**Research Strategy**

## Aim 1: The Dissertation Research Project (F99 Phase) – To explore the formation of social and non-social uncertainty judgements among healthy, neurotypical adults.

## A.1. Significance

A.1.1. Social situations can produce pervasive and aversive feelings of uncertainty 26–29. Increased uncertainty and/or difficulty tolerating it are hallmarks of negative psychological conditions like anxiety and depression 17,26,30,31. However, dealing with uncertainty situations and outcomes is an unavoidable reality of daily life. Uncertainty can manifest in both social contexts (e.g., "Am I being told the truth?") 1 and non-social contexts (i.e., "Was the traffic light yellow or red?") 5–7,22. Many clinical disorders are characterized by issues with evaluating and regulating responses to uncertainty, including schizophrenia 32, autism spectrum 17, and anxiety disorders 17, moreover, high uncertainty intolerance predicts emotion dysregulation 33. This speaks to the clinical and public health importance of understanding the neural and behavior bases of social and non-social uncertainty, and identifying strategies that can be used to regulate the negative states that it elicits. Prior work has found that assessing social and non-social ambiguity recruits unique neural circuitry 5,6, which may stem from differences in cognition underlying social and non-social ambiguity assessments. That is, non-social assessments may demand greater focus on unimodal sensory details and calculations while social assessments may instead demand greater focus on heuristics, schemas, and prior experiences 6,12. Thus, social uncertainty may be especially difficult to manage 1 but*few studies have differentiated how social versus non-social uncertainty judgments form using complex, dynamic, and ambiguous social stimuli.*

A.1.2. Complex, feature-rich stimuli are an ecologically valid means of studying context-dependent social phenomena 9,34–36. Social uncertainty has typically been studied in the context of economic games (e.g., Trust Game, Ultimatum game) 37 in which a participant collaborates with a real or fictitious participant to make economic decisions. These interactions, while offering a great deal of experimental control, are not faithful representations of how these kinds of decisions are made in the real world 38,39, in which our representations about others is accrued gradually, across multiple situations, and updated based on new information. 1,7. Video narratives offer a well-validated, feature-rich, socially-relevant alternative to traditional stimuli while incorporating greater ecological validity and comparable experimenter control 8,11. Using video stimuli in neuroimaging research to study context-sensitive phenomena is growing rapidly 40, but *demands specialized data collection approaches and analytic techniques sensitive to the multivariate nature of the complicated neural patterns they elicit.*

A.1.3. Intersubject neural synchrony is a multivariate measure of intersubject overlap in social cognition. Synchrony, or the correlative strength in activity between two or more individuals across a time series, differ from univariate methodologies, which are sensitive to changes in activation magnitude but not activation patterns within a region 41,42. High intersubject neural synchrony in response to the same information suggests similar processing of that information and provides evidence of neural signatures, or regions that definitively contribute to a specific neural mechanism 10. Complex social and cognitive phenomena are often represented at the voxel level and analyses sensitive to patterns, such as Intersubject Correlations (ISC), are required to quantify these representations 10. Different psychiatric disorders are associated with dysfunction in neural synchrony, including ASD 43 and anxiety disorders 44. *This speaks to the importance of using synchrony and other multivariate approaches when examining neural data in normative and clinical populations.*

A.1.4. Intersubject neural synchrony predicts downstream decision-making. For example, intersubject neural synchrony as calculated by ISC positively predicts cooperation, agreement, communication, coordination, empathy, and perspective-taking 44–48. However, these studies only examine how neural synchrony predicts decision-making outcomes rather than the decision-making process 38. Time series analyses of continuous behavioral measurements have precedence in the social and affective literature 38,49, but have not yet been applied to paradigms using dynamic, feature-rich stimuli examining intersubject neural synchrony. Using dynamic narratives to elicit and continuously sample judgments of uncertainty and neuroimaging data concurrently could use neural intersubject synchrony to predict intersubject synchronization in subjective downstream behavioral assessments of uncertainty 38. *This approach could identify associations between the role that specific neural regions play in generating subjective assessments of social and non-social certainty judgments.*

A.1.5. Innovative Features of this Proposal. We use a single dynamic, feature-rich video stimulus (length: ~45 mins) to examine how participants gather information and build personal hypotheses about uncertain social events (i.e., whether or not a character committed a crime). Our proposed naturalistic approach optimizes ecological validity and allows us to gain a better understanding for how people assess social factors like trustworthiness. While prior research (cites) has used passive viewing paradigms to examine intersubject synchrony, our task incorporates continuous behavioral assessment of situational certainty. This behavioral measure is time-locked with neural activity, which will yield a direct association between neural and behavioral activation. In our design, we will also directly compare the neural and behavioral correlates of social uncertainty (i.e., evaluating a character’s guilt) with non-social uncertainty (i.e., evaluating the continuous luminance of the movie frame) (*see* **A.2.2. Task Design**). Lastly, my application of an advanced computational method (ISC) has not previously been applied to explorations of uncertainty-related cognition and offers improved neural resolution to a complex social topic.

