

# Labeling Behaviors are Associated with the Identification of Emotion Events

**Zhimeng Li (zhimeng.li@yale.edu)**

Department of Psychology, Yale University  
New Haven, CT 06511 USA

**Maria Gendron (maria.gendron@yale.edu)**

Department of Psychology, Yale University  
New Haven, CT 06511 USA

## Abstract

The framework of event perception suggests that people segment continuous perceptual input into discrete events by forming mental representations of ongoing activity. Prior work extending the segmentation framework to emotion perception shows that a richer emotion vocabulary is associated with segmentation of emotion events in greater agreement with the cultural ingroup. However, little is known about how labeling behaviors themselves shape the segmentation of emotion events. Here, we look at the effect of labeling on emotion segmentation. Participants were randomly assigned to simply segment videos into discrete emotion events or to segment only when an emotion label is available and to label the segmented event. We found that compared to the group that segmented without providing labels, the group that segmented with explicit labeling behaviors were less sensitive at discriminating emotion events from non-emotion events and more conservative to identify an emotion event. The results are discussed with respect to competing theoretical accounts of the impact of labeling on emotion perception and suggest that the conceptual broadening account (where labels invoke idiographic emotion representations) may best account for the findings.

**Keywords:** language; emotion label; emotion perception

## Introduction

Language and associated conceptual knowledge are proposed to guide our inferences about others' emotions (Barrett et al., 2007; Lindquist & Gendron, 2013). Emotion labels, specifically, may play a critical role in organizing and representing categorical knowledge of emotions that further guides emotion perception (Lindquist & MacCormack et al., 2015). Yet it is not clear whether requiring participants to label emotions in experiments may shape the very phenomena we wish to study. In previous work, we demonstrated that emotion perception can be quantified as a form of event perception, such that there are individual differences in the degree to which people identify changes in others' emotions (i.e., segment) from continuous dynamics. This skill is associated with a having a broader and more sophisticated emotion vocabulary (Li et al., 2023). Here, we revisit the recently developed Emotion Segmentation Paradigm to examine whether experimentally manipulating whether individuals explicitly label or not impacts how they segment emotional events.

## Language Impacts Event Segmentation

Literature on event perception provides a theoretical foundation for the potential impact of labeling on emotion perception. According to the framework of event perception (Kurby & Zacks, 2008; Richmond & Zacks, 2017; Zacks, 2020), people segment continuous experiential input into meaningful events that unfold across time and space. As people process incoming information in a certain spatiotemporal setting, they form mental representations of current happenings, which include concrete entities such as people and objects as well as the causal relationships between the entities. The event perception framework terms these perceptual representations of current experiences working event models. Working event models can be hierarchically structured, ranging from general events (e.g., baking) to discrete actions (e.g., pouring milk, cutting butter, etc.). It is proposed that these mental models are infused with prior knowledge that enables predictions of how the event may unfold. Prior knowledge about baking, for instance, can predict that the actor will start mixing the ingredients after putting them in a bowl. However, if the actor walks towards the hallway instead of mixing the ingredients, this disparity between the prediction and the incoming information can give rise to prediction errors, calling for the placement of an event boundary. The working event model may then be updated from “baking” to “answering the door”.

The prior knowledge involved in this predictive process is structured by the language that represents aspects of the event structure (Zacks, 2020). Empirical evidence from cross-linguistic studies suggests that linguistic differences can be related to differences in event unit perception (for an overview, see Bohnemeyer et al., 2007). In the study by Gerwien et al. (2018), for instance, when watching videos with changes in the actor's moving orientation and direction, French speakers were more likely to identify an event boundary than German speakers, possibly due to the French language prefers path verbs over manner verbs, hence selectively prioritizing perception of change in direction. However, others also find that speakers of different languages demonstrate comparable event encoding and memory during passive viewing tasks (Papafragou et al., 2008; Trueswell & Papafragou, 2010; Skordos et al., 2020), suggesting that language differences may emerge only when active meaning making is actively required during the task (e.g., segmenting continuous information into meaningful events). Indeed, it is

proposed that language selectively brings forward relevant conceptual knowledge, which further constrains the processing of low-level input, consistent with predictive processing accounts (Lupyan & Clark, 2015).

