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REPLY

Beyond Dichotomies in Generalization Research: A Reply to Lee and Schlegelmilch (2025)

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Lee and Schlegelmilch (2025) reanalyzed data from Zaman, Yu, and Verheyen (2023), arguing that the role of perception in generalization is overemphasized and that higher level cognitive processes (in the form of a similarity-based rule) provide a better account. In this reply, we make the argument that their reanalysis contains flaws and inconsistencies and present additional evidence for consideration. While acknowledging the role of higher level cognition in generalization, we maintain that the available evidence supports stimulus perception and memory as important predictors. We view this exchange as a reminder that stimulus representation and higher level cognition exist on a spectrum, with their relative importance varying across contexts. Consequently, more research into the interactions between these processes is necessary. We argue that rather than adhering to existing theoretical frameworks, researchers should continue to challenge our understanding of human generalization by incorporating new evidence and insights into existing models and comparing them across diverse contexts. This approach will foster a more comprehensive and nuanced understanding of human generalization processes.

Public Significance Statement

This scientific exchange highlights the ongoing challenge in understanding human generalization processes. It underscores the importance of carefully integrating new evidence from perception and memory research into existing theories of generalization that focus on higher level cognitive processes. By encouraging open scientific discourse and the rigorous examination of diverse perspectives, this exchange promotes a more comprehensive understanding of how people apply learned information to new situations, which is crucial to advance psychological theory and its practical applications.

Keywords: generalization, perception, memory, individual differences

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In our recent study (Zaman, Yu, & Verheyen, 2023), we demonstrated that a model that incorporates individual differences in color perception and memory outperformed traditional stimulus-based approaches in predicting generalization patterns. This finding underscores the importance of understanding idiosyncratic representations of stimuli in explaining postlearning behaviors. However, in their commentary, Lee and Schlegelmilch (2025) reanalyzed our data and argued that our findings were compromised by a limited set of model alternatives and an overreliance on model fit and subjective interpretation. They proposed that a combination of an exponential decay function with stimulus as a predictor and a generalization rule better accounts for the generalization responses in our data set.

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Furthermore, they raised concerns about our study's procedural aspects, including potential carryover effects from sequential testing, continuous reinforcement during the generalization phase, as well as the interpretation of our perceptual variables. In our response, we engage with the analyses and arguments presented in the commentary. We contend that their claims may reflect limitations in model comparisons and a lack of integration of recent theoretical advances in human perception, memory, and generalization research. Crucially, we emphasize the need to acknowledge the complexity of generalization behavior and our limited understanding of it. Our original article emphasized the role of stimulus representations in generalization behavior without dismissing higher level cognitive processes as potential contributors. We maintain that developing a comprehensive theory of human generalization necessitates further investigation into the interplay between various perceptual and cognitive mechanisms. Although the evidence from Zaman, Yu, and Verheyen (2023) underscores the importance of considering idiosyncratic perception and memory in generalization studies, it represents just one piece of a complex puzzle that requires continued research and integrated modeling approaches.

Analysis

To highlight the importance of cognitive rules on generalization behavior, Lee and Schlegelmilch (2025) proposed three alternative generalized linear models with function-dependent variables, ostensibly to address limitations in our original model selection. These models incorporated (a) a similarity-based variable, (b) a rule-based variable, and (c) a combination of both approaches. For the similarity-based variable, they employed Shepard's exponential decay function (Shepard, 1987), $d_s^+ = e^{-c \cdot |s-4|}$, where d_s^+ represents the similarity to the positive conditioned stimulus (CS+; predictive of the unconditioned stimulus [US]), c is the generalization rate, and s is the current stimulus (ranging from one to 14, with four being the CS+). For the rule-based variable, they utilized the ratio $p_s = \frac{d_s^+}{d_s^+ + d_s^-}$, where p_s is the probability of response and d_s^- represents the similarity to the negative conditioned stimulus (CS−; predictive of the absence of the US). The third model constituted a mixture of both approaches. Lee and Schlegelmilch (2025) contend that these theoretically motivated alternatives provide more insight than our initially tested models. They present results suggesting that their proposed models outperform our reported models, attributing our models' predictive power for generalization to statistical properties, thereby discarding the contribution of the perceptual predictors to the participants' generalization behavior. However, we argue that this conclusion may benefit from additional considerations. Our reexamination of their analysis suggests that the apparent superiority of their models is influenced by issues with model specification and comparison processes rather than being attributable to theoretical considerations.

