Emotional congruency facilitates statistical learning

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Abstract

Detecting regularities and extracting patterns is a vital skill that helps us to organize complex information in our environments. Statistical learning, a process through which we detect regularities by attending to the relationships between cues in our environment, contributes to knowledge acquisition across myriad domains. However, less is known about how emotional cues—specifically facial configurations of emotion—influence statistical learning. These cues pose challenges for statistical learning because they can vary both inter- and intra-individually and across contexts. Thus, the degree of congruence between the emotional and statistical information may diverge in important ways. In the current study, we tested two pre-registered aims to advance knowledge about emotional congruency and statistical learning: (1) We examined statistical learning of emotional information when compared to non-emotional information, and (2) We assessed how congruency influences regularity extraction. Using data from two independent samples (total N=671; 49% female, 50% male, 1% “other” or did not report gender; <1% American Indian or Alaskan Native; 14% Asian, 14% Black or African American, 5% Hispanic or Latinx; 4% Multiracial; 63% White), we demonstrated statistical learning across emotional cues similar to non-emotional cues (i.e., shapes). We also established that congruent cues facilitated statistical learning but found little evidence that incongruent information interfered with statistical learning. The results shed light on the application of a well-studied cognitive skill to the social domain and fill a knowledge gap about how cue congruency impacts statistical learning, including how we use emotional cues to make predictions in our social world.

Keywords: emotion, statistical learning, congruency

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Emotional congruency facilitates statistical learning

Detecting regularities and extracting patterns from vast and varied inputs is critical for making sense of the many complex environments that we encounter. This skill, referred to as statistical learning, helps us to track and organize auditory, visual, and tactile cues. An extensive literature provides evidence for statistical learning in humans from infancy through adulthood (e.g., recent reviews include Frost et al., 2015; Krogh et al., 2013; Santolin & Saffran, 2018; Siegelman et al., 2017). Researchers initially discovered that infants track transitional probabilities across units of speech to detect word boundaries (Saffran et al., 1996). Since that seminal study, research shows that we attend to regularities in many other types of stimuli, including tones (Creel et al., 2004), musical sequences (Saffran, 2003), color sequences (Turk-Browne et al., 2008), shapes (Kirkham et al., 2002), visual scenes (Brady & Oliva, 2008), and touch (Conway & Christiansen, 2005). Thus, statistical learning appears to be a domain general mechanism that operates with little or no explicit instruction (Aslin, 2017). Statistical learning allows us to predict relationships between cues and ultimately extract meaningful information from noisy input.

However, we know comparatively less about how inputs from social contexts influence statistical learning, which could help to elucidate how regularities guide learning and behavior in complex social situations that make up many daily living environments. Prior work reported that individuals extract statistical regularities from streams of dynamic human motion (e.g., shaking and drinking from a bottle), suggesting that statistical learning allows us to segment human action (Baldwin et al., 2008). A more recent study argued that emotional content helps to direct attention, which in turn facilitates statistical learning of the social context (Everaert et al., 2020). In this study, participants viewed visual scenes that contained positive, negative or neutral

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content (e.g., soldier holding a gun for negative content; baby for positive content; boy playing chess for neutral content). These images were organized into triplets such that certain images were more likely to follow others. Participants were better at recognizing triplets of emotional images (either negative or positive) than neutral images (Everaert et al., 2020). Thus, emotional content may enhance our ability to extract statistical contingencies. However, surprisingly, no prior studies have explored how emotional facial expressions—one of the most frequent and utilized inputs within social contexts (Feldman Barrett et al., 2019; Zebrowitz, 2017)—influence statistical learning. Knowledge about statistical learning in the social world could thus be improved by exploring how emotional information provided by others through facial expressions might shape learning.

At the same time, statistical learning in social environments is likely made difficult because, unlike patterns of shapes, the expression of emotional information varies depending on the emoter and the context (Barrett et al., 2019). That is, internal emotions are often hidden. Even within a single learning environment (e.g., classroom, store, or office), the emotional content conveyed by someone may not be congruent with that of those around them or with the situation. This incongruity has the potential to influence our ability to extract regularities amid emotional content. Indeed, incongruity impedes statistical learning (Glicksohn & Cohen, 2013), whereas congruent cues enhance statistical learning (Forest et al., 2019; Glicksohn & Cohen, 2013; Mitchel & Weiss, 2014). However, there is no research on congruency and statistical learning amid emotional content. Additionally, prior studies have only assessed congruency and incongruity across modalities, including a task where statistical regularities of a visual stream were either matched or mismatched with the statistical regularities of an audio stream (Glicksohn & Cohen, 2013). Knowledge about congruency effects could be improved by

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considering congruency *within* a modality, which would provide insight into how emotional cues contribute to attention to visual social content.