This effect of language on event perception has recently been extended to the study of emotion perception. Similar to action events, emotions can also be perceived as events given that they unfold over time with predictable causal connections, are constrained by preceding emotions, and the broader situational context. Past research shows that people reliably track the affective dynamics of others (Zaki et al., 2008) and can detect the onset of and transitions between emotional expressions (Prohovnik et al., 2004; Korolkova, 2018). Moreover, people also form mental representations of these dynamics which can predict future mental states of the social targets (Thornton & Tamir, 2017; Thornton, Weaverdyck & Tamir, 2019; Zhao, Thornton & Tamir, 2020). Discrete emotion labels index and may even structure conceptual knowledge to guide emotion inferences (Barrett et al., 2007; Lindquist & Gendron, 2013). A growing body of empirical work demonstrates that having (or lacking) semantic access to emotion labels can activate (or disrupt access to) relevant emotion concepts, subsequently facilitating (or hindering) emotion perception (for review see Lindquist & MacCormack et al., 2015). Combining this line of evidence with work showing the effect of language on event perception, one may hypothesize that, when people face the continuous flow of emotional cues, emotion labels, similar to action verbs, can bring online conceptual models of specific emotions, which constrain how people process incoming cues and place boundaries on discrete emotional events. Prior work shows that individual differences in emotion segmentation performance are associated with people's active emotion vocabularies, such that a richer and more complex emotion vocabulary predicts segmentations of emotional events more in consensus with the cultural ingroup (Li et al., 2023). However, it is not clear from these correlational findings whether actively labeling impacts how individuals segment. In the present study, we investigated this question by studying the behavior of actively generating labels during dynamic segmentation of emotional events.

## The Present Study

In the present pre-registered study (found here: [osf.io/a6w5z](https://osf.io/a6w5z)), we examined the impact of active labeling behavior on emotion perception. We measured emotion perception behaviors using the recently developed and validated Emotion Segmentation Paradigm, which evaluates emotion perception performance using a consensus-based approach. A similar consensus-based approach of evaluating individual performance based on the level of agreement with the group has been applied to evaluate agreement in segmentations of general action events (Kurby & Zacks, 2011). We hypothesize that there are reliable individual differences in emotion segmentation performance, quantified as the sensitivity to discriminate consensus instances of emotion from non-consensus timepoints and the criterion for

the identification of emotional events. We further hypothesize that people who generate labels for the emotions they segment will segment emotions differently from those who do not generate labels.

Relevant theoretical and empirical work supports competing sets of predictions regarding how labeling behavior may impact individuals' sensitivity in emotion segmentation behaviors. In the Emotion Segmentation Paradigm, emotion events are constructed based on group consensus. Labeling behaviors thus may bring online conceptual knowledge of emotion that presumably is shared within cultural groups. In previous work, we found evidence that individual differences in the breadth of active emotion vocabulary is associated with having more normative situational knowledge of emotions (Li et al., 2023). And individuals who had broader active emotion vocabularies, in turn, segmented emotion in consensus with others to a greater degree. This convergence in working event models may narrow the range of perceptual cues indicating event boundaries, facilitating the identification of emotion events in agreement with the group. Hence, according to this conceptual narrowing account, labeling behavior may result in greater sensitivity.

On the other hand, it is also possible that the emotion knowledge brought online reflects idiosyncratic conceptual representations of emotions, resulting in divergent judgments and perceptions of incoming information. People can have different ideas of what facial expressions are associated with the same emotion categories, which can in turn bias their categorization of emotional faces (Binetti et al., 2022). People who have similar conceptual knowledge of two discrete emotions also tend to perceive the corresponding facial expressions as more similar, and this similarity in conceptual structure is also reflected in the neural representations of faces (Brooks and Freeman, 2018). The idea that conceptual knowledge shapes perception aligns with the simulation hypothesis proposed by Barrett et al (2007), which argues for the top-down influence of simulations (i.e., representations that anticipate incoming sensory events and corresponding action plans) on the perception of incoming sensory input. This conceptual variation may manifest online as labeling behaviors require people to access the semantic knowledge that may further shape perception. Therefore, according to this conceptual broadening account, labeling may encourage deviation from the group consensus and greater variation in emotion segmentation, resulting in lower sensitivity on the individual level.

