MODELING SPATIAL AND TEMPORAL CONTIGUITIES IN THE OVERSHADOWING EFFECT OF LEARNING

A Thesis Proposal

by

Shanzeh Amirali

Approved by:

Dr. Estibaliz Herrera
School of Psychology
Georgia Institute of Technology

Date Approved: [April 23, 2025]

Dr. N. Apurva Ratan Murty
School of Psychology
Georgia Institute of Technology

Date Approved: [April 23, 2025]

TABLE OF CONTENTS

CHAPTER 1.	**Abstract**	**3**
CHAPTER 2.	**Introduction**	**4**
CHAPTER 3.	**Literature Review**	**5**
CHAPTER 4.	**Methods**	**7**
CHAPTER 5.	**Results**	**9**
CHAPTER 6.	**Discussion**	**12**
REFERENCES		**15**

Abstract

The overshadowing effect occurs when the presence of a more salient cue reduces learning about a competing cue presented simultaneously. While overshadowing was traditionally believed to occur in all circumstances of associative learning, recent findings suggest that the effect only emerges under specific spatial and temporal conditions. Building on the hypothesis that contiguity between cues and outcomes is necessary for cue competition, this study uses supervised machine learning to identify the features that predict when overshadowing occurs. Behavioral data from Herrera et al. (2022) was analyzed across four experiments manipulating spatial (Exp 5, Supplementary Experiments 1 and 2) and temporal (Exp 2) contiguity. A series of random forest classifiers were trained to predict whether participants exhibited overshadowing based on task features such as landmark proximity, cue salience, trace duration, and performance metrics. Models trained with theory-based labels outperformed data-driven baselines, achieving up to 94.4% accuracy in spatial tasks. In the temporal domain, overshadowing was more prevalent in conditions with strong temporal proximity, and classifier performance was high despite a limited test set. A final combined model integrating both domains achieved 92.5% accuracy, with feature importances generalizing across spatial and temporal contexts. These results support the view that overshadowing is not a universal learning outcome but rather a parameter-dependent phenomenon. This is particularly evident in how spatial and temporal contiguity shape whether cues compete or are learned independently, highlighting contiguity's general role across learning domains. This work provides a scalable computational framework for mapping the boundary conditions of cue competition and lays the groundwork for future modeling of cue interactions along a continuum that ranges from competition to facilitation with a diversity of outcomes (including an intermediate zone in which competition is not observed).

Introduction

Modeling the spatial and temporal contiguities in the overshadowing effect provides a nuanced perspective on how organisms process multiple stimuli. Cue competition refers to a family of learning phenomena where the relationship between a target cue and an outcome not only depends on the information about the target and outcome themselves, but also on the presence of other cues (De Houwer et al., 2005). The overshadowing effect, a specific type of cue competition, describes a phenomenon where a more salient stimulus impairs the learning associated with a simultaneously presented, less salient stimulus (Pavlov, 1927). For example, when navigating using familiar landmarks, an individual primarily relies on notable features, such as the size or color of buildings, neglecting less prominent environmental details. The reliance on more salient environmental features emphasizes the role of cue salience, a principle that plays a central role in both Pavlovian conditioning and selective attention. In Pavlovian conditioning, more salient cues are more likely to become associated with outcomes, while in selective attention, organisms prioritize processing of prominent stimuli over less noticeable ones to guide learning and behavior (Mackintosh, 1975). However, the influence of cue salience is not absolute, and the overshadowing effect does not reliably occur across all learning contexts. Understanding overshadowing is therefore essential to clarify how organisms allocate attention to competing cues, which is a question that is fundamental to many learning theories (Mackintosh, 1975; Pearce & Hall, 1980; Rescorla & Wagner, 1972; Wagner, 1981).