Random Slopes

The comparison methodology in Lee and Schlegelmilch's (2025) reanalysis warrants careful consideration, particularly in their differential application of random effects structures. While random slopes are valuable tools for capturing between-person variance and individual differences—a key consideration in generalization research—their selective inclusion in the new models but not the original ones creates an uneven basis for comparison. Lee and Schlegelmilch (2025) argue that, because our model accounts for different generalization shapes through idiosyncratic perception and memory predictors, it is only appropriate to also accommodate individual patterns in their models. However, this approach requires careful consideration: While our model's individual differences stem from experimentally manipulated variables with a clear theoretical grounding, the addition of random slopes provides a different form of flexibility in modeling individual variations.

Random slopes allow models to account for individual differences in predictor effects across participants, providing additional flexibility at the cost of increased parameters. The apparent differences in model performance should be interpreted in light of the different modeling approaches used to capture individual variation. When comparing models with consistent structures, our representation-based models remain competitive or superior. Evidence for this can be found in Table 1 of their commentary, where results for fixed-slope models are also presented. In this comparison, their newly proposed models and our representation-based models showed comparable performance. To further validate our findings, we conducted an additional analysis that included random slopes for both our nonidiosyncratic model with perceptual predictors and their best performing model. This ensured that both models had the same structure: nonidiosyncratic predictors and random slopes. As shown in Table 1, our model maintains its competitive edge under random slope conditions. These findings underscore the importance of consistent model comparison procedures. When evaluated on a level playing field (i.e., identical number of free parameters), our representation-based models demonstrate better performance, challenging Lee and Schlegelmilch's (2025) conclusions. This reveals the interplay between model structure and the interpretation of predictor effects, emphasizing the need for cautious and comprehensive analyses in future generalization research. The approach taken by Lee and Schlegelmilch (2025), while seemingly justified in the commentary, may actually introduce

Table 1
Model Comparison Results From Our Reanalysis

Model	*df*	BIC		Rank		R^2	
		Block 1	Block 2	Block 1	Block 2	Block 1	Block 2
(M1) Mean Blue Ratings + Mean CS+ Identifications	10	13,770.6	13,746.2	1	1	0.63 [0.54, 0.70]	0.61 [0.55, 0.68]
(M5) Similarity + Rule	10	13,807.9	13,764.7	2	2	0.62 [0.54, 0.69]	0.61 [0.56, 0.66]

Note. M1 = model with group-level perceptual and memory predictors, including random slopes and intercepts; M5 = model with group-level similarity and rule predictors, including random slopes and intercepts; BIC = Bayesian information criterion; R^2 = conditional explained variance, 95% CIs in brackets; CS = conditioned stimulus.

more problems than it solves, in that it yields misleading conclusions about the relative merits of different theoretical approaches to understanding generalization.

