Affective context and uncertainty drives momentary affective experience

Erkin Asutay [1, *], Alexander Genevsky [2, 3], Paul Hamilton [4], Daniel Västfjäll [1, 5]

[1] Department of Behavioral Sciences and Learning, Linköping University, Sweden

[2] Rotterdam School of Management, Erasmus University, The Netherlands

[3] Department of Economics, Linköping University, Sweden

[4] Center for Social and Affective Neuroscience, Department of Clinical and Experimental Medicine, Linköping University, Sweden

[5] Decision Research, Eugene OR, USA

* Corresponding author: Erkin Asutay, Department of Behavioral Sciences and Learning, Linköping University, SE-58183, Linköping, Sweden. Tel: +46762439909. Email: erkin.asutay@liu.se

Abstract

Affect fluctuates in a moment-to-moment fashion; and it reflects the continuous relationship between the individual and the environment. Despite substantial research, there remain important open questions regarding how the continuous stream of sensory input is dynamically represented in experienced affect. Here, approaching affect as a temporally dependent process, we show that momentary affect is shaped by a combination of changes in recent stimuli (i.e. visually presented images for the current studies) and previously experienced affect. We also found that this temporally dependent relationship is influenced by context uncertainty. Participants, in each trial, viewed sequentially presented images and subsequently reported their affective experience, which was modeled based on images' normative affect ratings and participants' previously reported affect. Study 1 showed that self-reported valence and arousal in a given trial is partly shaped by the affective impact of the given images and previously experienced affect. In Study 2, we manipulated context uncertainty by controlling occurrence probabilities for normatively pleasant and unpleasant images in separate trials. Increasing context uncertainty (i.e. random occurrence of pleasant and unpleasant images) is associated by increased negative affect when the overall effect context is controlled. In addition, the relative contribution of the most recent image to momentary affect increased with increasing context uncertainty. Taken together, these findings provide clear behavioral evidence that affective experience fluctuates in a temporally dependent and continuous fashion based on recent changes in input variables and previous internal state, and that these fluctuations are sensitive to the affective context and its certainty.

Keywords: momentary affect, affective context, uncertainty, affective fluctuations

Our brains ensure that we adapt to changing environmental circumstances to keep us alive. The brain's core task is to produce physiological adaptations to meet future demands depending on biological and environmental circumstances (i.e. allostasis; Ganzel et al., 2010; Sterling 2012). To accomplish this, the brain continually represents the bodily consequences of physiological adaptations that occur in response to environmental and biological demands (Craig, 2015). It is hypothesized that affect is linked to these ongoing sensory changes within the body resulting from changes in physiological systems such as the autonomic nervous system, the immune system, and the neuroendocrine system (see Barrett, 2017; Kleckner et al., 2017; Lindquist et al., 2016). This makes affect a fundamental aspect of allostasis and suggests, that every waking moment is infused with affective feelings (Wundt, 1897). Experienced affect fluctuates in a moment-to-moment fashion prompted by sensory information (Cunningham et al., 2013; Lindquist et al., 2016). However, there is still much to be learned about how various sources of evocative stimuli are dynamically represented in momentary affect. Researchers have attempted to model affect dynamics based on temporal sensory information flow (e.g. Carver, 2015; Cunningham et al., 2013) but these models have not yet received definitive empirical support. Here, approaching affect as a temporally dependent process, we explicitly test the hypotheses that affective experience at a given time is shaped by what is currently occurring in the environment (i.e. visually presented images in current studies) and previously experienced affect; and that the affective context is one of the determining factors in this process.

Humans navigate complex environments and we continually receive stimuli that evoke changes in our affective experience that reflects our ongoing relationship with the environment (Barrett & Russell, 1999; Russell & Barrett, 1999). Thus, affect is a continuous and temporally dependent process, whose state at a given time carries information about changes in input variables and prior information represented in the system. However, this view of affect is at odds with the traditional trial structure of most investigations, which utilize fully randomized consecutive trials and assume that a participant's response at a given trial is solely shaped by the given stimuli and random noise (see Huk, Bonnen, & He, 2018; Hutchinson & Barrett, 2019). Previous research has shown that processing of incoming information occurs in a temporally dependent fashion and is also affected by the current internal state of the organism (Huk et al., 2018). Arguably, changes in sensory information flow are dynamically represented in affective fluctuations and this relationship is influenced by several factors, such as environmental context, expectations, and goal-relevance. In a previous study using visually presented images, we have shown that momentary affect is shaped by a combination of temporally integrated recent stimuli and prior affect (Asutay et al., accepted for publication). Here, using a similar paradigm, we focused on affective context, in which evocative images are viewed. We investigated fluctuations in self-reported affect as a function of the normative affective impact of visually presented images and participants' previously experienced affect, and the influence of affective context on this temporal dependency. In particular, we manipulated uncertainty of the affective context by introducing *a priori* occurrence probabilities for normatively pleasant and unpleasant images in separate blocks (Figure 1.B).

Uncertainty is an important feature in the sensory environment. An uncertain context may increase vigilance, enhance bias for stimuli that evoke unpleasant affect, and cause anxiety (Herry et al., 2007; Jackson, Nelson, & Proudfit, 2014; Whalen, 2007). Further, in a rapidly changing environment, past information is uninformative about current circumstances. Therefore, current information should be more heavily weighted than past information for learning to occur (Courville et al., 2006). Moreover, according to predictive processing, organisms build probabilistic internal models of the causes of their sensations and attempt to predict sensory inputs based on these models (Clark, 2013; 2016; Friston, 2009;

2010). An organism's primary directive then is to minimize prediction error between predicted and actual sensory input. Thus, an uncertain context leads to an increase in prediction error, which in turn may cause increased weighting of sensory information (Feldman & Friston, 2010). Some investigators have also suggested that a decrease in prediction error may lead to pleasant affect, whereas increased prediction error is likely to evoke unpleasant affect (Joffily & Coricelli, 2013), which is in line with findings showing that an uncertain context (i.e. high prediction error) may cause anxiety (e.g. Herry et al., 2007). We argue that, in many investigations of affect, the random presentation of evocative stimuli would cause the brain to operate in a mode dominated by prediction error. Consequently, as prediction error increases, affect might fluctuate more closely with ongoing sensory stimulation together with an overall increased negative affect. However, this would mean that experimental frameworks based on fully randomized trial structures ignore the fact that affect is a temporally dependent process and introduce bias in studies of affect. Here, we aim to investigate whether (1) momentary affect fluctuates in a continuous and temporally dependent fashion (i.e., experienced affect at a given trial depends on some combination of the given stimuli and previous affective experience), and (2) whether these fluctuations are sensitive to the uncertainty of the affective context.