There are also competing accounts regarding how labeling may impact the decision criterion in emotion segmentation. The competitive account of semantic selection argues that lexical candidates that are semantically related can activate brain regions such as the left temporal lobe similarly during labeling (Piai & Knight, 2018). People striving to make fewer errors may therefore take a longer time with the lexical decisions (Nozari & Hepner, 2019). In this paradigm, we would expect lexical competition to translate into a more stringent threshold for identifying emotion events when

participants are asked to label. On the other hand, the current paradigm allows for the generation of multiple labels, thus potentially reducing the competition of lexical candidates and the subsequent behavioral trade-offs (Nozari & Hepner, 2019). Hence, according to this semantic non-competitive account, people may be equally liberal at identifying emotion events with or without labels.

## Method

### Participants

The study was approved by Yale University Institutional Review Board (IRB #: 2000026863). We conducted a power analysis which indicated a sample size of 352 is needed to detect a moderate effect size of 0.3 ( $\alpha = 0.05$ , power = 0.8). We oversampled to account for potential data loss/attrition. We recruited 370 participants (labeling:  $n = 173$ ,  $M_{\text{age}} = 35.72$ ,  $SD_{\text{age}} = 11.09$ , 76 female, 93 male, 4 non-binary/other, 110 white, 21 black, 9 Hispanic, 5 Asian, 28 mixed-race or other; no-labeling:  $n = 197$ ,  $M_{\text{age}} = 37.13$ ,  $SD_{\text{age}} = 11.50$ , 104 female, 87 male, 6 non-binary/other, 133 white, 21 black, 7 Asian, 4 Hispanic, 32 mixed-race or other) who are native English speakers, born and currently living in the United States, and removed 14 low-effort individuals who did not segment all stimuli, resulting in a final sample size of  $N = 356$  (labeling:  $n = 163$ ,  $M_{\text{age}} = 35.49$ ,  $SD_{\text{age}} = 10.96$ , 71 female, 89 male, 3 non-binary/other, 105 white, 20 black, 9 Hispanic, 5 Asian, 24 mixed-race or other; non-labeling:  $n = 193$ ,  $M_{\text{age}} = 37.01$ ,  $SD_{\text{age}} = 11.4$ , 102 female, 85 male, 6 non-binary/other, 130 white, 20 black, 7 Asian, 4 Hispanic, 32 mixed-race or other).

### Procedures

We conducted the study online via Qualtrics and a custom-built platform. Participants were randomly assigned to either the labeling condition or the no-labeling condition. Both conditions used the previously developed and validated Emotion Segmentation Paradigm, which presented 9 documentary clips featuring a diverse range of emotions in randomized orders with length ranging from 66s to 166s (Li et al., 2023). Participants completed an audio test to ensure that they had full audio access and were then directed to the task. In the no-labeling condition, participants were instructed to “Click the button whenever you think there is a change in emotion in any person.” In the labeling condition, participants were given the additional instruction to “provide a label for the emotion you perceive”. Participants in this condition were told to only pause when they had a word already in mind for the emotion. Participants then proceeded to the practice trial. After they passed the practice trial by segmenting at least three times, they proceeded to the formal trials.

### Data Analysis

We first calculated the consensus events (i.e., time points where a significant number of people indicate the presence of an emotion) for each video within the sample by using the R package *segmag* (Papenmeier & Sering, 2014) to identify peak events by centering a Gaussian ( $sd=0.8$ ) around each key press. Events were merged if the start and end times of two events were within 800 ms (Meitz et al., 2020). To account for individual differences in the identification of emotion events, we then identified for each consensus event a consensus event time window using the R package *changept* (Killick et al., 2012) by detecting time points with statistically significant changes in mean and variance centering the group-level segmentation magnitude at the time points (for details see Li et al., 2023). We adopted the same penalty value from our prior work, which led to 3 consensus event timepoints sharing the same event window. We split the window into three equivalent lengths to create distinct windows for each consensus event. This resulted in a total of 75 consensus events. In addition, we also calculated the consensus events within each condition group using the same method. This resulted in 57 consensus events for the labeling condition and 82 consensus events for the non-labeling condition.