Artificial Generalization Rate

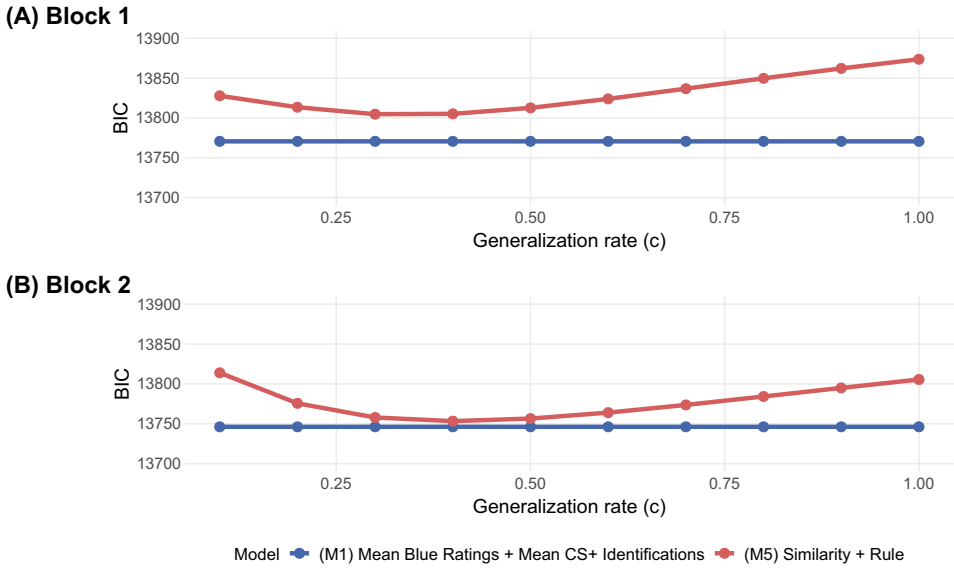
The second concern about Lee and Schlegelmilch's (2025) reanalysis is their use of a predetermined, arbitrary value for the generalization rate parameter in the exponential decay function (i.e., $c = 0.25$). This practice is problematic for several reasons. First, it is not substantially different from arbitrarily selecting values for slope and intercept in a generalized linear model. The chosen generalization rate is not theoretically driven or estimated from the data but appears to be selected at random, which undermines the scientific rigor of the analysis. Second, this arbitrary selection introduces a source of potential bias. As demonstrated in Figure 1, the performance of their proposed model is sensitive to the chosen generalization rate. Specifically, as the generalization rate increases, the performance of their model decreases. Third, by fixing this parameter rather than estimating it from the data, Lee and Schlegelmilch (2025) potentially miss important information about the nature of generalization in their data set. The specification of generalization rate parameters presents an important methodological challenge in the field. While fixed rates offer simplicity, they may not capture context-specific variations in generalization patterns. A promising solution lies in Bayesian hierarchical approach (Yu, Beckers, et al., 2024; Yu et al., 2023; Yu, Vanpaemel, et al., 2024), where generalization rate parameters could be treated as random variables with informed priors based on theoretical expectations. This approach would allow one to leverage data from multiple studies to estimate study-specific rates while maintaining coherence across contexts through shared higher level distributions. As new evidence accumulates, the model's posterior distributions would provide increasingly refined estimates of generalization rates, balancing between completely fixed and purely data-driven approaches.

Theoretical Concerns

Lee and Schlegelmilch (2025) characterized their rule-based models as more theoretically grounded than our representation-focused approach. Recent advances in human perception (Funamizu et al., 2016; Petzschner et al., 2015; Weiss et al., 2002) and memory (Brady & Alvarez, 2011, 2015; Brady et al., 2024) research have revealed the dynamic and probabilistic nature of human representational systems, suggesting the need to integrate these insights into generalization theories. These insights have been empirically demonstrated to influence generalization behavior across numerous studies (for a review, see Zaman, Chalkia, et al., 2021). Our modeling choices were not arbitrary but firmly grounded in and motivated by new insights from both human representation and generalization studies, which allowed us to preregister them (https://osf.io/chu3w). We suggest that theoretical approaches should engage with both established frameworks and emerging perspectives in the field. Additionally, in Zaman, Yu, and Verheyen's (2023) study, we did not disregard Lee and Schlegelmilch's (2025) theoretical perspective. Although we did not use an exponential function, we incorporated models that included physical dimensions as predictors, utilizing stimulus as a linear predictor and a second-order polynomial categorical predictor.