The present studies

To investigate affect as a temporally dependent process; we employed a basic paradigm. In each trial, participants viewed four (Study 1a & 2) or six (Study 1b) sequentially presented images and subsequently reported their affective experience on two descriptive features: valence and arousal (Figure 1.A). We then constructed predictive models of self-reported affect as a linear combination of the images' normative affect ratings and participants' previously reported affect (see also Asutay et al., accepted for publication). In other words, self-reported affect in a given trial is modeled based on normative affect ratings of the given images and self-reported affect in the previous trial (i.e., prior affect). The normative stimulus ratings were taken as a proxy of the normative affective impact prompted by each individual image. In the current paradigm, we expect the temporal dependency of affect to the viewed images to occur according to a weighted-averaging model, which means: (1) all images have positive and significant contributions to momentary affect; and (2) the relative contribution of a given image increases as it is presented later in a trial (Figure 1.C). Furthermore, we expect to find positive and significant coefficient estimates for prior affect, given our hypothesis that momentary affect, to some extent, carries information about previous affective experience. We found this pattern of results in a previous study where pleasant and unpleasant images were presented in separate blocks (Asutay et al., accepted for publication). Here, in Studies 1a & 1b, we aim to replicate these results with randomly occurring pleasant and unpleasant images.

In Study 2, we manipulated context uncertainty by assigning *a priori* occurrence probabilities to normatively pleasant and unpleasant images in separate blocks. For instance, in a context where pleasant images occur 90 % of the time uncertainty would be low. On the other hand, an uncertain affective context occurs when participants view randomly occurring pleasant and unpleasant images (Figure 1.B). We hypothesize that a random context leads to an increase in prediction error, which would result in an increase in the weights given to the current sensory stimuli. In particular, increased randomness may lead to increased coefficient estimates for either all (blue bars in Figure 1D) or only the most recent stimuli (red bars in Figure 1D). These outcomes have different implications for the temporal span of the weighted-averaging. More heavily weighted recent information indicates a focused and narrow averaging window (red line Figure 1D).

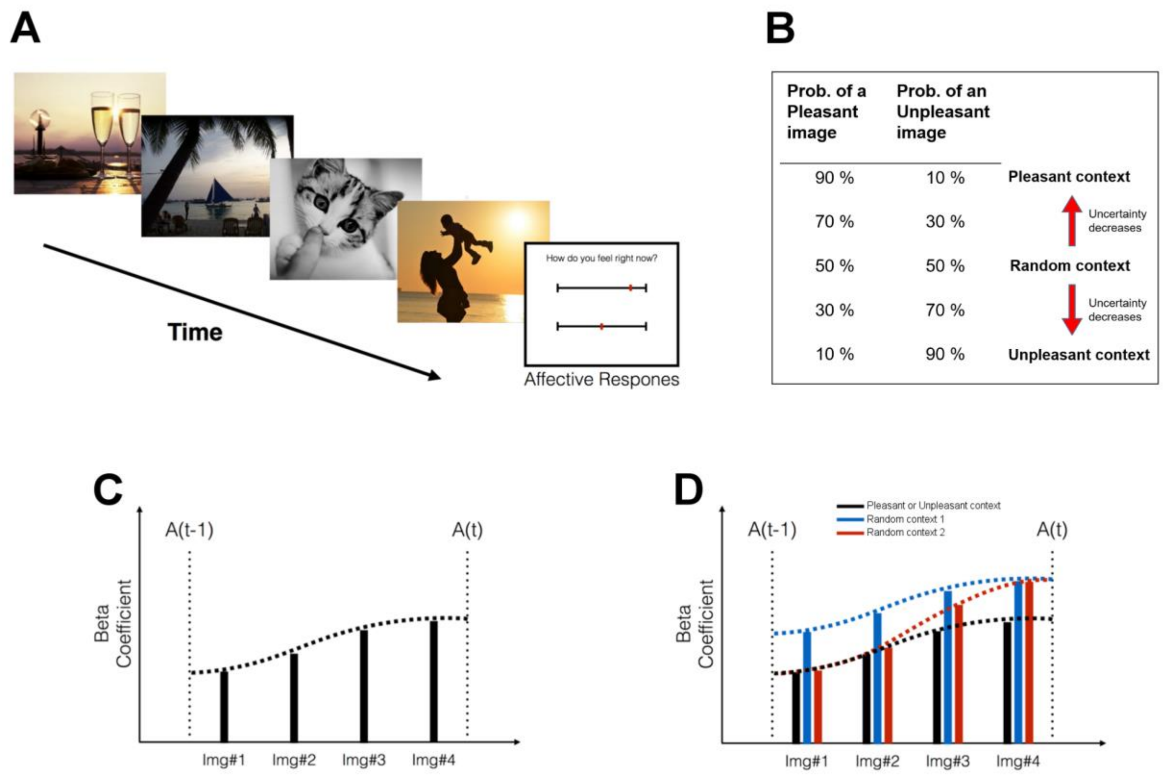

Figure 1. Trial structure of the current studies and illustrations of the hypotheses. **(A)** Participants, in each trial, viewed a number of sequentially presented images and subsequently reported their momentary affect using valence and arousal scales. **(B)** Context uncertainty was manipulated by introducing *a priori* occurrence probabilities of normatively pleasant and unpleasant images in five separate blocks in Study 2. **(C)** We constructed predictive models of self-reported affect as a function of normative affect ratings of the images viewed in each trial. The graph illustrates the expected weights for sensory stimuli predicting affect measured at time *t*; i.e. *A(t)*. We expected to see a recency effect: decreasing estimates for past input. The dashed line represents the shape of a hypothetical weighted-averaging window. **(D)** The graph shows two hypothetical modulations of affective integration as a function of context uncertainty in Study 2 (blue and red). (1) Increased weights given to all stimuli without a change in the weighted-averaging window (blue bars and dashed blue line), and (2) increased weights given only to recent information (red bars and dashed red line).