We treated each consensus event window as ‘signal trials’, and intervals between consensus event windows as ‘noise trials’ (we also treated the beginning and end of the video as noise trials). Participants responses were coded as the following: Pauses within each signal trial were coded as a “hit;” failures to pause within each signal trial were coded as a “miss;” pauses within each noise trial were coded as a “false alarm;” and failures to pause within each noise trial were coded as a “correct rejection.” For each condition group, we then computed the hit rate (hr), calculated as the sum of the number of hits and misses divided by the number of hits, and the false alarm rate (far), calculated as the sum of number of false alarms and correct rejections divided by number of false alarms. We then computed two metrics of Signal Detection Theory to quantify emotion segmentation performance,  $d'$  and  $c$  (Macmillan & Creelman, 2004).  $d'$  represents sensitivity at discriminating instances of emotion from non-emotion. A greater value of  $d'$  suggests greater sensitivity. It was calculated as the difference between the z-score of hit rate (zhr) and the z-score of false alarm rate (zfar).  $c$  represents criterion, the threshold for the identification of an emotion event. A greater value of criterion suggests a more conservative threshold. It was calculated as half the negative sum of zhr and zfar. We computed both metrics across all videos. For participants that did not have any hits or false alarms within certain videos, we adopted loglinear transformation to address these extreme proportions (Hautus, 1995).

After the computation of the metrics, we removed outliers using the outlier\_mad function from the R package *Routliers* ( $b = 1.4826$ , threshold = 3) (Leys et al., 2013). This process resulted in 3 data points of  $c$  being removed from the no-labeling condition.

To examine individual differences in sensitivity and decision criterion for emotion segmentation performance for each group, we computed the  $\omega$  as a measure of the reliability of the metrics. To compare the emotion segmentation performance between conditions, we conducted independent-sample t-tests for both the average  $d'$  and the  $c$ .

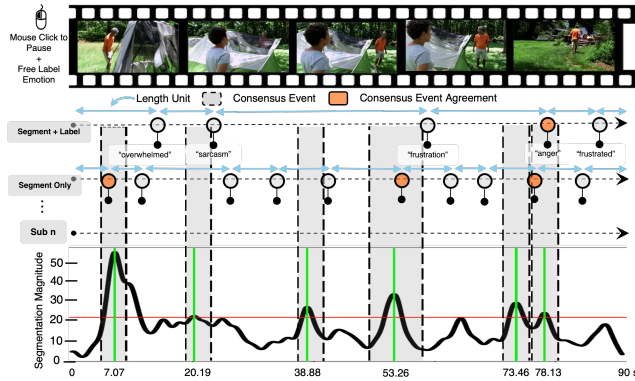


Figure 1: Study procedure using Emotion Segmentation Paradigm. Grey stripes represent group-level consensus events. Orange circle represents identification of the consensus event (i.e., in agreement with the consensus events).

## Results

The findings indicate that for both conditions, both  $d'$  ( $\omega_T = 0.48$  for labeling condition,  $\omega_T = 0.68$  for no-labeling condition) and  $c$  ( $\omega_T = 0.93$  for label condition,  $\omega_T = 0.88$  for no-labeling condition) demonstrate adequate levels of reliability. Furthermore, the two groups differ in their emotion segmentation performance. Specifically, compared to the no-labeling group, the labeling group had a lower  $d'$  ( $t(350) = 6.97, p < .001; 95 \text{ CI } [0.20, 0.36]$ ) (Figure.1) and a higher  $c$  ( $t(331) = -8.82, p < .001; 95 \text{ CI } [-0.41, -0.26]$ ) (Figure.2). In other words, the labeling group on average demonstrated a lower sensitivity at discriminating emotion events from non-emotion events and had a more conservative threshold for identifying an emotion event.

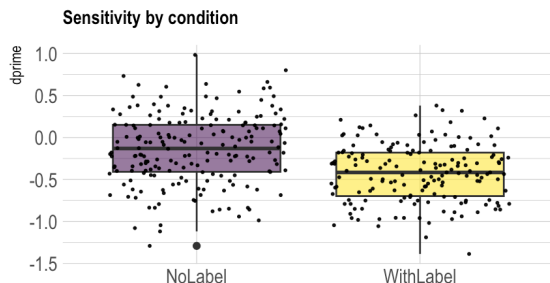


Figure 2: The labeling group shows lower sensitivity than the no-labeling group.

We also computed  $d'$  and  $c$  using both consensus events constructed using data within each condition group. We performed the same analyses, which resulted in the same

general findings. When being evaluated against consensus within one's own condition group, the labeling group still demonstrated lower sensitivity ( $t(349) = 5.24, p < .001; 95 \text{ CI } [0.13, 0.29]$ ) and a more conservative threshold compared to the no-labeling group ( $t(340) = -4.02, p < .001; 95 \text{ CI } [-0.22, -0.07]$ ).