Figure 1

BIC Values for Competing Models Across a Range of Generalization Rate (c) Values in the Exponential Decay Function



Note. In the calculation of BIC, the parameter c is not treated as free parameters but predetermined values. M1 = model with group-level perceptual and memory predictors, including random slopes and intercepts; M5 = model with group-level similarity and rule predictors, including random slopes and intercepts; BIC = Bayesian information criterion; CS = conditioned stimulus. See the online article for the color version of this figure.

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With a consideration of modern knowledge about human perception, a more theoretically sound approach would be to consider different plausible assumptions (motivated by both new and custom knowledge) under their proposed rule-based approach. This would necessitate comparing exponential function as it occurs with physical distance, static mental distance, and dynamic mental distance. Indeed, the main arguments in our article can be integrated into this framework, suggesting that stimulus distance in mental space is nonstatic. Recent work by Yu et al. (2023) and Yu, Vanpaemel, et al. (2024) has done precisely this, demonstrating that dynamic perceptual distance outperforms traditional static assumptions for many individuals. This finding implies that generalization behavior is indeed influenced by perceptions that change over time for some individuals. In light of these considerations, Lee and Schlegelmilch's (2025) critique appears not as a defense of theoretical rigor but as a resistance to necessary theoretical evolution. Their reanalysis reveals a notable discrepancy: While advocating for theoretical rigor, they overlook robust evidence from recent studies showing how individual differences in perception systematically influence generalization behavior. This approach may not only limit our ability to advance our understanding of generalization processes but also risks impeding progress by relying on assumptions that do not adequately capture the complexities of human cognition demonstrated in contemporary research.

While generalization may be a cognitive mechanism beyond stimulus discrimination, we note that Holt et al. (2014), which Lee and Schlegelmilch (2025) cite to support generalization in discriminable stimuli, actually found that "generalization did not occur above discrimination thresholds." Our broader research program (Yu et al., 2023; Yu, Vanpaemel, et al., 2024; Zaman, Ceulemans, et al., 2019; Zaman, Struyf, et al., 2019, 2021; Zaman, Yu, & Lee, 2023) aims not to position stimulus representation as the primary process of generalization but rather to highlight the importance of integrating contemporary insights from both representation and generalization research. By examining different theoretical assumptions about the precursors of generalization and their relationships, we hope to contribute to a more comprehensive understanding of these processes.

Experimental Procedure

Carryover Effect

In addition to their analytical and theoretical concerns, Lee and Schlegelmilch (2025) raised several issues regarding our experimental procedures. First, they suggested a potential carryover effect, arguing that identification is a good predictor of generalization not because of its perceptual status, but because the identification judgements were influenced by the generalization responses, which came directly before them (Lee & Schlegelmilch, 2025). This critique raises a valid and important methodological question about the potential influence of task order on our results. Indeed, such concerns are crucial for ensuring the robustness of experimental findings in cognitive science. However, we can address this concern based on existing evidence. Zaman, Yu, and Lee (2023), coauthored by the lead author of Lee and Schlegelmilch (2025), explicitly tested for order effects by analyzing data separately for each task sequence (identification first vs. generalization first). The consistency of results across these conditions directly challenges the notion that our findings of the relationship between identification and generalization are artifacts of testing order. Furthermore, the relationship between identification and generalization is corroborated by studies employing diverse experimental designs. For instance, Struyf et al. (2017) and Zaman, Ceulemans, et al. (2019) utilized designs where identification and generalization were tested simultaneously within the same trial yet demonstrated similar effects of stimulus identification on generalization. Particularly noteworthy is the study by Struyf et al. (2017), which combined a large sample ($N = 368$) with a one-trial generalization design. In this approach, each participant was exposed to only one generalization stimulus, completely eliminating the possibility of within-subject carryover effects. The fact that this study found similar relationships between identification and generalization provides compelling evidence that these effects are not artifacts of repeated testing or order effects. Additionally, recent studies using different perceptual response modalities, such as estimation or reproduction (Yu et al., 2023; Yu, Vanpaemel, et al., 2024; Zenses et al., 2021), have yielded comparable results regarding the relationship between identification and generalization. While the concern raised by Lee and Schlegelmilch (2025) is methodologically sound, the cumulative evidence from multiple studies using diverse designs provides strong support for the validity of our findings.

