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Implicit Learning and Metacognition: A Computational, Behavioral, And Neural Analysis

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Implicit Learning and Metacognition:

A Computational, Behavioral, And Neural Analysis

A dissertation submitted in partial satisfaction of the requirements

for the degree of Doctor of Philosophy in Psychology

by

Julia Marie Schorn

2023

ABSTRACT OF THE DISSERTATION

Implicit Learning and Metacognition: A Computational, Behavioral, And Neural Analysis

by

Julia Marie Schorn

Doctor of Philosophy in Psychology

University of California, Los Angeles, 2023

Professor Barbara Knowlton, Chair

Perceptual decision-making, evaluating the sensory world in order to choose an action, is often done in conditions of uncertainty. People can implicitly learn from past experiences in order to help the decision-making process but the conditions in which this happens and how metacognition impacts this is unknown. Furthermore, how this ability to implicitly learn priors changes with healthy aging has not been studied. In these three studies, participants performed a perceptual decision-making task in which different colored stimuli were associated with different prior biases (e.g., 75% of the red trials go leftward). In Study 1, we examined the differences between learning priors implicitly through experience versus explicit instruction and how that affects performance and metacognition with two computational models, Linear Ballistic Accumulator Model (LBA) and a Hierarchical Bayesian Estimation of metacognition (H-Meta- d'). Participants were able to learn priors implicitly and used them to guide decision-making. Bias primarily influenced decisions with the least sensory information, but not for stimuli with more robust information. Those who were instructed of the priors were more confident for prior- consistent (vs. inconsistent) stimuli while this was not seen in participants who experienced the priors implicitly. However, there were no differences in metacognitive efficiency between the two instruction groups. Our results suggest that implicitly learned priors can influence decision-making when sensory information is unreliable, but do not contribute when sensory information is more robust. In Study 2, older and younger adults performed the same decision-making task with prior instruction manipulation but with different prior conditions. Instead of opposite-oriented priors, one prior was biased towards a side while the other prior was equally likely to go left or right. When participants were instructed of priors, younger adults were faster and more accurate compared to older adults. Younger adults were more confident for Positive prior (biased) trials while older adults' confidence was unaffected by prior condition. In contrast, in the implicit "experience" group, younger and older adults largely matched on speed and accuracy, but younger adults were more confident than older adults overall. LBA parameter estimates largely align with past research that suggests that older adults have a slower information processing rate, greater response caution and require more evidence before making a decision (Garton et al., 2019). In Study 3, I present preliminary results of functional magnetic resonance imaging to examine the neural correlates of implicit learning and decision-making. Activation in the putamen and thalamus was observed during prior-consistent Equal prior trials with little sensory information. Motor and visual areas, as well as frontal gyri were primarily activated for the Positive Prior trials that were prior-consistent. Findings from these studies may augment understanding of

the decision-making mechanisms in healthy aging as well as in clinical patient populations and may provide insight into novel therapies or rehabilitation.

The dissertation of Julia Marie Schorn is approved.

Michele Basso

Alan Castel

Hongjing Lu

Barbara Knowlton, Committee Chair

University of California, Los Angeles

2023

This dissertation is dedicated to my family.

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EDUCATION

2017-2023	**University of California, Los Angeles** Ph.D. Candidate, Psychology (Cognitive Neuroscience Area) Advisor: Barbara Knowlton, Ph.D.
2017-2018	M.A., Psychology
2013-2017	**Princeton University** A.B., Psychology (Certificates: Neuroscience, Musical Performance, Italian Language & Culture)

FELLOWSHIPS & AWARDS

2021	Cognitive Area Research Award, UCLA.
2019	Graduate Summer Research Mentorship Fellowship, UCLA.
2019	National Science Foundation Graduate Research Fellowship Honorable Mention
2018	Graduate Research Mentorship Fellowship, UCLA.
2017	Department of Psychology Fellowship, UCLA.

PUBLICATIONS

Manuscripts

Landon, L., **Schorn, J.,** Russel, M., Whiting, S., Passmore, R. & Roma, P. (*in press*). Risks of Integrating Private Astronauts into NASA Spaceflight Operations: An Initial Examination. *Aerospace Medicine and Human Performance*.

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Schorn, J., Liu, H., Knowlton, B. (2020). "Contextual Interference Effect in Motor Skill Learning: An Empirical and Computational Investigation" *Proceedings of the 42nd Annual Meeting of the Cognitive Science Society*. Remote: Cognitive Science Society.

Selection of conference posters & presentations

Schorn, J.*, Walsh, C., Castel, A., Knowlton, B. (accepted for April 2022). *The Effect of*

Retention Interval on Directed Forgetting in Older Adults. Poster presentation at Cognitive Neuroscience Society, San Francisco, CA.

Schorn, J.*, Knowlton, B (2021). *Implicitly Learned Bias Influences Perceptual Decision-Making under Conditions of Uncertainty*. Oral presentation at The Psychonomic Society, Virtual.

Schorn, J.*, Hennesee, J., Castel, A., Knowlton, B. (2020). *Enhanced Memory for Task-Irrelevant Stimulus Features in Older Adults*. Poster presentation at The Association for Psychological Science, Chicago, IL. (Conference canceled)

Schorn, J., Knowlton, B.*, Hennessee, J., Patterson, T., Castel, A. (2019). *Strategic and Automatic Encoding Effects in Value-Directed Remembering*. Oral presentation at The Psychonomic Society, Montréal, CA.

Schorn, J.*, Knowlton, B. (2019*). Interleaved Practice Supports Motor Sequence Learning Transfer*. Poster presentation at The Association for Psychological Science, Washington, D.C.

Roma, P.*, **Schorn, J.,** Qi, K., & Agrawal, A. (2019). *Operational Performance Measures of Neurobehavioral Function for Long-Duration Space Missions*. Presentation at the 16th annual congress of the Society for Brain Mapping & Therapeutics, Los Angeles, CA, USA.

TRAINING

2019	NIH-Funded Training Course in fMRI, U. Michigan.
2019	NIH-Funded BRAIN Initiative Course on Models & Neurobiology, U. Missouri.

TEACHING EXPERIENCE

2019-2023	Psych 85 (Introduction to Cognitive Science), UCLA
2020-2022	Psych 100B (Research Methods in Psychology), UCLA
2021-2022	Psych 120A (Introduction to Cognitive Psychology), UCLA.
2021	Psych 120B (Sensation and Perception), UCLA.
2018	Neuro M170 (Music, Mind, and the Brain), UCLA
2018	Psych 10 (Introduction to Psychology), UCLA

ADDITIONAL RESEARCH EXPERIENCE

2022	**User Experience Research Intern,** Google Play Store, Privacy & Security
2021	**User Experience Research Intern,** Google Augmented Reality
2020	**User Experience Research Intern,** Google Maps
2018-2023	**NASA Intern**, Johnson Space Center, Behavioral Health & Performance Lab
2017	**NASA Intern**, Ames Research Center, Reproduction & Development Lab
2016	**NASA Intern**, Marshall Space Flight Center. Mentor: Dr. Mat Park

CHAPTER 1

General Introduction & Overview of Studies

Perceptual decision-making is the process by which we evaluate the sensory world and choose a course of action based on sensory evidence, but this evidence is often vague or missing. Over time and with experience, the brain picks up on statistical regularities in the environment and can use that information to make decisions. People are good at picking up these probabilities through trial-by-trial experience (Bar-Hillel, 1983; Carroll & Siegler, 1977; Christensen-Szalanski & Beach, 1982). Paradoxically, humans are bad at using base rates in higher level decision making (base rate neglect; Kahneman & Tversky, 1973). However, this is theorized to be because trial-by-trial experience elicits learning that is automatic and implicit and base rate neglect experiments usually explicitly instruct participants of the biases. Explicitly encoding the biases make it hard to translate over to an implicit frequency detection test. People can implicitly learn biases (or priors) in a perceptual learning task and use them to make decisions when sensory information is unclear. However, it is yet unknown if these biases are applied only when information is ambiguous, if they affect metacognition, and if this ability to implicitly learn priors changes across the lifespan.

