. However, a replication of this effect is needed to confirm this explanation (see Study 4). In addition, in all the models prior affect made robust contributions to currently experienced affect as in Study 1. This shows that previous affective experience is partly responsible in shaping current affective experience. In summary, we replicated the main findings of Study 1 and found potential differences due to stimulus presentation rate. In Study 3, we investigated whether increased number of stimuli would lead to changes in how affective integration over time occurs.

Study 3

In the first two studies, we found that previous affective experience and affective averaging of recent stimuli partly shaped currently experienced affect. Further, the findings from Study 2 indicated that when the presentation rate increased from 2 s to 4 s the relative contribution of the peak-valence parameter to the currently experienced valence increased. In Study 3, we therefore investigated another parameter: number of images in a sequence. Our main aim was to study whether the use of an increased number of stimuli would yield a similar pattern of results.

Method

Participants. Forty-nine (21 women, *M* age = 23.5, *SD* = 3.18) individuals participated in the study. Recruitment procedures and the stopping rule for data collection were the same as in the first two studies.

Experimental design, procedure, and materials. In each trial, participants viewed six images presented at a 2-s per image rate and subsequently reported their momentary affective experience. The instructions, measurement scales, and visual stimuli were the same as in the first two studies. Participants went through 60 trials in total. Image sequences were formed pseudo-randomly for each individual and block (i.e., pleasant and unpleasant) with the following requirements. (a) Stimuli from different arousal groups were shown at each temporal position at equal times, and (b) each sequence was a unique combination of arousal groups. In addition, we calculated the mean arousal group for each sequence (low-arousal: −1; middle-arousal: 0; high-arousal: 1). Then, to increase variance, we allowed a maximum of five sequences to have the same mean arousal group for any given participant. Thus, we ensured that there were no statistical differences in normative valence or arousal of images at different temporal positions.

Data analyses and modeling. The analysis and modeling strategy were the same as in previous studies. First, we inspected participants' mean responses and variances and removed six individuals with log variances lower than two standard deviations below the group mean prior to running the predictive models. These individuals' responses did not seem to depend on the presented stimuli, instead they responded at the lower end or midpoint in each trial. We constructed single parameter models and temporal order models to predict valence and arousal based on the normative image ratings within each sequence and prior affect in the same manner as in the first two studies.

Results

Single parameter models. Valence prediction revealed that prior valence (B = 0.16, 95% CI [0.1, 0.22], $p < .001$), average normative valence (B = 0.32, 95% CI [0.13, 0.51], $p < .001$) and peak-valence (B = 0.4, 95% CI [0.26, 0.54], $p < .001$) reliably entered in the model (see Study 3 in Table 1). On the other hand, only prior arousal (B = 0.19, 95% CI [0.13, 0.26], $p < .001$) and average normative arousal of images (B = 0.6, 95% CI [0.39, 0.81], $p < .001$) were significant predictors of currently experienced arousal (see Study 3 in Table 1).

Temporal order models. Prior valence and arousal made significant contributions to predictive models of both valence and arousal with the same coefficient estimates as in the single parameter models (see Study 3 in Tables 1 and 2). The coefficient estimates were higher for the later images. However, the valence predictions showed that the first (B = 0.14, 95% CI [0.08, 0.2], $p < .001$) and the last image (B = 0.19, 95% CI [0.12, 0.26], $p < .001$) had somewhat higher estimates in comparison to the other images (see Study 3 in Table 2).

Discussion

In Study 3, we studied the effect of increased number of images in each trial on affective integration models. Participants viewed six images in each trial. First, the averaging mechanism was the best account for integration over time for the arousal feature of affect. Thus, the averaging account of arousal does not seem to depend on either the duration or the number of stimuli. In addition, temporal order models indicated that the contribution of an image to currently experienced arousal increased as it appeared later in a trial. Like the findings of the first two studies, this finding supports a temporal averaging account of affective integration. Second, both average and peak normative valence contributed to currently experienced valence. Taken together with findings from previous studies, this suggests that peak-valence parameter emerged as a reliable predictor when the sequences were longer due to longer duration or higher number of stimuli. Third, we found a primacy effect for valence predictions in six-image sequences, which could potentially represent a memory related effect. Finally, as in previous studies, prior valence and arousal robustly contributed to current valence and arousal, which supports the hypothesis that, previous affective experience partly shapes currently experienced affect.

Study 4

Research shows that physiological activity fluctuates with affective changes (e.g., Lang et al., 1993; Larsen et al., 2003; Mauss & Robinson, 2009). Our main aim in Study 4 was to investigate changes in participants' peripheral physiology during the experiment and used this information in the predictive models of affect. Arguably, assessing physiological activity together with self-reported affect would increase the information represented in the models. We recorded participants' facial EMG over corrugator supercilii (CS) and zygomatic major (ZM) muscles, electrodermal activity (EDA), respiration, and pulse during the experiment. We then constructed predictive models of affect based on the changes in participants' physiological responses and compared them to the models based on normative image ratings.

Method

Participants. Twenty-nine (16 women; *M* age = 25.6, *SD* = 5.18) individuals participated in the study. Informed consent was received prior to inclusion in the experiment and participants were compensated after the study. The study was conducted in accordance with the ethical standards in the Declaration of Helsinki. Participants completed the study protocol individually in a psychophysiology laboratory. The data collection was open for three weeks.

Experimental design and procedure. In each trial, participants viewed four images presented at a 4-s per image rate and subsequently reported their momentary affective experience. The instructions, measurement scales, and visual stimuli were the same as in the first three studies. Participants engaged in 60 trials. Image sequences were formed pseudorandomly with the same requirements as in Study 3. Images were assigned to trials randomly for each individual.