However, the overshadowing effect is not consistently observed across all situations involving multiple cues. As many studies have failed to replicate various cue competition phenomena (Pearce et al., 2001; Redhead & Hamilton, 2007; Schmidt & De Houwer, 2019) empirical evidence suggests that the phenomenon only emerges under specific parameters. Herrera et al., hypothesize that the presence of a strong temporal or spatial contiguity between predictors and outcomes is a necessary condition for overshadowing (Herrera et al., 2022). In a series of experiments spanning both predictive and spatial learning contexts, overshadowing was only observed when cues and outcomes were presented in close proximity. When the contiguity was weakened by imposing a temporal delay or increasing spatial distance, the overshadowing effect disappeared. This pattern led Herrera et al. to argue that contiguity is a critical determinant of whether stimuli will compete during learning, challenging classical models that assume cue competition is a universal process. However, their analysis focused primarily on binary comparisons within fixed experimental conditions, leaving unanswered questions about the precise thresholds at which competition breaks down, how multiple features (e.g., distance, salience, geometry) interact.

Additionally, while previous models treated the absence of overshadowing as a neutral baseline, recent evidence suggests that overshadowing exists on a continuum. Facilitation has been proposed as the inverse of overshadowing, referring to cases where the presence of multiple cues actually improves, rather than hinders, associative learning (Rescorla, 1988; Al Alcalá et al, 2023). Despite their inverse effects, overshadowing and facilitation are rarely studied in tandem, leaving the relationship between the phenomena poorly understood. In fact, most studies in associative learning only describe cue competition even though evidence for facilitation exists (Alcalá et al., 2023). Although this project does not directly model facilitation, it helps define the boundary conditions in which overshadowing is expected to occur. By identifying the features that predict when cue competition breaks down, this work contributes to a clearer mapping of the conditions that separate competitive and non-competitive learning processes, laying the groundwork for future efforts to model facilitation more explicitly.

The goal of this project is to computationally test whether spatial and temporal contiguities are necessary conditions for observing cue competition. Using behavioral data from Experiment 5 and Supplementary Experiments 1 and 2 of Herrera et al. (2022), I trained binary classification models—specifically, random forest classifiers—to predict whether overshadowing was observed in each condition. These models were used to identify which task features, such as landmark proximity and cue salience, most strongly influenced cue competition outcomes. The central research question is whether machine learning models can predict the presence or absence of overshadowing based on structural features of the learning environment, and whether those predictions replicate known boundary conditions for competition. Unlike prior studies that test individual parameters in isolation, this approach generalizes across experimental contexts and makes it possible to map where cue competition breaks down. The longer-term aim is to extend the model toward a broader continuum of cue interactions, including facilitation, by identifying the conditions under which multiple cues enhance, rather than impair learning. By doing so, this work contributes a scalable, data-driven framework for understanding when and how cue competition arises.

Literature Review

In the presence of competing stimuli, humans and other organisms often prioritize the most salient stimuli over the less salient ones while forming associations or learning about an environment, known as the overshadowing effect (Pavlov, 1927). For example, animals may use proximal landmarks instead of distal landmarks to remember where to find and store food because using a closer identifier makes it easier to locate the target (Chamizo, 2003). The reliance on salient features can impair the encoding of surrounding, less distinctive information, reflecting a broader cognitive process related to selective attention. Selective attention refers to the tendency to allocate perceptual resources toward stimuli with prominent properties, such as color or sound, to efficiently filter environmental input (Lee et al., 2005). Understanding overshadowing is critical because it reveals how organisms structure learning when faced with multiple competing cues. The effect has informed key theories of associative learning and has been used to explain how organisms allocate attention, resolve ambiguity, and navigate complex environments (Mackintosh, 1975; Pearce & Hall, 1980). Whether or not overshadowing occurs can shape how learners respond to redundant or competing information, making it central to understanding how cues are prioritized and encoded during learning. However, the phenomenon is not consistently observed, leading researchers to examine the contextual and methodological variables that modulate the effect.