Metacognition, the ability to monitor and evaluate one's own cognitive processes, plays an important role in perceptual decision-making as well as social interaction and conscious awareness (Frith & Frith, 2007; Magnussen & Helstrup, 2007). It provides a mechanism for adaptive decision-making by allowing one to know when to commit to a decision or to change strategies and gather more information (Pescetelli & Yeung, 2021). Metacognition can be impaired in neuropsychiatric disorders such as schizophrenia and can also decline over the lifespan in healthy aging (David et al., 2012, Palmer et al., 2014). This could perhaps be due to an increase in neural noise with age (Welford, 1977). Neural noise can affect decision-making and confidence but it is unknown how big of a role it plays in either of these processes. Maniscalco & Lau, 2016 propose three different architectures in a signal detection theory framework for how sensory information and noise drive decisions (type 1) and confidence (type 2). The single-channel model suggests that incoming information is affected by internal noise, which then influences both type 1 decisions and type 2 confidence judgments. In the dual-channel model, there are two sources of internal noise, with each primarily influencing either type 1 or type 2 judgments. The hierarchical model, considered the best fit by empirical evidence, posits that the noise corrupting type 1 decisions is accompanied by additional type 2 noise (or signal decay), resulting in at least as much noise in type 2 judgments as in type 1 judgments. Empirical evidence for these models is sparse, and computational modelling studies in aging have primarily focused on decision-making with a drift diffusion model or a variant, like the Linear Ballistic Accumulator model (LBA).

The LBA can better account for aging differences and noise between groups and trials as compared to more commonly used models (Goldfarb et al., 2014), but research in this area is still sparse. Findings from decision-making modelling studies show that older adults often exhibit longer non-decision times and adopt more conservative reporting strategies compared to younger adults, possibly due to age-related changes in cognition, like declines in processing speed and working memory capacity (Starns & Ratcliff, 2010). However, with enough training sessions, older adults can match younger adults in accuracy and speed on motion discrimination tasks (Forstmann et al., 2011; Ratcliff et al., 2001, 2006). When learning biases through trial-by-trial experience, older adults were able to increase their speed like younger adults (Fozard et al 1976, Melis et al 2002), and this was shown in greater start point variability (Heathcoate et al 2015). Older adults also demonstrate superior higher- level decision-making skills as compared to younger adults, such as decisions that are relevant to everyday life and that rely on crystallized intelligence, like economic decision-making (Li et al.,2013). It is not yet known how metacognition impacts perceptual decision-making during implicit learning, and a greater understanding may help those with Parkinsons' Disease or other psychiatric illnesses that are associated with impaired metacognitive or decision-making ability (like schizophrenia; Moritz et al., 2014; Rouault et al., 2018).

The focus of this dissertation was to investigate the differences in metacognition and decision-making between base-rate priors that are explicitly known versus when they are implicitly learned through experience, and how these might change during healthy aging. We used two computational models to better elucidate the mechanisms behind learning and decision-making. In Study 1 (Chapter 2), we conducted an experiment on how priors were encoded (implicitly through experience versus explicitly through instruction) impacts decision-making and metacognition. In Study 2 (Chapter 3), we conducted this same experiment but with two age groups: younger and older adults. In Study 3 (Chapter 4), I present preliminary fMRI results on how activation of brain areas varies across participants who learned and applied the priors implicitly. Finally, concluding remarks in Chapter 5 summarize these findings, consider limitations, and suggest future research.

CHAPTER 2

Implicit and explicit encoding of priors on decision-making & metacognition

Introduction

In everyday life, a cloudy sky is often associated with rain, but whether one takes a raincoat out may depend on if rain is likely in the area (e.g., Seattle vs. Los Angeles). In the Bayesian framework of decision-making, these conscious (explicit) or unconscious (implicit) memories of past experiences are called priors. Decisions are not solely influenced by sensory evidence; internal and external factors, such as stimulus probabilities and task demands, can bias decision-making (White & Poldrack, 2014).

Past research indicates that explicit and implicit encoding have differential effects on how people learn priors. People are proficient at frequency detection tasks, which involve learning base- rates through experience, utilizing an implicit and automatic process (Hasher & Zacks, 1984). Experiments that find that base rates are underutilized typically involved explicitly instructing participants with summary statistics of the base rate followed by a test of verbal responses about the probabilities (Spellman, 1984). Holyoak and Spellman (1993) proposed a two-component model for base-rate use. The first component is acquisition, which can be effectively accomplished through implicit learning in a trial-by-trial format. The second component is access, which depends on the type of test and may involve either the implicit or explicit learning system. When both acquisition and the access test tap into implicit knowledge individuals tend to utilize base rates effectively (Bohil & Wismer, 2015). However, when the tasks are verbal and explicit, individuals are more likely to disregard base rates unless they are explicitly reminded to use them.

Many decision confidence frameworks posit that evidence accumulates as an internal decision variable until a decision is made. Explicit and implicit learning of priors might affect this process in different ways. In the decision-making process, it has been proposed that evidence accumulation is a linear process (drift rate). This is influenced by stimulus quality as higher drift rates indicates faster accumulation. Stimuli with high base rates might also have a higher drift rate, as they are easier to recognize due to their frequency (Brown & Heathcote, 2008). Thakur et al. (2021) found that both implicit and explicit learners adjusted the starting point of evidence accumulation in order to implement a general bias. The explicit learners also adjusted drift rate offset in order to implement a stimulus specific bias.

Some posit that the evidence that accumulates in order to make a decision is the same evidence used to determine confidence. This explanation accounts for the strong correlation observed between decision confidence and accuracy, as the evidence, including any noise present in the stimulus, internal representations, and decision process, influences both an individual's choices and their confidence judgments (Baranski & Petrusic, 1994). A person with high metacognitive sensitivity would give higher confidence ratings after correct judgments and lower confidence ratings following wrong judgments. However, assessing metacognitive sensitivity by correlating confidence with accuracy presents a confound between type 1 performance (d') and type 2 response bias; easier tasks produce confidence ratings that better predict accuracy (Fleming & Lau, 2014; Masson & Rotello, 2009). Further, confidence ratings do not always align with task accuracy and can be influenced by other factors like attention and fatigue (Lau & Passingham, 2006; Rahnev, Lau, et al., 2011; Rahnev, Maniscalco, et al., 2011). Metacognitive efficiency is influenced by metacognitive noise, which are fluctuations in metacognitive judgments unrelated to perceptual accuracy (Maniscalco & Lau, 2015). It represents the inherent uncertainty present in metacognitive monitoring and evaluation processes. Various sources can contribute to noise, like changes in arousal and attentional states, previous confidence ratings, and working memory manipulations (Allen et al., 2016; Maniscalco & Lau, 2015; Rahnev, 2021). Changes in stimulus processing or other internal noise may also explain why attentional manipulations can influence metacognition. Attentional manipulations shifted decision and confidence decision boundaries consistent with anticipated reduction in noise commonly observed with heightened attention (Denison et al., 2018); type of encoding could affect attention, as those who are explicitly instructed might be more alert in the task.

