Project Proposal

Title:

Contextual and Intrapersonal Factors in Fear Conditioned Response Latencies and their Association with Cognitive-Computational Learning Processes

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**Background**

Learning to avoid threats is a critical mechanism for human survival. Researchers study this learning process extensively with Pavlovian fear-conditioning, the repeated pairing of naturally aversive stimuli (the unconditioned stimulus or US) with naturally benign stimuli (the conditioned stimulus or CS) to associate fear with the CS. The acquisition of learned fear has been measured extensively, both behaviorally and physiologically, with robust and reliable conditioned responses (CR) reported in the literature. However, less consideration has been given to the computational substrates of fear-conditioning and their role in the formation of aversive action tendencies. Some formal learning models have been explored, but they have largely focused on physiological responses to fear-conditioning such as conditioned skin conductance, which are insufficient for indexing action tendencies. We will develop a formal learning model of fear-conditioning using response latency as an indirect measure of fear. Conditioned response latencies will be studied across varied levels of intrapersonal and contextual learning factors (e.g., intrapersonal: trait anxiety, behavioral inhibition; contextual: CS reinforcement rates, CS-US contingency instructions) to determine how each level moderates the acquisition, extinction, and retention of response latency CRs. Our formal learning model will incorporate a hybrid of model-based and model-free algorithms to represent contingency awareness and US expectancy, respectively. The weighted influence of these algorithms on CRs will elucidate the role of direct knowledge of CS-US contingencies on CR generation.

**Objectives**

Our research objectives are as follows:

* To determine the retrodictive validity of conditioned response latencies as a marker of fear-conditioning.
* To identify the intrapersonal and contextual learning factors that may moderate CS+/CS- discrimination during the acquisition, extinction, and retention of fear-conditioned response latencies.
* To compare the retrodictive validity of fear-conditioned response latencies with that of conditioned skin conductance responses.
* To develop a formal learning model of CS-US contingency awareness and US expectancy, and to assess the relationship between US expected value, latent processes of learning and conditioned response latencies.

**Research Questions**:

“*What is the retrodictive validity of fear-conditioned response latencies?*

* We will identify variance in response latencies explained by CS type and intrapersonal covariates, as well as unexplained variance. CRs that have minimal experimental aberration (e.g., variance explained by intrapersonal covariates instead of the CS+/CS- difference) and minimal measurement error (i.e., unexplained variance) are considered to have high retrodictive validity, or greater precision for detecting CS+/CS- trials. We will assess retrodictive validity in phases of acquisition, extinction, and retention.

“*What effects do contextual learning factors have on the retrodictive validity of fear-conditioned response latencies?*

* Procedural variations in fear-conditioning protocols are known to either attenuate or amplify the experimentally induced distinction for CS+/CS-. Although controlled variations in contextual procedures such as reinforcement rate and schedule have been studied with respect to conditioned skin conductance responses, no study has experimentally manipulated contextual learning factors with respect to response latencies. We will assess the effect of reinforcement rate, reinforcement schedule, CS-US onset-offset interval, and CS-US contingency instruction on retrodictive validity in phases of acquisition, extinction, and retention.

“*How does the retrodictive validity of fear-conditioned response latencies compare to that of conditioned skin conductance response?*

* The retrodictive validity of fear-conditioned skin conductance response is most established in the literature relative to all other empirically studied CRs. To evaluate the utility of conditioned response latencies as a measure of fear learning, we will concurrently collect response latency and skin conductance data within a single sample to compare their retrodictive validity.

“*How do latent processes of learning affect fear-conditioned response latencies?*