Physiological data recording and preprocessing. We used a BIOPAC MP150 system (Biopac Systems Inc., Goleta, CA) to record participants' facial EMG (using EMG100C amplifiers), EDA (using a GSR100C amplifier), respiration rate (using a RSP100C amplifier), and pulse (using a PPG100C amplifier). Facial EMG data were recorded from the left corrugator supercilii (CS) and zygomatic major (ZM) muscles, using surface Ag/AgCl electrodes (4 mm in diameter). For recording EDA, surface Ag/AgCl electrodes (8 mm in diameter) were attached to the medial phalanges of the second and third digits of participants' nondominant hand. We recorded pulse using a photoplethysmogram transducer attached to the distal phalange of the fourth digit of participants' nondominant hand. Participants also wore a respiratory effort transducer attached to a Velcro strap around their chests. All physiological signals were sampled at 1,000 Hz, amplified, and recorded for offline data analysis.

EMG signals were band-pass filtered from 20 Hz to 480 Hz. The filtered signal was full-wave rectified and low-pass filtered at 40 Hz for smoothing. For each EMG signal, we calculated change scores by calculating the difference between the average activity within four consecutive 4-s intervals during image presentation and the average activity during a 2-s interval preceding the first image onset (baseline).

Raw EDA signals were resampled at 10 Hz and low-pass filtered at 1 Hz to remove the high frequency noise. From the resulting signal, we computed the following measures: phasic-EDA, tonic-EDA, and skin conductance response rate (SCR-rate). For computation of the phasic-EDA, the signal was high-pass filtered at 0.02 Hz (to remove the slow adapting tonic component), full-wave rectified, and averaged within four, consecutive, 4-s windows starting 1 s after the onset of the first image. These average scores then were log transformed (Figner & Murphy, 2011). For calculating tonic EDA, we applied a 10-s moving average filter to the resampled EDA signal and averaged the resulting signal within the 16 s of image viewing. From the resampled EDA signal, we also calculated SCR-rate. To do this, we first located the trough of the EDA signal (i.e., where it transitioned from a negative to positive slope). Then, we looked for the first point where the signal increased to 0.02 μS above the trough before arriving at a zero or negative slope. If this point occurred within 500 ms from the trough, we counted that as an

SCR onset. The SCR-rate was the total number of SCR onsets that occurred within a 16-s window that started 1 s after the onset of the first image.

The raw respiration signal was resampled at 10 Hz and bandpass filtered between 0.1 and 1 Hz. The filtering was applied in order to center the signal around zero and remove high frequency noise. From the resulting signal, we extracted the respiratory peaks to calculate respiration rate. We calculated change scores by computing the difference between the average respiration rate within four, consecutive, 4-s time windows after the first image onset and the average respiration rate during a 4-s baseline period measured prior to the first image.

The pulse signal was resampled at 40 Hz and low pass filtered at 10 Hz to remove high frequency noise. Then, we applied a high-pass filter at 0.5 Hz to remove low-frequency drift. Finally, the pulse rate in beats-per-minute was computed from the first order time derivative of the signal. Similar to respiration rates, change scores were calculated by calculating the difference between the average pulse rates within four 4-s time windows from the average pulse rate during the baseline period prior to the onset of the first image. The changes in pulse rate were not reliably associated with either valence or arousal and did not make a significant contribution to valence or arousal predictions ($p > .25$). This might be due to the unreliable and noisy measurement methodology (i.e., pulse photo-plethysmography) in comparison with the other physiological measures. More reliable heart rate measures based on ECG may provide results that are more suitable. The time-course analysis only indicated a general pulse rate deceleration while participants viewed both pleasant and unpleasant images (see Figure S4.1 in the online supplemental material). Therefore, pulse rate data are not presented in the Results section. All physiological measures were individually standardized to account for individual differences in responsiveness.

Data analyses and modeling. As in previous studies, we inspected participants' mean responses and variances in self-reports and removed five participants with log variances lower than two standard deviations below the group mean prior to running the predictive models. Similar to the individuals in the first three studies, these individuals responded at the lower end or midpoint of the scales in most of the trials.

We constructed single parameter models and temporal order models to predict valence and arousal based on the normative valence and arousal of the given images and prior affect. In addition, we tested a model informed by participants' physiological activity to predict self-reported valence and arousal. The predictors of this model, physiological measures (explained above) and prior affective experience, were entered in the models in all possible orders. The removal criterion was, again, set at $p > .1$. Like the other models, the physiologically informed model contained a dummy-coded block variable (unpleasant = −1 and pleasant = 1) and subject random effects.

Results

Single parameter models. Prior valence (B = 0.17, 95% CI [0.1, 0.23], $p < .001$), average normative valence (B = 0.3, 95% CI [0.08, 0.53], $p = .008$) and peak-valence (B = 0.31, 95% CI [0.13, 0.48], $p < .001$) reliably contributed to the predictive model of current valence (see Study 4 in Table 1). Similar to previous studies, the reliable predictors of current arousal were prior arousal (B = 0.27, 95% CI [0.18, 0.35], $p < .001$) and average normative arousal (B = 0.53, 95% CI [0.33, 0.73], $p < .001$; see Study 4 in Table 1).

Temporal order models. Temporal order models yielded similar results as in Studies 1 and 2. Prior affect made significant contributions with the same coefficient estimates as in the single parameter models (see Study 4 in Tables 1 and 2). In addition, there was a general trend of increasing coefficient estimates for later images (see Study 4in Table 2). However, the trend seemed somewhat weaker in arousal predictions as in Study 2.

Physiological responses. We first compared physiological activity during trials, in which participants reported experiencing negative versus positive affect (see Figure 2A). We found significant differences in facial muscle activity, respiration rate, and tonic-EDA ($p < .05$). Higher ZM and lower CS activity, lower respiration rate, and lower tonic-EDA were all associated with trials in which participants reported experiencing positive affect. A similar analysis along the arousal dimension comparing low arousal and high arousal trials yielded significant differences in ZM activity, phasic-EDA and SCR-rate (all $p < .05$; see Figure 2B). In particular, higher ZM activity, phasic-EDA, and SCR-rate were all associated with trials in which participants reported experiencing high-arousal.