### A.2. Approach

#### A.2.1. Rationale and Overview. While research on ambiguous non-social uncertainty has been exhaustive, we know comparatively little about how individuals form judgments in response to ambiguous social sources. This is a meaningful research gap, given the extent to which , despite social uncertainty being is closely tied to negative psychological reactions and outcomes. 17,26,30,31. My dissertation work (i.e., Aim 1) explores neural and behavioral differences in uncertainty assessments of social and non-social uncertainty using a naturalistic fMRI paradigm. Using an adult population, I will apply ISC analyses 10 to characterize common neural signatures of domain-specific certainty judgments among over 400 unique functionally defined cortical parcels 25 and to examine the degree to which activity in each cortical parcel informs behavioral assessments of uncertainty. My stimulus models important features of social ambiguity (e.g., incremental learning, informational filtering), which are relatively absent from other existing approaches, which tend to focus on the final product of a certainty judgment (e.g., selecting low- or high- risk slot machines).

#### A.2.2. Task Design. The fMRI task (**Fig 1**) has been pilot tested and is currently being used to capture data from adult participants. Participants first complete a training exercise to ensure comfortably using a handheld device (i.e., button box/joystick) and assess ability to clearly hear audio. During the primary (social) uncertainty task, participants are introduced to the target and supporting characters by reviewing necessary background information (e.g., character’s names, general roles, and relationships to other characters). Participants then watch video (i.e., *The Undoing*, HBO Television) while continuously rating how certain they are of a given outcome (i.e., a character’s innocence or guilt) using their handheld device. Behavioral certainty ratings are sampled at the stimulus’s average framerate (24 Hz). A rotating checkered pattern precedes and follows each stimulus for 30 seconds, which is standard practice to assess responses from the visual system when using dynamic video stimuli 34. The stimulus is split into two 22 minute 17 second components and presented to participants across two sequential runs. The first 17 seconds of each run is ignored to account for initial scanner lag. Participants are randomly assigned to rate one of the halves and to passively watch the other half, but to engage with the stimulus and form uncertainty judgments as if they were providing ratings. Following the primary task, participants watch 5 minutes of video from a different episode of the source show, but containing the same characters, and rate how certain they are that the luminance of each frame is lighter or darker than a target image. The luma value (i.e., luminance) of each frame is calculated using a standard formula 50 adapted into an R function built by the applicant. The target image is displayed during the task and is the frame closest to the median luminance of all frames contained within the stimulus, such that an approximately even number of frames are lighter and darker than the target image. This measures the formation of perceptual certainty judgments. Participants then complete questionnaires outside of the scanner to assess anxiety 51, uncertainty intolerance 52,53, depression 54, demographics, character assessments (e.g. “How agreeable was character X?”) based upon a validated measure of person perception dimensions 55, task engagement and difficulties, and how their personal theories of which character committed the crime evolved over time.

**Figure 1.** fMRI task. Participants receive background information and view one minute of visual baseline (fixation cross, rotating checked pattern). Participants continuously indicate their certainty as events occur.

#### A.2.3. Task Validation. To validate our task, we ran a preliminary sample (*n* = 26). Based upon extant literature 5,6, we hypothesized that the orbitofrontal (OFC), dorsolateral prefrontal (dlPFC), anterior insula (AI), precuneus, dorsal anterior cingulate (dACC), and inferior frontal gyrus (IFG) activation during social uncertainty tasks specifically would be associated with periods of increased uncertainty in the social uncertainty task. For additional validation, I queried Neurosynth meta-analytic software 56 using the terms “social cognition”, “ambiguous”, and “uncertainty” to identify key regions that we might expect to respond if our paradigm is prompting social ambiguity-related cognition. Neurosynth’s composite association z-statistic map was largely consistent with our hypothesized circuitry. We then used FSL’s FEAT 57 to conduct a parametric analysis using data from 26 adult subjects that have completed the outlined paradigm (*See* **A.2.2. Task Design**). Subjects’ certainty ratings from moment to moment were detrended (resulting in a time course of only rating inflections), demeaned, and z-standardized, to reduce spurious correlative influences and lagged by 10 seconds to capture the decision-making cognitive processes that precede rating changes. Such a lag is analogous to standard practices in the memory event-segmentation literature 9,36. We found strong activation within each of the previously outlined regions during our social task, according to the Automated Anatomical Labeling (AAL) atlas (**Fig 2**). This suggests our task is successfully targeting social ambiguity-related cognitions.