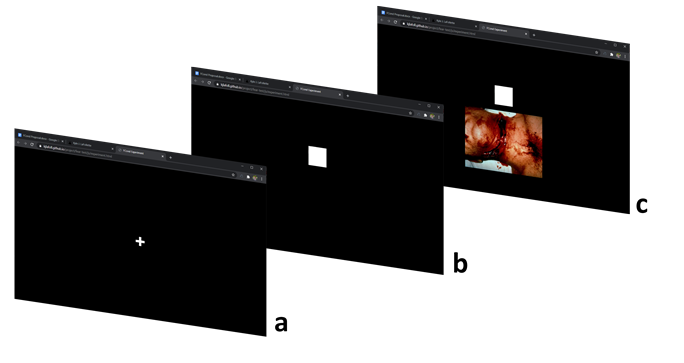
* We will develop a formal learning model of fear conditioning that will incorporate a hybrid of model-based and model-free learning algorithms to represent CS-US contingency awareness and US expectancy without contingency awareness, respectively. US expected value from both algorithms will be correlated with response latencies to determine whether variance in CR can be explained computationally. Furthermore, we will determine the importance of CS-US contingency awareness for CR by assessing the weighted influence of these two algorithms on US expected value. Various latent learning parameters, such as updating rate and noise sensitivity, will be correlated with interpersonal measures and contextual learning factors that are identified as predictors of retrodictive validity. This will provide a mechanistic account for the influence that those predictors have on fear-conditioning.

**Approach**

We will conduct two studies concurrently, and will collect data for one study each academic semester (4-5 months). See Table 1 for a study/phase breakdown. Study 1 will investigate the retrodictive validity of fear-conditioned response latencies across an array of contextual learning factors. A large multi-cultural sample will be collected online, and a battery of intrapersonal factors will be measured to determine any modulatory effects on CS+/CS- discrimination. Study 2 will see the development of a formal learning model of CS-US contingencies. Trial-by-trial US expected values will be examined, alongside latent learning process parameters (e.g., updating rate, noise sensitivity), and correlated with response latencies to determine their cognitive-computational substrates. We will identify a combination of contextual learning factors that maximize retrodictive validity in Phases 1-3, and compare retrodictive validity with that of skin conductance in Phase 4, within a single sample.

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| ***Table 1*** | | |
|  | **Study 1:**  **Retrodictive validity of response latency CRs** | **Study 2:**  **Cognitive-computational substrates of response latency CRs** |
| **Phase 1:**  **Continuous vs. Partial reinforcement** | What is the effect size to distinguish CS+/CS- in a continuously versus partially reinforced learning environment? How do intrapersonal factors and phases of acquisition and extinction modulate this effect? | What learning algorithm(s) is most accurate in predicting response latency CRs in continuously versus partially reinforced learning environments? How do intrapersonal factors and phases of acquisition and extinction modulate learning? |
| **Phase 2:**  **Delay vs. Trace US onset** | What is the effect size to distinguish CS+/CS- with delayed onset CS-US intervals versus trace intervals? How do intrapersonal factors and phases of acquisition and extinction modulate this effect? | What learning algorithm(s) is most accurate in predicting response latency CRs learned with delayed onset CS-US intervals versus trace intervals? How do intrapersonal factors and phases of acquisition and extinction modulate learning? |
| **Phase 3: Instructed vs. Incidental CS-US contingency** | What is the effect size to distinguish CS+/CS- when CS-US contingencies are instructed versus incidentally learned? How do intrapersonal factors and phases of acquisition and extinction modulate this effect? | What learning algorithm(s) is most accurate in predicting response latency CRs when contingencies are instructed versus incidentally learned? How do intrapersonal factors and phases of acquisition and extinction modulate learning? |
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| **Phase 4: Response latency and skin conductance** | When contextual learning factors are manipulated to maximize the retrodictive validity of response latency CRs, how do these CRs compare to those of skin conductance? | To what extent do learning algorithms that are predictive of response latency CRs predict skin conductance CRs? |

**Study 1 design.**To determine the retrodictive validity of response latency CRs, we will recruit a large multi-cultural online sample to participate in an aversive Pavlovian learning task (see Figure 1). On each trial, a cue (CS+/CS-) will be presented slightly above a centered fixation cross. The cue will be shortly followed by the presentation of either a picture that has been predetermined to elicit neutral or fearful discrete emotions (US). Participants will be tasked with responding to the US onset with a key press as quickly as possible without making false starts. Intertrial intervals will vary and participants will be instructed to use the cues to anticipate and prepare for action. Halfway through the learning task, fear extinction will be manipulated and measured, followed by a brief period of reinstatement. Contextual learning factors such as CS-US reinforcement rate, CS-US onset interval, and whether participants are instructed about CS-US contingencies will be manipulated between study phases. In addition to basic demographic information, various intrapersonal factors will be measured via questionnaires administered before and after the learning task. Using hierarchical Bayesian regression, we will determine the strength of evidence for an effect of CS type on US response latency at all stages of learning (acquisition, extinction, and reinstatement). We will also examine the variance explained by intrapersonal factors and measurement error (unexplained variance). Effect sizes will be compared within study phases. After identifying the contextual learning factors that are associated with the greatest retrodictive validity for response latency CRs, we will directly compare response latency CRs with skin conductance CRs within a single sample.