In Study 1, we used a perceptual decision-making task in which participants make orientation judgements of dynamic Glass pattern stimuli followed by confidence judgements and audio feedback. The stimuli, unbeknownst to some participants, were biased towards one side more than the other. It is unclear if how the prior is acquired- whether it was explicitly instructed or learned implicitly through experience- affects decision-making and metacognition and thus is the main aim of this study. Understanding metacognitive inefficiencies is important for insights into decision-making as well as treating disorders that are associated with impaired metacognition (Klein et al., 2013; Rouault, Seow, et al., 2018; Stephan et al., 2009).

Methods and Materials

Participants

Data were collected from 159 undergraduate students (18 - 37 years old) at University of California, Los Angeles (UCLA) using a shared pool of psychology research subjects ("SONA") for course credit (Table 2.1 for participant demographics). The experiment was built on PsychoPy and hosted online using Pavlovia (Bridges et al., 2020). Participants were eligible if they met the following requirements: not colorblind, have normal or corrected-to-normal vision, did not have an active medical, neurological, or psychiatric diagnosis and are not taking chronic medications that could affect sensory processing, movement, or cognition. All participants gave informed consent that was approved by the Institutional Review Board of the University of California.

Table 2.1.

Participant descriptive statistics.

	Mean (SD) or % (N=159)
Average age	20.6 (2.9); range:18-37
Gender	128 Female / 1 Non-binary
Race/Ethnicity	47% Asian, 23% White 12% Other, 5% Hispanic 3% Black

Visual Stimuli

Stimuli were two differently-colored dynamic Glass patterns with four difficulty levels manipulated through dot-pair coherences: 0%, 13%, 35%,100% (Glass, 1969). Dynamic glass patterns are 30 frames of translational dot patterns presented at 85 frames/s to simulate dots moving. Each frame contains 150 dots, with a size of 0.1° degree and separated by 0.18° degree. Glass patterns are two identical dot patterns that are super imposed onto one another with one pattern translated in a particular position with respect to the other.

With 100% coherence, all dots are paired so that they are all oriented in the same direction, and thus is the easiest condition. At 0% coherence, the hardest condition, no dots are paired so there is no meaningful sensory information or orientation signal and responses should be at chance. The other two coherence levels represent relatively hard or relatively easy trials (13% and 35% respectively). Positive coherence values mean that the dots are oriented in the "rightward" direction, while negative coherence values mean the dots are oriented in the "leftward" direction. Thus, there are seven coherence levels: -100, -35, -13, 0, 13, 35, 100. In some analyses, just the absolute values of coherences were used in order to represent four difficulty levels.

Behavioral Task

We used the perceptual decision-making task first reported in Perugini et al., (2016) and subsequently Thakur et al. 2021, with the novel addition of a post-decision confidence rating (Figure 2.1). In this two-alternative-forced-choice task, participants judged the direction of the moving dots in the stimulus (rightward or leftward). Bias was introduced by varying the frequency of occurrence of a particular orientation for particular colored stimulus (e.g., red stimuli oriented rightward 75% of the time and green stimuli oriented leftward 75% of the time). Color and the biased orientation direction were counterbalanced, so for Prior condition, we refer to the stimulus biased rightward as "Positive" and the stimulus biased leftward as "Negative". We used a 75%-25% bias for both stimuli. To experimentally manipulate awareness, participants in the "instructed" group were explicitly told about the Bayesian priors ($N_{Instructed}$=41) while those in the "experience" group were not ($N_{Experience}$=32) given this tip and only learned the priors implicitly by trial-by-trial experience.

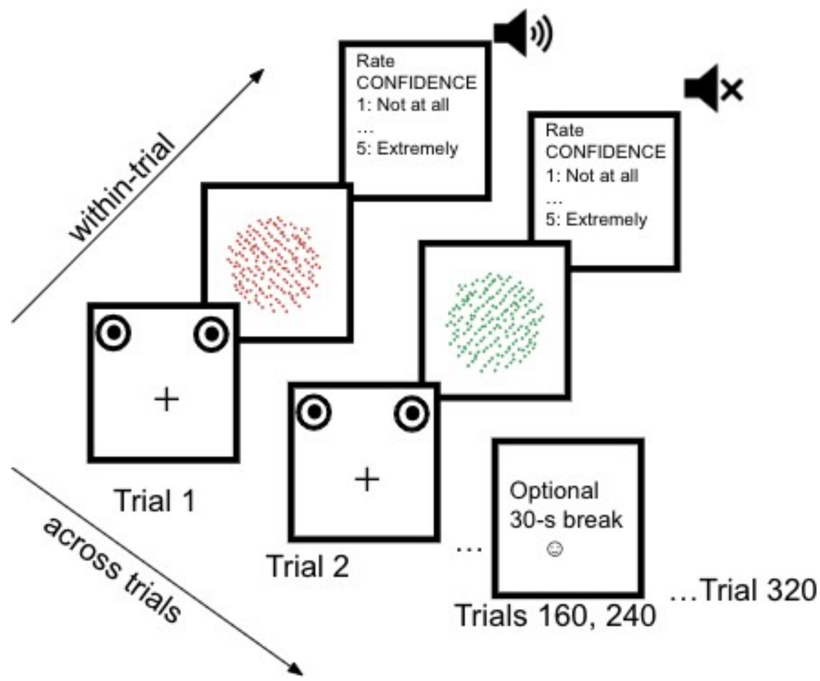

Figure 2.1. Procedure for Study 1 and Study 2. Each trial started with a fixation cross with two targets in the corners. Then, a stimulus appeared and participants made an orientation judgement followed by a confidence rating and audio feedback (if incorrect).

Procedure

After providing informed consent, participants read the instructions: to make an orientation decision as quickly and accurately as they can. For only the "instructed" group, participants were explicitly told the priors in summary form: "Here's a tip: green trials will be going LEFT 75% of the time, while red trials will be going RIGHT 75% of the time". In each trial, a fixation cross quickly flashes on the screen (500ms), followed by a dynamic Glass pattern (either green or red), which is displayed until the participant makes a decision, pressing the "O" key for 'leftward' and the "P" key for 'rightward'. After, participants rated their confidence on a scale from 1 (Not at all confident) to 5 (Extremely confident). Then, audio feedback would play for incorrect trials (no tone followed correct trials). Reaction time, accuracy, and confidence were measured on every trial.

Participants completed 320 trials, comparable to previous research. Half (160) of the trials were red Glass patterns, while the other half were green. There were 40 trials per coherence for each color. To mitigate fatigue effects, participants were given two optional 30-second breaks on trials 160 and 240. After completing the experiment, participants were redirected to Qualtrics where they completed a final questionnaire probing awareness of the biases, distraction during the task, and demographic information. Participants were asked the following multiple choice question (for both colored stimuli): "What was the proportion of left and right orientations of the RED dots? For example, 50/50 means you saw ~half of the red trials go to the LEFT and half go to the RIGHT" And chose between the following choices: 0 L/ 100 R, 25 L/ 75 R, 50 L/ 50 R, 75 L/ 25 R, 100L / 0R, Other: [text entry].