Reinforcement at Test

Similar to their concern about carryover effects, Lee and Schlegelmilch (2025) argued that continuous reinforcement during generalization testing artificially sharpens gradients around the CS+ and inflates the similarity between generalization and identification gradients. However, we contend that this critique oversimplifies the complex learning processes involved and overlooks several crucial aspects of our findings. First, it is important to recognize that learning is a continuous process, so even without more CS+-US parings, inhibitory learning is still going on. The assumption that learning abruptly ceases after the conditioning stage is overly simplistic. During the generalization phase, participants continue to learn—specifically, they learn that stimuli other than the CS+ are not associated with the US. This leads to lower responding to these stimuli due to inhibitory learning, while the associative strength between the CS+ and US is maintained. Consequently, the sharpening of the generalization gradient can also be attributed to this ongoing inhibitory learning process rather than being solely an artifact of the reinforcement schedule. Moreover, studies using diverse experimental designs have shown similar relationships between perception and generalization—including studies with different reinforcement schedules and various perceptual measurement approaches (Struyf et al., 2017; Yu et al., 2023; Zaman, Ceulemans, et al., 2019; Zaman, Yu, & Lee, 2023; Zenses et al., 2021).

Interpretation of the Color Ratings and CS+ Identification

Lee and Schlegelmilch (2025) extend their argument about shared mechanisms between identification and generalization, questioning the validity of attributing color ratings and identification solely to perceptual or memory processes. They posit that these measures might be more appropriately interpreted as products of

associative learning rather than direct indicators of perception or memory. This critique challenges our fundamental interpretation of the data, suggesting that the observed relationships between stimulus representation and generalization might stem from a common associative learning process rather than distinct perceptual or memory mechanisms. The authors argue:

> Some of the overlap in the blueness ratings and generalization gradients also appears to be artefactual. It is not clear whether the same results would be obtained if the CS+ was located at the blue/green color boundary near the midpoint of the dimension, and the identity of the CS− counterbalanced.

However, this concern has been addressed by several studies using different-sized circles as CSs, with the CSs counterbalanced and at different locations between experiments. These studies consistently documented the profound influence of stimulus identification on generalized responding (for a review, see Zaman, Chalkia, et al., 2021), suggesting that the observed effects are robust across various experimental conditions.

Furthermore, Lee and Schlegelmilch (2025) claim that identification gradients can be predicted solely by similarity-based generalization (Shepard, 1987). This assertion warrants a closer examination of the underlying theoretical framework. In Shepard's theory of similarity-based generalization (Shepard, 1987), stimulus distance in the exponential function is manipulated on the mental rather than physical dimension. This theory first considers perception, treating the mental representation of stimuli as points in a psychological space. The higher level cognitive process of generalization is then built upon this assumed perceptual foundation. In Yu et al.'s (2023) study, we not only incorporate dynamic perception under the similarity-based generalization framework but also account for individual differences in associative learning. Even when controlling for these individual learning differences, the effect of dynamic perception on generalization remains evident.

Conclusion

In their commentary, Lee and Schlegelmilch (2025) present a multifaceted critique of the findings reported by Zaman, Yu, and Verheyen (2023), arguing from analytical, experimental, and theoretical perspectives that the observed data are better accounted for by higher level cognitive mechanisms rather than perceptual or memory-based mechanisms. While we appreciate the authors' engagement with our work and their contribution to the ongoing dialogue in the field, we suggest that strengthening their conclusions with additional empirical support and incorporating recent theoretical advances alongside established frameworks would enhance their argument.