Although temporal and spatial contiguities (the closeness between two events or sources of information) have long been recognized as critical actors in associative learning (Rescorla, 1988), their role in cue competition phenomena such as overshadowing has received less empirical attention. Specifically, there are a number of studies that have failed to replicate results for the cue competition phenomena (Pearce et al., 2001; Redhead & Hamilton, 2007; Schmidt & De Houwer, 2019). Recent studies suggest that the overshadowing effect is only observed under specific conditions, and its inconsistent replication across studies has prompted reevaluation of the mechanisms that underlie cue competition (Urcelay, 2017). In a comprehensive review, Maes et al., (2016) identified fifteen rodent studies in which the cue competition was not replicated, proposing that the absence of clearly defined spatial and temporal parameters may explain these null findings. The findings from the review article are also supported in a pigeon study where the researchers argue that while scientists always expect animals to display the overshadowing effect, competition is not absolute and depends on context and the nature of the task (Packheiser et al., 2020). These papers are important because they emphasize the need for a more comprehensive framework to explore how and when overshadowing occurs and how contextual variables might alter outcomes. Therefore, it is proposed that overshadowing exists on a continuum of cue interaction. Herrera suggests that the phenomenon exists on an extreme end of the continuum where overshadowing is observed when there is a high contiguity between cues, and the effect diminishes as the contiguity weakens (Herrera et al, 2022). At the other end of this continuum lies facilitation, where the presence of multiple cues enhances, rather than impairs, learning. Between these two extremes lies a substantial neutral zone, in which the presence of multiple cues neither helps nor hinders learning, suggesting that cue interaction is not binary, but graded and highly sensitive to structural conditions (Urcelay, 2017).

Empirical support for facilitation has begun to emerge, particularly under conditions where contiguity between cues and outcomes is weak. For instance, Alcalá et al. (2023) found that in an action-outcome task, the insertion of an intervening cue enhanced both performance and perceived causality when the temporal relationship between action and outcome was degraded. In contrast, when the temporal gap between action and outcome was short, indicating strong contiguity, the same signal disrupted learning and reduced perceived causality. These findings suggest that when temporal contiguity between an action and outcome is weak, the presence of an additional cue can improve learning, an effect that contrasts with overshadowing, where additional cues typically interfere with learning under conditions of strong contiguity.

While overshadowing is often interpreted as the result of automatic associative mechanisms, such as those proposed in the Rescorla-Wagner model where more salient cues acquire greater associative strength, recent work has raised the possibility that higher-order reasoning processes also contribute to cue competition. For example, Schmidt et al. (2019) found that the overshadowing effect was only observed when participants were explicitly instructed to learn the relationships between cues and outcomes. When no instructions were given, participants did not show evidence of overshadowing, even though the stimuli and outcomes were identical. This suggests that cue competition may not emerge solely from stimulus salience or co-occurrence, but also from participants' goals and interpretive strategies during learning. De Houwer et al. (2005) similarly argued that cue competition can arise from deliberative reasoning, where individuals assess the likelihood that each cue is causally responsible for an outcome. This perspective contrasts with early associative models by proposing that overshadowing can be the result of inferential processes, especially in tasks involving human judgment. Together, these studies suggest that the absence of overshadowing in some contexts does not invalidate the phenomenon but instead highlights its dependence on how learners engage with the task. While the present project does not directly model these higher-order processes, recognizing their role is essential to interpreting when and why cue competition occurs. These findings also underscore the challenge of modeling such abstract cognitive factors, which are difficult to quantify but may fundamentally shape learning behavior.

Despite its importance in learning theory, the relationship between the overshadowing effect, facilitation, and cue contiguities are not fully understood in a single framework. While facilitation has been proposed as the opposite of overshadowing along a continuum of cue interaction, it remains vastly understudied. While the project does not model facilitation directly, it focuses on defining the conditions under which overshadowing occurs. Using machine learning techniques, such as a random forest classifier (RFC), this work models behavioral outcomes from previously published experimental data by identifying the key variables that predict whether cue competition will arise. An RFC is a model that builds an ensemble of decision trees and aggregates their predictions to improve accuracy and reduce overfitting. By understanding the influence of contiguity on overshadowing, the model provides a scalable framework for simulating and predicting learning outcomes across a broader range of conditions than traditional experiments. The modeling approach offers new insights into how cue configurations and proximities shape learning processes.

