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Affective Context and Its Uncertainty Drive Momentary Affective Experience

Erkin Asutay
Linköping University

Alexander Genevsky
Erasmus University and Linköping University

J. Paul Hamilton
Linköping University

Daniel Västfjäll
Linköping University and Decision Research, Eugene, Oregon

Affect fluctuates in a moment-to-moment fashion, reflecting the continuous relationship between the individual and the environment. Despite substantial research, there remain important open questions regarding how a 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 the affective impact of stimuli (i.e., visual images for the current studies) and previously experienced affect. We also found that this temporal dependency is influenced by uncertainty of the affective context. 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 blocks. Increasing context uncertainty (i.e., random occurrence of pleasant and unpleasant images) was associated with increased negative affect. In addition, the relative contribution of the most recent image to experienced pleasantness increased with increasing context uncertainty. Taken together, these findings provide clear behavioral evidence that momentary affect is a temporally dependent and continuous process, which reflects the affective impact of recent input variables and the previous internal state, and that this process is sensitive to the affective context and its uncertainty.

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

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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, Morris, & Wethington, 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, Satpute, Wager, Weber, & Barrett, 2016). This makes affect a fundamental aspect of allostasis and suggests that every waking moment is infused with affective feelings (Wundt, 1897). Therefore, experienced affect fluctuates in a moment-to-moment fashion prompted by sensory information (Cunningham, Dunfield, & Stillman, 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 tested the hypotheses that affective experience at a given time is shaped by what is currently occurring in the envi-

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Erkin Asutay, Department of Behavioral Sciences and Learning, Linköping University; Alexander Genevsky, Rotterdam School of Management, Erasmus University, and Department of Economics, Linköping University; J. Paul Hamilton, Center for Social and Affective Neuroscience, Department of Biomedical and Clinical Sciences, Linköping University; Daniel Västfjäll, Department of Behavioral Sciences and Learning, Linköping University, and Decision Research, Eugene, Oregon.

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Correspondence concerning this article should be addressed to Erkin Asutay, Department of Behavioral Sciences and Learning, Linköping University, SE-58183 Linköping, Sweden. E-mail: erkin.asutay@liu.se

ronment (i.e., visually presented images in the current studies) and previously experienced affect and that the affective context is a determining factor in this process.

Humans navigate complex environments, and we continually receive stimuli that evoke changes in our affective experience, which reflects our ongoing relationship with the environment (Barrett & Russell, 1999; Russell & Barrett, 1999). Thus, affect is a continuous and temporally dependent process, and its 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 in most investigations, which utilize fully randomized consecutive trials and assume that a participant's response at a given trial is independent from all other trials and 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 affective experience is shaped by a combination of temporally integrated recent stimuli and individuals' own previous affective experience (Asutay et al., 2021). Here, using a similar paradigm, we focused on the 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. Studies employing experience sampling methods (ESM) to investigate dynamic affective processes on a larger time scale often control for affective responses at a previous measurement point in order to determine the temporal directionality between various affective states as well as their own fluctuations (e.g., Bringmann et al., 2016; Pe et al., 2015). The conceptualization of affect as a temporally dependent process in the current study has parallels with this approach in an experimental context. However, one major difference is the time scale, which may vary between an hour and a day in ESM studies. Here, we were particularly interested in moment-to-moment changes in low-dimensional affective experience (i.e., pleasantness and activation) prompted by information processing and the uncertainty of the affective context, which is manipulated by introducing a priori occurrence probabilities for normatively pleasant and unpleasant images in separate blocks (Figure 1B).

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, 2015; 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, Daw, & Touretzky, 2006). Moreover, according to predictive processing models, 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 is then 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 aimed to investigate (a) whether momentary affect fluctuates in a continuous and temporally dependent fashion (i.e., experienced affect at a given trial depends on a combination of the given stimuli and previous affective experience) and (b) 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 (Studies 1a and 2) or six (Study 1b) sequentially presented images and subsequently reported their affective experience on two descriptive features: valence and arousal (Figure 1A). Previous research has shown that low-dimensional affective sensations have features of pleasantness accompanied by a certain degree of arousal (e.g., Russell & Barrett, 1999). Therefore, our operationalization of momentary affect included valence and arousal features. We then constructed predictive models of self-reported valence and arousal as linear combinations of the images' normative valence and arousal ratings together with the participants' previously reported affective experience. In other words, self-reported affect in a given trial is modeled based on the 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 for the normative affective impact prompted by each individual image (see also Asutay et al., 2021). We employed this basic paradigm in an earlier study, in which participants viewed a number of sequentially presented images (four or six images presented at a rate of 2 or 4 s per image) and subsequently reported their momentary affective experience using valence and arousal scales (Asutay et al., 2021). We found that affective impact of the given stimuli and participants' previous affective experience accounted for distinct contributions to currently experienced affect. Here, we aimed to replicate and extend these findings. In the previous studies, pleasant and unpleasant images were presented in separate blocks; that is, the affective context was always stable (either pleasant or unpleasant). Therefore, in Studies 1a and 1b, we aimed to replicate the previous findings with randomly occurring pleasant and unpleasant stimuli (i.e., an uncertain context). Next, in Study 2, we directly manipulated the uncertainty of the affective context to investigate its