Using participants' physiological responses in each trial, we carried out hierarchical regressions predicting valence and arousal. ZM activity in the last 4-s window (Zm4; B = 0.1, 95% CI [0.03, 0.17], $p = .004$) and initial phasic-EDA (pEDA1; B = 0.07, 95% CI [0.001, 0.13], $p = .048$), together with prior arousal (B = 0.26, 95% CI [0.18, 0.35], $p < .001$) were positively associated with currently experienced arousal (see Table 3). For predicting valence, CS and ZM activity during the last 4-s window (Cs4; B = −0.11, 95% CI [−0.16, −0.06], $p < .001$; and Zm4; B = 0.09, 95% CI [0.02, 0.15], $p = .007$) provided significant negative and positive contributions, respectively. Moreover, initial respiration rate (RR1; B = −0.06, 95% CI [−0.11, −0.01], $p = .014$) was negatively associated with overall valence (see Table 3). Interestingly, among the three valence models tested in Study 4, the physiologically informed model resulted in the best fit based on Akaike's information criterion (AIC). Likelihood ratio tests confirmed that for valence prediction, the physiology model performed significantly better than the single parameter model, $\chi^2(2) = 27.2, p < .001$. Finally, we tested a set of models informed by both normative image ratings and physiological measures. Results showed that combined models performed better than either model alone for valence and arousal predictions (based on AIC; see Table 3).

Discussion

The main objective of Study 4 was to investigate whether the inclusion of physiological responses would improve the predictive models of affect. The results showed that changes in facial muscle activity (both CS and ZM), tonic-EDA, and respiration rate were associated with valence, whereas ZM activity and phasic-EDA were associated with arousal. This pattern of results are consistent with previous studies (e.g., Bradley & Lang, 2000; Cacioppo et al., 1986; Lang et al., 1993; Larsen et al., 2003; Mauss & Robinson, 2009). For valence

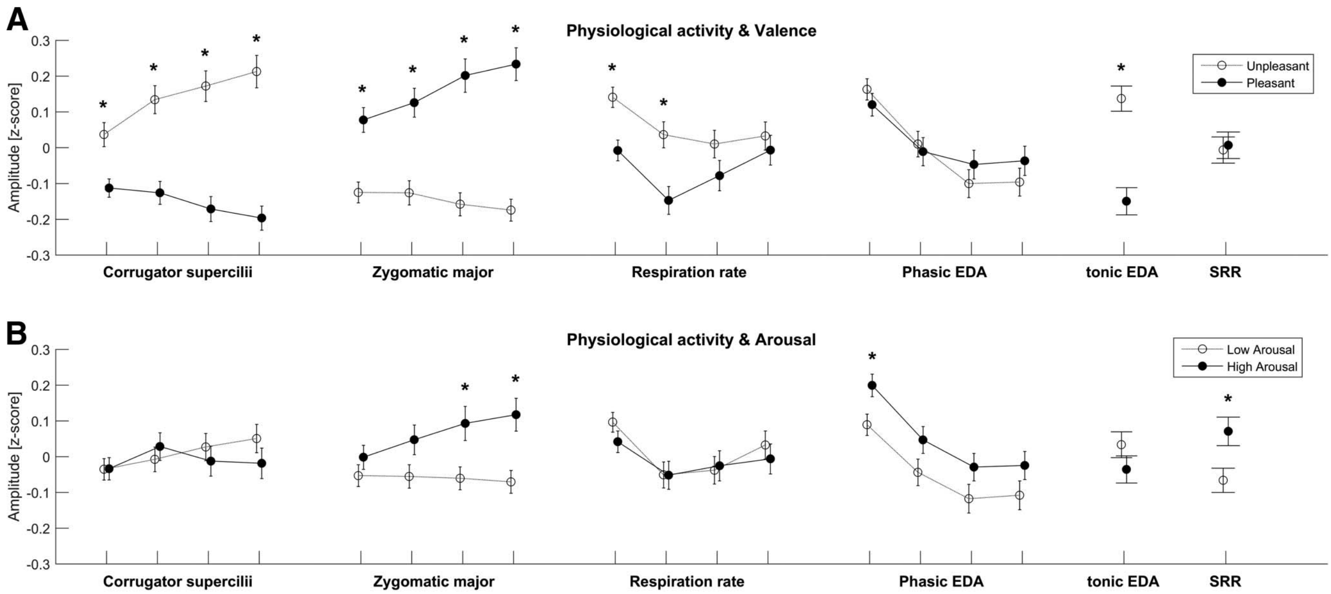


Figure 2. (A) Averaged physiological activity indices for trials during which participants reported unpleasant and pleasant affect. (B) Averaged physiological activity associated with participants' reports of low and high arousal. Error bars represent standard errors of the means. Each point on the horizontal axes for facial muscle activity, respiration rate, and phasic level of electrodermal activity (phasic-EDA) represent a 4-s window during image viewing. Data points for tonic level of electrodermal activity (tonic-EDA) and skin conductance response rate (SRR) represent activity over the entire 16-s period of image viewing. * $p < .05$.

predictions, the models incorporating physiological reactivity performed better than the models based on normative image ratings. It is perhaps not surprising that participants' own peripheral physiology proved a better proxy for their subjective affective states than normative image ratings. In addition, even in these models, prior affective experience made a robust contribution to currently experienced affect. Furthermore, the models that utilized both physiological responses and normative image ratings together with prior affect performed better than either model alone, which suggests that incorporating the fluc-

Table 3
Results of Different Models Predicting Self-Reported Valence and Arousal in Study 4

