Affect Influences Feature Binding in Memory: Trading Between Richness and Strength of Memory Representations

Philipp Spachtholz

University of Munich and University of Regensburg

Christof Kuhbandner

University of Regensburg

Reinhard Pekrun

University of Munich

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Author Note

Philipp Spachtholz, Department of Psychology, University of Munich, Munich, Germany, and Department of Psychology, University of Regensburg, Regensburg, Germany; Christof Kuhbandner, Department of Psychology, University of Regensburg, Regensburg, Germany; Reinhard Pekrun, Department of Psychology, University of Munich, Munich, Germany.

The first two authors contributed equally to this work.

Correspondence concerning this article should be addressed to Philipp Spachtholz, Department of Psychology, University of Munich, 80802 Munich, Germany. E-mail: spachtholz@psy.lmu.de, or to Christof Kuhbandner, Department of Psychology, University of Regensburg, 93053 Regensburg, Germany. E-mail: christof.kuhbandner@ur.de.

Abstract

Research has shown that long-term memory representations of objects are formed as a natural product of perception even without any intentional memorization. It is not known, however, how rich these representations are in terms of the number of bound object features. In particular, because feature binding rests on resource-limited processes, there may be a context-dependent trade-off between the quantity of stored features and their memory strength. We examined whether affective state may bring about such a trade-off. Participants incidentally encoded real-world objects while experiencing positive or negative affect, and we later measured memory for two features. Results showed that participants traded between richness and strength of memory representations as a function of affect, with positive affect tuning memory formation towards richness and negative affect tuning memory formation towards strength. These findings demonstrate that memory binding is a flexible process that is modulated by affective state.

Keywords: emotion, feature binding, affective state, object memory, resource allocation

Affect Influences Feature Binding in Memory: Trading Between Richness And Strength of Memory Representations

While awake, we perceive thousands of objects, most of which are not processed with the intention of remembering them later. Nevertheless, research has shown that people are able to correctly differentiate between originally seen and unseen objects (Castelhano & Henderson, 2005), indicating that long-term memory representations of objects are formed as a natural product of perception, even without any intentional memorization. However, the quality of these representations is unclear. Objects are characterized by a number of different features such as color, shape, etc., and it is unclear how many of these features are bound into such incidentally formed object memory representations, a process that is termed memory binding (Zimmer, Mecklinger, & Lindenberger, 2006).

At first glance, it would seem functional if object memory representations contained as many features as possible because this would make them rich and reliable. However, unfortunately, such a way of storing objects may come at a cost. For the formation of long-term object memory representations, a number of processing steps are necessary. Initially, the features of an object have to be stored in sensory memory (Zhang & Luck, 2011), then they have to be selected by attention (Treisman & Gelade, 1980) and transferred to and maintained in working memory (Woodman & Vogel, 2008; Zokaei, Heider, & Husain, 2014). Critically, as shown by numerous studies, processing resources are limited at all of these stages (see, e.g., Navon & Gopher, 1979, for a review). Thus, in order to obtain an enriched storing of objects, these limited resources have to be allocated more broadly across features. As a consequence, less processing resources will be allocated to the individual features, with the detrimental effect that individual features will be more superficially processed and thus more weakly stored in memory (e.g., Cowan, Blume, & Saults, 2013; Fougnie, Asplund, & Marois, 2010; Oberauer & Eichenberger, 2013). To store features with higher memory strength, an alternative strategy would be to focus resources only on a few object features, which would result in stronger but less rich object memory representations. An illustration of such an account and a model simulation based on the present data are shown in Figure 1.

The dynamics described above suggest that there may be a trade-off between the richness of representations in terms of the number of stored features and the individual feature memory strength. However, to our knowledge, it is currently unknown whether memory binding is indeed flexible enough to allow such a trade-off, and if so, which factors might influence it. From a functional perspective, both strategies have their own merits. Increased richness of representations would make memories more reliable so that misclassification errors are reduced; increased feature memory strength would make memories more durable so that future recognition is enhanced. However, given resource limitations, both strategies cannot be followed simultaneously. Accordingly context factors may determine whether memory formation is tuned towards richness or strength.