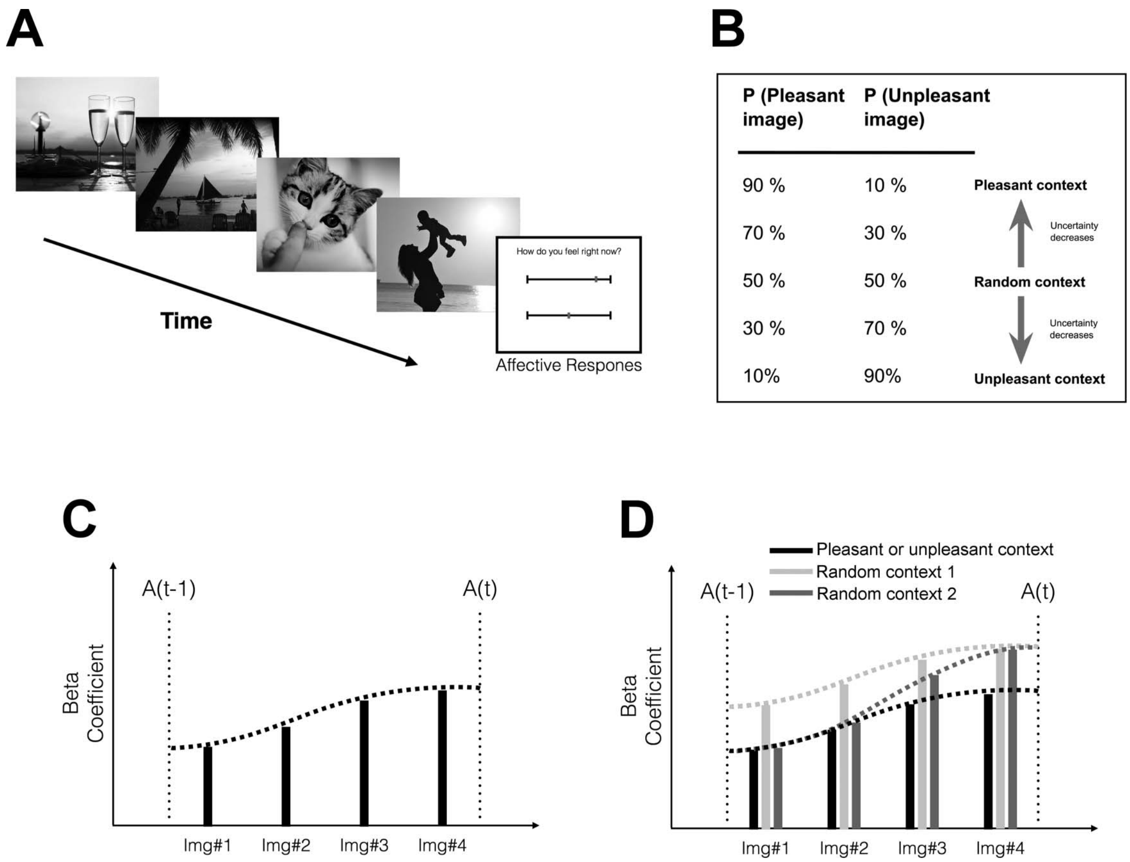

Figure 1. Trial structure of the current studies and illustrations of the hypotheses. Panel A: Participants in each trial viewed sequentially presented images (four in the illustration) and subsequently reported their momentary affect using valence and arousal scales. Images are from the OASIS database ("Introducing the Open Affective Standardized Image Set," by B. Kurdi, S. Lozano, and M. R. Banaji, 2017, *Behavior Research Methods, 49,* pp. 457–470). Panel B: Context uncertainty was manipulated by introducing a priori occurrence probabilities of normatively pleasant and unpleasant images in five separate blocks in Study 2. Panel 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 pattern of expected coefficient estimates for sensory stimuli predicting affect measured at time t, that is, 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. Img = image. Panel D: The graph shows two hypothetical modulations of affective integration as a function of context uncertainty in Study 2: (a) increased weights given to all stimuli without a change in the weighted-averaging window (light gray bars and dashed line) and (b) increased weights given only to recent information (dark gray bars and dashed line).

influence over the temporal dependency of affect to sensory stimuli and prior affect.