*Figure 1.* Pavlovian learning task. (a) Fixation, 5.5-10.5 seconds. (b) Conditioned stimulus, 4-8 seconds. (c) Unconditioned stimulus + conditioned stimulus, 4 seconds. All durations are specific to the delay design (times will vary for the trace interval design in Phase 2).

**Study 2 design.**To identify the cognitive-computational substrates of response latency CRs, we will develop a formal learning model of fear-conditioning that incorporates both model-based and model-free learning algorithms. Specific algorithms are to be determined throughout Study 2 phases during ‘design’ periods (see Table 3). Presently, we anticipate using some variant of the Rescorla-Wagner (RW) algorithm to represent model-free learning. RW updates expected values based on the sum of the previous expected value and an experienced prediction error:

Qt= Qt-1 + α(Rt-1 - Qt-1)

Where *Q* is the expected value of trial *t*, *R* is the value of the US, and *α* is a free parameter reflecting learning rate. Note that this algorithm neglects the identity of the CS present on trial *t*. We anticipate using some variant of Bellman’s equation to represent model-based learning, incorporating the identify of the CS, or the state:

Qt = ∑R R \* P(R│St)

Where *P(R│St)* is the probability of some reward given some state *S* at trial *t*. After deciding upon the specific algorithms we will use to represent model-free and model-based learning, we will further consider a hybrid model defined as a weighted sum of the two algorithms:

Qt = w \* QtMB + (1-w) \* QtMF

Where *w* is a free weighting parameter that reflects the weight of both model-free and model-based algorithms in the computation of expected US value. Each of these three models will be used to simulate trial-by-trial expected US values. During Phases 1-3, the observed trial-by-trial conditioned response latencies will be correlated with these expected US values to determine the best fitting model for each subject. We will further investigate variations in these algorithms by specifying the values of free parameters (e.g., simulating values from a model with a small learning rate α and a model with a large learning rate α). Last, we may consider modeling conditioned response latencies with a sequential sampling model that is informed by the formal learning model. For example, we may consider fitting a hierarchical drift-diffusion model with a single bound to participant data. To incorporate the formal learning model, we may decompose the drift rate parameter of the DDM to be the product of the expected value at trial *t* and some free parameter *v* reflecting the rate at which the participant accumulates evidence for the presence of US:

driftt = v \* Qt

Posteriors for free parameters will be inferred with a Hamiltonian Monte Carlo No-U-Turn sampler, which is a specific Markov Chain Monte Carlo sampler available in the Stan probabilistic programming language. Model specifics will be determined throughout Phases 1-3.

**Pavlovian learning task.** Throughout Phases 1-3, we will consistently use a continuously reinforced, delayed conditioning design and explicitly instruct participants about CS-US contingencies (see Figure 1). We refer to this consistent design as the **‘Default’**. Variations of the default will be manipulated throughout Phases 1-3. The design that yields the greatest retrodictive validity will be carried over to Phase 4 for comparing response latencies to skin conductance. The default design will begin with 4 habituation trials, during which only CS+/CS- will be presented. All trials will begin with a 5.5-10.5 second intertrial interval, during which participants will fixate on a centered fixation cross. The conditioned stimulus will then be presented for 4-8 seconds. 40 acquisition trials will follow habituation, with ranged durations (e.g., 4-8 seconds) sampled from a uniform distribution. Durations are identical to those of habituation, with the exception that after the 4-8 seconds of CS, the CS will be presented for an additional 4 seconds alongside the US. Acquisition trials will be evenly divided between CS+ and CS- (20 each). CS+/CS- trials are ordered pseudorandomly, such that no more than two trials of the same +/- type can be presented sequentially. Furthermore, the first trial will always be CS- to avoid any potential “bleed-over” effect than an initial reinforced CS+ could have on learning CS-. Reinforcement is continuous, such that all CS+ trials will be followed by a fear-inducing US. After the 40 acquisition trials, 30 extinction trials will be presented. Extinction trials are identical in design to acquisition trials with the exception that CS+ is no longer reinforced. 10 reinstatement trials will follow extinction, which are exactly identical in design to acquisition. Random durations for extinction and reinstatement trials are not uniform. Rather, they are sampled from an iterative subset of the previously used distributions, with the iteration ensuring that the sum of all sampled times converges to the distribution mean.