Study 1a & 1b

Studies 1a & 1b, approaching affect as a temporally dependent and continuous process, aims to test our hypothesis that momentary affect is shaped by some combination of affective impact of current stimuli and previously experienced affect.

Methods

Participants

54 (19 women, 35 men, mean-age=24.1, SD=4.42) and 47 (24 women, 23 men, mean-age=23.7, SD=2.62) individuals participated in Study 1a and 1b. They gave informed consent prior to inclusion in the experiment and were compensated after the study. The experiments were conducted in accordance with the ethical standards in the Declaration of Helsinki. The studies were carried out in a computer laboratory. Participants were admitted to the room in groups (maximum 10 participants in a session).

We estimated the sample size using simulations, which were carried out to assess the minimum sample size to detect a small effect of 0.1 (coefficient estimate / error SD) with a power of 0.8. For each simulation, we randomly assigned images to each individual and trial (60 trial/participant). We simulated 5000 data sets with a given sample size and used generalized linear mixed models (GLMMs) to analyze the data (i.e. the same analysis strategy defined in *Data analysis and modeling* section below). The simulations showed that a minimum sample size of 30 is needed to detect a small effect in both arousal and valence models with a simulated power of 0.8. The data collection for both studies were initially open for three weeks, after which we stopped the experiment since both sample sizes were well above 30.

Materials, experimental design and procedure

In Study 1a, participants sequentially viewed four images in each trial at a 2 sec/image presentation rate; and subsequently reported their momentary affective experience (“How do you feel right now?”) using two visual analog scales: hedonic valence (pleasant to unpleasant) and arousal (sleepiness to high activation). Participants were explicitly instructed to assess how they currently feel at the moment of reporting. The experimenters were instructed participants to ‘look inwards’ and assess how they felt at that moment. After going through the instructions, each participant completed three practice trials before going through 60 trials divided in 2 blocks.

Visual stimuli were taken from the OASIS database (Kurdi, Lazano, & Banaji, 2017) complete with normative valence and arousal ratings (measured on a 7-point scale from 1-7). We first removed all the neutral images (normative valence ratings between 3.5 and 4.5). From the remaining stimuli, we selected 180 images (90 pleasant and 90 unpleasant). We ensured that the selected images to have various content. Pleasant and unpleasant images were also matched in arousal. During the experiment, images were assigned to trials for each individual separately. We formed image sequences pseudo-randomly in a way that normative valence and arousal of images were balanced among temporal positions in sequences. Since we had a limited number of images, participants had to see some images more than once. Each participant viewed 60 stimuli twice (30 positive and 30 negative). The twice-viewed images were randomly determined for each participant. We introduced a minimum of 10 trials between the two repetitions of any image.

In Study 1b, we investigated the role of sequence length. All the procedures were identical to Study 1a except that participants viewed six images in each trial. The presentation rate (2 sec/image) and the total number of trials (60 trials) were the same as in Study 1a. Participants viewed each image twice.

Data analyses and modeling

We formulated predictive models of valence and arousal based on normative image ratings within each sequence. We first centered the normative image ratings around zero (i.e. -3 to +3 range) and scaled the self-reported valence and arousal between -3 and +3. The predictions were carried out in a GLMM framework with a maximum likelihood estimation approach. All models contained subject random effects. Predictive models of valence and arousal contained the fixed effects of normative image ratings in a given trial depending on its presentation order. In addition, we introduced a prior affect parameter (as measured in the previous trial). Thus, a model predicting trial-by-trial valence was in the following form:

$$V_t \sim 1 + \sum (nV_i)_t + V_{t-1}$$

Here, V_t and V_{t-1} denote valence ratings collected at the current and previous trials, respectively. Whereas, nV_i denotes the normative valence of the *i*th image in the current trial. We constructed an equivalent model for arousal predictions.

Results

GLMMs predicting experienced valence and arousal included fixed effects of normative image ratings in the presentation order and subject random effects. In Study 1a, each image made significant contributions to both valence and arousal predictions with positive and significant coefficient estimates (Table 1). For valence predictions, the relative contribution of an image was higher when it was presented later in a sequence (Figure 2.A). This pattern points to a weighted-averaging mechanism that assigns higher weights to more recently presented stimuli. However, this pattern did not emerge for arousal predictions. In addition, both prior valence ($B=0.08$, 95% CI = [0.05, 0.1], $p<.001$) and arousal ($B=0.16$, 95% CI = [0.11, 0.21], $p<.001$) made significant contributions to predictive models of affect (Table 1).

Table 1. Results of valence and arousal predictions in Study 1a. Coefficient estimates, R-squared statistics, and AIC are presented.

Predictors	Valence Model	Arousal Model
Img#1	0.2 [0.18, 0.23]**	0.1 [0.04, 0.16]**
Img#2	0.25 [0.23, 0.27]**	0.07 [0.01, 0.13]*
Img#3	0.24 [0.21, 0.26]**	0.1 [0.05, 0.16]**
Img#4	0.29 [0.27, 0.32]**	0.11 [0.05, 0.17]**
Prior Affect	0.08 [0.05, 0.1]**	0.16 [0.11, 0.21]**
(Constant)	-0.23 [-0.31, -0.14]**	-0.01 [-0.13, 0.15]
R^2	.51	.29
AIC	9018	9866

* p<.05, ** p<.005; numbers in parentheses reflect the 95% confidence intervals.