In Study 1, we expected the temporal dependency of self-reported valence and arousal to the viewed images to occur according to a weighted-averaging model, which means (a) all images have positive and significant contributions to momentary valence and arousal and (b) the relative contribution of a given image increases as it is presented later in a trial (Figure 1C). Furthermore, we expected 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.

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, individuals would expect to view pleasant images in the future trials; hence, this represents a pleasant context with low uncertainty. On the other hand, an uncertain affective context occurs when individuals view randomly occurring pleasant and unpleasant images (Figure 1B). We hypothesized that increased randomness leads to increased prediction error, which would result in an increase in the weights given to the current sensory stimuli. In particular, increased context uncertainty may lead to increased coefficient estimates for either all (light gray bars in Figure 1D) or only the most recent stimuli (dark gray 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 (dark gray line Figure 1D).

Studies 1a and 1b

In studies 1a and 1b, we approached affect as a temporally dependent and continuous process. Here, we tested our hypothesis that momentary affect is shaped by a combination of affective impact of current stimuli and previously experienced affect.

Method

Participants. Fifty-four (19 women, 35 men, *M* age = 24.1, *SD* = 4.42) and 47 (24 women, 23 men, *M* age = 23.7, *SD* = 2.62) individuals participated in Studies 1a and 1b. Individuals were recruited from a participant pool at Linköping University, which consists mostly of college students. 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.

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 standard deviation) with a power of 0.8. For each simulation, we randomly assigned images to each individual and trial (60 trials per participant). We simulated 5,000 data sets with a given sample size and used generalized linear mixed models (GLMMs) to analyze the data (i.e., the same analysis method defined in the "Data analyses 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 3 weeks, after which we stopped the data collection since both sample sizes were well above 30.

Materials, experimental design, and procedure. The studies were carried out in a computer laboratory. Participants were admitted to the room in groups (maximum 10 participants in a session). Each participant sat in front of a 21-in. computer screen at a comfortable distance. Partition panels were placed between the individuals to block their vision for other participants' screens.

In Study 1a, participants sequentially viewed four images in each trial at a 2-s-per-image presentation rate and subsequently reported their momentary affective experience ("How do you feel right now?") using a mouse and a computer screen on two visual analog scales: hedonic valence (pleasant to unpleasant) and arousal (sleepiness to high activation). The scales did not have a midpoint anchor (e.g., "neutral"). Participants were explicitly instructed to assess how they currently feel at the moment of reporting. They were instructed to "look inward" and assess how they feel at that moment. After going through the instructions, each participant completed three practice trials before going through 60 trials divided into two blocks.

Visual stimuli were taken from the OASIS database (Kurdi, Lozano, & Banaji, 2017) complete with normative valence and arousal ratings (measured on 7-point scales, ranging from 1 = *very negative or very low arousal* to 7 = *very positive or very high arousal*). 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; see online Supplemental Materials S2 for the list of images). We ensured that the selected images had various content. The final set of pleasant images included content such as cute animals, nature scenery, babies, flowers, food, couples kissing, and various activities (diving, rafting, bungee jumping, rollercoasters, etc.). The set of unpleasant images included scenes of war, destruction, bodily injuries, aggressive animals, and crying and agitated individuals. Pleasant and unpleasant images were matched in arousal. During the experiment, images were assigned to trials for each individual separately. We formed image sequences pseudorandomly 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 s per image) and the total number of trials (60 trials) were the same as in Study 1a. Participants viewed each image twice in different combinations.

Data analyses and modeling. All data analyses were done in Matlab (Version 2017b) using the fitglme function (Statistics and Machine Learning Toolbox). We formulated predictive models of valence and arousal based on normative image ratings within each trial. 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 reported in the current article contain fixed effects together with random intercepts and slopes at the participant level. Predictive models of valence and arousal in Studies 1a and 1b contained the fixed effects of the normative image ratings in a given trial depending on its presentation order. In addition, we introduced a prior affect parameter (valence or arousal reported in the previous trial). Thus, a linear model predicting trial-by-trial valence in Study 1a (four images per trial) was in the following form:

$$V_t \sim 1 + V_{t-1} + \sum_i^4 S_{V,i} \tag{1}$$

Here, V_t and V_{t-1} are valence ratings collected at the current (t) and previous ($t-1$) trials, respectively, whereas $S_{V,i}$ denotes the normative valence of the ith stimulus in the current trial. Note that the effects in the above model are mixed effects. Hence, the model includes both random intercept and slopes at the participant level. We constructed an equivalent model for trial-by-trial arousal ratings. Wald tests were used for post hoc comparisons of the estimated effects for each image. Holm-Bonferroni corrections were applied to correct for multiple comparisons.