One such factor may be whether a situation is experienced as harmful or beneficial, which is signaled by the affective state induced by situations (Frijda, 1988). From an evolutionary perspective, harmful and beneficial situations place rather opposing requirements on our processing system. Regarding potentially harmful situation, it is commonly assumed that it is better to be safe than to be sorry, whereas regarding potentially beneficial situations, it is assumed that it is better to be sorry than to be wrong (e.g., Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Forbes, Purkis, & Lipp, 2011; Öhman & Mineka, 2001; Taylor, 1991). The reason is that the costs of erroneously *not responding* can be ultimately much higher for situations not recognized as harmful than for situations not recognized as beneficial, whereas the costs of erroneously *responding* can be ultimately much higher for situations misclassified as beneficial than situations misclassified as harmful. Imagine, for instance, one does erroneously not correctly recognize the existence of a harmful versus a beneficial object in the environment. Whereas the absence of withdrawing from the harmful object may cause death, the absence of approaching the beneficial object is less likely to be so dire. By contrast, imagine one misclassifies a harmful object as beneficial versus a beneficial object as harmful. In such a case, erroneously approaching the object misclassified as beneficial may cause death, whereas erroneously withdrawing from the object misclassified as harmful will less likely to be so dire.

Thus, regarding the trading between richness of memory representations and feature memory strength, in harmful situations, as signaled by negative affect, a tuning towards increased memory strength would be more functional because an increased likelihood of recognition is more important than an increased reliability. By contrast, in beneficial situations, as signaled by positive affect, a tuning towards richness would be more functional because an increased reliability is more important than an increased likelihood of recognition. In fact, consistent with such an assumption, previous research has shown that affective state indeed modulates the allocation of processing resources, with the general finding that negative affect narrows resource allocation and positive affect broadens resource allocation. This has been demonstrated for sensory memory storage (Kuhbandner, Lichtenfeld, & Pekrun, 2011), attentional selection (Rowe, Hirsh, & Anderson, 2007), and working memory (Spachtholz, Kuhbandner, & Pekrun, 2014). However, it is currently unknown whether such differential resource allocation brought about by affective states also results in long-term object memory representations that differ in their richness and the memory strength of their features.

The aim of the present study was to examine the role of affect on the binding of features in memory. We induced positive and negative affect and measured participants' memory binding for incidentally encoded real-world objects varying along two feature dimensions (for examples see Fig. 2A). Based on the above assumptions, we expected to observe an asymmetry between the two affect conditions in the trade-off between the richness of representations and their memory strength, with positive affect tuning memory formation towards richness and negative affect tuning memory formation towards strength. Finding such an affect-dependent trading of richness of representations for memory strength would demonstrate that memory binding is indeed a flexible process that is modulated by affective state.

Method

Participants

A power analysis revealed that to achieve a power of .80 for detecting small-sized effects (dependent t-test, $d = 0.3$, $\alpha = .05$), a sample size of at least 90 would be required. Thus, we decided to collect at least 90 participants and continue data collection until the end of a semester. In total, we recruited 99 undergraduates (74 females, $M_{age} = 24.0$, $SD = 6.1$) who participated for course credit.[1] All participants provided written informed consent and reported normal or corrected-to-normal vision acuity and normal color vision (Ishihara color plates). The study was conducted in accordance with the Helsinki declaration and the University Research Ethics Standards. All data exclusions, all manipulations, and all measures in the study are reported.

Material

We selected 200 images of real-world objects from published sets of stimuli (Brady, Konkle, Alvarez, & Oliva, 2008; Brady, Konkle, Alvarez, & Oliva, 2013). For each object, we created four different images, resulting from the combination of two different states (e.g., open/closed) and two different colors (e.g., yellow/blue). The two state versions were already available from the stimulus sets. To create two color versions, we first selected a random hue value for the first version and then rotated this hue value (which can be represented as an angle on an isoluminant color circle) by 180° for the second version. We only selected objects whose colors were not intrinsically related to the objects (see Fig. 2A for examples).

Design and Procedure

Participants were tested individually using E-Prime 2.0 (Psychology Software Tools, Inc., Pittsburgh, PA), using a procedure adapted from Brady et al. (2013). The experiment consisted of an incidental study phase and a surprise test phase. During the study phase, participants were asked to decide whether or not to buy each of the centrally presented objects, to ensure focused attention. Each trial started with the presentation of an object for 200 ms, followed by a blank screen for 1,700 ms during which participants made their buying decisions through button presses. The next trial started after a blank screen of 500 ms duration.

The study phase was divided into two blocks of 100 objects each. At the beginning of each block, either positive or negative affect was induced. Participants were asked to recall a happy or sad autobiographical event for three minutes while listening to appropriate music (Jefferies, Smilek, Eich, & Enns, 2008). The order of affect conditions and the assignment of objects to affect conditions were counterbalanced across participants. In the test phase, participants completed a forced-choice recognition memory test. Each object was presented in all four possible feature combinations, and participants were asked to select the picture they had seen during the study phase (see Fig. 1A). Memory for half of the objects of each affect condition was tested immediately after the study phase. The remaining half was tested in a delayed memory test one day after the study phase (resource allocation effects in the delayed test were not analyzed because participants' performance showed a floor effect both in the negative condition, $M_{P\text{both}} = 0.03$, $SD = 0.06$, and the positive condition, $M_{P\text{both}} = 0.08$, $SD = 0.10$).