In the current study, we aimed to better understand how social context impacts statistical learning via a multifaceted approach. Our statistical learning task featured a stream of images organized into triplets, following classic statistical learning designs (e.g., Saffran et al., 1996). To investigate the impact of within-modality congruency, images were models depicting emotional expressions (happy, angry, sad, or fearful) that were emotionally congruent or incongruent with other images within each triplet. We assessed implicit, online statistical learning via reaction times to the second and third images within the triplet relative to the first image (Siegelmann et al., 2018). This implicit approach allowed us to test whether participants were faster to respond to emotionally-congruent versus emotionally-incongruent images. We also used an explicit recognition measure to assess whether participants could identify triplets they had viewed relative to novel, “foil” triplets at the end of the experiment. We included a comparison condition featuring triplets of abstract shapes for which color information (as opposed to emotional expression) was either congruent or incongruent within triplets. We also included a second comparison condition in which participants viewed triplets of images where all three were neutral emotional expressions. To address our first aim, we tested whether statistical learning to emotional faces occurs, hypothesizing that via both the implicit and explicit recognition tests, participants would evidence statistical learning. To address our second aim, we tested whether congruency affected statistical learning, hypothesizing that congruent information would facilitate statistical learning (relative to statistical learning of neutral faces without congruency cues) and that incongruent emotional information would impair statistical learning.

Methods – Study 1

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The experimental questions, manipulations, and analyses were preregistered at: <https://aspredicted.org/blind.php?x=vy4mu5>. The experiment, de-identified dataset, and analysis script are available online at Open Science Framework (https://osf.io/gc3u5/?view_only=137ba5942d4747418574ea0a0cc64518). R version 3.6.3 was used for all analyses (R Core Team, 2019). We used the tidyverse package (Wickman et al., 2019) for data organization, lme4 package (Bates, Maechler, Bolker, & Walker, 2015) for linear mixed effect models, and ggplot2 package (Wickman, 2016) for visualization. G*Power was used to conduct the power analysis to determine sample size (Faul et al., 2007; Faul et al., 2009). The experimental task was programmed in jsPsych version 6.1.0 (de Leeuw & Motz, 2016) and hosted on Pavlovia (<https://pavlovia.org/>).

Participants

Participants were 317 adults (186 female, 127 male, 1 “other,” 3 did not report gender; $M_{\text{age}}=20.01$ years, $SD_{\text{age}}=1.780$ years; 85 Asian, 24 Black or African American, 23 Hispanic or Latinx, 21 Multiracial, 164 White) who were recruited from an undergraduate subject pool at a large university in the Northeast region of the United States. The G*Power calculation for three predictors (condition, congruence, and trial) and assuming a small effect (small effect size chosen based on Siegelman et al., 2018 reporting an R^2 of 0.23 for their online statistical learning measure) recommended a sample size of 77 for each condition, which we exceeded. All participants provided informed consent and received course credit for their participation. The Institutional Review Board approved the research.

Stimuli and Materials

Face stimuli. We selected twelve models each producing four facial configurations (happy, angry, fearful, and sad) from the RADIATE stimulus set, a validated stimulus set that

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includes a diverse representation of models (Conley et al., 2018). We included four White (2 female, 2 male), four Black (2 female, 2 male), two Asian (1 female, 1 male), and two Hispanic (1 female, 1 male) models. Our selection of models was narrowed using validation ratings from RADIATE set to include those with Kappa $>.59$ for at least one expression of happy, sad, fear, and angry (open or closed mouth). Convergence across stimuli indicated that open-mouthed happy, angry, and fear and closed-mouthed sad faces had the best reliability. When comparing multiple models that fit this criterion, the model with the highest average proportion correct identification rating was chosen. The final list of models was: AF07, AM04, BF06, BF10, BM03, BM04, HF02, HM09, WF02, WF14, WM02, WM04. The neutral face stimulus of each of these models was chosen for the non-emotional face condition.

Shape stimuli. Shape stimuli were adapted from stimuli used in previous research (Schapiro et al., 2012). Twelve unique stimuli were edited in Procreate to create four versions delineated by color (blue, pink, yellow, and orange). There were two border designs added to the stimuli (characterized by a smooth line and a jagged line). The addition of this feature was meant to add to the complexity of the stimuli. Specifically, the border varied across stimuli but was not systematically manipulated within the task (i.e., similar to model gender in the conditions with faces). Although it may be impossible to fully equate facial and not-facial stimuli, these images contained a number of features to enhance attentional-orienting. In doing so, we aimed to maximize their use as a contrast condition.