As a robustness analysis, we have constructed control models in which we additionally controlled for the normative affective impact of the images presented in the previous trial (i.e., trial $t-1$). This additional analysis was conducted to study whether the prior affective experience continues to predict currently experienced affect when the affective impact of the images in the previous trial is controlled for.

Results

GLMMs predicting experienced valence and arousal included fixed effects of normative image ratings in the presentation

Table 1
Results of Valence and Arousal Predictions in Study 1a

Model parameters	Main model	Control model
Valence models		
(Constant)	−0.23 [−0.31, −0.14]**	−0.22 [−0.3, −0.14]**
Image 1	0.2 [0.18, 0.23]**	0.21 [0.18, 0.23]**
Image 2	0.25 [0.23, 0.27]**	0.25 [0.23, 0.27]**
Image 3	0.24 [0.21, 0.26]**	0.24 [0.21, 0.26]**
Image 4	0.29 [0.27, 0.32]**	0.29 [0.27, 0.32]**
Prior valence	0.08 [0.05, 0.1]**	0.08 [0.04, 0.13]**
Image 1 (trial $t-1$)		0.006 [−0.017, 0.029]
Image 2 (trial $t-1$)		−0.007 [−0.031, 0.016]
Image 3 (trial $t-1$)		−0.001 [−0.024, 0.022]
Image 4 (trial $t-1$)		−0.011 [−0.035, 0.013]
R^2	.51	.51
AIC	9,018	9,017
Arousal models		
(Constant)	−0.01 [−0.15, 0.13]	−0.01 [−0.15, 0.12]
Image 1	0.1 [0.04, 0.16]**	0.1 [0.04, 0.16]**
Image 2	0.07 [0.01, 0.13]*	0.07 [0.01, 0.13]*
Image 3	0.1 [0.05, 0.16]**	0.1 [0.05, 0.16]**
Image 4	0.11 [0.05, 0.17]**	0.11 [0.05, 0.17]**
Prior arousal	0.16 [0.11, 0.21]**	0.16 [0.11, 0.21]**
Image 1 (trial $t-1$)		0.023 [−0.03, 0.076]
Image 2 (trial $t-1$)		0.011 [−0.041, 0.063]
Image 3 (trial $t-1$)		−0.04 [−0.1, 0.021]
Image 4 (trial $t-1$)		−0.006 [−0.063, 0.051]
R^2	.29	.29
AIC	9,866	9,876

Note. Coefficient estimates, R^2 statistics, and Akaike information criterion (AIC) are presented. Numbers in brackets represent 95% confidence intervals. Image 1–4 = normative affective impact of images; Image 1–4 (trial $t-1$) = normative affective impact of images presented in the previous trial ($t-1$).
$^{*}p < .05$. $^{**}p < .005$.

order and prior affect. In Study 1a, each image made significant contributions to self-reported valence and arousal with positive and significant coefficient estimates (see Table 1). The coefficient estimates for images were compared using Wald tests (Holm-Bonferroni corrections were applied). For valence predictions, the relative contribution of an image was higher when it was presented later in a sequence (Figure 2A). 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, prior valence ($B = 0.08$, 95% CI [0.05, 0.1], $p < .001$) and arousal ($B = 0.16$, [0.11, 0.21], $p < .001$) made significant contributions to currently experienced valence and arousal, respectively. As a robustness analysis, we formulated control models in which we additionally controlled for the normative affective impact of the images presented in the previous trial. The results