Participants initially completed 20 practice trials of the study task using objects different from those used later in the experiment. Success of affect induction was retrospectively measured after each affect-induction block using the affect grid (Russell, Weiss, & Mendelsohn, 1989) which assesses experienced affect on the dimensions of valence (1 = extremely negative, 9 = extremely positive) and arousal (1 = low arousal, 9 = high arousal).

Data analysis

An illustration of the model underlying the analytical approach followed in the present study is shown in Figure 1A. The basic assumption is that overall available resources are allocated between the two features of an object, resulting in corresponding feature memory strengths. Due to resource limits, allocating more resources to one of the features comes at the cost of decreased memory strength for the other feature, leading to differential memory strengths (i.e., strong vs. weak feature), and thus differential recall rates (i.e., P_{Strong} vs. P_{Weak}). The magnitude of resource allocation is reflected by the proportion of overall available resources that is allocated to the stronger feature at the cost of the weaker feature. The overall available resources are reflected by the mean between P_{Strong} and P_{Weak} [i.e., $P_{\text{Overall}} = (P_{\text{Strong}} + P_{\text{Weak}}) * 0.5$)]. The resources that are allocated to the stronger feature at the cost of the weaker feature are reflected by half of the difference between P_{Strong} and P_{Weak} [i.e., $(P_{\text{Strong}} - P_{\text{Weak}}) * 0.5$)]. Accordingly, the magnitude of resource allocation can be determined by the formula $(P_{\text{Strong}} - P_{\text{Weak}}) / (P_{\text{Strong}} + P_{\text{Weak}})$, resulting in a value that varies from 0 % = equal distribution across features to 100 % = complete allocation to one of the features.

As the type of feature that is more strongly stored may vary across objects, P_{Strong} and

P_{Weak} cannot simply be determined by comparing the probabilities of remembering the color and the state features. However, as illustrated in Figure 1A, the probabilities of remembering the stronger and weaker features can directly be derived from the observed probabilities of remembering both features (P_{Both}) or only one feature (P_{Single}). As can be easily seen in Figure 1A, P_{Weak} equals P_{Both} because P_{Weak} includes all of the cases where the weaker feature is remembered, which implies that also the stronger feature is remembered. As can also be seen in Figure 1A, P_{Strong} equals the sum of P_{Both} and P_{Single} because P_{Strong} includes all of the cases where (i) only one feature is recalled (which is naturally the stronger feature) and (ii) where both the stronger and the weaker feature are recalled.

One crucial theoretical assumption of the above model is that the features of an object are not processed independently from each other because resources have to be allocated between the features, implying that P_{Both} equals P_{Weak}. Such an assumption is trivially supported by the fact that the features of an object occur at the same point in time (they are both a part of the same object) so that they are jointly processed. Furthermore, as shown in Figure 1B, this is also supported by the empirical fact that the probabilities for remembering both features (P_{Both}) or only one feature (P_{Single}) in the negative and positive affect conditions are perfectly in line with such a dependent model (i.e., $P_{\text{Both}} = P_{\text{Weak}}$), but are outside the range that could be explained by independent models (i.e., $P_{\text{Both}} = P_{\text{Weak}} * P_{\text{Strong}}$). In fact, such an assumption is also suggested by previous research, showing that at short retention intervals features appear to be stored in a dependent fashion due to common encoding factors, although they appear to be stored in an independent fashion at long retention intervals because they are forgotten independently from each other (Brady et al., 2013).

P_{Both} and P_{Single} are directly related to the observed proportions of reporting both features correctly, only one of the features (either color or state), or neither of the features. However, in order to estimate the respective probabilities, the effect of guessing has to be taken into account. Observers only report neither of the features correctly when they do not remember any features ($1 - P_{Both} - P_{Single}$) and do not guess one by chance. When observers report only one feature correctly, there are two possibilities: Either they remember only one feature and do not guess the other feature by chance, or they remember neither of the features and guess exactly one by chance. When observers report both of the features correctly, there are three possibilities: Either they remember both features, they remember only one feature and guess the other by chance, or they remember neither of the features and guess both features by chance. In order to estimate P_{Both} and P_{Single}, we formulated a model representing these relations (see Table 1). Parameters were restricted to a possible range of [0, 1], and best fitting parameters were determined for each participant and condition using maximum likelihood estimation (Myung, 2003).

Results

One participant was excluded for failing to perform the study task satisfactorily (90% missed responses in one condition). Additionally, three participants were excluded because their proportions of reporting neither of the two features correctly was larger than 0.25, indicating that they did not have any memory for the features so that binding processes could not be examined.