Data Analysis

Data from the last half of the training session was used (160 trials) so that participants in the "experience" condition had a chance to implicitly learn the priors in the first half of the training session. We fit the data to the following logistic function using Quickpsy, an R package that uses bootstrapping to fit psychometric functions to multiple comparison groups (Linares & López- Moliner, 2016).

The proportion of Positive choices was calculated as:

$$prop.\,(Positive\ choice) = \lambda + \frac{1-2*\lambda}{1+\exp\,(-\beta*\mathrm{C}-\alpha))}$$

Where C is dot pair coherence; response bias (α) and sensitivity (β) are determined by the maximum likelihood method. The third and fourth parameters, lapse and guess rate, indicate small lapses of attention that occur during the task (Wichmann & Hill, 2001). They equal the difference between perfect performance and actual performance. We ran this by participant to estimate 4 parameters for each Prior condition (Positive/Negative). To assess quality of model fit, we calculated Akaike information criterion (AIC) values for each participant. One participant was excluded for having an AIC 3 SD above the mean.

Consistent with prior research, we excluded people who were unable to discriminate the visual stimulus with accuracy equal to or greater than 80% for the easiest condition (100% coherence trials). Trials that were less than .2 seconds and longer than 6 seconds were removed from analysis. We also excluded those who failed to complete the experiment or failed attention checks in the post-task questionnaire. After exclusions, 73 participants were included in analyses (63 female).

Linear Ballistic Accumulator

In the Linear Ballistic Accumulator (LBA) model, two independent evidence accumulators "race" towards a response threshold in a linear manner (Brown & Heathcote, 2008). As soon as the evidence reaches a threshold for one option, a response is made. This model is considered a simpler alternative to the DDM and it still accounts for the reaction time distribution shape, speed- accuracy tradeoffs, and relative speed of correct and incorrect responses. There are three parameters of particular interest: evidence accumulation rate (drift rate; v), how much evidence is required before making a decision (threshold; b) and the amount of non-decision time (Ter). Other parameters include the start point distribution noise (A) and between-trial drift rate variability (*s*). Estimating LBA parameters from data involves the search for a set of parameters (e.g., b, A, v, s, and Ter) that produce predictions for accuracy and RT that closely resemble the data.

To implement the LBA, we used the supplementary R code and parameter ranges provided in Donkin et al., 2009,2011 which takes in three main categories of data: difficulty (coherence), correctness, and reaction time (in ms). This is done for each participant, separately for each instruction condition, each Prior condition, and difficulty level (absolute value of coherences). Thus, we obtained 16 parameter estimates, with four drift rates (one per coherence level): b, A, v1, v2, v3, v4, s, and Ter. For 0% coherence trials, proportion of 'biased' choices rather than accuracy was used in the model. This model uses Quantile Maximum Probability Estimation as quantiles are more robust to outliers (Heathcote et al., 2002). For each iteration, the fitter finds the optimal parameters to give the best value for the objective function for a set of data.

<u>H-Meta-D'</u>

We analyzed metacognitive sensitivity and efficiency using a Hierarchical Bayesian Estimation model (H-Meta-D; Fleming, 2017). In Bayesian estimation of cognitive models, prior information is specified in the form of probability distributions over model parameters, and observed data update beliefs to make a posterior distribution. It is 'hierarchical' because multiple instances of a particular parameter (e.g. across different subjects) are estimated in the same model. Estimating meta-d' using hierarchical Bayesian approach is less noisy than calculating it with signal detection theory and is ideal with trial counts are low, as the model takes this uncertainty into account.

First, the model fits the distribution of confidence ratings conditional on whether a decision is correct of incorrect. For each confidence level, the conditional probability P(confidence =y | accuracy) is calculated and makes up the type 2 ROC curve when plotted. Data was split by coherence level (absolute value). Coherence levels did not need to be negative or positive as calculating the conditional probability takes orientation into account; e.g., when the stimulus was rightward, counts of confidence ratings when correct (e.g., participant responds rightward) and incorrect (e.g., participant responds leftward) were used. In the single subject estimation of meta- d', there are $(k-1)\times 2$ confidence criteria, where k is the number of confidence ratings available (k=5). These criteria are response-conditional, for S1 (positive or 'rightward') stimuli and S2 (negative or 'leftward') stimuli.

The model gives estimates for meta-d' (metacognitive sensitivity) and M-ratio metacognitive efficiency). Meta-d', is a measure within signal detection theory for metacognitive sensitivity which is the expected value of type 1 performance (d') that would have given rise to the observed confidence rating data if an ideal observer had d' = meta-d' (Maniscalco and Lau , 2012). For a measure that is independent of task performance, meta-d' is compared to d' either as a ratio (meta-d'/d') or subtraction (meta-d'-d'; Fleming & Lau, 2014). Meta-d' was calculated using the maximum likelihood method for obtaining single subject parameter estimates. To calculate M-ratio, the model specified group-level prior densities over each of the subject-level parameters using MCMC sampling to estimate the joint posterior distribution of all model parameters given the data. An M-ratio value of 1 is considered metacognitively "ideal"; less than this indicates metacognitive inefficiencies. If under a time pressure or attentional constraint, participants might make hasty mistakes and be acutely aware of them, resulting in an M-ratio greater than 1 (Charles et al., 2013).

Results

The results are divided into two major sections. First, I compare between prior instruction conditions (implicit “experienced” versus explicit “instructed”) to examine how dot-pair coherence and prior condition impacts learning and usage of biases, accuracy, reaction time and confidence. LBA and H-Meta-D’ parameter estimates are presented. In the second section, I present exploratory analyses solely on “implicit” group and examine differences between those who explicitly learned the priors by the end of the experiment and those who did not as evidenced by their responses in the post-task questionnaire.