Methods

The dataset used for this study was sourced from Herrera et al. (2022), which investigated the role of spatial and temporal contiguity in modulating the overshadowing effect. Four experiments were selected for analysis: Experiment 2 (temporal domain), Experiment 5, Supplementary Experiment 1, and Supplementary Experiment 2 (spatial domain). All four experiments follow a between-subjects design. For the spatial experiments, test-phase scores (time spent in the region of interest during the final trial) and training-phase performance metrics (i.e., average latency to find the goal across acquisition trials) were extracted to capture both outcome learning and acquisition dynamics. No equivalent training-phase variable was available for the temporal dataset, which consisted solely of test-phase cue responses. A preprocessing pipeline was developed to clean and harmonize the datasets. In the spatial datasets, participants were labeled according to contiguity conditions (control, contiguous, or discontiguous) and landmark size (e.g., small, medium, large, or none for supplementary experiments only). In the temporal dataset, participants were grouped by trace duration (0s or 3s), reflecting the temporal contiguity conditions.

Categorical variables were encoded for model training. A binary target variable was created to indicate whether overshadowing occurred. In the spatial domain, two labeling strategies were used. A data-driven label was defined as a binary indicator for whether a participant's test score was below the median score for their experiment. A theory-driven label marked participants in contiguous landmark groups (with small or medium salience) as overshadowed if their test scores were lower than the corresponding control group mean. For the temporal dataset, group membership and test performance were integrated into the same feature space.

An RFC was implemented using the scikit-learn library in Python to predict the presence of overshadowing based on spatial and temporal parameters (Fig. 1). An RFC model was chosen for its ability to handle non-linear feature interactions and its interpretability through feature importance measures. The dataset was split into a training set (70%) and a testing set (30%) using stratified sampling to preserve class balance.

Following model training, performance was assessed using classification accuracy, confusion matrices, and precision-recall metrics. Feature importances were extracted to identify which experimental parameters contributed most strongly to overshadowing predictions.

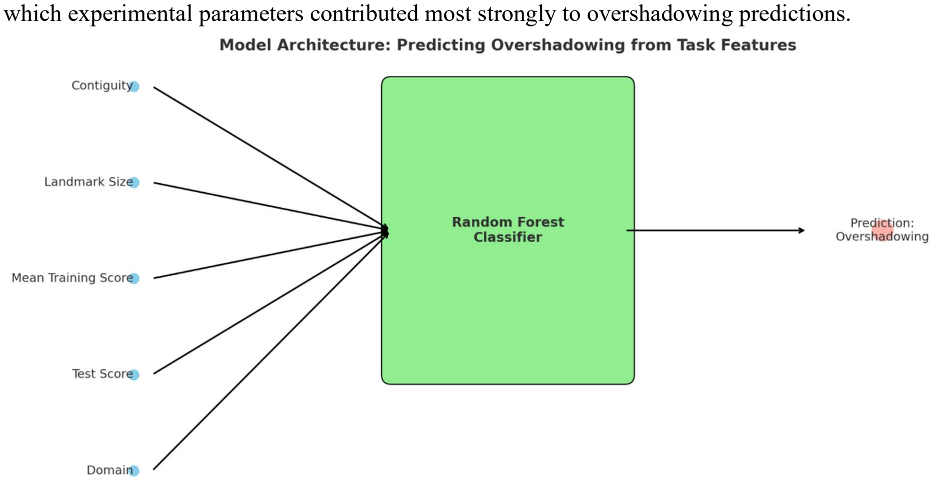

Figure 1. Model architecture used to predict overshadowing from task features. An RFC was trained on a set of experimental variables to classify whether overshadowing occurred. This architecture allowed for flexible modeling of non-linear interactions between features across both spatial and temporal paradigms.