**Figure 2.** Thresholded Z-statistic map from preliminary analyses of paradigm with adult participants (n = 26)

IFG = Inferior Frontal Gyrus; Cortex; AI = Anterior Insula; dlPFC = Dorsolateral Prefrontal Cortex; PCun = Precuneus  
dACC = Dorsal Anterior Cingulate Cortex

A.2.4 Analyses. ***Intersubject Neural Synchrony Within and Across Domains.*** Intersubject correlations will be calculated using the voxel-wise approach that nltool’s ISC function 58 employs in Python. The ISC function correlates the time series of each voxel's activity within each participant with the average time series of that same voxel across all other participants, yielding a coefficient representing how similar neural activity patterns are in that voxel among people on average. To adjust for autoregression (i.e., a statistical relationship between prior and subsequent datapoints; violating the assumption of observation independence), temporal smoothing, voxel-wise detrending, and nuisance regression functions from the nltools package will be applied to our data. The ISC-generated coefficients of each voxel contained within each of the 400 discrete functionally-defined regions from Schaefer’s 2018 cortical atlas 25 will be averaged to compute a region-level value of intersubject synchrony. Nonparametric permutation analyses will test for significance by generating correlations of randomly permutated activity within each subject iteratively (n ≥ 5000) and comparing confidence intervals for our observed against a null distribution, as has been applied in previous examples of ISC analyses 11. The degree of synchrony across participants will be visualized using cortical heat maps to highlight which specific regions are involved in either social or non-social uncertainty judgments while processing complex, feature-rich stimuli across individuals. ***Neural Synchrony Predicting Behavioral Synchrony.*** We will also the explore the link between neural signals of certainty judgments and subjective behavioral indicators of uncertainty by using the neural synchrony exhibited between subjects for a given parcel to predict the behavioral synchrony they exhibit as well. Intersubject correlations among behavioral ratings will be generated using generalized estimating equations (GEEs), which do not assume normality or observation independence, in R via the gee package 59. My primary sponsor has experience with this approach, having used GEE modeling in recent research 60. Intersubject neural correlation values within a given region will be used to predict correlation between subjects among lagged behavioral values using mixed effects hierarchical linear modeling (HLM) via the lme4 package 61 in R. We will employ an information theoretic approach by comparing Bayesian Information Criteria (BIC) values for competing models in chi square comparisons. Our initial null model will include a random intercept for the correlated subject pair in each observation. We will iteratively add fixed effects of neural ISC values, the region which generated the ISC value, and covariates as appropriate (e.g., visual contrast, etc. 8,35) until a model of best fit is determined. We will also take a data-driven approach to determine the appropriate lag between our neural and behavioral activity by incrementally varying lag magnitude and adopting the model of best fit.

A.2.5. Predicted Results. We anticipate increased neural synchrony across participants within parcels containing the dlPFC and components of the OFC during the non-social certainty task. We also anticipate seeing increased synchrony from the PCun, IFG, dACC, AI, and dlPFC when performing the social uncertainty task. We hypothesize that synchronization across these regions will predict increased synchronization of behavioral certainty ratings. The degree of synchrony will likely vary depending upon which character a subject hypothesizes had committed the crime during the social task. We theorized that subject hypotheses should be divided into two groups: subjects suspecting our target character and subjects suspecting another character. A confirmatory factor analysis conducted using the lavaan package 62 in R applied to the time series of behavioral ratings collected thus far supports this data structure (*rmsea* = 0.07, p > 0.05) across both video halves. As such, subject hypothesis at the time of rating will be a moderator in our analyses such that individuals entertaining similar hypotheses will be expected to demonstrate greater neural synchrony than individuals entertaining different hypotheses.