Model parameters	Physiology	Single parameter model	Temporal weighting model	Physiology + Single Parameter
Valence models				
Predictors and coefficient estimates	V_0: .18 (.03)** CS4: −.11 (.03)** ZM4: .09 (.03)* RR1: −.06 (.03)*	V_0: .17 (.03)** Av: .3 (.11)* Pk: .31 (.09)**	V_0: .17 (.03)** P1: .12 (.04)* P2: .14 (.04)** P3: .13 (.04)** P4: .21 (.04)**	V_0: .17 (.03)** Av: .28 (.11)* Pk: .28 (.09)** CS4: −.11 (.02)** ZM4: .08 (.03)* RR1: −.06 (.03)*
R^2	.74	.72	.72	.75
AIC	3,208	3,232	3,249	3,158
Arousal models				
Predictors and coefficient estimates	A_0: .26 (.04)** ZM4: .1 (.04)** pEDA1: .07 (.03)*	A_0: .27 (.04)** Av: .53 (.1)**	A_0: .27 (.04)** P1: .11 (.03)** P2: .09 (.03)* P3: .14 (.05)** P4: .18 (.04)**	A_0: .27 (.04)** Av: .51 (.1)** ZM4: .08 (.03)* pEDA1: .05 (.03)
R^2	.35	.39	.39	.4
AIC	4,039	3,963	3,978	3,956

Note. Numbers in parentheses represent standard errors. V0 = prior valence; A0 = prior arousal; Av = average normative rating; Pk = peak normative rating; P1 = normative rating of the first image in a trial; CS4 = corrugator activity in the fourth 4-s window; ZM4 = zygomatic activity in the fourth 4-s window; RR1 = respiration rate in the first 4-s window; pEDA1 = phasic electrodermal activity in the first 4-s window; AIC = Akaike information criterion.
* $p < .05$. ** $p < .005$.

tuations in physiological activity increased the information represented in the predictive models of affect.

Furthermore, behavioral findings from previous studies were replicated in Study 4. Affective averaging was the best parameter to account for the variation in self-reported arousal. On the other hand, for valence predictions, best accounting mechanism was averaging that also takes the peak-valence into account, which replicates findings from Study 2. Finally, in Study 4, prior affect made robust contributions to both valence and arousal models as in all the three previous studies, which strengthens the position that prior affect is partly responsible for current affect.

In four studies, we showed that prior affective experience and affective averaging of recent sensory stimuli partly determine current affect. Moreover, changes in physiological activity during image viewing period accounted for additional variations in self-reported valence and arousal. In the next section, we present further analyses where we combine the behavioral findings and underline the parallels and divergences between the studies.

Summary of the Findings and Internal Meta-Analysis

Exploratory Analyses

In all four studies, we found that the prior affect made robust contributions to current affect. First, direct comparisons of single parameter models based on the AIC showed that inclusion of prior affect improved both valence and arousal predictions in all models (without altering the coefficients of other predictors), despite the penalty for an additional predictor (see Tables S2.1 and S2.2 in the online supplemental material). This indicates that prior affect and recent sensory input account for distinct contributions to currently experienced affect.

Moreover, to further investigate the contribution of prior affect to currently experienced affect, we pooled behavioral data from all four studies and carried out exploratory analyses, in which we tested different models where the prior affect parameter was taken from 1 to 4 trials earlier than the current trial. We then compared the coefficient estimates of different time lags. In all models, prior affect had positive and significant coefficient estimates (see Table 4). However, the coefficient estimates decreased with increasing trial lag between the current and the previous trials, with the largest drop between one and two trials earlier. This finding suggests that current affective experience is partly determined by prior affect and that the contribution of prior affect decreases with increasing temporal distance between the current and the previous self-reports. In addition, this point supports our hypothesis that affect is a temporally dependent and continuous process.

Finally, we investigated whether the contribution of peak-valence differed between pleasant and unpleasant blocks. In these exploratory analyses, we only tested the main effects of and the interaction between the peak-valence and the block parameters (for details, see the online supplemental material). We found that peak-valence had larger contributions during unpleasant blocks to experienced valence in Studies 2, 3, and 4. When we run the same model with the pooled data from all four studies, we found a significant interaction effect showing that peak normative valence had a larger contribution to self-reported valence in unpleasant compared to pleasant blocks (B $= -0.17$, 95% CI $[-0.23, -0.12]$, $p < .001$). Taken together, these analyses indicate that the peak negative valence had a stronger contribution in comparison to the peak positive valence.

Table 4
Coefficient Estimates of Prior Affect Predictor

Prior affect rating	Valence	Arousal
Trial (t-1)	.17 [.14, .2]	.19 [.16, .23]
Trial (t-2)	.06 [.03, .09]	.09 [.06, .12]
Trial (t-3)	.06 [.04, .09]	.09 [.06, .12]
Trial (t-4)	.05 [.03, .08]	.07 [.04, .1]

Note. Trial (t-*n*) denotes that self-reported prior affect was taken as a predictor from *n*-trials before the current trial. Numbers in brackets represent 95% confidence intervals.

Power Simulations and Internal Meta-Analysis

We estimated the statistical power using simulations, which were carried out after the data collection, to assess the minimum detectable effect size (coefficient estimate/error standard deviation) for the normative image ratings with 0.8 power for a sample size of 24 (i.e., the final sample size of Study 4) with 60 data points each (30 positive and 30 negative trials). For each simulation, we randomly assigned images to each individual and trial. We simulated data sets with different effect sizes (10,000 simulations for each effect size) and used GLMMs to analyze them (i.e., the same analysis strategy used in all four studies). The simulations showed that effects of 0.148 for valence and 0.104 for arousal could be detected with 0.8 power. To place this in context, the smallest effects we found in Study 4 were 0.137 for valence (error $SD = 0.8$) and 0.087 for arousal (error $SD = 1.03$). Thus, the smallest behavioral effects detected in Study 4 might be lacking the adequate statistical power.[1] Then, we repeated the same procedure with $N = 37$ (i.e., the final sample size of Study 1), because Study 1 was the second smallest sample among our studies. The simulations showed that the minimum effects that could be detected with 0.8 power were 0.122 and 0.085 for valence and arousal, respectively. The smallest effects we found in Study 1 were 0.156 for valence (error $SD = 0.88$) and 0.107 for arousal (error $SD = 1.11$). These simulations, while conducted following data collection, indicate that the study was adequately powered for detecting a small behavioral effect. However, because we had a smaller sample in Study 4 and the power simulations were not conducted a priori, we carried out an internal meta-analysis to combine the effects in four studies to help us interpret the findings. We used a multivariate generalized least squares (GLS) approach to combine the coefficient estimates (Becker & Wu, 2007). GLS is a meta-analytic approach to synthesize regression slopes that weighs the effects by precision, provides entire pooled model, and accounts