Results

Model	Accuracy	F1-score (Class 1)	Precision (Class 1)	Recall (Class 1)
Spatial (Data-Driven)	0.611	0.632	0.6	0.667
Spatial (Theory-Driven)	0.944	0.778	0.875	0.7
Temporal (Experiment 2)	0.889	0.889	0.8	1
Combined (Spatial + Temporal)	0.925	0.8	0.75	0.857

Table 1. Classification performance metrics across spatial, temporal, and combined models. Accuracy, precision, recall, and F1-scores are reported for the overshadowing class (Class 1). The theory-driven and combined spatial-temporal model achieved the highest overall accuracy.

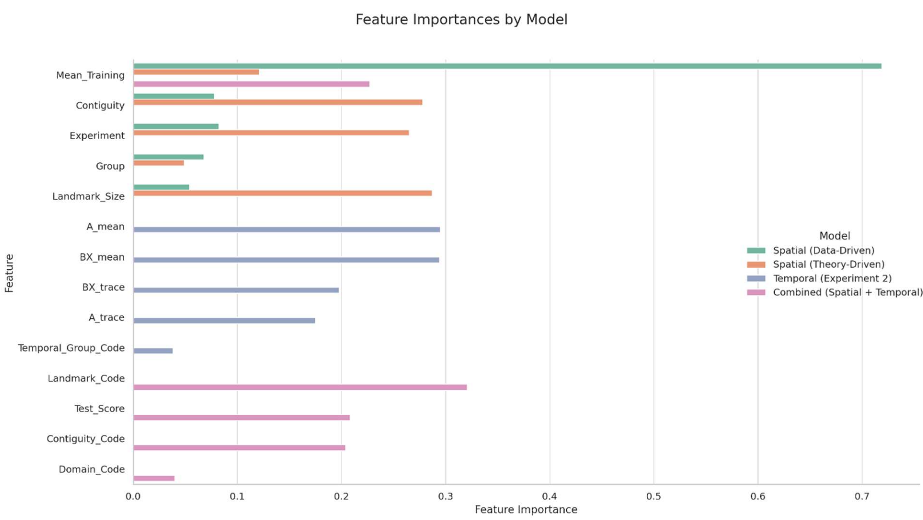

Figure 2. Relative feature importances across spatial, temporal, and combined models predicting overshadowing.

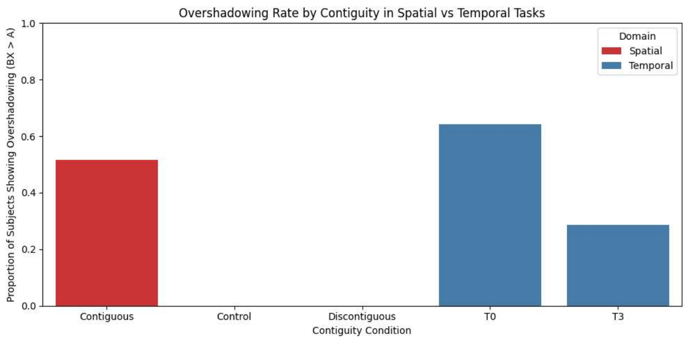

Figure 3. Overshadowing was more prevalent under strong contiguity in both spatial (Contiguous) and temporal (T0) conditions, supporting the role of proximity in cue competition.
Spatial Domain:

Confusion Matrix (Spatial, Data Driven)

	Predicted: No (0)	Predicted: Yes (1)
Actual: No (0)	20	16
Actual: Yes (1)	12	24

Table 2. Confusion matrix for RFC using data-driven labeling. The model achieved moderate performance, correctly classifying 24 of 36 overshadowing cases. Misclassifications were even across classes, reflecting overlap in test scores near median threshold.

Two labeling strategies were used to define overshadowing in spatial tasks. Using a data-driven label (based on median test scores), the RFC achieved a classification accuracy of 61.1% (Table 1). Precision and recall for overshadowing cases were 0.60 and 0.67, respectively, with a corresponding F1-score of 0.63 (Table 1). The confusion matrix revealed that 24 of 36 overshadowing cases were correctly classified (Table 2). The most important predictor was mean training latency, accounting for 71.9% of total feature importance, followed by contiguity (7.8%) and experiment ID (8.2%) (Fig. 2).