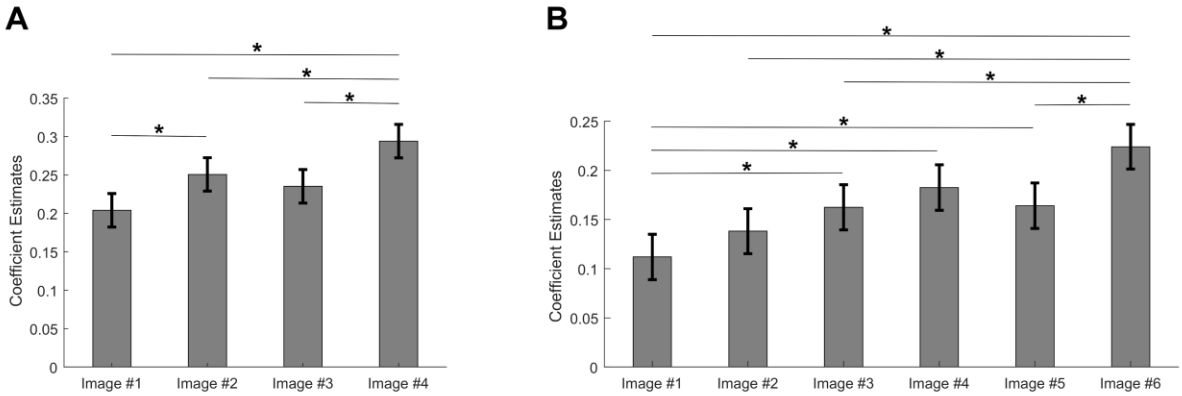

Figure 2. Coefficient estimates for the normative valence ratings of each image at a given trial for Study 1a (panel A) and 1b (panel B). Wald tests were used to compare the coefficient estimates. Holm-Bonferroni corrections were applied; * p<.05.

The results in Study 1b were similar to Study 1a. Normative image ratings and previously reported affect made significant contributions to currently experienced valence and arousal (Table 2). In Study 1b, valence predictions showed that the relative contribution of an image increased as it appeared later in a trial (Figure 2.B). However, similar to Study 1a arousal predictions did not yield the same pattern. Moreover, both prior valence (B=0.07, 95% CI = [0.02, 0.11], p=.004) and arousal (B=0.11, 95% CI = [0.04, 0.18], p=.002) made robust contributions to currently experienced valence and arousal. Taken together, the findings from Studies 1a & 1b indicate that, in line with our hypothesis, affective impact of the given stimuli and previous affective experience partly shape currently experienced affect.

Table 2. Results of valence and arousal predictions in Study 1b. Coefficient estimates, R-squared statistics, and AIC are presented.

Predictors	**Valence Model**	**Arousal Model**
Img#1	0.11 [0.09, 0.13] **	0.08 [0.01, 0.14]*
Img#2	0.14 [0.12, 0.16]**	0.05 [-0.004, 0.11]
Img#3	0.16 [0.14, 0.19]**	0.07 [0.004, 0.14]*
Img#4	0.18 [0.16, 0.21]**	0.08 [0.02, 0.14]*
Img#5	0.16 [0.14, 0.19]**	0.16 [0.11, 0.22]**
Img#6	0.22 [0.20, 0.25]**	0.17 [0.11, 0.23]**
Prior Affect	0.07 [0.02, 0.11]*	0.11 [0.04, 0.18]**
(Constant)	-0.32 [-0.4, -0.24]**	-0.06 [-0.24, 0.13]
R^2	.42	.34
AIC	7824 / 7925	8548 / 8648

* p<.05, ** p<.005; numbers in parentheses reflect the 95% confidence intervals.

Discussion

Studies 1a & 1b set out to investigate fluctuations in momentary affect as a function of a stream of images' normative tendency to induce affective changes. The results showed that self-reported affect reflected the affective impact of the given visual stimuli and participants' previously reported affective experience. All visual stimuli robustly contributed to momentary affect as evidenced by positive and significant coefficient estimates. We also found a recency effect for the valence predictions; that is, the relative contribution of an image increases as it appears later in a sequence. Importantly, prior affect made significant contributions to currently experienced affect. In other words, self-reported valence and arousal in the previous trial accounted for a part of the variation in valence and arousal reported in the current trial. We have found the same pattern of results in an earlier study, in which pleasant and unpleasant images were presented in separate blocks (Asutay et al., accepted for publication). Here, we replicated and extended those results with randomly occurring pleasant and unpleasant images. Taken together, these findings support our hypothesis that affect is a continuous and temporally dependent process that is shaped by some combination of changes in the current sensory input and previously experienced affect. In Study 2, we focus on the role of uncertainty of the affective context in fluctuations of momentary affect.

Study 2

We have shown that affective impact of visually presented images and prior affect are independent predictors of currently experienced affect. In Study 2, we investigate how the affective context and its uncertainty influence this temporally dependent relationship.

Methods

Participants

49 (17 women, 32 men, mean age=23.61, SD=3.30) individuals participated in the study. They gave informed consent prior to inclusion in the experiment and were compensated after the study. The experiments were conducted in accordance with the ethical standards in the Declaration of Helsinki. The studies were carried out in a computer laboratory. Participants were admitted to the room in groups (maximum 10 participants in a session).

We estimated a minimum sample size to detect a small interaction effect of 0.1 (coefficient estimate / error SD) due to the uncertainty manipulation (see Model#2 and Model#4 in *Data analysis and modeling* section below) with a power of 0.8 using simulations. We simulated 5000 data sets with a given sample size and used the same analysis strategy defined in *Data analysis and modeling* section below. These simulations indicated that with 37 participants it is possible to detect a small interaction effect with a power of 0.8. We decided a minimum data collection period of three weeks, after which we stopped the study since the sample size was above 40.