[1] These simulations do not concern physiological data. We also carried out power simulations to assess the minimum detectable effect size (coefficient estimate/error standard deviation) for physiological responses with a 0.8 power for a sample size of 24. Physiological responses were selected to have a standard distribution for each participant. The simulations showed that an effect of 0.07 could be detected with 0.8 power. The smallest significant effects found in Study 4 were 0.09 for valence and 0.07 for arousal predictions.

for covariation. Since we had the raw data, we also used covariance matrices from each study.

We have found that average normative valence and prior valence made reliable contributions to currently experienced valence in all studies. However, when the presentation rate was increased from 2-s to 4-s per image (Study 2 and 4) the peak-valence parameter emerged as a reliable predictor. To quantify this difference, we first carried out GLMMs including prior valence, average normative valence, and peak normative valence to predict self-reported valence in separate studies. All the models included a dummy-coded block variable and subject random effects. Then, we combined the effects depending on the presentation rate using a multivariate GLS approach (see Figure 3). The peak effect was not significant for four-image sequences with a 2-s per image presentation rate (B = 0.07, 95% CI [−0.04, 0.18]), whereas it was different from zero for the 4-s per image presentation rate (B = 0.33, 95% CI [0.21, 0.45]). Importantly 95% CIs of the effects did not overlap (see Figure 3). This finding indicates that the peak normative valence emerged as a reliable predictor of currently experienced valence when the presentation rate or the number of stimuli was increased.

Second, in different studies we found a general trend of increasing coefficient estimates for images that were presented later in a trial. We combined the effect of image position from temporal order models in all four studies. Because we tested six-image sequences in Study 3, this model was different from the rest. However, the GLS approach does not require that all the models must be the same. As long as the focal variables are available in all models, GLS can be used to combine those effects (Becker & Wu, 2007). Therefore, we synthesized the effects of last four images in all studies. The coefficient estimates for both valence and arousal models showed that the contribution of an image increased as it was presented later in a sequence (see Figure 4). This trend was slightly less pronounced for arousal predictions. We compared the coefficient estimates for each image using Wald tests (Holm-Bonferroni corrections were applied to correct for multiple comparisons; see Figure 4). The contribution of the last image (see $\text{Image}_{t\text{-}1}$ in Figure 4) to experienced valence was significantly larger in comparison to all earlier images (all at $p < .05$ level). In addition, $\text{Image}_{t\text{-}2}$ had a significantly larger coefficient estimate compared with $\text{Image}_{t\text{-}4}$ (p = .037). On the other hand, the comparisons of coefficient estimates in the arousal model showed that the contribution of $\text{Image}_{t\text{-}1}$ was significantly larger in comparison to both $\text{Image}_{t\text{-}3}$ and $\text{Image}_{t\text{-}4}$ (all at $p < .05$ level). Taken together, these results support a weighted-averaging mechanism for affective integration, in which the contribution of a given image increases as it appears later in a sequence.

Study 5: Control Study

The current research aimed to investigate momentary affect as a function of recent sensory input in the form of evocative images. In four studies, we have shown that affective averaging of recent stimuli and prior affect partly shape currently experienced affect. However, a concern with the current studies may be related to the measurement of affect. We assumed that participants, when asked, reported how they felt at that moment. Therefore, we collected self-reports as an assessment of participants' momentary affective experience. An alternative explanation, however, could be that participants, instead of reporting how they felt in each trial, actively considered and rated the images they viewed and provided an average account for all the images they could remember.[2] We carried out an additional experiment in order to investigate this alternative explanation, in which we manipulated instructions given to the participants in a between-subjects design. One group received the same instructions as in all four previous studies and assessed how they felt at each trial: current affect (CA) group. Whereas a second group was told to actively think about the images they viewed in each trial and try to provide a rating that summarizes them on pleasantness and arousal dimensions: summary rating (SR) group. Then, we investigated similarities and differences between these groups.

Method

Participants. 80 (31 women; *M* age = 23.7, *SD* = 3.1) individuals participated in the study. The study was run online using Inquisit 5 (Inquisit 5, 2016) and on Millisecond.com server and participants were compensated after the study. The study was conducted in accordance with the ethical standards in the Declaration of Helsinki. Participants were recruited through a university participant pool. Based on power simulations presented in the previous section, we have decided that each group should consist of at least 37 participants. Participants were randomly assigned to one of the two groups (CA group or SR group) at the beginning of the experiment. The data collection was open for 3 weeks, at the end of which we decided to stop the data collection because the CA group had 38 individuals (18 women; *M* age = 23.2, *SD* = 3.02) and the SR group had 42 individuals (13 women; *M* age = 24.2, *SD* = 3.2).

Experimental design and procedure. In each trial, all participants viewed four images presented at a 4-s/image rate. Subsequently, participants in the CA group were asked to report their momentary affective experience ("How do you feel right now?") using visual analog scales of valence and arousal. For this group, the instructions and measurement scales were the same as in the first four studies. On the other hand, SR group were asked to provide average ratings for all the four images in a trial using visual analog scales of valence and arousal. They were instructed to think about the images they have viewed and provide an average rating that summarizes the images. All participants completed 60 trials. Image sequences were formed pseudorandomly with the same requirements as in Studies 3 and 4. Images were assigned to trials randomly for each individual.