Confusion Matrix (Spatial, Theory-Based)

	Predicted: No (0)	Predicted: Yes (1)
Actual: No (0)	61	1
Actual: Yes (1)	3	7

Table 3. Confusion matrix for the spatial model using theory-driven labels. The RFC correctly identified 61 of 62 non-overshadowing cases and 7 of 10 overshadowing cases, with minimal false positives and false negatives.

When using the theory-driven label, model performance improved substantially, achieving a classification accuracy of 94.4% (Table 1). Precision and recall for overshadowing cases were 0.88 and 0.70, respectively (Table 1). Here, landmark size (28.7%), contiguity (27.8%), and experiment identity (26.5%) emerged as the most influential features compared to the null expectation of equal contribution (20%) (Fig. 2). Only 4 of 72 test instances were misclassified, demonstrating strong alignment between theoretical expectations and model predictions (Table 3).

Temporal Domain:

Confusion Matrix (Temporal)

	Predicted: No (0)	Predicted: Yes (1)
Actual: No (0)	4	1
Actual: Yes (1)	0	4

Table 4. Confusion matrix for the temporal model trained on Experiment 2. The classifier was evaluated on a held-out test set (N = 9). The model correctly classified all overshadowing cases and misclassified one non-overshadowing participant, resulting in high precision and recall for both classes.

In the temporal condition, overshadowing was defined by a greater response to the compound cue (BX) than to the elemental cue (A). Overshadowing was more prevalent in the contiguous trace-0 group (64%) compared to the discontiguous trace-3 group (29%), consistent with predictions based on temporal contiguity (Fig. 3). A classifier trained on cue-level response features (signal and trace periods) achieved a test accuracy of 88.9%. However, the test set included only 9 participants due to the 70/30 train-test split, limiting interpretability. Despite this, the model showed high precision and recall across both classes, with all overshadowing cases correctly identified and only one non-overshadowing case misclassified. Feature importance analysis highlighted responses to A and BX during the signal period as the most informative predictors.

Combined Interpretation:

Confusion Matrix (Combined spatial + temporal)

	Predicted: No (0)	Predicted: Yes (1)
Actual: No (0)	62	4
Actual: Yes (1)	2	12

Table 5. Confusion matrix for the combined spatial-temporal model. The classifier correctly identified 12 of 14 overshadowing cases and 62 of 66 non-overshadowing cases. This demonstrates effective generalization across domains when spatial and temporal features are integrated.

A final model was trained on the combined spatial and temporal dataset, integrating all relevant features (e.g., spatial contiguity, landmark salience, domain labels, and cue responses). This model achieved the highest overall performance, with a classification accuracy of 92.5% (Table 1) and correct identification of 12 of 14 overshadowing cases (Table 5). Precision and recall for the overshadowing class were 0.75 and 0.86, respectively, yielding an F1-score of 0.80 (Table 1). Feature importances were distributed across both domains, with landmark salience (32%), mean training latency (23%), and test score (21%) emerging as the strongest contributors (Fig. 2). These results suggest that a shared representational structure can successfully capture cue competition across both spatial and temporal learning contexts.

Discussion

This study set out to computationally test the hypothesis proposed by Herrera et al. (2022) that spatial and temporal contiguity are necessary conditions for observing cue competition. By applying supervised machine learning to previously collected data, the aim of the project was to identify which experimental parameters best predict overshadowing and to evaluate whether these patterns generalize across domains of learning. Across both spatial and temporal tasks, the results broadly support Herrera et al.'s findings and offer additional insight into the structural features that underlie cue competition.