#### A.2.6. Participants and Power Analysis. Participants will be healthy individuals, ages 18 to 85. Using Stanford’s Neuropower 63 Toolkit with pilot data collected in our lab suggested that 53 subjects would be required for 1 - β = 0.80, as indicated by the random field theory parameter. However, 60 subjects will be recruited (34 more in addition to the 26 subjects thus far) in total to account for 15% attrition. Further details can be found in the **Human Subjects** Section.

#### A.2.7. Image Acquisition and Pre-processing. Scanning will be performed on a 3T Siemens Tim Trio MRI system at Temple University (*See* **Equipment and Facilities** for more details). Acquisition parameters for the T2\* EPI BOLD sequence includes 3 mm slice thickness, a TR = 2000 ms; TE = 25 ms; flip angle of 75°, and a FOV = 1680 x 1680 mm. Neuroimaging data will be preprocessed with the standard fMRIPrep pipeline 64 to maintain generalizability. It should be noted that MVPA analyses like ISC, which are sensitive to the voxel-level patterns that spatial smoothing could distort, are robust to the standard gaussian kernel size that fMRIPrep applies during spatial smoothing 65. Behavioral rating data will be averaged across 2 second periods to match the TR. Though traditional fMRI video paradigms often bin segments of video (e.g., 30 seconds) into trials 34, such an approach would be inappropriate in conjunction with our behavioral measure, as it would necessitate averaging ratings across the length of the bin. As such, our analysis takes inspiration from event segmentation and defines each event as any rating inflection, indicating a change in cognition regarding the predetermined outcome 9. Motion outliers will be assessed using the FSL Motion Outlier Tool 57, which defines outlier thresholds as the 75th percentile plus 1.5 times the interquartile range. Head motion can be a pernicious issue with adolescents and, as such, outlying TRs will be statistically censored. If greater than 15% of TRs that compose a trial are outliers, the TR will not be used for analyses.

A.2.8. Potential Pitfalls. We may fail to find significant synchrony in neural patterns. Prefrontal regions can be especially difficult to synchronize 8. However, stimulus engagement increases prefrontal synchronization 66 and subjects thus far report high engagement during our post-task questionnaire (*See* **Recruitment and Retention Plan**). If we fail to find synchronization in neural regions, we will use smaller parcellations from Schaefer et al. 25. These smaller parcellations may serve a more homogenous function relative to larger parcellations. If this fails, we will pivot to a whole-brain approach with adjustments for multiple comparisons. This drops the assumption that functional parcellations are an appropriate level of granularity and instead analyzes each voxel independently 11. If this fails to yield significant neural synchrony, we would conduct supplemental behavioral studies to assess the presence of additional unforeseen covariates (e.g., responses to stimulus features) which could add heterogeneity into our sample and respecify our models adjusting for these covariates. Our stimulus is context-specific (i.e., represents a limited section of the uncertainty experience continuum) which also may affect neural synchrony. While this design will be adapted to other stimuli eventually, a lack of neural synchrony would motivate me to adapt this paradigm to other stimuli much sooner to fully explore alternative approaches. In our HLM approach, we may find that no model performs better than our null model. If encountered, we would test non-linear model fit or non-parametric comparisons, as is determined appropriate by the characteristics of our data. We have thus far observed no issues with recruitment, attrition, or head motion, despite scan length. However, if recruitment lags relative to our timeline, I will contact collaborating labs at Temple to supplement our sampling pool. Additionally, if head motion increases as we collect new data, we would revisit our scanning protocols and incorporate more stringent training to reduce its incidence rate.

## B. Aim 2: The Postdoctoral Research Direction (K00 Phase) – *To explore the formation of social and non-social uncertainty judgements across normative adolescent development.*

## B.1. Significance

B.1.1. Adolescence is a unique period of pronounced social development. These changes are motivated by significant biological, cognitive, and environmental changes that introduce new social pressures, expectations, and norms 67,68. As adolescents are expanding their complex social networks and navigating novel experiences, they are also experiencing dramatic structural and functional changes in social reward processing and salience structures such as the anterior insula (AI) and amygdala 69 while developments in the self-regulatory prefrontal structures lag 70–74. *This results in a pronounced sensitivity to and prioritization of social rewards* *13,14 without sufficient cognitive control to manage this drive or the negative affective consequences* 75.