Affect Induction

Compared to the positive condition, participants' ratings in the negative condition were lower on both the valence ($M_{Negative} = 3.2$, $SD = 1.3$; $M_{Positive} = 7.2$, $SD = 1.2$), $t(94) = -21.2$, $p < .001$, $g_{rm} = 3.23$, and arousal dimensions ($M_{Negative} = 3.7$, $SD = 1.6$; $M_{Positive} = 5.9$, $SD = 1.8$), $t(94) = -10.1$, $p < .001$, $g_{rm} = 1.31$, indicating that affect induction was successful.[2]

Memory Performance

Overall, the model for estimating P_{Both} and P_{Single} fitted the data very well ($R^2_{Negative}$ = .97, $R^2_{Positive}$ = .97; positive affect condition: $M_{P\text{both}}$ = 0.30, SD = 0.18, $M_{P\text{single}}$ = 0.30, SD = 0.18; negative affect condition: $M_{P\text{both}}$ = 0.26, SD = 0.18, $M_{P\text{single}}$ = 0.38, SD = 0.21). Memory performance for the features of an object as a function of affective state is shown in Fig. 2B. P_{overall} which reflects the amount of overall available resources did not differ between affect conditions (positive affect: $M_{P\text{overall}}$ = 0.45, SD = 0.16; negative affect: $M_{P\text{overall}}$ = 0.45, SD = 0.18), $t(94) = 0.20$, $p = .842$, $g_{\text{rm}} = 0.02$, indicating that overall available resources did not differ between affect conditions. However, the amount of resources allocated to the stronger and weaker features differed as a function of affect, as reflected by a 2 (feature strength: weak vs. strong) x 2 (affect condition: negative vs. positive) analysis of variance on the probability of remembering a feature, which revealed a significant interaction between feature strength and affect condition, $F(1, 94) = 9.88$, $p = .002$, $\eta_p^2 = .095$. Whereas the probability of remembering the stronger feature was higher in the negative ($M_{P\text{strong}}$ = 0.64, SD = 0.20) than the positive conditions ($M_{P\text{strong}}$ = 0.60, SD = 0.22), $t(94) = 2.04$, $p = .044$, 95% CI [0.001, 0.089], $g_{\text{rm}} = 0.22$, the probability of remembering the weaker feature was lower in the negative ($M_{P\text{weak}}$ = 0.26, SD = 0.18) than the positive conditions ($M_{P\text{weak}}$ = 0.30, SD = 0.18), $t(94) = -2.23$, $p = .028$, 95% CI [-0.074, -0.004], $g_{\text{rm}} = 0.22$. Figure 2C shows the amount of allocation of the overall available resources as a function of affect. Asymmetry of allocation was higher in the negative ($M_{\text{Allocation}}$ = 48.1 %, SD = 30.6) than in the positive condition ($M_{\text{Allocation}}$ = 38.1 %, SD = 27.2), $t(94) = 2.91$, $p = .005$, 95% CI [0.032, 0.169], $g_{\text{rm}} = 0.34$.

To examine whether the effect of affective state on allocation asymmetry was driven by differences in valence or arousal levels, we examined within subject correlations (Bland & Altman, 1995). Results showed that the allocation-asymmetry score was significantly correlated with valence, $r = -.27$, $p = .008$, indicating that lower valence scores (i.e. more negative affect) are associated with higher allocation asymmetry. By contrast, the allocation asymmetry score was not significantly correlated with arousal, $r = -.12$, $p = .259$, indicating that observed effects were driven by valence rather than arousal.

Discussion

The present study investigated whether feature binding in memory varies as a function of affective state. The results showed that observers trade between the quantity of stored features and their memory strength as a function of affect, with positive affect tuning memory formation towards quantity and negative affect tuning memory formation towards strength. These findings reveal that object memory formation is flexible enough to allow a trade-off between the richness of representations and their memory strength, and show for the first time that memory binding is modulated by affect.