Materials, experimental design and procedure

For Study 2, we introduced an additional 20 images (10 positive and 10 negative) from the OASIS database (Kurdi et al., 2017) to the stimulus set that were used in the first study. In each trial, participants viewed four images at a rate of 2 sec/image; and they went through 100 trials presented in five separate blocks. Unbeknown to participants, each block had two parts. The first ten trials of each block (40 images) contained *a priori* occurrence probabilities for normatively pleasant and unpleasant images (see Figure 1.B). Whereas the last ten trials of each block contained equal number of pleasant and unpleasant images presented randomly. Hence, this design enabled us to determine the changes in model parameters predicting valence and arousal when individuals adapted to a given affective context (i.e. comparison between blocks during the first ten trials), and when this context was removed (i.e. comparison between the first and last ten trials within a block).

The order of blocks were counterbalanced among participants. Participants viewed each image twice throughout the experiment. The two presentations of an image never occurred within the same block. Participants took small breaks in between blocks.

Data analyses and modeling

We employed the same modeling strategy from the first study with the following changes in order to investigate the effects of context and uncertainty. The modeling was divided into two parts. In the first part, we focused on the first ten trials of each block. We constructed a base model using a dummy coded *context* variable (-1 = 90% negative; -0.5 =

70% negative; 0 = 50% negative; 0.5 = 70% positive; 1 = 90% positive) together with an *uncertainty* variable (0 = 90/10; 0.5 = 70/30; 1 = 50/50).

$$V_t \sim 1 + \text{Context} + \text{Uncertainty} \qquad \text{(Model \#0)}$$

Model #0 allowed us to see the mean differences between blocks (reflected in *Context* variable) and context uncertainty represented in separate blocks (reflected in *Uncertainty variable*). Next, we introduced mixed effects of image ratings and prior affect to Model #0:

$$V_t \sim 1 + \text{Context} + \text{Uncertainty} + \sum (nV_i) + V_{t-1} \qquad \text{(Model \#1)}$$

Then, to investigate the role of uncertainty, we added the interaction terms of interest:

$$V_t \sim 1 + \text{Context} + \text{Uncertainty} + \sum (nV_i) + V_{t-1} + \sum (\text{Uncertainty} *nV_i) + \text{Uncertainty} *V_{t-1} \qquad \text{(Model \#2)}$$

Model #2 allowed us to study how weights assigned to images and prior affect change depending on the context uncertainty. We also formulated equivalent models for arousal.

In the second part, we investigated how fluctuations in momentary affect change when stimuli in a certain context start occurring randomly. For this purpose, we fitted GLMMs to the entire 90/10 negative and 90/10 positive blocks. We used the following dummy coded regressors to control for the order and block effects: *Context* (-1 = 90/10 negative; +1 = 90/10 positive) and *Uncertainty* (0 = first ten trials – 90/10; 1 = last ten trials – 50/50).

$$V_t \sim 1 + \text{Context} + \text{Uncertainty} + \sum (nV_i) + V_{t-1} \qquad \text{(Model \#3)}$$

Finally, we added interaction terms to Model#3 to study the influence of context uncertainty on the weights assigned to images and prior affect.

$$V_t \sim 1 + \text{Context} + \text{Uncertainty} + \sum (nV_i) + V_{t-1} + \sum (\text{Uncertainty}*nV_i) + \text{Uncertainty}*V_{t-1} \qquad \text{(Model \#4)}$$

Results

In the first stage, we focused on the first ten trials of each block in order to investigate the differences in model parameters depending on context and uncertainty. Not surprisingly, Model #0 (Table 3) showed that an increased likelihood of viewing positive images was associated with increased self-reported valence (B=1.24, 95CI = [1.12, 1.37], p<.001). In addition, we found that increased uncertainty was significantly associated with increased negative valence (B=-0.23, 95CI = [-0.38, -0.08], p=.003). However, these factors were not significantly associated with self-reported arousal (*p*s>.25; see Table 3).

Next, we introduced fixed effects of normative image ratings in the presentation order and prior affect parameters (see Model #1 in Table 3). Both prior valence (B=0.09, 95CI = [0.105, 0.13], p<.001) and arousal (B=0.18, 95CI = [0.12, 0.24], p<.001) and image ratings made positive and significant contributions to the predictive models of valence and arousal. In addition, coefficient estimates of image ratings in the valence model increased as a function of their order of appearance; i.e., later images contributing more strongly to experienced valence.

Finally, we introduced critical interaction terms of interest (see Model #2 in Table 2) to investigate changes in model parameters depending on context uncertainty. We found that as uncertainty increased the relative contribution of prior valence to current valence (B=-0.1, 95CI = [-0.19, -0.02], p=.014). Additionally, in valence predictions, with increasing uncertainty the relative contribution of the last image increased significantly (B=0.08, 95CI = [0.01, 0.15], p=.018) with no significant change in other images' contribution. Importantly, this finding was independent of 'block pleasantness' (see Supplementary Table S1.1). Hence, context uncertainty independent of context valence is responsible for the effects found in Model #2. On the other hand, beta coefficients of stimuli did not interact with context uncertainty in the arousal model. Taken together, these findings indicate that when the uncertainty of the affective context is high, fluctuations in experienced valence, but not arousal, becomes biased towards the most recent stimuli.

Table 3. Results of valence and arousal predictions of Model #1 and Model #2 in Experiment 2. Coefficient estimates, R-squared statistics, and AIC are presented.