B.1.2. Uncertainty represents an especially prominent threat to this vulnerable developmental stage. The associations between uncertainty processing and psychopathologies outcomes among adults extend to adolescents as well. However, the long-term effects of uncertainty within a child’s environment which extend beyond those of the typical adult are well-documented and severe 76. Social ambiguity has significant health ramifications for adolescents, as the presence of social stressors in early adolescence predicts depression susceptibility two years later 15. *Performance in experimental paradigms using ambiguous stimuli have predicted adolescents’ real-world risk-tasking behavior*20,22**.**

B.1.3. Adolescents and adults demonstrate qualitatively different responses to uncertainty 13,14. Adolescents, unlike adults 24,77–79, do not demonstrate ambiguity aversion in lab studies 19,22. Neither familiarity biases 24 nor pessimistic attitudes towards outcomes 80 explain why adults and adolescents differ. Fear of others’ negative evaluations may predict differences in ambiguity aversion 78, a factor which would disproportionately affect adolescents, given their strong focus on social others/social evaluation 13. However, the extant developmental work is limited by an absence of ambiguous social stimuli in use. To date, a single study has probed ambiguity-related cognition in adolescents using social sources 12 and found that decisions to trust others gradually become more influenced by empirically-based information between 10 and 16 years old. Consistent with this account, individual sensitivity to varying degrees of uncertainty 81 and the ability to calibrate uncertainty judgments to the different courses of action increases throughout normative development 82,83. This relative inability to integrate uncertainty in the environment with risk-related decision-making manifests as overconfidence early in life when interpreting ambiguous circumstances.

B.1.4. Innovative Features of this Proposal. My outlined K00 proposal builds upon my F99 research proposal by adapting the novel video paradigm established within my predoctoral phase and exploring these same associations among an adolescent sample. This would constitute one of only a few studies using social sources of ambiguity to compare neural or behavioral responses to uncertainty between adults and adolescents. Moreover, it would be the first that we are aware of to do so with a dynamic, feature-rich, multimodal video stimuli. We suspect that the pronounced developmental differences in social reward processing will yield substantial differences in neural responses within regions commonly implicated in social reward processing (i.e., AI, dACC, IFG). However, this study is also well situated to connect neural activation with behavioral decision-making and highlight the neural components that contribute to the subjective global experience of social uncertainty across developmental stages. Furthermore, our exploratory analysis will identify important stimulus features that elicit different appraisals from adults and adolescents and provide clearer direction for theoretically-informed investigations into *why* adult and adolescent uncertainty appraisals differ (e.g., different processing of same features).

### B.2. Approach

#### B.2.1. Rationale and Overview. Extant literature has highlighted significant ways in which adolescents deviate from their older counterparts in their assessments of uncertainty, but the reasons why they differ are still not well understood. My postdoctoral work (i.e. Aim 1) will extend my predoctoral work by exploring the formation of social and non-social uncertainty judgments across normative adolescent development using a naturalistic fMRI paradigm.

#### B.2.2. Methods and Predictions. This phase of the research will adapt the paradigm created and tested within the F99 phase of my research to adolescent samples. The protocols and analyses will be markedly similar with a few adaptations. Notably, I anticipate requiring a larger sample size to adequately model the heterogeneity present in adolescent uncertainty judgments at different points in the age group. Uncertainty-related social cognitions even between early and mid-adolescence appear significantly different 12 and domain-generalizations also develop between early and late adolescence 84. As such, age will be an important moderator in our analyses, especially as we incorporate our adult F99 data for comparison. Similar investigations into the social and affective development of adolescent cognitions have revealed non-linear trajectories 85 and our analytic approach will need to explore these possibilities as well. I will solicit and incorporate feedback and ideas from my postdoctoral advisor, who will be an established developmental neuroscientist, as to how this paradigm can be better adapted to an adolescent sample. I anticipate that regions tracking social reward that undergo significant structural and functional changes during adolescence (dACC, AI, IFG) may peak in neural synchrony during mid-adolescence, in line with existing affective work. I also anticipate that this increased neural activity and synchrony will yield a stronger relationship between synchrony in these regions and influence upon behaviors. An exploratory analysis will investigate why adolescent and adult certainty assessments differ. Within regions demonstrating high intersubject synchrony, peaks of activation across the time series will be extracted and correlated with the presence of features within the stimulus to identify differences and similarities in the features that elicited synchrony among adults and adolescence. This approach has been used during single unit mapping and passive viewing studies 8.