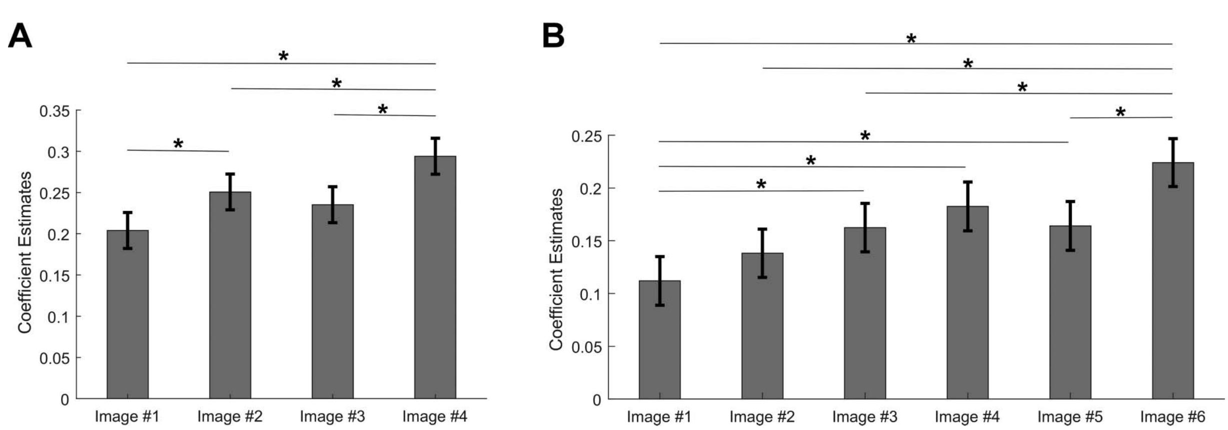

Figure 2. Coefficient estimates for the normative valence ratings of each image at a given trial for Study 1a (Panel A) and 1b (Panel B). Wald tests were used to compare the coefficient estimates. Holm-Bonferroni corrections were applied. $^{*}p < .05$.

Table 2
Results of Valence and Arousal Predictions in Study 1b

Model parameters	Main model	Control model
Valence models		
(Constant)	−0.32 [−0.4, −0.24]**	−0.31 [−0.4, −0.23]**
Image 1	0.11 [0.09, 0.13]**	0.11 [0.09, 0.14]**
Image 2	0.14 [0.12, 0.16]**	0.14 [0.12, 0.16]**
Image 3	0.16 [0.14, 0.19]**	0.16 [0.14, 0.19]**
Image 4	0.18 [0.16, 0.21]**	0.18 [0.16, 0.21]**
Image 5	0.16 [0.14, 0.19]**	0.16 [0.14, 0.19]**
Image 6	0.22 [0.20, 0.25]**	0.22 [0.20, 0.25]**
Prior valence	0.07 [0.02, 0.11]**	0.08 [0.03, 0.13]**
Image 1 (trial $t-1$)		0.005 [−0.018, 0.029]
Image 2 (trial $t-1$)		−0.013 [−0.036, 0.011]
Image 3 (trial $t-1$)		−0.006 [−0.029, 0.018]
Image 4 (trial $t-1$)		−0.019 [−0.043, 0.005]
Image 5 (trial $t-1$)		0.006 [−0.018, 0.03]
Image 6 (trial $t-1$)		−0.009 [−0.033, 0.015]
R^2	.42	.42
AIC	7,824	7,844
Arousal models		
(Constant)	−0.06 [−0.24, 0.13]	−0.06 [−0.24, 0.12]
Image 1	0.08 [0.01, 0.14]*	0.07 [0.01, 0.13]*
Image 2	0.05 [−0.004, 0.11]	0.05 [−0.007, 0.11]
Image 3	0.07 [0.004, 0.14]*	0.07 [0.004, 0.14]*
Image 4	0.08 [0.02, 0.14]*	0.08 [0.03, 0.14]*
Image 5	0.16 [0.11, 0.22]**	0.16 [0.1, 0.22]**
Image 6	0.17 [0.11, 0.23]**	0.16 [0.1, 0.22]**
Prior arousal	0.11 [0.04, 0.18]**	0.12 [0.05, 0.19]**
Image 1 (trial $t-1$)		−0.051 [−0.116, 0.013]
Image 2 (trial $t-1$)		−0.011 [−0.08, 0.058]
Image 3 (trial $t-1$)		0.004 [−0.058, 0.066]
Image 4 (trial $t-1$)		−0.022 [−0.078, 0.034]
Image 5 (trial $t-1$)		−0.061 [−0.118, −0.004]*
Image 6 (trial $t-1$)		−0.083 [−0.141, −0.024]*
R^2	.34	.35
AIC	8,548	8,549

Note. Coefficient estimates, R^2 statistics, and Akaike information criterion (AIC) are presented. Numbers in brackets represent 95% confidence intervals. Image 1–6 = normative affective impact of images; Image 1–6 (trial $t-1$) = normative affective impact of images presented in the previous trial ($t-1$).
$^{*}p < .05$. $^{**}p < .005$.

showed that the images viewed in the previous trial did not predict experienced affect in the current trial. Instead, the effect was due to the prior affective experience (see Table 1).

Study 1b yielded similar results. Normative image ratings and previously reported affect made significant contributions to currently experienced valence and arousal (see Table 2). Post hoc comparisons showed that the relative contribution of an image increased as it appeared later in a trial for valence predictions (Figure 2B). However, similar to Study 1a, arousal predictions did not yield the same pattern. Moreover, prior valence ($B = 0.07$, 95% CI [0.02, 0.11], $p = .004$) and arousal ($B = 0.11$, [0.04, 0.18], $p = .002$) made significant contributions to currently experienced valence and arousal. The control models further confirmed that prior affective experience predicts currently experienced affect even when we control for the affective impact of images shown in the previous trial (see Table 2). Taken together, the findings from Studies 1a and 1b indicate that, in line with our hypothesis, affective impact of the given stimuli and previous affective experience shape currently experienced affect.