Although participants traded between richness and strength of object memory representations as a function of affect, overall available binding resources did not vary as a function of affect. Such a finding refutes simpler theories, postulating that negative affect generally reduces available cognitive resources (e.g., Ellis & Ashbrook, 1988). Rather, our results are in line with theories that are based on the assumption that affect signals the requirements placed on the cognitive system by a given situation, postulating that negative affect signals a problematic situation where a narrowed processing style is functional, whereas positive affect signals a beneficial situation where a broadened processing style is functional (e.g., Clore & Huntsinger, 2007; Fredrickson, 1998), an assumption that is supported by several previous findings showing that negative affect narrows and positive affect broadens cognitive processing at several levels of processing (e.g., Kuhbandner et al., 2011; Rowe et al., 2007; Wegbreit, Franconeri, & Beeman, 2015). Going beyond previous studies, the finding that the number of the features of an object that are stored in long-term memory varies as a function of affect demonstrates that such an effect of affect is also observed in the formation of object memories. In particular, our findings show that such an affect-induced adjustment of cognitive resources can have complementary effects on the strength of processed contents. In fact, this is in line with studies demonstrating similar complementary relationships in related domains. For instance, in working memory, observers trade the number of stored objects (i.e., capacity) for the quality of stored features (i.e., precision; e.g., Zhang & Luck, 2008, 2011), and it has been shown recently that this trade-off is similarly susceptible to affective influences (Spachtholz et al., 2014). Taken together, these results suggest that affect plays an important role in the shaping of memory representations because affect influences the trade-off between quantity and quality in both short and long term retention.

It has long been suggested that the relationship between emotion and cognition can be investigated in two fundamentally different ways (Derryberry & Tucker, 1994): (1) How does the emotional state of a person affect the processing of neutral stimuli, and (2) how does a person in an emotionally neutral state process emotional stimuli. Our study addressed the first question, demonstrating that the experience of emotions can modulate the formation of memory representations for neutral objects. With regard to the second question, there is a relatively large body of research that has examined how the binding of features is influenced by the presence of an emotionally significant stimulus. A prominent finding is the so-called “weapon focus” which refers to the phenomenon that attention and later memory is narrowed to the negative stimulus of a scene (i.e., the weapon) at the expense of peripheral details (e.g., Christianson & Loftus, 1990). In more recent research, this general pattern has been supported and elaborated, showing that the binding of the constituent features is enhanced for emotionally arousing objects both in terms of quantity and strength, whereas the binding of distinct object and background features is impaired (e.g., Earles, Kersten, Vernon, & Starkings, 2016; Kensinger, 2007; Mackay et al., 2004; for a review and an integrating theory, see Mather, 2007). However, as the quantity of stored features and their memory strength have never been concurrently measured in that line of research, it remains to be shown whether a similar trade-off between quantity and memory strength exists in the processing of emotional stimuli, a question which awaits future research.

In summary, our results demonstrate that affect can determine what we will remember about situations later. When experiencing negative affect, object memories will be more durable, but memories will be less reliable because only a few characterizing features are retained. By contrast, when experiencing positive affect, object memories will be less durable, but memories will be more reliable because more characterizing features are retained. Thus, affect seems to play an important role in the way we acquire knowledge about our world.

Footnotes

[1] For a subset of the sample, we additionally collected EEG data, which will be reported elsewhere. Additional EEG data collection did not modulate the effect of affect on allocation asymmetry, as indicated by the absence of an interaction in a 2 (EEG data collection: yes vs. no) x 2 (affect condition: negative vs. positive) ANOVA on allocation asymmetry scores, $F(1, 93) = 0.04$, $p = .839$.

[2] To examine potential effects of the order of the affect induction, we conducted a 2 (order of affect induction: positive first vs. negative first) x 2 (affect condition: positive, negative) ANOVA on valence and arousal ratings. There was no main effect of the order of affect induction and no interaction between the order of affect induction and affect condition, neither for valence nor for arousal ratings (all ps > .282).

References

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*, 323–370. doi:10.1037//1089-2680.5.4.323

Bland, J. M., & Altman, D. G. (1995). Statistics notes: Calculating correlation coefficients with repeated observations: Part 1--correlation within subjects. *British Medical Journal*, *310*, 446. doi:10.1136/bmj.310.6977.446

Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2008). Visual long-term memory has a massive storage capacity for object details. *Proceedings of the National Academy of Sciences of the United States of America*, *105*, 14325–14329. doi:10.1073/pnas.0803390105

Brady, T. F., Konkle, T., Alvarez, G. A., & Oliva, A. (2013). Real-world objects are not represented as bound units: Independent forgetting of different object details from visual memory. *Journal of Experimental Psychology: General*, *142*, 791–808. doi:10.1037/a0029649

Castelhano, M., & Henderson, J. M. (2005). Incidental visual memory for objects in scenes. *Visual Cognition*, *12*, 1017–1040. doi:10.1080/13506280444000634

Christianson S.-A., & Loftus, E. F. (1990). Some characteristics of people's traumatic memories. *Bulletin of the Psychonomic Society, 28*, 195–198. doi: 10.3758/BF03334001

Clore, G. L., & Huntsinger, J. R. (2007). How emotions inform judgment and regulate thought. *Trends in cognitive sciences*, *11*, 393–399. doi:10.1016/j.tics.2007.08.005

Cousineau, D. (2005). Confidence intervals in within-subject designs: A simpler solution to Loftus and Masson’s method. *Tutorials in Quantitative Methods for Psychology*, *1*, 42–45.