#### B.2.3. Potential Pitfalls. Adapting neuroimaging research to an adolescent sample demands solutions to age-specific practical issues, including: subjects with semi-permanent ferrous materials (e.g., braces), excessive head motion, lack of age-appropriate cortical models, consent and assent procedures, coordinating travel for study sessions, managing difficult schedules, and task disengagement and non-compliance. Although I have not conducted neuroimaging research using adolescent participants, I encountered and found solutions to many of the formerly listed problems as a researcher at the Children’s Hospital of Philadelphia. Travel, scheduling, and non-compliance issues can be solved with careful planning, training, and distribution of resources. For example, reasons for adolescents’ disengagement can be forecasted by study staff and solutions to curtail this disengagement will be written into our standard operation procedures. Study staff will practice these scenarios to improve their success in real circumstances. Mock scan trials will be used to reduce the incidence of head motion. My postdoctoral advisor, who will be an experienced developmental neuroscience researcher, will advise me on matters of adapting traditional analysis pipelines to adolescent data. Regarding analytic pitfalls of this project, all of the previously mentioned F99 pitfalls and potential solutions will apply to adolescent populations. In our comparison of activation across groups, though, we may find no statistically significant differences in the recruitment of regions recruited for these tasks. If this occurred, we would likely incorporate alternative multivariate pattern analyses differently sensitive to neural patterns so that we could understand this phenomenon. One option could be using pattern classification which would be trained on the passive viewing dataset in the hopes of identifying a distinct developmental neural signature of certainty judgment formation. A similar approach (e.g., LASSO-PCR and k-fold cross validation) was recently applied to distinguish context-general and context-specific signatures of fear using dynamic, feature-rich video stimuli 35 and such an approach would be especially well-powered with the volume of our data 86.

#### B.2.4. Career and Professional Development. ***Becoming an Independent Researcher****:* By developing greater expertise in the social developmental neuroscience literature with the assistance of my post-doctoral advisor, I will be better equipped to pursue my goal as a social developmental neuroscientist defining my own independent line of research. Social affective phenomena are rich and complex and, as such, often difficult to parse without equally complex models. The computational approaches I will have learned in the process of completing my predoctoral research with the assistance of this award are crucial to explore these phenomena and identify associations that would otherwise go unnoticed without these methods. As such, the value of an education in computational neuroscience will only increase as the developmental field progresses. ***Research & Writing****:* When I begin my postdoctoral phase, I will revise and publish manuscripts based upon my dissertation research. I also plan to review and synthesize relevant topics from the extant literature on social developmental neuroscience into manuscripts to strengthen my expertise and my contributions to the field. Lastly, I would like to work with my postdoctoral advisor to develop my skills related to grant production and review to better prepare me for my future as an independent researcher. ***Teaching & Mentorship****:* Building a sustainable, diverse, and accessible lab culture is of the utmost importance to me. I will work directly with the graduate and undergraduate researchers within my lab to not only share the skills that I’ve developed, but also build sustainable research infrastructure which others can reference and learn from after I have moved to new positions. As both the first graduate student in my lab and a director of the Coding Outreach Group (COG), I already have experience creating neuroimaging and statistical analysis pipelines from scratch and documenting every step of those processes for others to use and adapt. Given my expertise in programming, I aim to join an organization like COG at my postdoctoral institution, where I can help others troubleshoot issues and learn new skills relevant to psychological and neuroscience research.

#### B.2.6. Identifying My K00 Institution and Postdoctoral Mentor. My ideal K00 institution would be an R1 research institution, possibly in or near a large population center, with robust access to developmental populations. My experiences in studying self-regulation, affect, and development has reinforced my belief that access to a diverse community is critical for accurate representation of any social phenomenon. An institution with a strong emphasis on collaboration would help me gain new skills and increase my academic network. My ideal mentor has a history of working with developmental populations in social and affective cognitive neuroscience and is interested in applying computational neuroscience techniques to explore how complex, feature-rich processing matures through early development. My primary training goals are (1) to apply advanced multimodal computational approaches to analyze social affective developmental phenomenon; and (2) to improve my skills in behavioral task design and hypothesis testing to mitigate the methodological concerns that using naturalistic stimuli can introduce while maximizing the ecological validity of the results. I will begin identifying potential postdoctoral mentors during the spring of 2024, one year before my expected PhD completion date. I will seek the input of my PhD mentor and advisory committee; especially Dr. Steinberg given his unparalleled knowledge of the field and researchers within it. I hope to be able to network at in-person conferences during this time and the summer, before finally reaching out to my finalized list of postdoctoral mentors in the fall of 2025.