Data analyses and modeling. The analysis and modeling strategy were the same as in previous studies. Initially, we inspected participants' mean responses and variances and removed five individuals (two from the CA group and three from the SR group) with log variances lower than two standard deviations below their group mean prior to running the predictive models. As in our previous studies, these individuals mostly responded at the lower end or midpoint of the scales in each trial. Further, because the control study was run online, we also collected response times (RT) to be able to monitor the timing of the experiment and used RTs to identify invalid trials. We removed individual trials in which participants responded in less than 1,500 ms, because it seems unlikely that participants had the time to consider and assess within such a short time. We then removed the trials where the

[2] We thank an anonymous reviewer for bringing this alternative explanation of the current findings into our attention.

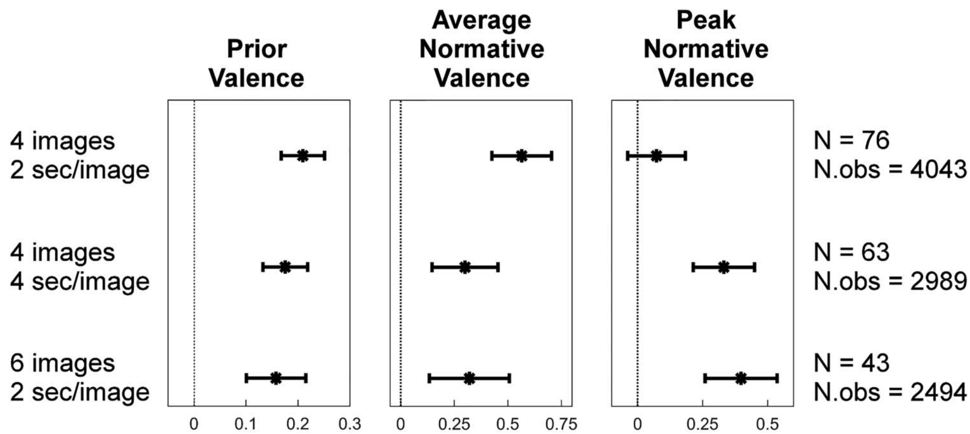


Figure 3. The results of internal meta-analysis showing the effects of average and peak normative valence together with prior valence depending on the duration and the number of images in each trial. The error bars represent 95% confidence interval (CI) for each effect.

response times occurred outside two standard deviations of individual average response times. As a result, 128 (6%) and 99 (4%) trials were removed from the CA and SR groups, respectively.

Next, we constructed single parameter models and temporal order models based on normative image ratings separately for each group and compared the effect sizes, because instructions and the main dependent variables were not the same. We constructed the models based on results from earlier studies. Single parameter models in valence predictions contained fixed effects of average and peak normative valence. Whereas, the arousal model contained the average normative arousal as a fixed effect. Temporal order models contained fixed effects of normative image ratings in the presentation order. All the models contained a dummy-coded block variable (unpleasant = −1; pleasant = 1) and random intercepts and slopes at the participant level.

Results

Single parameter models. Valence prediction for the CA group showed that both average ($B = 0.24$, 95% CI [0.05, 0.42], $p = .01$) and peak normative valence ($B = 0.36$, 95% CI [0.21, 0.5], $p < .001$) were positively associated with currently experienced valence (see Table 5). The same effects were found in the SR group, however, the coefficient estimate for the average nor-

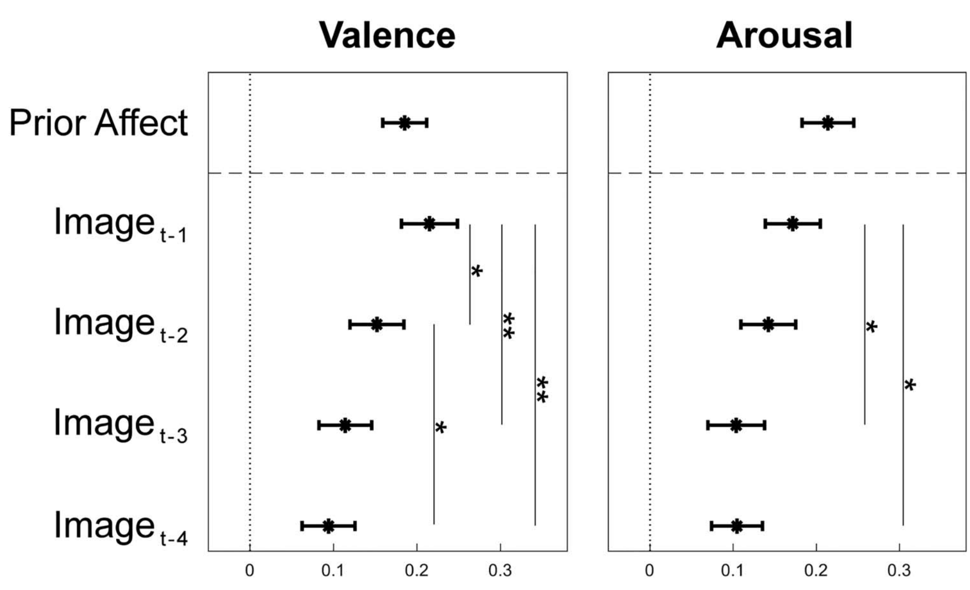


Figure 4. The results of internal meta-analysis of the temporal order models showing that the relative contribution of an image increased as it appeared later in a sequence (9,526 observations from 143 participants). The error bars represent 95% confidence intervals (CIs) for each effect. The coefficient estimates for images were compared using Wald tests. Holm-Bonferroni corrected significant differences are plotted. $\text{Image}_{t\text{-}1}$ = the last seen image. * $p < .05$. ** $p < .001$.