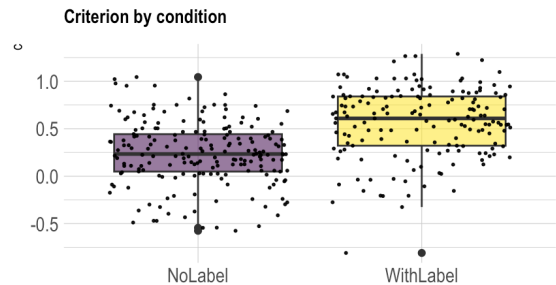


Figure 3: The labeling group adopts more conservative criteria than the no-labeling group.

## Discussion

The findings provide preliminary evidence for the impact of labeling on emotion perception processes. People who actively generate labels for emotions, compared to those who do not, are less sensitive at discriminating between emotion and non-emotion events. They are also more conservative to identify an emotion event. These results support the hypotheses that fall under the conceptual broadening account and the competitive semantic selection account. According to the conceptual broadening account, it is possible that labeling activates idiosyncratic conceptual representations of different emotions, resulting in a heightened variability that is also reflected in a lower number of consensus events. This is consistent with recent evidence that individuals have internal representations of emotional facial expressions that are highly idiosyncratic (Binetti et al., 2022). Though prior finding suggests that richer emotion vocabulary is associated with greater consensus in segmentation performance (Li et al., 2023), this is not inconsistent with the current results of the labeling group demonstrating a lower sensitivity at identifying consensus events. Exploratory analysis suggests that within the labeling group, the positive link between the number of unique labels generated and the sensitivity at detecting consensus events generated using the entire sample (Spearman's  $\rho = .45, p < .001$ ) is preserved. This finding suggests that the impact of labeling behavior might be decoupled from the individual differences associated with the active emotion vocabulary. Future studies may consider further unpacking this finding by including other explicit measurements of conceptual knowledge such as the Situational Test of Emotional Understanding (Allen et al., 2014).

Despite being given the option of providing multiple labels which arguably counteracts the accuracy-latency trade-off, people who are asked to actively label the emotion events still appear to adopt a more conservative threshold at identifying

emotion events. On average, participants generated 1.14 label per response, suggesting that they still engage in a high level of semantic selection, despite the less constraining instructions. It is also worth noting that, different from common lexical selection tasks which often involve referential decisions (e.g., picture naming), the Emotion Segmentation Paradigm may require more complex inferential judgments. Semantic processes co-occur with word retrieval during referential processing but typically precede word retrieval in inferential processing (Fargier & Laganaro, 2017). Given the dynamic nature of the task, it is hence possible that the semantic processes and the ensuing word retrieval contributed to longer reaction times. By the time the label is generated, people may have already passed the time point at which they had identified an emotion event and thus do not make a key press (i.e., the “event” has passed by).

There are some alternative explanations for the between-group differences in sensitivity and criterion. For one, it is possible that the task of the labeling group, which involved label generation, is more difficult. The labeling group did demonstrate a lower number of segmentations on average ( $M = 6.16$ ,  $sd = 3.41$ ) compared to the no-labeling group ( $M = 9.97$ ,  $sd = 6.84$ ) ( $t(292) = 6.80$ ,  $p < .001$ ; 95 CI [2.71, 4.91]). However, this difference could also be attributed to the “chunking” behavior of segmentation (i.e., coarse-grained segmentation), observed in people with greater domain knowledge who group smaller events into larger events that are more meaningful (Newberry et al., 2021). Future studies could investigate this possibility by examining the activated conceptual knowledge specifically.

A number of future directions that would be interesting to pursue. First, it would be interesting to examine the impact of language priming on performance in this task. If the current findings are best explained by the conceptual broadening account, we would expect this manipulation to still result in weaker sensitivity because the underlying representation of emotion labels that participants bring online will still be variable. If, however, the present results are explained by a *linguistic* broadening account where participants ended up generating a more diverse set of categories because of labeling, we might expect language priming to lead to increased sensitivity (conceptual narrowing) or no impact on sensitivity.