The commentary by Lee and Schlegelmilch (2025) serves as a valuable reminder of the importance of considering higher level cognitive processes in human generalization. However, the evidence provided by Zaman, Yu, and Verheyen (2023), along with a growing body of recent studies, offers robust support for the significant role of stimulus representation—encompassing both perception and memory—in human generalization processes (for a review, see Zaman, Chalkia, et al., 2021). These findings cannot be easily dismissed or fully explained by rule-based accounts alone. We acknowledge that the interplay between lower level perceptual processes and higher level cognitive functions in generalization is complex and warrants further investigation. However, it is crucial to recognize that the involvement of one process does not negate the importance of the other. Rather than framing the discussion in terms of mutually exclusive mechanisms, we propose that a more productive approach would be to investigate how different processes influence generalization behavior across various contexts and populations. Moving forward, we see an exciting challenge for the field: developing more sophisticated experimental designs and analytical methods to explore how cognitive processes at various levels operate both independently and in concert to shape human generalization behavior.

We concur with Lee and Schlegelmilch (2025) that advancing our understanding of how diverse cognitive processes interact to shape generalization behavior demands meticulous attention to experimental design. Future studies should prioritize careful experimental manipulations aimed at isolating specific cognitive processes and mitigating potential confounding variables. Integrating sophisticated computational modeling techniques with these experiments could yield significant insights. Such models can simulate the interplay between multiple processes and generate testable predictions about their relative contributions under various conditions. By employing the principle of selective influence—where experimental manipulations are designed to affect only specific model parameters—researchers can rigorously test hypotheses about the underlying cognitive architecture of generalization behavior. This combined approach of refined experimental design and computational modeling holds great promise for disentangling the complex web of processes involved in generalization, potentially revealing how different mechanisms dominate or interact across diverse contexts, tasks, and populations.

We also recognize that cognitive processes likely exist along a continuum, from low-level perception to higher level cognition, with dynamic interactions between them. It is challenging to precisely delineate where the influence of one process ends and another begins, as even processes often considered "low level," such as perception, or those viewed as distinct, like memory, can involve aspects of higher level cognition. Similarly, higher level processes like reasoning or decision making may be influenced by perceptual and memory mechanisms. Future research should embrace this complexity by exploring the intricate interactions across this continuum rather than reinforcing binary distinctions between low- and high-level cognition. Such an approach could uncover the interplay of various cognitive functions, enriching our understanding of human generalization. By acknowledging and investigating these relationships, researchers can develop more comprehensive models that better reflect the true complexity of cognitive processes and provide new insights into how they collectively influence generalization behavior.

References

Brady, T. F., & Alvarez, G. A. (2011). Hierarchical encoding in visual working memory: Ensemble statistics bias memory for individual items. *Psychological Science*, *22*(3), 384–392. https://doi.org/10.1177/0956797610397956

Brady, T. F., & Alvarez, G. A. (2015). Contextual effects in visual working memory reveal hierarchically structured memory representations. *Journal of Vision*, *15*(15), Article 6. https://doi.org/10.1167/15.15.6

Brady, T. F., Robinson, M. M., & Williams, J. R. (2024). Noisy and hierarchical visual memory across timescales. *Nature Reviews Psychology*, *3*(3), 147–163. https://doi.org/10.1038/s44159-024-00276-2

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Funamizu, A., Kuhn, B., & Doya, K. (2016). Neural substrate of dynamic Bayesian inference in the cerebral cortex. *Nature Neuroscience*, *19*(12), 1682–1689. https://doi.org/10.1038/nn.4390

Holt, D. J., Boeke, E. A., Wolthusen, R. P. F., Nasr, S., Milad, M. R., & Tootell, R. B. H. (2014). A parametric study of fear generalization to faces and non-face objects: Relationship to discrimination thresholds. *Frontiers in Human Neuroscience*, *8*, Article 624. https://doi.org/10.3389/fnhum.2014.00624