Cowan, N., Blume, C. L., & Saults, J. S. (2013). Attention to attributes and objects in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *39*, 731–

747. doi:10.1037/a0029687

Derryberry, D., & Tucker, D. M. (1994). Motivating the focus of attention. In P. M. Niedenthal & S. Kitayama (Eds.), *The heart's eye: Emotional influences in perception and attention* (pp. 167–196). San Diego, CA, US: Academic Press

Earles, J. L., Kersten, A. W., Vernon, L. L., & Starkings, R. (2016). Memory for positive, negative and neutral events in younger and older adults: Does emotion influence binding in event memory? *Cognition & Emotion*, *30*, 378–388. doi:10.1080/02699931.2014.996530

Ellis, H. C., & Ashbrook, P. W. (1988). Resource allocation model of the effects of depressed mood states on memory. In K. Fiedler & J. P. Forgas (Eds.), *Affect, cognition and social behavior: new evidence and integrative attempts* (pp. 25–32). Toronto, Canada: Hogrefe.

Forbes, S. J., Purkis, H. M., & Lipp, O. V. (2011). Better safe than sorry: simplistic fear-relevant stimuli capture attention. *Cognition & Emotion*, *25*, 794–804. doi:10.1080/02699931.2010.514710

Fougnie, D., Asplund, C. L., & Marois, R. (2010). What are the units of storage in visual working memory? *Journal of Vision*, *10*, 27. doi:10.1167/10.12.27

Fredrickson, B. L. (1998). What Good Are Positive Emotions? *Review of general psychology*, *2*, 300–319. doi:10.1037/1089-2680.2.3.300

Frijda, N. H. (1988). The laws of emotion. *American Psychologist*, *43*, 349–358. doi:10.1037/0003-066X.43.5.349

Jefferies, L. N., Smilek, D., Eich, E., & Enns, J. T. (2008). Emotional valence and arousal interact in attentional control. *Psychological Science*, *19*, 290–295. doi:10.1037/t00741-000.

Kensinger, E. A. (2007). Negative Emotion Enhances Memory Accuracy: Behavioral and Neuroimaging Evidence. *Current Directions in Psychological Science*, *16*, 213–218.

doi:10.1111/j.1467-8721.2007.00506.x

Kuhbandner, C., Lichtenfeld, S., & Pekrun, R. (2011). Always look on the broad side of life: happiness increases the breadth of sensory memory. *Emotion*, *11*, 958–964. doi:10.1037/a0024075

Mackay, D. G., Shafto, M., Taylor, J. K., Marian, D. E., Abrams, L., & Dyer, J. R. (2004). Relations between emotion, memory, and attention: Evidence from taboo Stroop, lexical decision, and immediate memory tasks. *Memory & Cognition*, *32*, 474–488. doi:10.3758/BF03195840

Mather, M. (2007). Emotional Arousal and Memory Binding: An Object-Based Framework. *Perspectives on psychological science*, *2*, 33–52. doi:10.1111/j.1745-6916.2007.00028.x

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. *Journal of Mathematical Psychology*, *47*, 90–100. doi:10.1016/S0022-2496(02)00028-7

Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. *Psychological review*, *86*, 214–255. doi:10.1037/0033-295X.86.3.214

Oberauer, K., & Eichenberger, S. (2013). Visual working memory declines when more features must be remembered for each object. *Memory & Cognition*, *41*, 1212–1227. doi:10.3758/s13421-013-0333-6

Öhman, A., & Mineka, S. (2001). Fears, phobias, and preparedness: Toward an evolved module of fear and fear learning. *Psychological Review*, *108*, 483–522. doi:10.1037/0033-295X.108.3.483

Rowe, G., Hirsh, J. B., & Anderson, A. K. (2007). Positive affect increases the breadth of attentional selection. *Proceedings of the National Academy of Sciences of the United States of America*, *104*, 383–388. doi:10.1073/pnas.0605198104

Russell, J. A., Weiss, A., & Mendelsohn, G. A. (1989). Affect Grid: A single-item scale of pleasure and arousal. *Journal of Personality and Social Psychology*, *57*, 493–502. doi:10.1037/0022-3514.57.3.493

Spachtholz, P., Kuhbandner, C., & Pekrun, R. (2014). Negative affect improves the quality of memories: trading capacity for precision in sensory and working memory. *Journal of Experimental Psychology: General*, *143*, 1450–1456. doi:10.1037/xge0000012

Taylor, S. E. (1991). Asymmetrical effects of positive and negative events: The mobilization-minimization hypothesis. *Psychological Bulletin*, *110*, 67–85. doi:10.1037/0033-2909.110.1.67