**Phase 1 manipulation.** Participants will be randomly assigned to one of two designs: the default design, or a variation of the default design. The variation in Phase 1 will modify the later half of the acquisition trials to be partially reinforced. Partial reinforcement of CS+ will be set to 50%, with half of all CS+ trials in the latter half of acquisition being reinforced, and the other half not reinforced. The order in which reinforced and nonreinforced CS+ trials are presented will be pseudorandom. To prevent latent inhibition and early extinction, the last CS+ presented during acquisition will always be reinforced.

**Phase 2 manipulation.** The variation in Phase 2 will replace the delay conditioning design with a trace interval design. The key difference between delay and trace is that the CS and US no longer overlap in the trace design, and are instead separated by a trace interval. To ensure fair comparisons between the two designs, both designs will present US for exactly 4 seconds; all other durations will have to be modified accordingly to ensure comparability between US while keeping total experimentation time consistent between designs. In the trace design, ITI will be 3-8 seconds, CS will be 6 seconds flat, and the trace interval between CS and US will be 1-4 seconds.

**Phase 3 manipulation.** The variation in Phase 3 will remove the explicit CS-US contingency instructions. Participants will instead incidentally learn the association between CS and US.

**Phase 4.** We will review the results of Phases 1-3 and identify the design that yielded the greatest retrodictive validity of CS+/CS-. We will consider additional Phases to investigate further design variations. For example, if both the partial reinforcement group from Phase 1 and the trace design group from Phase 2 exhibit greater retrodictive validity than the groups given the default design, we will consider collecting additional data with a partially reinforced trace design. We will continue using whatever design yielded the greatest retrodictive validity into Phase 4. Here, we will collect data in-lab to collect skin conductance response data while following procedures identical to those of the winning design. The retrodictive validity of the conditioned skin conductance response data will be compared to that of the response latency data. Each measure's ability to discriminate CS+/CS- will be considered in the context of interpersonal factors and stage of learning (e.g., acquisition versus extinction).

**Anticipated Effect Sizes & Sample Sizes.** Reports of CS cuing effects on target response latencies are sparse in the literature. Those that have considered response latencies do so with more complex designs, such as exogenous cueing paradigms with congruent and incongruent cue-target pairs. We synthesized the results that best corresponded with our effects of interest in Table 2. Of those results, interpretations are consistent with CS+ capturing more attention than CS-. We anticipate that this will translate to shorter response latencies to CS+ trials than CS- trials in our design. Unfortunately, effect sizes range from small to large. Despite the plethora of design differences between these studies and that which we are proposing, we assume a moderate effect size (d=0.5). A power analysis using GPower with power set at 0.95 and α at 0.05 for a two-tailed paired t-test shows us that we will need ***N=210*** for each phase of Study 1 (n=105 per group). It is unknown what we should anticipate for an effect of CR modality (i.e., response latency versus skin conductance), so in Phase 4 we will aim to collect ***N=40*** (n=20 per group). In total, we will collect data for ***N=670***.