“Implicit” versus “Explicit” Instruction Groups

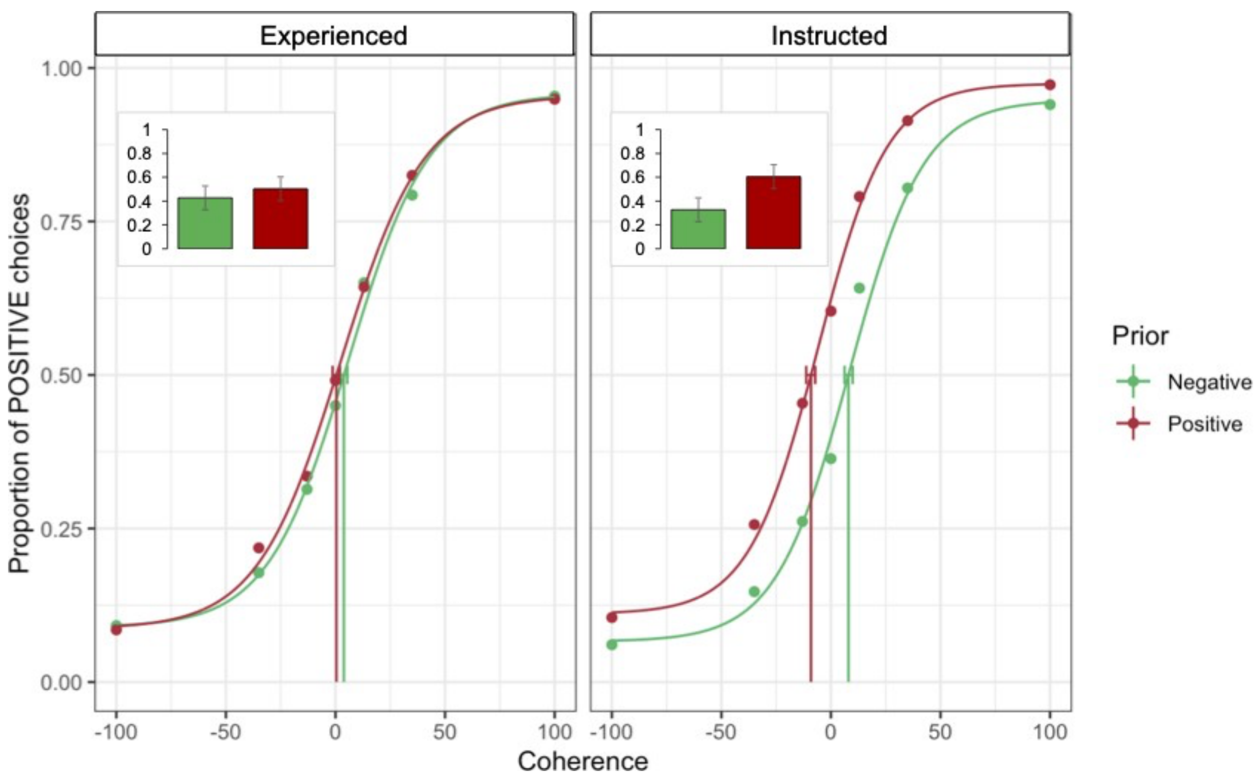

Figure 2.2: Psychometric Curves between instruction groups. On the X-axis, positive dot-pair coherences are the varying difficulties of rightward trials while negative coherences correspond to varying difficulties in leftward trials. On the y-axis, the proportion of Positive, or

rightward, choices the participants made for each of these stimuli. The inset bar graph shows the difference between priors only at 0% coherence (threshold).

Bias

A 2 instruction group x 2 prior repeated measures ANOVA was performed on all four estimated parameters, but two were of interest (α,β). There was a significant main effect of prior on estimated response bias (α ($F(1,71)= 6.18$, $p=.015$) in which response bias was lower for the negative prior (M= -1.50) versus the positive prior (M=1.07). A significant interaction between prior and instruction groups ($F(1,71)=4.55$, $p=.036$) indicated the effect of prior on response bias was larger for the explicit group ($p= .003$) as compared to the implicit group ($p=.78$) (Fig. 2.2).There were no significant differences between instruction groups or prior on sensitivity (β), indicating similar sensitivity despite different levels of awareness. There were no significant differences for the "guess" ($p=.057$) and "lapse" boundary parameters ($p=.09$).

Trials with 0% dot pair coherence contain no meaningful orientation information and participants should choose 'left' and 'right' at chance (50%), regardless of the color of the stimulus. For the implicit group, a paired samples t-test showed that 'rightward', or Positive, choices significantly differed between the Negative prior (43%) and Positive prior (51%) at 0% coherence, indicating that this group implicitly learned and applied the bias ($t_{Negative}(41) = 17.50$, $p <.001$; $t_{Positive}(41)= 20.40$, $p<.001$). A paired samples t-test also shows that these priors are significantly different from one another ($t(41)= -2.76$, $p=.0085$;Fig.2.2 inset). Explicitly instructed participants chose 'right' for 61% of Positive prior trials, compared to 33% of Negative trials (Fig.2.2 inset). Choice behavior is significantly different from chance performance for both the Negative and Positive prior ($t(30)= 8.45$, $p < .001$; $t(30)= 18.91$, p

<.001). A paired samples t-test also shows that the Negative and Positive priors are significantly different from one another, demonstrating how these participants learned and applied the prior (t(30)= - 5.47, p<.001).

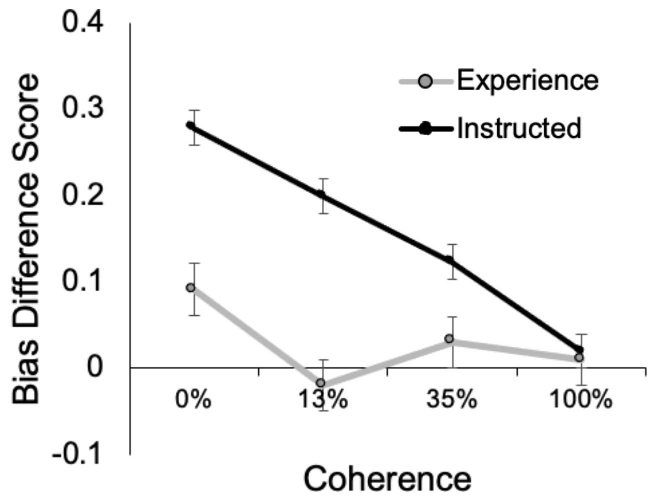

Figure 2.3 Bias Difference Score for both instruction groups. Bias Difference = proportion (Positive) choices for Positive stimulus – proportion (Positive) choices for Negative stimulus for each coherence level. Positive and negative coherences were averaged together.

A 2 (instruction group) x 4 (coherence) repeated measures ANOVA was performed on bias difference scores. To calculate the bias difference score, we subtracted the proportion of positive choices for the Positive stimulus minus the proportion of positive choices for the Negative stimulus at each coherence level. A significant main effect of coherence showed that participants used the bias less for stimuli with higher coherences ($F(3,213) = 13.06$, p <.001) (Fig 2.3). There was also a significant main effect of instruction group ($F(1,71) = 15.45$,p <.001) qualified by an interaction between coherence and instruction group ($F(3,213) = 5.41$, p =

.0013); the explicit group applied the bias more as compared to the implicit group, particularly when sensory information was poor (at 0% and 13% coherence; p's <=.001). The implicit group applied the bias but without regard to coherence; however, interpretation is difficult due to a floor effect.

Performance

A 2 (instruction group) x 3 (coherence) repeated measures ANOVA was performed on motion discrimination accuracy; a significant main effect of coherence showed that participants were more accurate as dot-pair coherence increased, as expected [M13% = 71%; M35% = 86%; M100%= 96%] ($F(2,142) = 198.23$, $p < .001$). There was no significant main effect of instruction group- the implicit and explicit groups were similarly accurate [M Explicit = 86%, M Implicit = 83%] ($F(1,71) = 1.82$, $p = .18$).

A 2 (instruction group) x 4 (coherence) repeated measures ANOVA was performed on reaction time (RT); a significant main effect of coherence indicated that participants were faster for easier, higher coherences [M0% = 2.09 s; M13% = 1.80 s; M35% = 1.49 s; M100%= 1.12 s] ($F(3, 213) = 91.52$, $p < .001$). There was no significant main effect of instruction group, the implicit and explicit groups did not differ in RT ($F(1, 71) = 0.11$, $p = .75$).