Treisman, A. M., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology*, *12*, 97–136. doi:10.1016/0010-0285(80)90005-5

Wegbreit, E., Franconeri, S., & Beeman, M. (2015). Anxious mood narrows attention in feature space. *Cognition & Emotion*, *29*, 668–677. doi:10.1080/02699931.2014.922933

Woodman, G. F., & Vogel, E. K. (2008). Selective storage and maintenance of an object's features in visual working memory. *Psychonomic Bulletin & Review*, *15*, 223–229. doi:10.3758/PBR.15.1.223

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*, 233–235. doi:10.1038/nature06860

Zhang, W., & Luck, S. J. (2011). The number and quality of representations in working memory. *Psychological Science*, *22*, 1434–1441. doi:10.1177/0956797611417006

Zimmer, H. D., Mecklinger, A., & Lindenberger, U. (2006). Levels of binding: types, mechanisms, and functions of binding in remembering. In H. D. Zimmer, A. Mecklinger, & U. Lindenberger (Eds.), *Handbook of Binding and Memory - Perspectives from Cognitive*

Neuroscience (pp. 2–22). Oxford: Oxford University Press.

Zokaei, N., Heider, M., & Husain, M. (2014). Attention is required for maintenance of feature binding in visual working memory. *Quarterly journal of experimental psychology*, *67*, 1191–1213. doi:10.1080/17470218.2013.852232

Table 1

Formulas for predicting the observed proportions of the three possible response events from the probabilities of remembering both of the features (P_{Both}) and only one of the features (P_{Single}).

Response Event	Probability
0 Features	p(0 features) = $(1 - P_{\text{Both}} - P_{\text{Single}}) * 0.25$
1 Feature	p(1 feature) = $P_{\text{Single}} * 0.5 + (1 - P_{\text{Both}} - P_{\text{Single}}) * 0.5$
2 Features	p(2 features) = $P_{\text{Both}} + P_{\text{Single}} * 0.5 + (1 - P_{\text{Both}} - P_{\text{Single}}) * 0.25$

Note. When participants are completely guessing, there are four options for them to choose from. One of those options has zero correct features, two options have exactly one correct feature, and one option has two correct features. Thus, when guessing, participants randomly choose an option with zero correct features in one out of four instances (i.e., 25%), an option with exactly one correct features in two out of four instances (i.e., 50%), and an option with two correct features in one out of four instances (i.e., 25%).