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| ***Table 2*** | | |
|  | **Finding** | **Interpretation and Effect Size** |
| **Schmidt, Belopolsky & Theeuwes, 2014** | Response latencies to targets were significantly longer when CS+ distractors present than CS- distractors; t(23) = 2.69, p < 0.05 | CS+ captures more attention than CS-. d=0.55; moderate effect |
| **Bockstaele et al., 2010** | Response latencies to targets were significantly shorter when cued by CS+ than CS-; t(66) = 3.75, p < 0.001 | CS+ captures more attention than CS-. No effect size reported. Using available information specific to their control (no attention manipulation) group, we calculate d=0.787; large effect |
| **Van Damme et al., 2004** | Response latencies to targets were significantly shorter when cued by CS+ than CS-; t(51) = 2.52, p < 0.05 | CS+ captures more attention than CS-. No effect size reported. Using available information, we calculate d=0.207; small effect |

**Resources**

Most experimentation will be conducted online with Amazon Mechanical Turk, and as such will require significantly less resources than traditional psychology experiments. Nonetheless, we will need to acquire permissions for affective picture systems (e.g., International Affective Picture System (IAPS; Lang, Bradley & Cuthbert, 2008); Nencki Affective Picture System (NAPS; Marchewka et al., 2014)), permissions for selected questionnaires, funds to compensate participants, a remote database store to post participant data, and undergraduate research assistants to assist with data management and cognitive-computational modeling.

**Affective Picture Systems**. We will request permission to use images from the IAPS and the NAPS as unconditioned stimuli. We will curate images from these two systems on the basis of discrete fear emotion ratings. Previous research has identified images that elicit discrete fear emotions by collecting descriptive emotional category ratings for both these picture systems (see Mikels et al., 2005; Riegel et al., 2016). We will use the ratings from these studies to identify unconditioned stimuli that maximally induce fear. We will also identify neutral stimuli to pair with CS-. Since there will be 40 acquisition trials, we will aim to curate 20 fear-inducing pictures and 20 neutral pictures. We will attempt to match all unconditioned stimuli along dimensions of luminance, contrast, and complexity. We will also attempt to have equal numbers of picture categories (e.g., 20 animals and 20 body parts, 10 per valence). Due to the nature of these pictures, we will develop an information sheet that will inform all lab personnel who may be exposed to them about the nature of the pictures with representative samples. All participants will be well-informed about the nature of these pictures during consent and will have the opportunity to discontinue participation at any time. Participants will also be debriefed and provided a list of resources to seek if distressed.

**Demographics & Questionnaires.** After confirming consent, participants will complete a basic demographics survey. We will survey age (year), biological sex, and gender as part of the basic demographics survey. After the survey, participants will complete the state anxiety portion of the Spielberger State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983). The Pavlovian learning task will follow. After the Pavlovian learning task, participants will be asked to rate the valence, arousal, and dominance associated with each of the conditioned stimuli with the Self-Assessment Manikin (SAM; Bradley & Lang, 1994). Participants will also be asked to rate the probability that a specific US follows a CS in a series of 10 CS-US pairs (5 of each CS+/CS- type, US randomly sampled). Together, the SAM and probability judgments will provide direct measures of participants’ CS-US contingency awareness. Following these measures, participants will complete a battery of personality questionnaires, including the following: the full Spielberger State-Trait Anxiety Inventory, the Beck Anxiety Inventory (BAI; Beck et al., 1988), the Beck Depression Inventory (BDI; Beck et al., 1961), the Intolerance of Uncertainty Questionnaire, the PTSD Checklist, the Childhood Trauma Questionnaire (CTQ short), and the Fear Survey Schedule III. Participants will be debriefed following completion of the questionnaire battery. We will request permission to use all listed questionnaires where necessary.

**Compensation.** Assuming a flat rate of $5 USD per hour (well above the MTurk median pay of $2 USD per hour; Hara et al., 2018), ~1 hour of total participation per participant, and 210 participants per phases 1-3, we anticipate $1,050 USD per phases 1-3 in participant compensation. MTurk takes a 20% commission, so we anticipate $210 USD per phases 1-3 in commission fees. Phase 4 will be in-lab and will recruit participants from the university study pool, compensating participants with course credit commensurate to their participation time. In total, we anticipate ***$3,780 USD*** in compensation costs. Funding will be secured with graduate research grants made to defray direct costs, and internal resources when necessary.