Confidence

A 2 (instruction group) x 4 (coherence) x 2 (prior-consistency) repeated measures ANOVA was performed on average confidence ratings of correct judgments (Fig 2.4); a significant main effect of coherence showed that confidence ratings were higher for high-coherence stimuli $F (3,210) = 125.52$, $p < .001$. There was a significant interaction between prior-consistent decisions and instruction group (F (1,210) = 11.00, p<.001) and a three-way interaction between prior-consistency, coherence, and instruction group (F(3,210) = 4.54, p=.004) on average confidence ratings. In the explicit group, participants were more confident for prior-consistent versus prior-inconsistent decisions (MC= 3.47 , SEC= .11MI= 3.32 , SEI = .11; p = .001), particularly when sensory information was poor (p0%=.01, p13%=.006). In the implicit group, confidence was not impacted by whether a decision was prior-consistent (MC= 3.57 , SEC = .12) or inconsistent (MI= 3.62 , SEI = .12; p =.19).

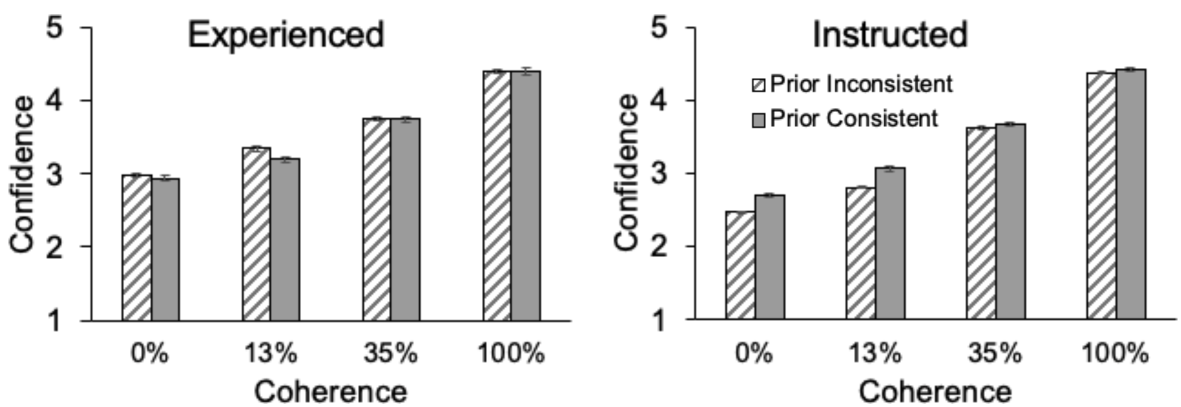

Figure 2.4: Average confidence ratings. Correct answers only. For prior-consistent (solid bars) vs. prior-inconsistent (striped bars) stimuli; all trials included for 0% coherence level.

Linear Ballistic Accumulator Model

A 2 (instruction group) x 4 (coherence) x 2 (prior) repeated measures ANOVA was performed on drift rate estimates (Table 2.2). A significant main effect of coherence showed that drift rate increased as dot-pair coherence increased as hypothesized (F(3,204)= 118.57, p<.001). There was an interaction between prior and instruction group (F(1,204)=5.34, p=.02) and a 3-way interaction between prior, instruction, and coherence on drift rate (F(3,204)= 6.48, p<.001).

In the explicit group, drift rates for the Negative prior were larger than those for the Positive prior(p =.017). However in the implicit group, drift rate estimates between the Negative and Positive prior only differed for 0% coherence (MPositive = .48, MNegative = .54, p=.04) and 100% coherence trials (MPositive = 1.22, MNegative = 1.09, p=.02). For the other parameters, 2 (instruction group) x 2 (prior) repeated measures ANOVAs revealed no significant effects.

Table 2.2.

Estimated parameters from LBA model

	Implicit		Explicit	
	Negative Prior	Positive Prior	Negative Prior	Positive Prior
s	0.35	0.36	0.39	0.39
A	1.42	1.36	1.28	1.31
Ter	0.09	0.08	0.09	0.05
b	0.74	0.80	0.79	0.76
$v_{0\%}$	0.54	0.48	0.62	0.59
$v_{13\%}$	0.65	0.63	0.70	0.64
$v_{35\%}$	0.84	0.88	0.90	0.80
$v_{100\%}$	1.10	1.22	1.22	1.04

*Note***.**Variables are : s (drift rate variability), A (start point noise), Ter(nondecision time), b (response threshold), v0% , v13%, v35%, v100% (drift rate estimates per coherence).

H-Meta D' Model

Figure 2.5.A presents the average d' for both instruction groups at each coherence level (absolute value). There was a significant main effect of coherence, such that d' was significantly higher for stimuli with high dot pair coherence than low dot pair coherences, F (2,142) = 284.07, p< .001. Instruction group did not significantly impact performance F (1,71) = 2.40, p=.12.

Those

who were explicitly instructed of the priors did not differ from (Minstructed = 2.30, SE = .12) those who experienced the priors (Mexperience = 2.02, SE = .12). Similarly for meta-d' and M-ratio, the only significant main effect was of coherence (Figure 2.4B/C); both meta-d' and Mratio values were significantly higher for stimuli with high dot pair coherence than low dot pair coherences, Fmeta-d (2,142) =160.20, $p< .001$; F Mratio (2,142) =104.13, $p< .001$. Neither metacognitive sensitivity (Minstructed = 1.92, Mexperience =1.67, SE = .13) F (1,71) = 1.63 p=.21. nor metacognitive efficiency (Minstructed =.74, Mexperience =.71, SE = .02) F (1,71) = .35, p=.56. differed between instruction groups.

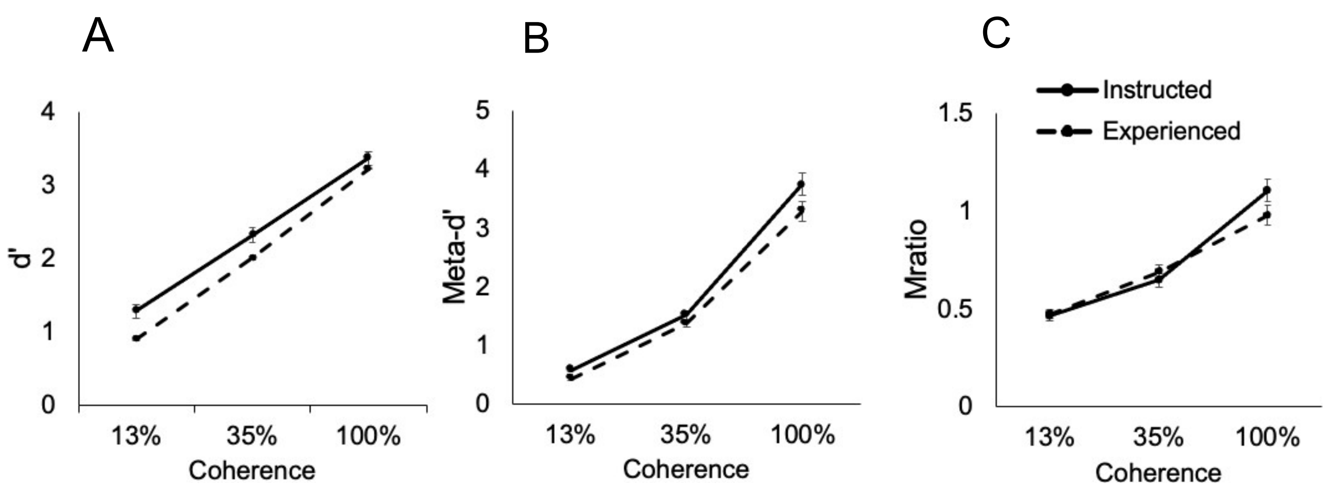

Figure 2.5: Performance and metacognitive measures using HMeta-D: Both groups: instructed (solid lines) and experienced (dashed lines). A) d' is type 1 performance in orientation discrimination task. B) Meta-d' is estimated metacognitive sensitivity C) M-ratio is a relative measure of metacognitive efficiency and is found by dividing meta-d' by d'.