Design

Participants were randomly assigned to complete the task with emotional face ($n=104$), neutral face ($n=104$), or shape ($n=109$) stimuli. Stimuli in the emotional face and shape conditions were randomly assigned to an emotion/color (Figure 1A and B). These stimuli were

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also randomly assigned to a triplet with the constraint that two triplets be congruent (i.e., each image in the triplet have the same emotion/color) and two triplets be incongruent (i.e., the triplets contain two different emotions/colors). In the neutral face condition, the stimuli were randomly assigned to triplets (Figure 1C). Triplets were then randomized to create a continuous stream with the constraint that the same triplet could not appear twice in a row across the 48 triplet presentations.

Procedure

Participants completed the task online. In an initial exposure phase, participants viewed one stimulus at a time. They were instructed to notice any co-occurrences and told that they would be tested at the end (see Arciuli et al., 2014 and Siegelman & Frost, 2015 for discussion of statistical learning paradigms with and without explicit instructions). Participants clicked on each image to proceed to the next and could advance the task at their own pace (participants saw 144 images in total). Next, participants completed a testing phase in which they viewed triplet streams and were asked whether streams were familiar or novel. This phase included three types of triplets (four of each were presented for a total of 12 trials of each trial type). “Target triplets” were the four triplets viewed during the exposure phase of the task. “Foil triplets” were images that participants had seen during the exposure phase, presented in novel orders. The images in foil triplets maintained their positions from the exposure phase (e.g., if triplets were ABC, DEF, and GHI during the exposure phase, then a foil might be AEI). “Part-triplets” maintained the images from positions two and three in the target triplets but had a different image in position one (e.g., AHI from the example above). There were four target trials and eight total non-target trials, presented in random order.

Analyses

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Sixteen participants were excluded based on preregistered criteria: reaction time (RT) responses that exceeded ± 3 *SD* of the sample mean or (not preregistered) use of only a single response option. For each participant, trials that exceeded ± 2 *SD* from their individual mean were trimmed to the cutoff value (3% of trials; preregistered). RT analyses used log-transformed RT to account for variance in baseline RT and to compare across individuals with different baseline RT. Accounting for baseline RT was important since participants were completing the experiment online, and internet connection speeds likely varied (see Siegelman et al., 2018 for a discussion of this issue). To examine the influence of condition and congruence on statistical learning, we used an online measure of statistical learning performance based on prior research (SLP; Siegelman et al., 2018). SLP was calculated by subtracting the mean log RT of stimuli in the second and third positions of triplets from the log RT of the stimulus in the first position of the triplets. Scores greater than zero reflect a learning of the statistical patterns via a relative increase of reaction time speed within, as compared to between, triplets. All analyses were included in the preregistration unless otherwise noted, and all analyses for the preregistration are presented in the main manuscript and Supplemental Materials. If linear mixed effects models resulted in singular fit when including the maximum random effects structure, they were simplified based on recommendations (Brauer & Curtin, 2018).

Results – Study 1

Participants Show Online Evidence of Statistical Learning with Emotional Faces

We tested for statistical learning during the exposure phase across all conditions in two ways. First, we regressed log RT on position within the triplet (position 1 set as the referent) with a by-participant random intercept. The effect of position was significant with differences between each stimulus position ($\chi^2(2)=82.05, p<.001$; position 2 vs. position 1, $b=-0.04, t=-6.39$;

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position 3 vs. position 1, $b=-0.06$, $t=-8.75$; position 3 vs. position 2, $b=-0.02$, $t=-2.36$), indicating implicit sensitivity to the triplet structure. Second, we computed the online SLP, which was greater than zero ($t(316)=10.61$, $p<.001$), indicating that participants were sensitive to the underlying statistical structure. To assess whether statistical learning occurred with emotional faces, we repeated analyses for participants in the emotion condition only. As before, there was an effect of position on log RT ($X^2(2)=41.86$, $p<.001$; position 2 vs. position 1, $b=-0.05$, $t=-4.45$; position 3 vs. position 1, $b=-0.07$, $t=-6.29$; position 3 vs. position 2, $b=-0.02$, $t=-1.85$) and SLP was greater than zero ($t(103)=5.90$, $p<.001$), suggesting again that participants responses were consistent with the statistical structure of the stimuli. When we regressed SLP on mean-centered trial number, SLP decreased over time ($b=-.001$, $X^2(1)=17.76$, $p<.001$), indicating less differentiation between stimulus position across the experiment. This significant effect disappeared if we removed the first trial from the analysis ($X^2(1)=2.73$, $p=.10$), which suggests that the effect of time may have been driven by the relatively longer RT for the trial that initiated the experiment ($\text{Mean}_{\text{TrialOne}}=2089.68\text{ms}$, $\text{Mean}_{\text{AllOtherTrials}}=837.20\text{ms}$). However, all other analyses remained significant when the first trial was excluded. In sum, statistical learning occurred in the task overall, including when participants specifically viewed patterns among emotional faces.