Lee, J. C., & Schlegelmilch, R. (2025). The role of perception in generalization: Commentary on Zaman, Yu, and Verheyen (2023). *Journal of Experimental Psychology: General*, *154*(4), 1167–1175. https://doi.org/10.1037/xge0001658

Petzschner, F. H., Glasauer, S., & Stephan, K. E. (2015). A Bayesian perspective on magnitude estimation. *Trends in Cognitive Sciences*, *19*(5), 285–293. https://doi.org/10.1016/j.tics.2015.03.002

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science*, *237*(4820), 1317–1323. https://doi.org/10.1126/science.3629243

Struyf, D., Zaman, J., Hermans, D., & Vervliet, B. (2017). Gradients of fear: How perception influences fear generalization. *Behaviour Research and Therapy*, *93*, 116–122. https://doi.org/10.1016/j.brat.2017.04.001

Weiss, Y., Simoncelli, E. P., & Adelson, E. H. (2002). Motion illusions as optimal percepts. *Nature Neuroscience*, *5*(6), 598–604. https://doi.org/10.1038/nn0602-858

Yu, K., Beckers, T., Tuerlinckx, F., Vanpaemel, W., & Zaman, J. (2024). The assessment of gender differences in perceptual fear generalization and related processes. *Behaviour Research and Therapy*, *183*, Article 104640. https://doi.org/10.1016/j.brat.2024.104640

Yu, K., Tuerlinckx, F., Vanpaemel, W., & Zaman, J. (2023). Humans display interindividual differences in the latent mechanisms underlying fear generalization behaviour. *Communications Psychology*, *1*(1), Article 5. https://doi.org/10.1038/s44271-023-00005-0

Yu, K., Vanpaemel, W., Tuerlinckx, F., & Zaman, J. (2024). The representational instability in the generalization of fear learning. *npj Science of Learning*, *9*(1), Article 78. https://doi.org/10.1038/s41539-024-00287-x

Zaman, J., Ceulemans, E., Hermans, D., & Beckers, T. (2019). Direct and indirect effects of perception on generalization gradients. *Behaviour Research and Therapy*, *114*, 44–50. https://doi.org/10.1016/j.brat.2019.01.006

Zaman, J., Chalkia, A., Zenses, A.-K., Bilgin, A. S., Beckers, T., Vervliet, B., & Boddez, Y. (2021). Perceptual variability: Implications for learning and generalization. *Psychonomic Bulletin & Review*, *28*(1), 1–19. https://doi.org/10.3758/s13423-020-01780-1

Zaman, J., Struyf, D., Ceulemans, E., Beckers, T., & Vervliet, B. (2019). Probing the role of perception in fear generalization. *Scientific Reports*, *9*(1), Article 10026. https://doi.org/10.1038/s41598-019-46176-x

Zaman, J., Struyf, D., Ceulemans, E., Vervliet, B., & Beckers, T. (2021). Perceptual errors are related to shifts in generalization of conditioned responding. *Psychological Research*, *85*(4), 1801–1813. https://doi.org/10.1007/s00426-020-01345-w

Zaman, J., Yu, K., & Lee, J. C. (2023). Individual differences in stimulus identification, rule induction, and generalization of learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *49*(6), 1004–1017. https://doi.org/10.1037/xlm0001153

Zaman, J., Yu, K., & Verheyen, S. (2023). The idiosyncratic nature of how individuals perceive, represent, and remember their surroundings and its impact on learning-based generalization. *Journal of Experimental Psychology: General*, *152*(8), 2345–2358. https://doi.org/10.1037/xge0001403

Zenses, A.-K., Lee, J. C., Plaisance, V., & Zaman, J. (2021). Differences in perceptual memory determine generalization patterns. *Behaviour Research and Therapy*, *136*, Article 103777. https://doi.org/10.1016/j.brat.2020.103777

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