	Valence Models		
	Model #0	**Model #1**	**Model #2**
Img#1		0.18 [0.16, 0.21]**	0.22 [0.18, 0.27]**
Img#2		0.22 [0.18, 0.26]**	0.2 [0.15, 0.24]**
Img#3		0.21 [0.19, 0.24]**	0.23 [0.18, 0.27]**
Img#4		0.3 [0.26, 0.34]**	0.26 [0.21, 0.3]**
Prior Affect		0.09 [0.05, 0.13]**	0.13 [0.08, 0.18]**
Uncertainty * Img#1			-0.07 [-0.14, 0.001]
Uncertainty * Img#2			0.04 [-0.03, 0.11]
Uncertainty * Img#3			-0.02 [-0.09, 0.05]
Uncertainty * Img#4			0.08 [0.01, 0.15]*
Uncertainty * Prior Affect			-0.1 [-0.19, 0.02]*
(Constant)	0.03 [-0.08, 0.13]	-0.03 [-0.13, 0.06]	-0.03 [-0.13, 0.06]
(Context)	1.24 [1.12, 1.37]**	-0.04 [-0.16, 0.07]	-0.06 [-0.21, 0.09]
(Uncertainty)	-0.23 [-0.38 -0.08]**	-0.17 [-0.3, -0.04]*	-0.19 [-0.33, -0.05]*
R^2	.42	.67	.65
AIC	6981	5934	5983
	Arousal Models		
	Model #0	**Model #1**	**Model #2**
Img#1		0.09 [0.02, 0.15]*	0.05 [-0.05, 0.14]
Img#2		0.09 [0.01, 0.18]*	0.06 [-0.05, 0.17]
Img#3		0.14 [0.07, 0.21]**	0.17 [0.07, 0.27]**
Img#4		0.16 [0.09, 0.24]**	0.19 [0.08, 0.3]**
Prior Affect		0.18 [0.12, 0.24]**	0.21 [0.14, 0.28]**
Uncertainty * Img#1			-0.1 [-0.27, 0.08]
Uncertainty * Img#2			-0.09 [-0.27, 0.09]
Uncertainty * Img#3			0.07 [-0.11, 0.26]
Uncertainty * Img#4			0.08 [-0.1, 0.26]
Uncertainty * Prior Affect			0.07 [-0.02, 0.17]
(Constant)	0.07 [-0.12, 0.27]	0.08 [-0.07, 0.24]	0.08 [-0.08, 0.24]
(Context)	0.05 [-0.12, 0.22]	0.07 [-0.06, 0.2]	0.07 [-0.06, 0.19]
(Uncertainty)	-0.07 [-0.2, 0.06]	-0.08 [-0.21, 0.05]	-0.07 [-0.2, 0.06]
R^2	.29	.34	.34
AIC	7096	6982	6986

* p<.05, ** p<.005; Numbers in parentheses reflect 95% confidence intervals for each beta coefficient. (Context: -1 = 90/10 negative; -0.5 = 70/30 negative; 0 = 50/50; 0.5 = 70/30 positive; 1 = 90/10 positive; Uncertainty: 0 = 50/50, 0.5 = 70/30, 1 = 90/10)

Next, we investigated the changes in model parameters when participants proceeded from a pleasant or an unpleasant context to an uncertain affective context where stimuli started occurring randomly. The base model here (Model #3 in Table 4) contained fixed effects of normative image ratings in the presentation order and prior affect together with context (-1 = 90/10 negative; 1 = 90/10 positive) and uncertainty dummy-variables (0 = the first ten trials – 90/10; 1 = the last ten trials – 50/50). Similar to the earlier findings, both prior valence and arousal, and normative image ratings had robust contributions to momentary valence and arousal with significant and positive beta coefficients (see Model #3 in Table 4). Coefficient estimate of an image in the valence model increased as it appeared later in a sequence. In addition, we found a main effect of *Uncertainty* on self-reported valence indicating that experienced affect was on average more unpleasant in the random part of the blocks (B=-0.2, 95CI = [-0.28, -0.12], p<.001).

Next, we introduced interaction terms of interest in order to investigate the differences in model parameters between the two parts of the blocks (Model #4 in Table 3). Similar to the previous results, when pleasant and unpleasant stimuli started occurring randomly the relative contribution of the last image significantly increased for the valence model (B=0.07, 95CI = [0.01, 0.13], p=.014; see Model #4 in Table 3). Finally, we found that the transition to an unpredictable context led to a decrease in the relative contribution of prior arousal (B=-0.17, 95CI = [-0.24, -0.09], p<.001). Taken together, these findings indicate that when context uncertainty (independent of pleasantness) increases, experienced valence starts fluctuating more closely with the current stimuli.

Table 4. Results of valence and arousal predictions of Model #3 and Model #4 in Experiment 2. Coefficient estimates, R-squared statistics, and AIC are presented.

	Valence Models	
	Model #3	**Model #4**
Img#1	0.2 [0.17, 0.23]**	0.23 [0.18, 0.28]**
Img#2	0.21 [0.18, 0.24]**	0.21 [0.16, 0.26]**
Img#3	0.21 [0.11, 0.25]**	0.18 [0.12, 0.24]**
Img#4	0.31 [0.27, 0.35]**	0.26 [0.2, 0.32]**
Prior Affect	0.11 [0.07, 0.14]**	0.14 [0.8, 0.19]**
Uncertainty * Img#1		-0.04 [-0.1, 0.02]
Uncertainty * Img#2		0.01 [-0.05, 0.07]
Uncertainty * Img#3		0.03 [-0.03, 0.09]
Uncertainty * Img#4		0.07 [0.01, 0.13]*
Uncertainty * Prior Affect		-0.04 [-0.1, 0.03]
(Constant)	-0.02 [-0.12, 0.08]	-0.02 [-0.11, 0.08]
(Context)	-0.05 [-0.11, 0.01]	-0.03 [-0.1, 0.03]
(Uncertainty)	-0.2 [-0.28, -0.12]**	-0.2 [-0.29, 0.12]**
R^2	.67	.67
AIC	5041 / 5135	5042 / 5163
	Arousal Models	
	Model #3	**Model #4**
Img#1	0.1 [0.01, 0.18]*	0.06 [-0.05, 0.16]
Img#2	0.11 [0.04, 0.18]**	0.05 [-0.06, 0.16]
Img#3	0.13 [0.06, 0.21]**	0.17 [0.06, 0.27]*
Img#4	0.21 [0.13, 0.19]**	0.14 [0.04, 0.25]*
Prior Affect	0.23 [0.17, 0.19]**	0.31 [0.24, 0.38]**
Uncertainty * Img#1		0.07 [-0.07, 0.2]
Uncertainty * Img#2		0.11 [-0.04, 0.25]
Uncertainty * Img#3		-0.07 [-0.21, 0.07]
Uncertainty * Img#4		0.12 [-0.03, 0.26]
Uncertainty * Prior Affect		-0.17 [-0.24, -0.09]**
(Constant)	0.12 [-0.03, 0.27]	0.11 [-0.04, 0.26]
(Context)	0.01 [-0.06, 0.09]	0.01 [-0.06, 0.08]
(Uncertainty)	-0.05 [-0.15, 0.05]	-0.03 [-0.13, 0.07]
R^2	.33	.33
AIC	5844 / 5938	5829 / 5951