*NOTE: Still need to budget for skin conductance equipment (MP150 is already available, but we will need other miscellaneous materials).*

**REDCap.** Though the learning task will be hosted on a private server, no data will ever be stored on that server. Participant data will be temporarily cached on the client side (i.e. local storage). After each trial of the learning task, a post request will be made to the REDCap API, and local data will be posted to REDCap. Information about the clock time of experiment onset and the participant’s browser and operating system will also be posted to REDCap. All demographic and questionnaire data will be entered directly into REDCap by the participant. In sum, participant data will only ever be in one of two locations: local storage of the participant’s web browser, or REDCap.

**Undergraduate Research Assistants.** We will recruit at most two undergraduate research assistants to support the project. Research assistants will manage the REDCap database, prepare experimental stimuli or scripts, and help design algorithms and/or computational models to analyze data. Duties will be a mix of meeting project needs and student enrichment. Examples of project needs include scoring questionnaires and tabulating data from REDCap for project update meetings. Examples of student enrichment include literature review, simulating data from simple learning models, and learning to program with Python. All work will be conducted remotely, with the opportunity for future in-lab duties during Phase 4 (e.g., running human subjects). Research assistants will be strongly encouraged to seek SOURCE funding (Support of Undergraduate Research and Creative Endeavors).

**MTurk-REDCap-Github Workflow**

HITs will be posted to MTurk with the title “Answer questions about your emotions and play an attention game (WARNING: This HIT may contain adult content. Worker discretion is advised.)”. The description will be “You will answer questions about how you feel or have felt emotionally, and you will play an attention game. In the game you'll be shown pictures and will have to respond as soon as you see the pictures”. Keywords will include “academic, research, psychology, study, survey, demographics”. Workers will be required to be located in the United States and to have a HIT approval rate of 90% or greater. The HIT will be tagged as containing potentially explicit or offensive content, and as such Workers who do not meet all qualifications will not be able to preview the HIT.

Responses will pay $5 USD each, and HITs will be limited to 30 unique workers per batch. Batches will be posted daily over the course of a week, for a total of 7 batches and 210 unique workers. Each HIT will be available from 12PM EST to 8PM EST. Workers will be allotted 2 hours to complete the HIT. We will reserve 7 days to reject Workers’ assignments before auto-payment. The HIT will contain two fields: a survey link to REDCap, and an entry field for the participant to provide a completion code. The survey link will be hidden until the Worker accepts the HIT. The survey link will contain a query string that pipes in the participant’s unique Worker ID. For example:

https://redcap.case.edu/surveys/?s=surveyid&MID=mturkworkerid

Where surveyid is the unique survey identifier and mturkworkerid is a unique Worker identifier. The query string MID will be passed to REDCap and automatically entered into a field with the variable name MID. This field will be tagged @READONLY so that the participant cannot modify it. The participant will be shown the Informed Consent Document on this first page of the REDCap survey and asked to indicate whether they agree to participate in the study. If they agree, they will continue in REDCap with the pre-learning task questionnaires. If they disagree, they will be thanked for their interest and asked to return the HIT, to avoid the HIT being rejected.

After completing the pre-learning task questionnaires, participants will be given a link in REDCap to kjlafoll.github.io, where the experiment is housed. This link will also contain a query string with their Worker ID:

https://kjlafoll.github.io/project/fear-test/js/experiment.html?MID=mturkworkerid

Their ID will be loaded in as a variable using URLSearchParams and will uniquely identify the participant’s experimental data. Data will be saved as a JSON and posted to REDCap. After completing the learning task, participants will be provided a final REDCap link to complete the post-task questionnaires. This link will also contain a query string for their Worker ID. A completion code will be provided to the participants after completing the final REDCap questionnaire, along with a debriefing script. Participants will enter this code into the appropriate field on MTurk to complete the HIT.

New batches will be managed with custom worker qualifications to exclude workers that are not unique to the project. This custom qualification will be managed with a csv that documents past Workers. During active data collection, a research assistant will export participant IDs daily from REDCap and update this csv on MTurk prior to new HITs going live.

**Timeline**

We anticipate that 4 manuscripts and a master thesis will be produced. See Table 3 for the project Gantt chart. We anticipate a start date of April 1st 2021 and an end date of August 1st 2022.

***Table 3***