In future studies researchers could also examine within-person effects of labeling on segmentation. Previous findings on event perception suggest that it can be influenced by not only changes in external input but also internal state changes including emotions and goals (for the most recent review see Wang et al., 2023). Wang and Egner (2022), for instance, found that changing task demands can create event boundaries during encoding of objects, such that switching between task demands resulted in exaggerated temporal distance memory for items encoded across a switch. We may similarly observe flexible criteria for identifying emotion events as the task demand switches from active labeling to no labeling. People may change to a more liberal criterion as the

additional process of word retrieval is removed and the standard for “accuracy” also alters.

Given that language can reflect not only within-culture individual differences but also cross-cultural variation in emotion knowledge, future work can also replicate these findings in cross-linguistic or cross-cultural contexts. Recent empirical work suggests that distinct cultural backgrounds shape people’s differential emphasis on which cues are used to draw event boundaries (Swallow & Wang, 2020). It will be interesting to examine if this culturally different emphasis on cues is present in emotion segmentation performance, and how this difference may change with or without labeling behaviors.

## Conclusion

Extending the framework of event perception to emotion perception, we examine how labeling behaviors impact the way people segment continuous activity into emotion events. The framework of event perception suggests that people segment continuous perceptual input into discrete events by forming mental representation of current experiences. These representations are infused with prior experience that guides segmentation. These mental representations can be structured and efficiently accessed by language, which may impose a top-down constraint on the processing of perceptual input. Building on prior correlational work on individual differences in the active emotion vocabulary, we show here that labeling impacts emotion segmentation. Compared to people who were not labeling, people who explicitly labeled the emotion event tended to be less sensitive at discriminating emotion event from non-emotion event (defined based on group consensus) and have a more stringent criteria for identifying an emotion event. These results are suggestive of the underlying mechanisms of how labeling may impact emotion perception, we speculate via activation of idiosyncratic conceptual knowledge. Future studies may further probe into the mechanism in intrapersonal or cross-cultural settings.

## References

- Allen, V. D., Weissman, A., Hellwig, S., MacCann, C., & Roberts, R. D. (2014). Development of the situational test of emotional understanding – brief (STEU-B) using item response theory. *Personality and Individual Differences*, *65*, 3–7.
- Barrett, L. F., Lindquist, K. A., & Gendron, M. (2007). Language as context for the perception of emotion. *Trends in Cognitive Sciences*, *11*(8), 327–332.
- Binetti, N., Roubtsova, N., Carlisi, C., Cosker, D., Viding, E., & Mareschal, I. (2022). Genetic algorithms reveal profound individual differences in emotion recognition. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(45), e2201380119.
- Bohnemeyer, J., Enfield, N. J., Essegbey, J., Ibarretxe-Antunano, I., Kita, S., Lüpke, F., & Ameka, F. K. (2007). Principles of event segmentation in language: The case of motion events. *Language*, *83*(3), 495–532.