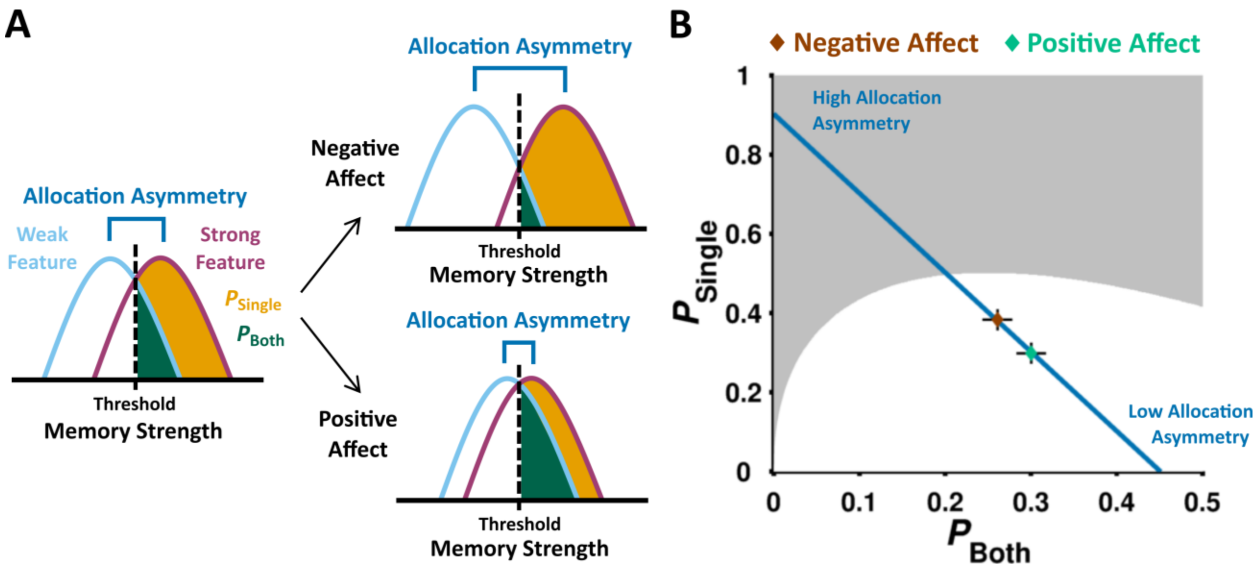

Figure 1. Illustration of the trade-off in memory binding between the quantity of stored features and their memory strength. (*A*) Basically, overall available resources are allocated between the two features of an object, resulting in corresponding feature memory strengths (light blue and purple probability density functions) and differential recall rates for the stronger and the weaker features (i.e., P_{Strong} and P_{Weak}). The overall available resources are reflected by the mean between P_{Strong} and P_{Weak} (i.e., $P_{Overall}$), and the magnitude of resource allocation is reflected by the proportion of overall available resources that is allocated to the stronger feature at the cost of the weaker feature, and should be larger in negative and smaller in positive affective states. P_{Strong} and P_{Weak} can be determined by the observed probabilities of remembering both of the features (i.e., P_{Both}) or only one of the features (i.e., P_{Single}). (*B*) A crucial assumption of the model in Figure 1A is that the stronger and weaker features are stored in a dependent fashion. Figure 1B shows a simulation of such a model (blue line) based on the observed overall available resources in the current experiment (i.e., $P_{Overall}$). The larger P_{Single} and the smaller P_{Both}, the more resources are allocated to one of the features at the cost of the other (i.e., upper left parts of the line). The model simulation indicates that the observed mean probabilities for remembering

both of the features (i.e., P_{Both}) or only one of the features (i.e., P_{Single}) in the negative and positive affect conditions are perfectly in line with a dependent model. The gray area shows the range of probabilities that can be explained by independent models, indicating that the observed probabilities are at odds with such an account. The horizontal and vertical error bars show within-subjects 95 % confidence intervals (Cousineau, 2005). See the online article for the color version of this figure.

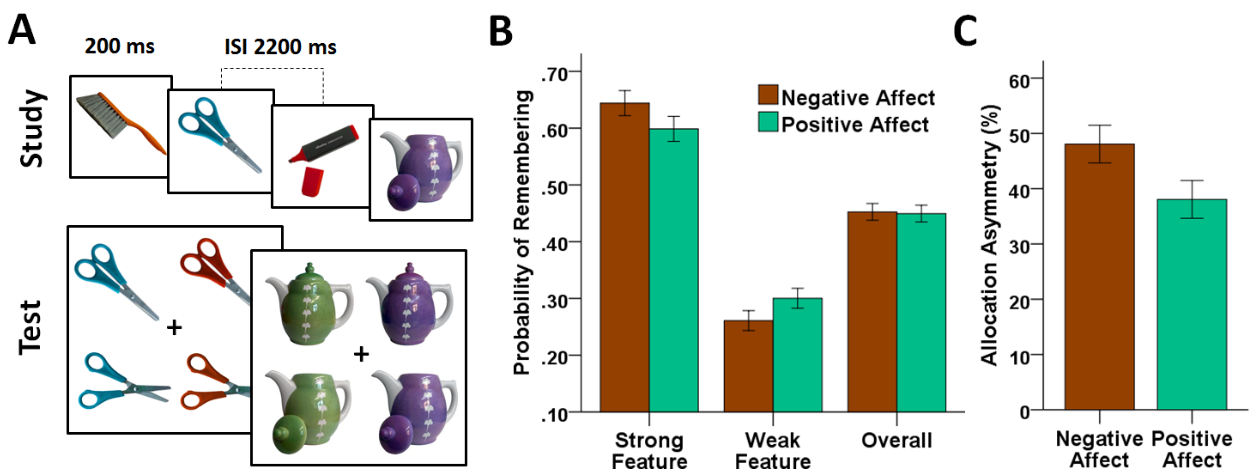

Figure 2. Experimental procedure and results of the experiment. (A) In an incidental study phase (upper panel), a series of visual objects was shown for 200 ms each with a blank interstimulus interval of 2,200 ms with the instruction to decide for each object whether to buy it or not. In a surprise memory test (lower panel), participants were asked to select the image they had seen during the study phase. Four response options were shown resulting from the combination of two features (state and color) with two values each. The object pictures shown here are for example only; for actually presented pictures, see Brady et al. (2008) and Brady et al. (2013) (*B*) The probabilities of remembering the weaker and stronger features of an object are shown as a function of affective state. The right bars show the mean between P_{Weak} and P_{Strong} (i.e., P_{Overall}), indicating that overall available resources did not differ between affect conditions. (*C*) Amount of asymmetry of allocation of the overall available resources is shown (varying from 0% = equal distribution across features to 100% = complete allocation to one of the features) as a function of affective state. Error bars represent within-subjects 95 % confidence intervals (Cousineau, 2005). See the online article for the color version of this figure.