* p<.05, ** p<.005; Numbers in parentheses reflect 95% confidence intervals for each beta coefficient.
(Context: -1 = 90/10 negative; 1 = 90/10 positive; Uncertainty: 0 = 90/10; 1=50/50)

Discussion

Study 2 set out to investigate how uncertainty of the affective context influences fluctuations in momentary affect. We manipulated uncertainty by introducing different occurrence probabilities for normatively pleasant and unpleasant images in separate blocks. The results showed that experienced valence fluctuated more closely with the most recent input, with increasing context uncertainty. Further, increased uncertainty led to increased negative affect, which is in line with the previous research indicating a causal relationship between an unpredictable context and negative affect.

General Discussion

In the current research, we investigated momentary affect as a temporally dependent process based on the given visual stimuli and the influence of context uncertainty in this relationship. Using a novel paradigm, we have shown that momentary affect in a given trial reflects the affective impact of the given images and experienced affect in the previous trial. In addition, we found a recency effect; that is, the relative contribution of an image to experienced valence was higher when it appeared later in a sequence. We then investigated the impact of context uncertainty on this temporally dependent relationship in Study 2, which also replicated the primary findings of Study 1. Importantly, with increasing context uncertainty fluctuations in experienced valence had a higher bias towards the most recent stimuli. Additionally, context uncertainty was associated with increased negative affect. Taken together, these findings indicate that a combination of previous affective experience and affective impact of recent stimuli shapes currently experienced affect, and with increasing context uncertainty, the relative contribution of the current stimuli to experienced pleasantness increases. Below, we discuss the implications of these findings for affective science.

In both studies, prior affect made significant contributions to currently experienced affect. In an earlier study, we have also shown that prior affect and affective impact of recent visual stimuli account for distinct contributions to currently experienced affect (Asutay et al., accepted for publication). This finding has critical implications for our understanding of the dynamic nature of affect, which continually represents the ongoing relationship between the organism and the environment (Barrett, 2006; Russell, 2003). We know that affect is a continuous and temporally dependent process. Hence, a person's affective experience at a given time carries some information about the changes in the sensory environment in addition to current affective state of the individual. The models of affect dynamics also formulate prior affective state as a determining factor of the current affective state (e.g. Carver, 2013; Cunningham et al., 2013). The current findings provide clear behavioral evidence for the formulation that prior affect and recent sensory input in the form of visually presented images are significant and independent contributors of currently experienced affect. These findings, therefore, highlight the need for affect to be studied as a temporally dependent process, in which fluctuations are not random but, rather, dynamically reflect the stream of evocative information from the world in addition to the prior information already represented in the system. In particular, experienced affect in our studies did not depend solely on a single image in a trial; instead, it was best represented as a temporal integration of the affective impact of the given stimuli and previous affective experience. This was true, even with the fully random presentation of pleasant and unpleasant images. However, the assumption behind the traditional fully randomized trial structure in most investigations is that measured state in a given trial depends on the structure of the given trial and random noise (see Huk et al., 2018). We believe that current findings point towards the benefit of adopting an experimental framework that attempts to understand internal states such as affect in terms of temporally dependent processes instead of investigating them as discrete individual events (Hutchinson & Barrett, 2019).

The findings in Study 2 showed that context uncertainty is associated with negative affect. Furthermore, with increasing context uncertainty, sensitivity of momentary pleasantness to later input is increased. These findings are in line with previous research showing that uncertainty may increase vigilance and lead to increased unpleasant affect (Herry et al., 2007; Jackson et al., 2014; Whalen, 2007; see also Joffily & Coricelli, 2013). Predictive processing (Clark, 2013; Friston, 2010), which postulates that an organism's main objective is to minimize prediction error, offers interesting explanations for the current findings. Increased prediction error due to an uncertain context leading to increased weighting of more recent input is a biologically and ethologically plausible model through which to interpret the present findings. Furthermore, predictive processing is central to a number of recent models of affect and emotion (see Barett, 2017; Seth & Friston, 2016), which argue interoceptive predictions driven by allostasis as the basis for affective experience. In line with these models, we argue that random presentation of stimuli causes the brain to operate in a mode that is dominated by prediction error, which results in the increased weighting of the recent information. This explanation is also consistent with research suggesting that in a rapidly changing environment, weights given to current information should be higher than those that are assigned to the past information (Courville et al., 2006) because past input is uninformative for the current environment. In light of these explanations, we argue that by adopting a traditional fully randomized trial structure investigators may force a prediction error dominated processing mode in research participants, which in turn may influence the results systematically.