- Brooks, J. A., Chikazoe, J., Sadato, N., & Freeman, J. B. (2019). The neural representation of facial-emotion categories reflects conceptual structure. *Proceedings of the National Academy of Sciences*, *116*(32), 15861–15870.
- Brooks, J. A., & Freeman, J. B. (2018). Conceptual knowledge predicts the representational structure of facial emotion perception. *Nature Human Behaviour*, *2*(8), 581–591.
- Fargier, R., & Laganaro, M. (2017). Spatio-temporal dynamics of referential and inferential naming: Different brain and cognitive operations to lexical selection. *Brain Topography*, *30*(2), 182–197.
- Fargier, R., & Laganaro, M. (2017). Spatio-temporal dynamics of referential and inferential naming: Different brain and cognitive operations to lexical selection. *Brain Topography*, *30*(2), 182–197.
- Gerwien, J., & von Stutterheim, C. (2018). Event segmentation: Cross-linguistic differences in verbal and non-verbal tasks. *Cognition*, *180*, 225–237.
- Hautus, M. J. (1995). Corrections for extreme proportions and their biasing effects on estimated values of  $d'$ . *Behavior Research Methods, Instruments, & Computers*, *27*(1), 46–51.
- Killick, R., Fearnhead, P., & Eckley, I. A. (2012). Optimal detection of changepoints with a linear computational cost. *Journal of the American Statistical Association*, *107*(500), 1590–1598.
- Korolkova, O. A. (2018). The role of temporal inversion in the perception of realistic and morphed dynamic transitions between facial expressions. *Vision Research*, *143*, 42–51.
- Kurby, C. A., & Zacks, J. M. (2008). Segmentation in the perception and memory of events. *Trends in Cognitive Sciences*, *12*(2), 72–79.
- Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766.
- Li, Z., Lu, H., Liu, D., Yu, A. N. C., & Gendron, M. (2023). Emotional event perception is related to lexical complexity and emotion knowledge. *Communications Psychology*, *1*(1), Article 1.
- Lindquist, K. A., & Gendron, M. (2013). What's in a Word? Language Constructs Emotion Perception. *Emotion Review*, *5*(1), 66–71.
- Lindquist, K. A., MacCormack, J. K., & Shablack, H. (2015). The role of language in emotion: Predictions from psychological constructionism. *Frontiers in Psychology*, *6*, 444.
- Lupyan, G., & Clark, A. (2015). Words and the World: Predictive Coding and the Language-Perception-Cognition Interface. *Current Directions in Psychological Science*, *24*(4), 279–284.
- Macmillan, N. A., & Creelman, C. D. (2004). *Detection Theory: A User's Guide*. Taylor & Francis Group.
- Newberry, K. M., Feller, D. P., & Bailey, H. R. (2021). Influences of domain knowledge on segmentation and memory. *Memory & Cognition*, *49*(4), 660–674.
- Nozari, N., & Hepner, C. R. (2019). To select or to wait? The importance of criterion setting in debates of competitive lexical selection. *Cognitive Neuropsychology*, *36*(5–6), 193–207.
- Papafragou, A., Hulbert, J., & Trueswell, J. (2008). Does language guide event perception? Evidence from eye movements. *Cognition*, *108*(1), 155–184.
- Papenmeier, F., & Sering, K. (2014). segmag: Determine event boundaries in event segmentation experiments. *R Package Version*, *1*(2).
- Piai, V., & Knight, R. T. (2018). Lexical selection with competing distractors: Evidence from left temporal lobe lesions. *Psychonomic Bulletin & Review*, *25*(2), 710–717.
- Prohovnik, I., Skudlarski, P., Fulbright, R. K., Gore, J. C., & Wexler, B. E. (2004). Functional MRI changes before and after onset of reported emotions. *Psychiatry Research: Neuroimaging*, *132*(3), 239–250.
- Richmond, L. L., & Zacks, J. M. (2017). Constructing Experience: Event Models from Perception to Action. *Trends in Cognitive Sciences*, *21*(12), 962–980.
- Skordos, D., Bunger, A., Richards, C., Selimis, S., Trueswell, J., & Papafragou, A. (2020). Motion verbs and memory for motion events. *Cognitive Neuropsychology*, *37*(5–6), 254–270.
- Swallow, K. M., & Wang, Q. (2020). Culture influences how people divide continuous sensory experience into events. *Cognition*, *205*, 104450.
- Thornton, M. A., & Tamir, D. I. (2017). Mental models accurately predict emotion transitions. *Proceedings of the National Academy of Sciences*, *114*(23), 5982–5987.
- Thornton, M. A., Weaverdyck, M. E., & Tamir, D. I. (2019). The Social Brain Automatically Predicts Others' Future Mental States. *Journal of Neuroscience*, *39*(1), 140–148.
- Trueswell, J. C., & Papafragou, A. (2010). Perceiving and remembering events cross-linguistically: Evidence from dual-task paradigms. *Journal of Memory and Language*, *63*(1), 64–82.
- Wang, Y. C., Adcock, R. A., & Egner, T. (2024). Toward an integrative account of internal and external determinants of event segmentation. *Psychonomic Bulletin & Review*, *31*(2), 484–506.
- Zacks, J. M. (2020). Event Perception and Memory. *Annual Review of Psychology*, *71*(1), 165–191.
- Zaki, J., Bolger, N., & Ochsner, K. (2008). It Takes Two: The Interpersonal Nature of Empathic Accuracy. *Psychological Science*, *19*(4), 399–404.
- Zhao, Z., Thornton, M. A., & Tamir, D. I. (2022). Accurate Emotion Prediction in Dyads and Groups and Its Potential Social Benefits. *Emotion (Washington, D.C.)*, *22*(5), 1030–1043.