Statistical Learning is Better for Congruent versus Incongruent Stimuli

Next, we examined whether the congruence of the triplets influenced statistical learning in the emotional face and shape conditions. We regressed SLP on the interaction between condition (shape=-.5, emotion=.5), congruence (incongruent=-.5, congruent=.5), and time (i.e., trial number, mean-centered) and all lower order effects. We included a by-participant random intercept and by-participant random slope for the interaction between congruence and time. First,

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we found a main effect of both time ($b=-0.001$, $X^2(1)=9.30$, $p=.002$) and congruence, with higher SLP to congruent stimuli ($b=0.03$, $X^2(1)=8.08$, $p=.004$) suggesting that within-model congruency affects statistical learning. There was a marginally significant interaction between condition and congruence ($b=0.03$, $X^2(1)=3.24$, $p=.07$; Figure 2) suggesting that participants showed greater differentiation between congruent and incongruent emotional faces as compared to congruent and incongruent shapes. Second, we examined a model including condition and time, without congruence, which resulted in a marginally significant effect of condition ($b=0.02$, $X^2(1)=3.52$, $p=.06$) and significant effect of time ($b=-0.001$, $X^2(1)=8.63$, $p=.003$), indicating somewhat higher SLP overall in the emotion condition. Finally, we tested for a difference in SLP by congruence in the emotion condition alone, which was significant ($b=0.04$, $X^2(1)=10.30$, $p=.001$). In sum, we found that congruence influences statistical learning and that statistical learning is marginally enhanced for emotional face stimuli versus shape stimuli.

Congruent Emotional Information *Facilitates* Statistical Learning

We investigated the effect of congruency further to better understand whether congruent information improves statistical learning and/or whether incongruent information interferes with statistical learning. To do this, we compared SLP for congruent triplets in the emotional face condition versus neutral face conditions. We regressed SLP on the interaction between condition (neutral face=-.5, emotional face=.5) and time (mean-centered) and all lower order effects with a by-participant random slope for time. First, we found an overall effect of condition ($b=0.03$, $X^2(1)=10.16$, $p=.001$; Figure 2) with higher SLP for congruent emotional faces, providing support that an additional, congruent, clue improves statistical learning. However, the effect of condition was not significant when comparing SLP for incongruent emotional faces to neutral faces ($p=.41$). In exploratory analyses, we found that SLP did not differ for neutral faces relative

to congruent ($p=.96$) or incongruent ($p=.42$) shapes. Across these contrasts, congruent emotional cues appear to boost online statistical learning performance.

Statistical Learning at Test is Similarly Influenced by Stimulus Features

In addition to online statistical learning performance, we examined evidence for statistical learning with an explicit test at the end of the experiment. Using a logistic mixed effects model we regressed participant responses (said triplet was familiar=1, said triplet was not familiar=0) on condition (emotional face condition set as referent), trial type (target, part-triplet, foil; part-triplet set as referent) and their interaction. We included a by-participant random intercept and a by-participant random slope for trial type. We report odds ratios (OR) for the logistic regressions to show how much the odds of saying that the triplet is familiar increase or decrease as a function of (a one-unit increase in) the independent variable of interest. All effects were significant (Figure 3). Across all conditions, participants were more likely to identify targets as familiar compared to part-triplets ($b=1.93$, $p<.001$, $OR=6.89$) and were more likely to identify part-triplets as familiar compared to foils ($b=1.17$, $p<.001$, $OR=3.22$; omnibus: $X^2(2)=178.17$, $p<.001$), providing evidence for statistical learning. The main effect of condition showed that participants were more likely to identify shape triplets as familiar, as compared to emotional face triplets ($b=0.44$, $p=.002$, $OR=1.55$; omnibus: $X^2(2)=10.89$, $p=.004$), but there were no difference between emotional and neutral face conditions, $p=.40$). The main effects were qualified by an interaction between trial type and condition. Participants were more likely to identify target triplets as familiar, as compared to part-triplets, in the emotion as compared to shape condition ($b=-0.77$, $p<.001$, $OR=0.46$; omnibus: $X^2(4)=19.65$, $p<.001$).