"Experience" awareness analysis

Of the participants in the "experience" instruction group, most did not notice anything about base rates (nimplicit=28) and by the end of training a minority only noticed partial information (nlearned=14), despite showing sensitivity to the prior in decision-making. As a secondary and exploratory analysis, we investigated differences between these two groups with repeated measures ANOVAs on accuracy, reaction time, and average confidence ratings (Table 2.3).

Table 2.3.

Performance measures for "experience" participants with different awareness levels

	Implicit (n=28)			**Learned** (n=14)		
Coherence	**Accuracy**	**RT**	**Confidence**	**Accuracy**	**RT**	**Confidence**
0%	-	1.86 (.80)	3.03 (.18)	-	2.41 (.91)	2.81 (.24)
13%	.66 (.13)	1.73 (.82)	3.22 (.17)	.78 (.14)	1.92 (.59)	3.37 (.23)
35%	.81 (.14)	1.49 (.72)	3.60 (.18)	.90 (.11)	1.47 (.60)	4.05 (.24)
100%	.95 (.07)	1.14 (.49)	4.19 (.16)	.97 (.04)	1.07 (.28)	4.83 (.14)

Note. Standard deviations in parentheses.

Participants were faster ($F(3, 213) = 61.98$, p <.001) and more accurate ($F(2,80) = 93.18$, p <.001) as dot-pair coherence increased. Significant interactions between coherence and prior awareness for both accuracy and reaction time qualified these main effects. Those who learned the priors were more accurate as compared to fully implicit participants [MLearn= 88%, MImplicit=80%] ($F(1,40) = 6.21$, $p = .017$) except for the easiest trials (100% coherence, $p=0.22$). In the absence of any meaningful sensory information (0% coherence), those who learned the priors were slower (MLearn = 2.41 s) as compared to fully implicit participants (MImplicit =1.85 s ; $p=.04$) ($F(3, 120) = 6.40$, $p < .001$).Higher confidence ratings were given to stimuli with higher dot pair coherences $F(3,120) = 63.59$ $p < .001$). There was also a significant interaction between coherence and awareness such that for the easiest trials(100% coherence; $p=.015$), those who learned the priors were more confident compared to the fully implicit group ($F(3,120)=4.79$, $p=.003$).

Discussion

In this study, we used a perceptual decision-making task with stimulus-specific base-rate priors to investigate how explicit instruction of priors differs from learning them implicitly through experience and how that impacts metacognition. Consistent with past findings, we found that both groups learned the priors implicitly and used them when no orientation information was available. Thakur et al 2021 found that both implicit and explicit learners adjusted the starting point of evidence accumulation in order to implement a general bias. The explicit learners also adjusted drift rate offset in order to implement a stimulus specific bias. We found a similar effect in that participants in the explicit group showed a widening difference in drift rates between priors as coherence increased. We did not find that either instruction group adjusted the starting point of evidence accumulation, however this task did not have a general bias.

Those who learned the priors through experience and those who were explicitly instructed of them both showed a difference in “rightward” choices based on the color of the stimulus when no meaningful sensory information was shown. There was no effect of instruction group on RT or accuracy, so being told the prior did not result in a speed-accuracy tradeoff. Those who were instructed of the Bayesian priors used them more, particularly at low coherences, as compared to those who experienced them. Priors were not as influential when stimuli information was more robust.

Past research paradoxically shows that people are bad at using base-rates but good at frequency detection tasks (Christensen-Szalanski & Beach, 1982). When base-rates were presented explicitly in summary statistic form, participants did not use them as well (or as quickly) as those who learned them through experience; when implicit learning occurs through extensive trial exposure in frequency detection tasks, implicit testing is considered the most suitable method to assess this learning (Reber, 1993). However, people improve use of base-rates when a causal framework or cover story is given (Spellman, 1996). In the current study, the task focused on frequency detection of low-level perceptual features (orientation, color) and is not as ecologically valid as other frequency detection tasks, like the Weather Prediction Task, or a task in which symptoms are associated with diseases occurring at different frequencies (Gluck & Bower, 1988).The explicit information about base rates provided to the "instructed" group may have facilitated a better causal framework for the task, enabling them to track frequencies and their relation to stimulus color. This framework might have enhanced the confidence of the explicit group specifically for decisions consistent with the prior. Notably, this confidence boost was most pronounced when meaningful sensory information was limited or absent, even though participants were essentially guessing. Conversely, the confidence of participants who only experienced the priors was not affected by prior-consistency. Furthermore, explicit instruction of the priors did not improve metacognition, as both instruction groups exhibited similar metacognitive efficiency. For both perceptual and cognitive decisions, confidence often shows a confirmation bias in that evidence that is ‘decision-congruent’- giving higher confidence judgements despite a lack of difference in accuracy (Michel & Peters, 2020; Koizumi et al., 2015; Maniscalco et al., 2016; Miyoshi & Lau, 2020; Samaha et al., 2016; Zylberberg et al., 2012). It is theorized that metacognitive sensitivity, but not metacognitive efficiency, should increase as task difficulty decreases, but there is only sparse empirical evidence and thus more research is needed (Fleming and Lau 2014, Shekar & Rahnev, 2021).

Overall, these results shed light on the differential effects of explicit instruction versus implicit learning on the use of base-rate priors and metacognitive processes in a perceptual decision-making task. While explicit instruction enhanced the usage of priors, especially under conditions of poor sensory information, it did not lead to improved accuracy, reaction time, or metacognition. For the “instructed” group, biased decision-making was driven by significantly different drift rates per prior. In Study 2, older and younger adults perform the same task with different prior conditions: an “Equally” biased prior and a “Positive” biased prior, resulting in a general bias (e.g., over the whole experiment, there will be more “rightward” trials overall).

CHAPTER 3

Implicit and explicit influences of bias on decision-making and confidence in healthy aging

Introduction

Healthy aging is often perhaps paradoxically associated with deteriorating perceptual abilities and increased decision-making abilities. While older adults show delays in sensory encoding, motor initiation, and execution in various tasks (Roger Ratcliff et al., 2004; Walker et al., 1997), they also show superior crystallized knowledge and better economic decision-making compared to younger adults (Li et al., 2013). There are two competing theories regarding the effects of aging on metacognition. One theory suggests that greater life experience leads to more accurate self-knowledge and higher metacognitive efficiency. This theory is based on the idea that older adults have accumulated a wealth of knowledge and wisdom over time. Some studies have found stable or even improved accuracy of confidence ratings and judgements of learning with age, particularly in tasks related to general knowledge, problem-solving.