Discussion

Studies 1a and 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 at a given time reflects 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 in both valence and arousal ratings. 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., 2021). 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 a combination of the affective impact of current sensory input and previously experienced affect. In Study 2, we focused on the role of uncertainty of the affective context in this temporal dependency.

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 investigated how the affective context and its uncertainty influence this temporally dependent relationship.

Method

Participants. Forty-nine (17 women, 32 men, *M* age = 23.61, *SD* = 3.30) individuals participated in the study. Individuals were recruited from a participant pool at Linköping University, which consists mostly of college students. 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.

We estimated a minimum sample size to detect a small interaction effect of 0.1 (coefficient estimate/error standard deviation) due to the uncertainty manipulation (see the "Data analyses and modeling" section below) with a power of 0.8. We simulated 5,000 data sets with a given sample size and analyzed each one with the same method defined below. These simulations indicated that a minimum sample size of 37 is required to detect a small interaction effect with 0.8 power. We decided on a minimum data collection period of 3 weeks, after which we terminated the data collection since the sample size was above 37.

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 (see online Supplemental Materials S2 for the list of images used in Study 2). In each trial, participants viewed four images at a 2-s-per-image rate, and they went through 100 trials presented in five separate blocks. Unbeknown to participants, each block had two parts. The first 10 trials of each block (40 images per block) contained a priori occurrence probabilities for normatively pleasant and unpleasant images (see Figure 1B), whereas the last 10 trials of each block contained an equal number of pleasant and unpleasant images presented randomly. Hence, this design enabled us to determine the changes in model parameters predicting self-reported affect when individuals adapted to a given affective context (i.e., comparison between blocks during the first 10 trials) and when this context was removed (i.e., comparison between the first and last 10 trials within a block).

The order of blocks was 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.

Study 2 was carried out in the same computer laboratory as Studies 1a and 1b. Participants were admitted to the room in groups (maximum 10 participants in a session). Each participant sat in front of a 21-in. computer screen at a comfortable distance. Partition panels were placed between the individuals to block their vision for other participants' screens.

Data analyses and modeling. We employed the same modeling strategy from the first study with the following changes to investigate the effects of context and uncertainty. The data analysis was divided into two parts. In the first part, we focused on the first 10 trials of each block. This model included dummy-coded context (−1 = 90% negative; −0.5 = 70% negative; 0 = 50% negative; 0.5 = 70% positive; 1 = 90% positive) and uncertainty (0 = 90/10; 0.5 = 70/30; 1 = 50/50) variables to control for the mean differences due to the affective context and its uncertainty represented in separate blocks. Critically, the model contained fixed effects of normative image ratings and prior affect together with their interaction with context uncertainty. Hence, Model 1 predicting trial-by-trial valence ratings during the first 10 trials in each block was in the following form:

$$\text{Model}\,\#\,1: V_t \sim 1 + C + U + V_{t-1} + U * V_{t-1} + \sum\nolimits_i^4 [S_{V,i} + U * S_{V,i}] \tag{2}$$

Here, V_t and V_{t-1} refer to self-reported valence at the current (t) and previous ($t-1$) trials, whereas $S_{V,i}$ denotes the normative valence of the ith stimulus in the current trial. Finally, U and C refer to the dummy-coded uncertainty and context variables. Hence, the term U^*V_{t-1} is the interaction between prior valence and uncertainty. Similarly, the term $U^*S_{V,i}$ represents the interaction between normative valence of the ith image and uncertainty. Model 1, presented in Equation 2, allowed us to study how weights assigned to images and prior affect change depending on the context uncertainty while controlling for the mean differences in the affective context and its uncertainty. Model 1 also included random intercepts and slopes at the participant level. We formulated an equivalent model for trial-by-trial arousal ratings in the first 10 trials in each block.

In the second part, we investigated how fluctuations in self-reported valence and arousal change when stimuli in a certain context started occurring randomly. For this purpose, we modeled 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 10 trials – 90/10; 1 = last 10 trials – 50/50). Additionally, Model 2 contained fixed effects of normative image ratings and prior affect together with their interaction with the uncertainty term to study the influence of context uncertainty on the weights assigned to images and prior affect. Model 2 also contained random intercepts and slopes at the participant level.

$$\text{Model}\,\#\,2: V_t \sim 1 + C + U + V_{t-1} + U * V_{t-1} + \sum\nolimits_i^4 [S_{V,i} + U * S_{V,i}] \tag{3}$$

Results

First, we focused on the first 10 trials of each block to investigate the differences in model parameters depending on context and uncertainty. The results showed that increased uncertainty was significantly associated with increased negative valence ($B = -0.17$, 95% CI [−0.31, −0.04], $p = .012$). However, uncertainty was not significantly associated with self-reported