To better understand the relation between performance in exposure versus test phases, we ran two exploratory follow-up analyses (preregistered for Study 2). First, we examined target

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triplets in the emotional face and shape conditions to test whether congruency during exposure influenced test performance. We regressed likelihood of (correctly) identifying a target as familiar on the interaction between condition and congruence, their lower order effects, a by-participant random intercept, and a by-participant random slope for congruence. The effect of congruence was significant ($b=0.58$, $X^2(1)=9.51$, $p=.002$, $OR=1.79$) and the effect of condition was marginal ($b=0.35$, $X^2(1)=3.10$, $p=.08$, $OR=1.42$), again suggesting that congruency plays an important role in statistical learning. Second, we tested whether SLP during exposure related to performance on test by regressing the likelihood of (correctly) identifying a target as familiar on the interaction between condition (all three conditions, emotional faces set as referent), SLP during exposure (mean-centered), the lower order effects, and a by-participant random intercept. The effect of SLP was significant ($b=5.84$, $X^2(1)=14.17$, $p<.001$, $OR=343.78$) suggesting that higher online statistical learning performance was associated with higher accuracy at test.

Discussion – Study 1

In a statistical learning paradigm incorporating facial cues to emotion, we provide evidence for statistical learning in an emotion-relevant context. Using both an online, implicit measure of statistical learning and a post-exposure, explicit measure, participants were sensitive to statistical information across emotional face configurations. Our results extend the prior literature (Baldwin, et al., 2008; Everaert, et al., 2020) and, for the first time, we establish statistical learning in contexts with emotional faces. Additionally, the marginal effects we found for condition suggest a slight advantage of emotional input to direct attention to underlying patterns. The notion that emotional content might benefit statistical learning aligns with recent research that used emotional scenes as stimuli (Everaert, et al., 2020). However, we readily acknowledge that unlike prior research (i.e., Everaert, et al., 2020), our stimuli did not provoke

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strong or even conscious emotional reactions in participants. Instead, emotional cues may serve to direct attention in ways that extend beyond emotion activation. Alternatively, it may be that our stimuli did evoke some unanticipated emotionality but not so much as to produce robust online differences in comparison to the non-emotional stimuli.

In addition to overall effects of statistical learning, we found that within-modal congruency benefits statistical learning. Congruency during exposure predicted greater accuracy at test for both emotional and shape stimuli. However, congruency only influenced online statistical learning performance for the emotional stimuli relative to the neutral faces. Thus, emotional information appeared to be meaningful in the context of faces, whereas color information was not necessarily meaningful in the context of shapes. Finally, in contrast to cross-modal findings (Glicksohn & Cohen, 2013) we did not observe a detrimental effect of incongruent cues. One possible explanation for this disparity is that incongruence is more disruptive when experienced cross-modally. Because this was the first investigation of statistical learning of emotional faces, we conducted a second pre-registered study where we ran the experiment in an independent sample of adult participants recruited via Amazon's Mechanical Turk (Mturk).

Methods – Study 2

Participants

Participants were 354 adults (142 female, 211 male, 1 did not report gender; $M_{\text{age}}=36.722$ years, $SD_{\text{age}}=10.173$ years; 2 American Indian or Alaskan Native, 12 Asian, 71 Black or African American, 7 Hispanic or Latinx, 3 Multiracial, 259 White) recruited on Mturk. All participants provided informed consent and received \$1.50 for their participation. The Institutional Review Board approved the research. The experimental procedures for Study 1 were identical to those

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described for Study 1 with one exception: “catch” trials were included during both the exposure and test phases to identify participants who were not attentive to the features of the task (preregistered; see Supplemental Materials for catch trial and exclusion information and Curran, 2016 and Thomas & Clifford, 2017 for reviews on exclusions in Mturk samples). The experiment and analyses were preregistered at aspredicted.org (<https://aspredicted.org/blind.php?x=3iq4wv>).

Results – Study 2

Participants Evidenced Statistical Learning, but did not Distinguish by Congruency

As with the undergraduate sample, the effect of position on log RT was significant with differences between position 1 and positions 2 and 3 ($X^2(2)=110.77, p<.001$, position 2 vs. position 1, $b=-0.09, t=-8.81$; position 3 vs. position 1, $b=-0.09, t=-9.40$; position 3 vs. position 2, $b=-0.01, t=-0.59$; emotion condition only: $X^2(2)=37.48, p<.001$, position 2 vs. position 1, $b=-0.08, t=-4.839$; position 3 vs. position 1, $b=-0.10, t=-5.67$; position 3 vs. position 2, $b=-0.01, t=-0.83$). SLP was also greater than zero, $t(353)=14.70, p<.001$ (emotion condition only, $t(120)=9.22, p<.001$). Additionally, SLP decreased over time ($b=-0.003, X^2(1)=39.16, p<.001$, which, along with other effects, maintained significance when the first trial and trials presented directly following the catch trials were excluded, $p=.04$). Consistent with Study 1, there was evidence of statistical learning. However, statistical learning performance decreased over the course of the task, even when accounting for inflated RTs for position 1 stimuli as a result of the first and catch trials. For the Mturk sample, there were no effects of condition or congruence in SLP ($ps>.09$). Additionally, there were no differences between conditions in comparing congruent or incongruent emotional and neutral faces ($ps>.14$).