Table 5
Results From the Control Study Predicting Valence and Arousal Ratings in Current Affect (CA) and Summary Rating (SR) Groups

Model parameters	Single parameter model		Temporal order model	
	CA group	SR group	CA group	SR group
Valence models				
Predictors and coefficient estimates	Av: .24 (.09)*	Av: .51 (.09)**	P1: .12 (.03)**	P1: .18 (.03)**
	Pk: .36 (.07)**	Pk: .21 (.07)**	P2: .14 (.03)**	P2: .09 (.03)**
			P3: .13 (.03)**	P3: .17 (.03)**
			P4: .18 (.03)**	P4: .25 (.03)**
Arousal models				
Predictors and coefficient estimates	Av: .63 (.1)**	Av: .63 (.11)**	P1: .16 (.04)**	P1: .19 (.03)**
			P2: .16 (.04)**	P2: .12 (.04)**
			P3: .07 (.04)[t]	P3: .16 (.04)**
			P4: .22 (.04)**	P4: .17 (.04)**

Note. Numbers in parentheses represent standard errors. Av = average normative rating; Pk = peak normative rating; P1 = normative rating of the first image in a trial.
[t] $p < .10$. * $p < .05$. ** $p < .005$.

mative valence increased to 0.51 (95% CI [0.33, 0.69], $p < .001$). On the other hand, the contribution of the peak valence was somewhat lower for the SR group (B = 0.21, 95% CI [0.07, 0.34], $p = .003$). Average normative arousal was positively associated with currently experienced arousal (B = 0.63, 95% CI [0.43, 0.83], $p < .001$) and average stimulus arousal (B = 0.63, 95% CI [0.42, 0.84], $p < .001$) with the same effect size.

Furthermore, we formulated models where we combined data from CA and SR groups and included interaction terms in order to quantify the differences between groups in valence predictions. The group (0 = CA; 1 = SR) by average normative valence interaction was significant (B = 0.25, 95% CI [0.01, 0.49], $p = .042$), showing that the SR group relied on average normative valence more than the CA group did. On the other hand, even though the group and peak normative valence interaction showed that the SR group relied on peak valence somewhat less than the CA group did, this effect did not reach significance (B = −0.18, 95% CI [−0.37, 0.01], $p = .058$).

Temporal order models. Similar to the findings of previous studies, in the CA group, each image contributed to current valence with positive and significant coefficient estimates; and the relative contribution of a given image increased as it appeared later in a sequence (see Table 5). However, the models predicting pleasantness ratings in the SR group yielded stronger primacy and recency effects. On the other hand, systematic differences could not be found between models of current arousal (CA group) and general arousal ratings (SR group).

Discussion

Study 5 aimed to explore the concern about the assessment of momentary affect in the previous four studies. In order to address this issue, we carried out a study in which two groups received different instructions on how to use the scales. Both groups went through the same number of trials and images. The CA group received the same instructions from the previous four studies while the SR group was instructed to focus on the images and provide a summary rating. We constructed models predicting the summary ratings and self-reported affect based on the normative image ratings and compared the models. As a result, we found that the relative contribution of normative average valence was higher to summary ratings than its contribution to self-reported affect. On the other hand, the peak normative valence had a slightly higher contribution to self-reported affect compared with its contribution to summary ratings. Further, predictions of self-reported valence showed the relative contribution of an image increased as it appeared later in a trial. However, predictions of the pleasantness ratings yielded stronger primacy and recency effects compared with predictions of self-reported valence. Taken together, these results indicate that different instructions yielded a varying pattern of results for valence ratings. When participants were asked to provide an average rating for the images, their assessment were mostly informed by the average normative valence. Further, we also found a primacy effect in valence predictions for the SR group, which, in line with the previous studies, was not found for the CA group.

On the other hand, the assessment of arousal did not differ depending on the instructions. In the previous studies, we found that the main integration mechanism for arousal was averaging. Therefore, it may not be surprising to find that the average normative arousal was also the main predictor when participants provided an average rating on the arousal dimension. Further, another reason could be that when reporting arousal ratings participants used similar mental processes. Compared with pleasantness, arousal is a heterogeneous construct and may not be as readily accessible as pleasantness. Therefore, participants' lower sensitivity and understanding of arousal dimension may be a contributing factor for the current findings (see also, discussion of arousal ratings in the General Discussion section). However, future studies that specifically aimed to disentangle these possible effects on arousal are needed, which is beyond the scope of the current research.

General Discussion

The current research set out to investigate momentary affective experience as a function of integrated affective impact of evocative images and prior affective experience. We used a simple and novel paradigm, in which we manipulated the temporal sequence of visual stimuli. First, to investigate how a stream of evocative images is represented affectively, we tested different models for predicting self-reported affect as a function of the viewed images' normative tendency to evoke affective changes. Our results suggest that for the arousal feature of affect an averaging mechanism provides the best account for integration over time. With respect to valence, however, the best fitting integration mechanism was averaging that also takes peak-valence into account. Critically, the relative importance of peak-valence depended on both the duration and the number of images (see Figure 3). A simple averaging mechanism was not always used—especially when there were a greater number of discrete stimuli to be represented in a longer time frame, the influence of the most affectively potent stimulus increased. In other words, peak normative valence contributed to fluctuations in experienced valence beyond averaging only when the time frame was sufficiently long. In a shorter time span, simple averaging described the affective experience adequately well. This might suggest that less potent stimuli have a short-lived effect on experienced valence, so that in a longer time interval the increased relative contribution of the most potent stimuli could be observed. Moreover, sensitivity of affective integration generally increased for later stimuli for both valence and arousal features (see Figure 4). Taken together, these results suggest that integration of the affective impact of evocative images occurs according to a weighted-averaging mechanism, in which higher weights are assigned to more recent and potentially more potent stimuli.