The arousal models were not influenced by the uncertainty manipulation. Additionally, in both studies, the contribution of prior arousal to current arousal was higher than the contribution of prior valence to current valence. This indicates that experienced arousal did not fluctuate as much as experienced valence did. Furthermore, arousal models generally performed worse compared to valence models as evidenced by AIC and R-squared statistics. We believe that one reason for this pattern of findings is that valence is a fundamental feature of human experience. Research shows that infants experience pleasure and discomfort, and can distinguish pleasant and unpleasant facial expressions (Farroni et al, 2007; Lewis, 2016). Moreover, humans can easily differentiate pleasant and unpleasant affective experiences. Nevertheless, many but not all can distinguish high and low arousing experiences (Barrett, 2004). In addition, arousal is a heterogeneous construct (Satpute et al., 2019) and may not be as readily accessible as valence, which could explain larger confidence intervals of estimates and overall larger unexplained variance in arousal predictions. Finally, in Study 2, uncertainty manipulation was based on normative pleasantness; and pleasant and unpleasant stimuli covered the same range of arousal. A study manipulating uncertainty based on arousal may find different results.

A number of factors, other than context and uncertainty, may influence momentary affect, including goal-relevance and perceptual salience. Using variations of the paradigm described here, subsequent investigations may study the role of these additional factors. For example, we envision incorporating an attentional task into the current paradigm that renders a selection of images as task-irrelevant. With this manipulation, the impact of behavioral relevance of stimuli on momentary affect could be studied. Moreover, a greater understanding of momentary affect as a function of temporal information flow has substantial implications for understanding how affect influences behavior. For instance, affect has a crucial influence on decision-making (e.g. Slovic et al., 2002). However, affective signals modulating decisions may or may not be relevant to the decision under consideration (i.e. incidental and integral affect; Västfjäll et al., 2016). Investigating incidental and integral affect as temporally dependent processes can further our understanding of the role of affect in behavior.

Humans navigate complex and dynamic environments and receive a stream of information that induce affective fluctuations. These fluctuations reflect the implications of environmental circumstances partly due to allostasis, which adds an affective layer to the representation of this information. Consequently, everyday stimuli (e.g. Asutay & Västfjäll, 2012; Juslin & Västfjäll, 2008; Kurdi et al., 2017; Russell & Pratt, 1980) can easily induce affect. Yet, we do not fully understand how this stream of input is dynamically represented in momentary affective experience. The current research, approaching affect as a continuous process, shows that fluctuations in momentary affect carries information about recent input and previously experienced affect, and this temporal dependency is influenced by context uncertainty. As a final note, in the current studies, we employed solely visually presented images as sensory stimuli. We see a clear benefit in adopting different experimental paradigms, in which other sensory input modalities including social information are tested. We believe that with future studies employing different modalities and moving beyond the traditional trial structure, we can have a better understanding of affect in terms of a temporally dependent process.

Author Contributions

EA and DV developed the study concept and design. EA conducted data collection and analysis and drafted the manuscript. DV, AG, and PH provided critical revisions.

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Supplementary Materials

S1. Supporting models for Study 2

In Model #2 in the main text, we presented that the inclusion of the interaction terms resulted in showing the impact of context uncertainty on trial-by-trial predictions of self-reported valence. Here, in order to show that the effects were independent of block pleasantness we included interaction terms with context variable to Model #2.

$$Vt \sim 1 + Context + Uncertainty + \Sigma(nVi) + Vt\text{-}1 + \Sigma(Uncertainty*NVi) + Uncertainty*Vt\text{-}1 + \Sigma(Context*NVi) + Context*Vt\text{-}1 \qquad \text{(Model \#2S)}$$

Model #2S allowed us to study the effect of block pleasantness together with uncertainty. As a result, we found that inclusion of the additional interaction terms did not influence the other beta coefficients (Table S1.1). Thus, we conclude that uncertainty independent of stimulus valence is responsible for the effects found in Model #2.

Table S1.2 Results of valence and arousal predictions. Coefficient estimates, R-squared statistics, and Akaike Information Criterion (AIC) are presented.

Valence Models		
	Model #2	**Model #2S**
Img#1	0.22 [0.18, 0.27]**	0.22 [0.17, 0.27]**
Img#2	0.2 [0.15, 0.24]**	0.2 [0.16, 0.25]**
Img#3	0.23 [0.18, 0.27]**	0.22 [0.17, 0.27]**
Img#4	0.26 [0.21, 0.3]**	0.26 [0.21, 0.3]**
Prior Affect	0.13 [0.08, 0.18]**	0.13 [0.08, 0.19]**
Uncertainty * Img#1	-0.07 [-0.14, 0.001]	-0.07 [-0.14, 0.005]
Uncertainty * Img#2	0.04 [-0.03, 0.11]	0.04 [-0.04, 0.11]
Uncertainty * Img#3	-0.02 [-0.09, 0.05]	-0.01 [-0.08, 0.06]
Uncertainty * Img#4	0.08 [0.01, 0.15]*	0.08 [0.01, 0.15]*
Uncertainty * Prior Affect	-0.1 [-0.19, -0.02]*	-0.1 [-0.19, -0.02]*
Context * Img#1		0.03 [-0.02, 0.07]
Context * Img#2		0.07 [0.03, 0.11] *
Context * Img#3		0.04 [-0.01, 0.08]
Context * Img#4		-0.01 [-0.06, 0.03]
Context * Prior Affect		0.01 [-0.04, 0.06]
(Constant)	-0.03 [-0.13, 0.06]	-0.18 [-0.32, -0.04]*
(Context)	-0.06 [-0.21, 0.09]	-0.06 [-0.21, 0.09]
(Uncertainty)	-0.19 [-0.33, -0.05]*	-0.02 [-0.21, 0.17]
R^2	.65	.65
AIC	5983	5979

* p<.05, ** p<.005; Numbers in parentheses reflect 95% confidence intervals for each beta coefficient. (Context: -1 = 90/10 negative; -0.5 = 70/30 negative; 0 = 50/50; 0.5 = 70/30 positive; 1 = 90/10 positive; Uncertainty: 0 = 50/50, 0.5 = 70/30, 1 = 90/10)