Statistical Learning at Test Influenced by Trial Type and Congruence

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At test, participants were more likely to identify targets as familiar compared to part-triplets ($b=0.26, p=.033, OR=1.30$) and were more likely to identify part-triplets as familiar compared to foils ($b=-0.42, p<.001, OR=1.52$; omnibus: $X^2(2)=21.42, p<.001$; Figure 4). The effect of congruence was significant for (correctly) identifying a target as familiar on the interaction between condition and congruence ($b=0.47, X^2(1)=16.07, p<.001, OR=1.60$). However, there were no effects of SLP during exposure influencing performance at test (p of main effect=.73; p of interaction with condition=.57).

Comparing the Undergraduate and Mturk Samples

There were disparities in behavior during exposure and test between the samples, and the pattern of online statistical learning performance in the Mturk sample was inconsistent with prior literature (Siegelman et al., 2018). Namely, statistical learning performance among the MTurk sample decreased over time and was not associated with accuracy at test. Additionally, we compared the Mturk sample performance at test with the undergraduate sample by regressing the likelihood of identifying a triplet as familiar on condition, triplet type, and sample (undergraduate=-.5, Mturk=.5). The Mturk participants had a significantly higher bias than the undergraduate participants for identifying a triplet as familiar ($b=0.77, X^2(1)=23.93, p<.001, OR=2.16$). Sample interacted with triplet type such that Mturk participants were less likely to identify target triplets as familiar ($b=-1.68, p<.001, OR=0.19$) and more likely to identify foil triplets as familiar ($b=0.73, p<.001, OR=2.08$) compared to the undergraduate sample (omnibus: $X^2(2)=84.80, p<.001$). These results raised concerns about the validity of the Mturk sample.

Learners Show Similar Patterns of Behavior at Test

To reconcile the differences and better understand the nature of the Mturk data, we therefore conducted follow-up analyses by identifying subgroups from within both samples that

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showed strong evidence of learning at test (defined as correctly identifying $>8/12$ target triplets as familiar *and* $>8/12$ foil triplets as not familiar). Fifty-three percent ($n_{total}=169$, $n_{emotion}=66$, $n_{shape}=49$, $n_{neutral}=54$) of the undergraduate sample and fourteen percent ($n_{total}=49$, $n_{emotion}=17$, $n_{shape}=14$, $n_{neutral}=18$) of the Mturk sample met these criteria. First, we confirmed that these criteria now eliminated sample differences at test, which they did for both the main effect of sample ($p=.46$) and the interaction between sample and triplet type ($p=.62$). Next, with the caveat that the smaller sample sizes may have rendered some of the tests underpowered, we repeated the primary analyses to test: (1) Whether the overall results of the undergraduate sample were similarly observed in the subgroup of learners, and (2) Whether the subgroup of the Mturk learners exhibited similar patterns of behavior to the undergraduate learners.

The undergraduate learners demonstrated all of the same effects as the entire sample at test including the main effect of triplet type ($X^2(1)=675.70$, $p<.001$), condition ($X^2(2)=19.58$, $p<.001$), and triplet type-by-condition interaction ($X^2(4)=16.09$, $p=.002$), which was driven by the difference in identifying targets and part-triplets between the emotional face and shape conditions ($b=-0.60$, $p=.01$, $OR=0.55$). The Mturk learners replicated these effects (triplet type $X^2(1)=181.40$, $p<.001$; condition $X^2(2)=7.56$, $p=.02$; triplet type-by-condition interaction $X^2(4)=22.07$, $p<.001$; see Figure 5 for comparison of learners and not learners in the Mturk sample). In addition to the difference in identifying targets and part-triplets between the emotional face and shape conditions ($b=-1.22$, $p=.001$, $OR=0.30$), there was also a difference in identifying foils and part-words as familiar between the emotional and neutral face conditions ($b=1.05$, $p=.006$, $OR=2.86$). In examining the role of congruence at test, there was an effect of congruence for the both the undergraduate ($b=0.74$, $X^2(1)=9.81$, $p=.002$, $OR=2.10$) and Mturk ($b=1.44$, $X^2(1)=14.63$, $p<.001$, $OR=4.22$) learners. There was also a relation between SLP and

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performance at test for the undergraduate learners ($b=5.32$, $X^2(1)=14.85$, $p<.001$, $OR=204.38$).