As expected, overshadowing **was observed more frequently under strong contiguity** (Fig. 3). In spatial learning tasks, the phenomenon was most prevalent in groups with proximal landmarks and diminished with discontiguity compared to the control conditions. **Similarly, in the temporal domain, overshadowing was more likely to occur in the trace-0 condition,**

where cues and outcomes were presented in close temporal succession, than in the trace-3 condition, where they were separated by a delay. These behavioral trends mirror the effects reported by Herrera et al. and suggest that proximity, whether spatial or temporal, is a necessary constraint for competitive cue interactions to emerge.

The machine learning models provided further evidence for the pattern that overshadowing emerges under strong contiguity and diminishes under weak spatial or temporal relationships. **Models trained using theory-based labeling outperformed those using data-driven thresholds**, supporting the claim that overshadowing is not a mere statistical artifact of outcome distributions, but rather a phenomenon rooted in specific configurations of task parameters. The theory-driven spatial model achieved a high degree of accuracy, and the most predictive features, landmark size, contiguity, and experiment identity (Fig. 2), align with those emphasized in prior empirical work (Herrera et al., 2022). In contrast, the data-driven model, which relied on median splits of test scores, performed less reliably and produced less interpretable decision boundaries. This discrepancy highlights the importance of theoretical alignment in labeling and evaluating learning phenomena.

While the model trained on the temporal data also demonstrated strong performance, its interpretability is limited by sample size. Due to the train-test split, only nine participants were included in the test set. Although the classifier achieved perfect recall for the overshadowing class and made only one misclassification, these results should be viewed cautiously. Nevertheless, the model identified cue-specific response measures, particularly signal and trace responses to A and BX, as important predictors, consistent with the idea that temporal dynamics modulate attentional processing during learning.

Importantly, the combined spatial-temporal model yielded the highest overall performance. The high performance suggests that overshadowing may be governed by a shared representational structure that generalizes across experimental domains. Features like landmark salience, training performance, and test-phase response proved predictive regardless of task type. These findings support the idea that cue competition is not governed by entirely domain-specific mechanisms, but rather emerges from a common set of cognitive constraints related to attention, proximity, and cue configuration.

Despite these findings, several limitations should be acknowledged. First, the models are constrained by the structure of the available dataset, which represents a narrow slice of the parameter space. The task conditions were defined categorically rather than continuously, limiting the model’s ability to define precise thresholds at which competition breaks down. Additionally, the models treat cue competition as a binary outcome, ignoring recent proposals that overshadowing and facilitation exist on a continuum (Alcalá et al., 2023). While this project does not directly model facilitation, it provides a foundation for identifying the boundary conditions under which competition fails, an important first step toward studying the broader continuum of cue interactions.

Overall, this study demonstrates that machine learning models can successfully identify the conditions under which cue competition is expected to occur. By modeling spatial and temporal contiguity effects side-by-side, the results offer empirical support for the notion that overshadowing is not an automatic or universal process, but one that depends on the structural relationships between cues and outcomes. This work advances our understanding of when and why overshadowing emerges and provides a framework for future research to explore graded cue interactions, including conditions that may give rise to facilitation or other forms of enhanced learning.

References

Alcalá, J. A., Kirkden, R. D., Bray, J., Prados, J., & Urcelay, G. P. (2023). Temporal contiguity determines overshadowing and potentiation of human action-outcome performance. *Psychonomic Bulletin & Review, 30*(1), 350-361.

Alcalá, J. A., Miller, R. R., Kirkden, R. D., & Urcelay, G. P. (2023). Contiguity and overshadowing interactions in the rapid-streaming procedure. *Learning & behavior, 51*(4), 482–501. https://doi.org/10.3758/s13420-023-00582-4

Chamizo, V. D., Aznar-Casanova, J. A., & Artigas, A. A. (2003). Human overshadowing in a virtual pool: Simple guidance is a good competitor against locale learning. Learning and Motivation, 34(3), 262–281. https://doi.org/10.1016/S0023-9690(03)00020-1

Buckley, M. G., Smith, A. D., & Haselgrove, M. (2016). Thinking outside of the box: Transfer of shape-based reorientation across the boundary of an arena. *Cognitive Psychology, 87*, 53–87. https://doi.org/10.1016/j.cogpsych.2016.04.001

De Houwer, J., Vandorpe, S., & Beckers, T. (2005). Evidence for the role of higher order reasoning processes in cue competition and other learning phenomena. *Learning & Behavior, 33*(2), 239-249.