Table 3
Results of Valence and Arousal Predictions of Model 1 in Experiment 2

Model parameters	Valence model	Arousal model
(Constant)	−0.04 [−0.13, 0.06]	0.08 [−0.08, 0.24]
Context	−0.08 [−0.2, 0.04]	0.07 [−0.06, 0.19]
Uncertainty	−0.17 [−0.31, −0.04]*	−0.07 [−0.2, 0.06]
Image 1	0.22 [0.17, 0.27]**	0.05 [−0.04, 0.14]
Image 2	0.21 [0.16, 0.26]**	0.06 [−0.05, 0.17]
Image 3	0.22 [0.18, 0.27]**	0.17 [0.07, 0.27]**
Image 4	0.26 [0.21, 0.31]**	0.19 [0.08, 0.3]**
Prior affect	0.14 [0.09, 0.19]**	0.21 [0.14, 0.28]**
Image 1 × Uncertainty	−0.06 [−0.13, 0.005]†	0.1 [−0.08, 0.27]
Image 2 × Uncertainty	0.02 [−0.05, 0.09]	0.09 [−0.1, 0.27]
Image 3 × Uncertainty	−0.01 [−0.08, 0.06]	−0.07 [−0.25, 0.11]
Image 4 × Uncertainty	0.09 [0.02, 0.16]*	−0.08 [−0.26, 0.1]
Prior Affect × Uncertainty	−0.09 [−0.17, 0.01]*	−0.07 [−0.17, 0.02]
R^2	.69	.34
AIC	5,921	6,996

Note. The model includes data from the first ten trials of each block. Coefficient estimates, R^2 statistics, and Akaike information criterion (AIC) are presented. Numbers in brackets represent 95% confidence intervals. Image 1–4 = normative affective impact of images; context = −1 (90/10 negative), −0.5 (70/30 negative), 0 (50/50), 0.5 (70/30 positive), 1 (90/10 positive); uncertainty = 0 (90/10), 0.5 (70/30), 1 (50/50).
† $p < .1$. * $p < .05$. ** $p < .005$.

arousal ($p > .25$; see Table 3). The results also showed that prior valence ($B = 0.14$, [0.09, 0.19], $p < .001$) and arousal ($B = 0.21$, [0.14, 0.28], $p < .001$) made significant contributions to the models with positive coefficient estimates. In addition, all images made positive and significant contributions to valence predictions, while the last two images made significant contributions to arousal predictions (all at $p < .001$ level). Critically, the interaction terms allowed us to investigate changes in model parameters depending on context uncertainty. We found that as uncertainty increased, the relative contribution of prior valence decreased ($B = -0.09$, [−0.17, −0.01], $p = .033$). Also, in valence predictions, with increasing uncertainty, the relative contribution of the last image increased significantly ($B = 0.09$, [0.02, 0.16], $p = .014$), with no significant change in other images' contribution. Importantly, this effect was independent of context pleasantness (see online Supplemental Table S1.1). This shows that context uncertainty independent of context pleasantness is responsible for the effect. On the other hand, coefficient estimates 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, become biased toward the most recent stimuli.

Next, we investigated the changes in model parameters when participants proceeded from a pleasant or an unpleasant context to an uncertain affective context where pleasant and unpleasant stimuli started occurring randomly. Similar to the earlier findings, both prior affect and normative image ratings had robust contributions to momentary affect with significant and positive beta coefficients (see Table 4). 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 ($B = -0.2$, 95% CI [−0.29, −0.12], $p < .001$). The models also contained interaction terms of interest to investigate the differences in model parameters between the two parts of the blocks. Similar to the earlier findings, when pleasant and unpleasant stimuli started occurring randomly, the relative contribution of the last image significantly increased for the valence model ($B = 0.07$, [0.01, 0.13], $p = .027$). Finally, we found that the transition to an uncertain context led to a decrease in the relative contribution of prior arousal ($B = -0.17$, [−0.26, −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 most recent stimulus.

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. Moreover, 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. Below, we discuss these findings together with those from Study 1.