However, the relation between SLP and performance was not straightforward for the Mturk sample, where we found an interaction with condition ($X^2(1)=4.57$, $p=.033$; main effect of SLP was marginal: $b=2.12$, $X^2(1)=3.33$, $p=.068$) driven by a difference between the emotional and shape conditions ($b=6.70$, $p=.010$, $OR=812.41$). There was a relation between SLP and performance in the shape condition ($b=4.60$, $X^2(1)=5.94$, $p=.01$, $OR=99.48$) but not the emotion condition ($p=.787$).

Learners Show Similar Patterns of Behavior During Exposure

The undergraduate learners showed more robust differences between conditions than the full sample. In examining the effects of congruence and condition there was a main effect of condition ($b=0.04$, $X^2(1)=5.89$, $p=.02$), congruence ($b=0.05$, $X^2(1)=29.67$, $p<.001$), and a significant interaction between condition and congruence ($b=0.06$, $X^2(1)=9.61$, $p=.002$). As would be expected by these results, the model including condition alone yielded a main effect ($b=0.04$, $X^2(1)=13.64$, $p<.001$), and there was an effect of congruence in the emotion condition alone ($b=0.08$, $X^2(1)=34.21$, $p<.001$). For the Mturk learners, in the full model, there was an effect of congruence ($b=0.10$, $X^2(1)=9.06$, $p=.003$) and a marginal condition-by-congruence-by-trial interaction ($b=-0.01$, $X^2(1)=3.59$, $p=.06$). This pattern suggested that there was a relatively greater difference between congruence and incongruent stimuli early in the experiment in the emotion condition but later in the experiment in the shape condition. The effect of condition was not significant when congruence was removed from the model ($p=.565$). The effect of congruence in the emotion condition was marginal ($b=0.08$, $X^2(1)=3.36$, $p=.07$).

Discussion – Study 2

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In a second independent sample of participants, we replicated statistical learning in the context of emotional face stimuli, which we showed to be as robust as with other types of stimuli (i.e., shapes and neutral faces). In contrast, the effects of condition and congruency we had demonstrated in the undergraduate sample were largely absent in the full sample of Mturk participants. However, since there were inconsistencies between our two datasets, and relative to reports from prior research using a similar method (Siegelmann et al., 2018), including a decrease in SLP over time. Therefore, we employed a post-hoc and highly stringent test to identify “learning” in the current paradigm. This approach led to a notable reduction in the number of Mturk participants that were included in analyses, which raises concerns about the overall validity of this sample. At the same time, among the MTurk participants who were classified as “learners”, we were able establish behavior patterns that more closely approximated those observed in Study 1, including a subsample of undergraduates from that study who were classified as “learners”. We found that the undergraduate learners replicated (and strengthened) the effects of the full sample. Importantly, the Mturk learners subsample replicated the pattern of effects of congruency, although condition differences were less clear. Thus, statistical learning with emotional face content may be similar to other types of stimuli. Overall, these data provide further support for the existence of statistical learning using social cues.

General Discussion

In a comprehensive assessment of statistical learning using implicit and explicit measures, two comparison groups, and two independent samples, we provide evidence for statistical learning following exposure to facial cues of emotion. This work contributes to the vast, and still rapidly growing, corpus of research on statistical learning and is consistent with the view that statistical learning is domain general (Aslin, 2017). We also show that within-modal

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congruency facilitates statistical learning based on both implicit and explicit tests. These findings serve to further extend the reach of statistical learning into the emotional domain and expand our understanding of how individuals integrate multiple cues when tracking patterns in the social world.

Statistical learning is well-suited for learning contexts in which there are extensive numbers of stimuli and variability across stimuli (e.g., language; Weatherholtz & Jaeger, 2016). However, it has not been extensively explored in the social domain. Statistical learning could help with pattern acquisition in complex social environments, where many cues must be processed to organize information and make predictions. There is growing evidence that statistical learning may be particularly compatible with social contexts (see Plate, Woodard, & Pollak, In Press for a review). Moreover, statistical learning and emotional content may operate in tandem, with emotional content helping to orient attention to salient or relevant patterns moment-by-moment (Everaert et al., 2020). Our findings provide evidence that statistical learning can benefit from emotional content, at least among some individuals.

In addition to the general role of emotional information, we emphasize the role of congruency. Our emotional environments can differ in content (Plate, Bloomberg, Bolt, Bechner, Roeber, & Pollak, 2019). A better understanding of the role of congruency can help establish how learning in emotional environments might differ between individuals. We can also use these insights to understand flexibility of learning in emotional environments, particularly in an effort to address instances in which disruptions related to emotional processing might occur (Etkin & Wager, 2007). This task opens the door for questions regarding individual differences in statistical learning in emotional environments, which sits at the intersection of cognitive and social learning mechanisms.