Herrera, E., Alcalá, J. A., Tazumi, T., Buckley, M. G., Prados, J., & Urcelay, G. P. (2022). Temporal and spatial contiguity are necessary for competition between events. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 48*(3), 321.

Lee, K., Buxton, H., & Feng, J. (2005). Cue-guided search: a computational model of selective attention. *IEEE transactions on neural networks, 16*(4), 910-924.

Mackintosh, N. J. (1975). A theory of attention: Variations in the associability of stimuli with reinforcement. *Psychological Review, 82*(4), 276–298.

Maes, E., Boddez, Y., Alfei, J. M., Krypotos, A.-M., D'Hooge, R., De Houwer, J., & Beckers, T. (2016). The elusive nature of the blocking effect: 15 failures to replicate. *Journal of Experimental Psychology: General, 145*(9), e49–e71. https://doi.org/10.1037/xge0000200

Maes, E., Krypotos, A. M., Boddez, Y., Alfei Palloni, J. M., D'Hooge, R., De Houwer, J., & Beckers, T. (2018). Failures to replicate blocking are surprising and informative-Reply to Soto (2018). *Journal of experimental psychology. General, 147*(4), 603–610. https://doi.org/10.1037/xge0000413

Packheiser, J., Pusch, R., Stein, C. C., Güntürkün, O., Lachnit, H., & Uengoer, M. (2020). How competitive is cue competition? *Quarterly Journal of Experimental Psychology, 73*(1), 104-114.

Pavlov, I.P. (1927). *Conditioned reflexes.* Oxford University Press.

Pearce, J. M., & Hall, G. (1980). A model for Pavlovian learning: Variations in the effectiveness of conditioned but not of unconditioned stimuli. *Psychological Review, 87*(6), 532–552. https://doi.org/10.1037/0033-295X.87.6.532

Pearce, J. M., Ward-Robinson, J., Good, M., Fussell, C., & Aydin, A. (2001). Influence of a beacon on spatial learning based on the shape of the test environment. *Journal of Experimental Psychology: Animal Behavior Processes, 27*(4), 329–344.

Formatted: Spanish (Spain)

Formatted: Spanish (Spain)

Formatted: Spanish (Spain)

Formatted: Spanish (Spain)

Field Code Changed

https://doi.org/10.1037/0097-7403.27.4.329

Redhead, E. S., & Hamilton, D. A. (2007). Interaction between locale and taxon strategies in human spatial learning. *Learning and Motivation, 38*(3), 262–283. https://doi.org/10.1016/j.lmot.2006.11.003

Rescorla, R. A. (1988). Pavlovian conditioning: It's not what you think it is. *American Psychologist, 43*(3), 151–160.

Rescorla, R. A., & Wagner, A. R. (1972). A theory of Pavlovian conditioning: Variations in the effectiveness of reinforcement and nonreinforcement. In A. H. Black & W. F. Prokasy (Eds.), *Classical conditioning II: Current research and theory* (pp. 64–99). Appleton-Century-Crofts.

Schmidt, J. R., & De Houwer, J. (2019). Cue competition and incidental learning: No blocking or overshadowing in the colour-word contingency learning procedure without instructions to learn. *Collabra: Psychology, 5*(1), 15.

Urcelay, G. P. (2017). Competition and facilitation in compound conditioning. *Journal of Experimental Psychology: Animal Learning and Cognition, 43*(4), 303–314. https://doi.org/10.1037/xan0000149

Wagner, A. R. (1981). SOP: A model of automatic memory processing in animal behavior. In N.E. Spear & R. R. Miller (Eds.), *Information processing in animals*: Memory mechanisms (pp. 5–47). Erlbaum.