General Discussion

In the current research, we studied momentary affect as a temporally dependent process based on a stream of visual images and the individuals' previous affective experience, and we further investigated the influence of context uncertainty in this temporal dependency. Using a novel paradigm, we have shown that self-reported valence and arousal 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 in valence ratings; that is, the relative contribution of an image to experienced pleasantness 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 pri-

Table 4
Results of Valence and Arousal Predictions of Model 2 in Experiment 2

Model parameters	Valence model	Arousal model
(Constant)	−0.02 [−0.11, 0.08]	0.11 [−0.04, 0.26]
Context	−0.04 [−0.1, 0.02]	0.01 [−0.06, 0.08]
Uncertainty	−0.2 [−0.29, −0.11]**	−0.02 [−0.12, 0.08]
Image 1	0.23 [0.18, 0.28]**	0.06 [−0.05, 0.16]
Image 2	0.21 [0.16, 0.27]**	0.05 [−0.06, 0.16]
Image 3	0.18 [0.12, 0.24]**	0.17 [0.07, 0.27]**
Image 4	0.26 [0.21, 0.32]**	0.14 [0.04, 0.25]*
Prior affect	0.13 [0.8, 0.18]**	0.31 [0.24, 0.38]**
Image 1 × Uncertainty	−0.04 [−0.1, 0.02]	0.06 [−0.07, 0.2]
Image 2 × Uncertainty	0.01 [−0.05, 0.07]	0.1 [−0.04, 0.24]
Image 3 × Uncertainty	0.03 [−0.03, 0.09]	−0.07 [−0.21, 0.07]
Image 4 × Uncertainty	0.07 [0.01, 0.13]*	0.12 [−0.03, 0.26]
Prior Affect × Uncertainty	−0.03 [−0.09, 0.04]	−0.17 [−0.26, −0.09]**
R^2	.69	.34
AIC	5,030	5,838

Note. The data includes the whole 90/10 positive and 90/10 negative blocks. Coefficient estimates, R^2 statistics, and Akaike information criterion (AIC) are presented. Numbers in brackets represent 95% confidence intervals. Image 1–4 = normative affective impact of images; context = −1 (90/10 negative), 1 (90/10 positive); uncertainty = 0 (90/10), 1 (50/50).
* $p < .05$. ** $p < .005$.

mary findings of Study 1. Importantly, with increasing context uncertainty, fluctuations in experienced valence had a higher bias toward the most recent stimuli. Additionally, context uncertainty was associated with overall 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 uncertainty of the affective context, 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, previously reported valence and arousal made significant contributions to currently experienced valence and arousal (see also Asutay et al., 2021). This finding has critical implications for our understanding of the dynamic nature of affect, which continually represents the ongoing relationship between the organism and its surroundings (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 the internal 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., Cunningham et al., 2013). The current findings provide clear behavioral evidence for the formulation that prior affect and the affective impact of recent stimuli 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. Importantly, 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 in Studies 1a and 1b. The main assumption behind the rigid fully randomized trial structure in most investigations of behavior and affect is that the measured state (or response) depends solely on the structure of the given trial and random noise (see Huk et al., 2018). When we increased the uncertainty of the affective context by presenting pleasant and unpleasant images at random, we found that the relative contribution of prior affect was somewhat weakened while the contribution of the most recent image increased in the pleasantness dimension. It may seem that in this random condition, the assumptions behind the traditional fully randomized trial structure holds. However, the findings of Studies 1a and 1b clearly show that even with the fully randomized presentation of stimuli, previously reported affect had a significant predictive power for currently experienced affect (see Tables 1 and 2). Moreover, studying affect as discrete individual events independent from all other trials presents very much an unrealistic scenario because natural behavior is not discrete, and individuals rarely navigate fully random environments. We believe that the current findings point toward the benefit of adopting experimental frameworks that attempt 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 the most recent 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., 2015; Joffily & Coricelli, 2013; Whalen, 2007). 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 some recent models of affect and emotion (see Barrett, 2017; Seth & Friston, 2016), which argue interoceptive predictions 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 most recent stimuli. 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 the past input is uninformative for the current environment. In light of these explanations, we argue that by adopting a fully randomized trial structure, investigators may force a prediction-error-dominated processing mode in research participants, which in turn may bias the results.

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 Akaike information criterion 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 they can distinguish pleasant and unpleasant facial expressions (Farroni, Menon, Rigato, & Johnson, 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, Kragel, Barrett, Wager, & Bianciardi, 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, the current 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.

Several factors, other than affective context and its 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 our understanding of how affect influences behavior. For instance, affect has a crucial influence on judgment and decision-making (e.g., Slovic, Finucane, Peters, & MacGregor, 2002). Furthermore, 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 induces fluctuations in their affective state. These fluctuations reflect the implications of environmental circumstances partly due to allostasis, which adds an affective layer to the mental representation of this information. Consequently, everyday stimuli can easily induce affect (e.g., Asutay & Västfjäll, 2012; Juslin & Västfjäll, 2008; Kurdi et al., 2017; Russell & Pratt, 1980). 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 carry information about the affective impact of recent input and previously experienced affect, and this temporal dependency is influenced by the uncertainty of the affective context. As a final note, in the current studies, we employed 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 studied. We believe that with future studies employing different modalities and moving beyond the fully randomized trial structure, we can have a better understanding of affect.

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