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One persistent limitation in posing questions related to emotional content is ecological validity. We used static visual images of posed facial configurations of emotion, yet the emotional world contains myriad cues including body posture and vocal cues (Atias et al., 2019; Schirmer & Adolphs, 2017). Our research serves as a foundation to begin to ask more complex questions about how social cues influence attention to and use of statistical information. By comparing the emotional face condition to the neutral face condition (in addition to a non-face condition), we were able to better isolate the role of emotion and its impact on statistical learning by showing that congruent emotional faces enhance statistical learning relative to neutral faces. Research on cross-modal cue integration (Forest et al., 2019; Glicksohn & Cohen, 2013; Mitchel & Weiss, 2014) suggests that cross-modal cues more have a more robust affect on the relation between emotional cues and statistical learning. More research that systematically adds layers of complexity to learning contexts is needed to establish the generalizability of the conclusions.

Another limitation inherent in making comparisons between social and not social content is the nature of the stimuli. Faces, and particularly faces conveying emotional cues, involve the complex integration of individual facial musculature and patterns of movement that are often—but not always—associated with emotions (Barrett et al., 2019). Additionally, by using faces, participants could have tracked the patterns using a strategy of “naming” the models. And in trying to preserve some ecological validity in the stimuli, we used a models that varied in race, gender, and other characteristics (e.g., piercings). We tried to mitigate these concerns by including another face condition, therefore controlling for the ability to “name” stimuli and having complex individual variability across the triplets. We also included nonfacial stimuli that had multiple visual dimensions, including a border that was not informative of the underlying

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structure. Taken together, these conditions attempt to account for the unique features of social stimuli.

Finally, our ability to interpret the findings of Study 2 are limited by the sample. There was uncertainty about the degree of participant attention and engagement. We excluded participants who failed our pre-registered attention checks, but the data quality still appeared poor compared to the undergraduate sample included in Study 1 and when compared to samples reported in prior research using similar measures (Siegelman et al., 2018). There is some suggestion in the literature that attention checks can be limited in effectiveness (Chandler et al., 2014; Hauser & Scharz, 2016) and that other statistical approaches may be needed to identify engaged participants (e.g., Barends & de Vries, 2019; Dunn et al., 2018). Indeed, it is highly plausible that the seeming passiveness of the task (i.e., clicking on images as they appeared) rendered our experiment susceptible to participant distraction. At the same time, we were able to confirm some of the hypothesized patterns in a subset of these participants about whose engagement we were more confident.

In sum, the current study provides evidence for the influence of emotional cues on statistical learning. Participants tracked regularities amid emotional content, and congruency in emotion information facilitated monitoring of patterns. Through this work, we shed light on how the social context influences statistical learning. We also extend the reach of statistical learning as a mechanism supporting the ability to make sense of exceedingly complex and vast environments.

Research in Context

There is mounting evidence that statistical learning is a domain general mechanism that contributes to pattern detection and learning. And statistical learning appears to be well-suited for detecting patterns in vast and complex stimuli (e.g., streams of speech). Yet, we understand less about statistical learning of social stimuli. Social cues, specifically facial configurations of emotion, can vary across contexts and within and across individuals. This variability suggests that statistical learning may be particularly useful for detecting patterns in social environments. However, variability in facial cues also presents a challenge when there is incongruity between cues. The authors, who have backgrounds in cognition and learning and emotion, created a collaboration to ask questions about the influence of emotional information on statistical learning. We find supporting evidence for the role of statistical evidence in social contexts and highlight the function of congruency in facilitating statistical learning. We aim to continue lines of inquiry examining the dynamic interplay between cognition and learning and the social world.

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Figures

Figure 1. Example triplet configurations for the emotion (A), shape (B) and neutral (C) conditions. Relations within triplets are $p = 1$ and relations between triplets are $p = .33$. Triplets are outlined in green and yellow here for illustration purposes only, there were no cues—other than the probabilistic relations—to the triplets for participants. Face stimuli are from the RADIATE stimulus set (Conley et al., 2018).

Figure 2. Statistical learning performance by condition and congruence. Points are individual participant averages and error bars are +/- one standard error.

Figure 3. Likelihood of saying that a triplet was familiar at test by trial type and condition.

Points are individual averages, error bars are $\pm$ one standard error.

Figure 4. Likelihood of saying that a triplet was familiar at test for Mturk sample. Points are individual averages, error bars are $\pm$ one standard error.

Figure 5. Likelihood of saying that a triplet was familiar at test for Mturk sample only, divided into groups as “learners” and “non learners”. Points are individual averages, error bars are $\pm$ one standard error.