Second, we hypothesized that affect is a dynamical system and the current state of such a system should carry information about its own prior state. To test this hypothesis, we included self-reported affect from the previous trial (i.e., prior affect) as a predictor of currently experienced affect. Prior affect made robust contributions to both valence and arousal in all studies. Affect is continuous and prone to changes in the face of ongoing sensory stimulation. The prior state of such a process is one of the determining factors of its current state. In fact, the models of affect dynamics point to the importance of the prior affective state as a determining factor of the current affective state (e.g., Cunningham et al., 2013; Kuppens & Verduyn, 2017). Moreover, in our studies, prior affect improved all the models without influencing the coefficient estimates of the other parameters and the relative contribution of prior affect decreased with increasing temporal distance. The current findings provide clear empirical support for the formulation that prior affect and affective averaging of sensory information are significant and independent contributors of currently experienced affect.

The present findings also show that changes in facial muscle activity (both CS and ZM), and respiration rate were associated with valence, while ZM activity and phasic-EDA were associated with arousal. This pattern of results is consistent with previous studies (Bradley & Lang, 2000; Cacioppo et al., 1986; Lang et al., 1993; Larsen et al., 2003). Furthermore, we found that the model performance improved when participants' physiological responses were included in the models together with normative stimulus ratings and previously experienced affect. The fluctuations of affect are linked to the changes in the body's physiological systems (Barrett, 2017; Craig, 2015). Therefore, the inclusion of individual physiological responses increases the information represented in predictive models of affect and leads to an increase in the explained variance in momentary affective experience beyond normative stimulus information and previous affective experience.

One general pattern in our results was that arousal models performed worse compared with valence models. We believe that this is due to valence being a fundamental property of human experience. Humans can easily distinguish pleasant and unpleasant affect (Barrett & Bliss-Moreau, 2009). Infants can differentiate pleasant and unpleasant facial expressions in other people and experience discomfort and pleasure (Farroni, Menon, Rigato, & Johnson, 2007; Lewis, 2016). On the other hand, differentiating high and low arousal is not ubiquitous (Barrett, 2004; Feldman, 1995). Therefore, the larger unexplained variance in self-reported arousal may stem from individuals' lower sensitivity to discriminate high and low arousal experiences.

We acknowledge that several factors not manipulated or measured here may influence affective integration and fluctuations of affective experience. These factors may include but are not limited to situational context, prior knowledge, expectations, goal-relevance, and attention. Future research should build on the current findings and include factors unaddressed by the present studies. Additionally, the blocked design utilized in the current experiments may have influenced the relative contribution of prior affect. Because pleasant and unpleasant images were presented in separate blocks, the general pleasantness of not-yet-seen images become largely predictable, allowing prior affect to potentially play a larger role in influencing current affect. Thus, random presentation of both positive and negative stimuli may cause an increased weighting of current sensory information relative to prior affect. We believe that further exploration of the interaction of prior affect and integrated affective impact of stimuli will prove to be a fruitful area of continued research. Using variations of the basic paradigm used here, investigators can study the role of more complex real-world factors on affective fluctuations.

In sum, using a novel experimental paradigm we investigated the fundamental question of how individuals' affective experience fluctuates in the face of ongoing sensory stimulation. We approached affect as a continuous process and showed that momentary affective experience at a given time is partially determined by the changes in sensory input and previously experienced affect. Our studies provide clear empirical support for the following formulations: (a) The affective impact of a stream of evocative sensory stimuli is integrated over time that seems to occur according to a weighted-averaging model, in which higher weights are assigned to more recent and more potent stimuli. (b) An individual's affective state at a given time carries information about the recent changes in the environment as well as their own prior affective state. Affect is a fundamental aspect of human experience, and it is a continuous representation of an organism's relationship with its environment (e.g., Barrett & Bliss-Moreau, 2009; Russell, 2003; Russell & Barrett, 1999). Therefore, affect represents an organism's capacity to maintain allostasis in the face of ongoing environmental changes and suggests that every waking moment is colored with affective feelings (Wundt, 1897). This is in line with research showing that sensory input prompts affective changes in humans. We have affective reactions to images (e.g., Bradley et al., 2001; Kurdi et al., 2017), sounds (e.g., Asutay & Västfjäll, 2012; Bradley & Lang, 2000), films (e.g., Rottenberg, Ray, & Gross, 2007), odors (e.g., Zald & Pardo, 1997), social stimuli (e.g., Roberts, Tsai, & Coan, 2007), and the environment (e.g., Russell & Snodgrass, 1987). When we navigate our daily lives, our affective experience fluctuates in response to a continuous flow of events. Yet, we do not know how this stream of information is dynamically represented in affective experience. Arguably, one reason for this lack of evidence is that researchers, when studying affect, often use randomized stimulus orders presented in separate trials and assume that stimuli are presented in isolation from one another. The current research, approaching affect as a dynamical system, shows that affect is a temporally dependent and continuous process and that momentary affect carries information about recent sensory inputs that are integrated over time. We know that processing of incoming stimuli occurs in a temporally dependent fashion and is based on current internal state of the individual (see Hutchinson & Barrett, 2019). However, the traditional trial structure in investigations of affect is at odds with this fact (see Huk, Bonnen, & He, 2018). Most studies that have used a traditional trial structure have assumed that a measured response in a trial depends on the given stimuli and random noise. Here, we show that participants' response in a given trial depends on some combination of the given stimuli and the participants' prior internal state. We believe that the current research underlines the need to adopt experimental paradigms that attempt to understand affect as a temporally dependent and continuous process.

Finally, given the important role of affect in human psychology, understanding the underlying principles of how affect dynamically evolves with changing environmental and mental circumstances is fundamental to understanding the influence of affect on behavior. For instance, a greater understanding of affective integration has substantial implications for the study of decision making. Affect has a crucial influence on decision making (e.g., Slovic et al., 2002). Investigating how integration of various affective signals occurs during a decision context and how the integrated affect influences decisions can offer important advances to our understanding of the role of affect in decision-making (Västfjäll et al., 2016). As in other fields of psychology, most investigations of decision making make use of a traditional trial structure, which is constructed as random sequences of choices. Understanding internal states such as affect in terms of dynamic and temporally dependent processes may help us better understand their role on behavior and choices.

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