However, another theory proposes that aging-related atrophy in the prefrontal and parietal cortex, regions associated with metacognitive efficiency, may result in a decline in metacognitive abilities. The neural correlates of metacognitive judgments have been found to differ between younger and older adults. The Global Slowing Hypothesis postulates that the older adults are impaired in many different tasks because of an age- related slowing of information processing due to an increase in neural noise (Salthouse, 1996). Computational modelling studies support this in that increased internal noise best matched older adults' performance in motion discrimination tasks (Bennett et al., 2007). It's also possible that age-related latency differences are partially due to older adults being more cautious in general, as many report valuing accuracy over speed and requiring more evidence to make a decision (Ratcliff et al., 2001,2006 Dutilh et al., 2013). Older adults are also more likely to stick with their response thresholds despite task changes, while younger adults were able to flexible adjust thresholds on a trial-by-trial basis (Karayanidis et al., 2011). One challenge in studying age-related changes in metacognition is disentangling metacognitive accuracy from age-related changes in task performance. Common measures of metacognitive accuracy can be influenced by task performance, making it difficult to isolate the effects of age on metacognition. For instance, older adults may exhibit lower accuracy in predicting item recognition, but this may be attributed to age- related memory deficits rather than deficits in metacognition itself. In light of this, we use a metacognitive measure relative of task performance (M-ratio) to compare age groups.

In Study 2, we used a perceptual decision-making task first introduced in Perugini et al., (2016) in which younger and older adults make orientation judgements of Glass pattern stimuli followed by confidence judgements and feedback. The stimuli, unbeknownst to participants, were biased towards one side more than the other. In the current study, one Prior was "Positive biased" while the other color Prior was "Equal", meaning that it was not biased towards any particular orientation. It is unclear how the explicit versus implicit knowledge of base rate priors impacts decision making and metacognition in younger and older adults and thus is the main aim of this study.

We predicted that in line with previous work, young adults would be faster and more accurate as compared to older adults (Forstmann et al., 2011). Both older and younger adults will implicitly learn the biases and implement them when sensory evidence is unclear, though how that occurs may differ across age. We hypothesized that older adults would show more conservative reporting strategies (wider decision boundaries) and longer non-decision time as compared to younger adults (Ratcliff et al., 2001,2006). Regardless of age, we might find that implicit learners tend to alter decision boundaries while explicit learners demonstrate differences in drift rates (Thakur et al., 2021).

Methods and Materials

Participants

Data were collected from 56 older adults on Prolific and from 78 younger adults on Prolific and SONA (See Table 3.1 for participant demographics). The eligibility criteria, exclusion criteria and between-subjects instruction manipulation remained the same as Study 1. Participants in the “explicit” group were given summary statistic information about the Bayesian priors before the experiment (NYounger=26, NOlder=29) while those in the “implicit” group were not given this information and had to learn the priors through trial- by-trial experience (NYounger =52, NOlder =27). In the post-task questionnaire, some participants in the “implicit” group showed partial or full knowledge of the priors (NYounger =26, NOlder =11), while others demonstrated no explicit knowledge of the priors and thus were fully implicit learners (NYounger =26, NOlder =26).

Table 3.1

Participant descriptive statistics

	Younger Adults	**Older Adults**
Age (years)	22 (4.2); range (18-35)	67.5 (8.3); range (60-82)
Gender	66% Female, 31% Male 3% Non-binary	54% Female, 46% Male
Race/Ethnicity	95% White, 2% Asian, 2% Other, 1% Black	36% Asian, 31% White 24% Hispanic, 7% Other, 2% Black

Note. Mean and SD in parentheses. N=134.

Stimuli

The stimuli remained the same as Study 1 except for the levels in prior condition. In the current study, one colored stimulus was biased to a particular side (e.g., red stimuli oriented rightward 75% of the time), while the other colored stimulus was not biased towards any side (e.g., green stimulus oriented rightward 50% of the time). Color and the biased orientation direction were counterbalanced, so we refer to the stimulus biased rightward as "Positive" and the unbiased stimulus as "Equal".

Data Analyses

These analyses are largely similar to those in Study 1 with a few exceptions, like the Prior conditions (Positive/Equal) and the addition of the between-subjects age group variable. In Study 1, since both stimuli had the same but opposite priors, we used absolute value of coherence by averaging together the negative and positive coherence values. In the current study, we used seven levels of coherence in analyses to account for direction. In the H-Meta- d' model, only Positive prior trials were counted in this analysis.

Results

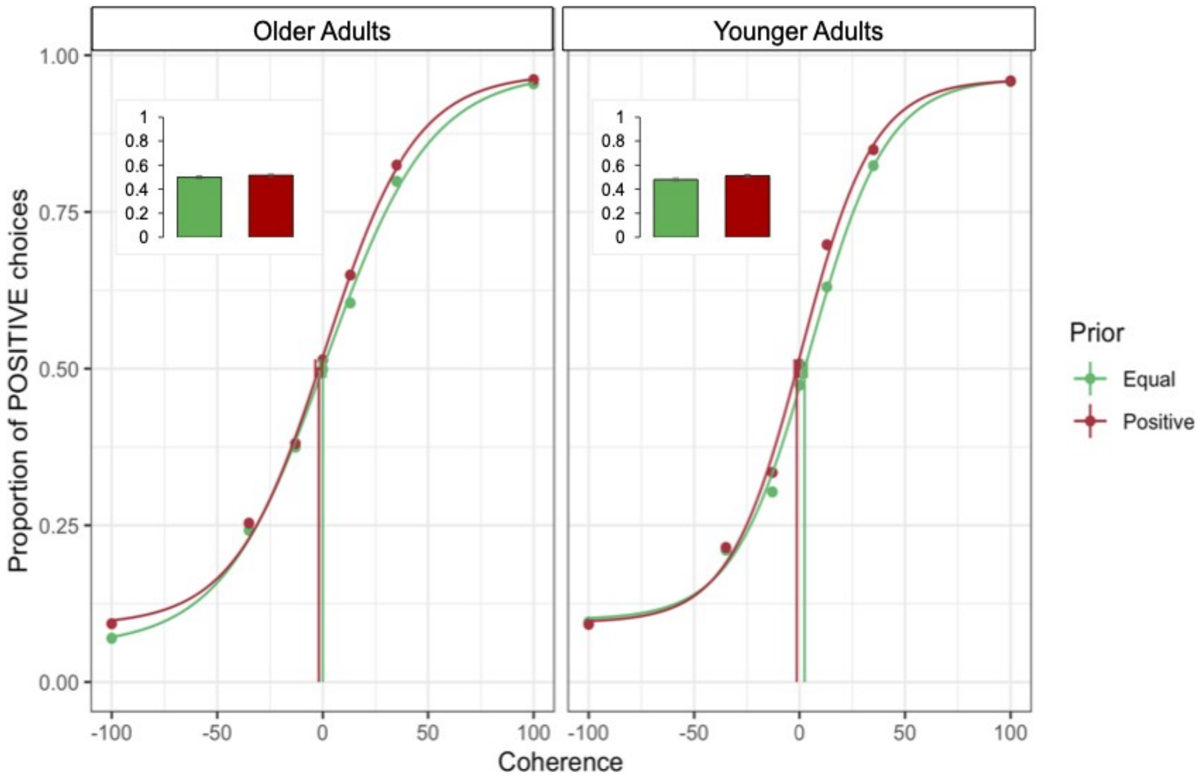

Figure 3.1. Psychometric Curves by age group. On the X-axis, positive dot-pair coherences are the varying difficulties of rightward trials while negative coherences correspond to varying difficulties in leftward trials. On the y-axis, the proportion of Positive, or rightward, choices the participants made for each of these stimuli. The inset bar graph shows the difference between priors only at 0% coherence.

Bias

There was a significant main effect of prior condition on estimated response bias (α) ($F(1,128) = 4.88$, $p=.028$) in which response bias was lower for the equal prior (M= -1.23) versus the positive prior (M=.048) (Fig 3.1). All other main effects and interactions were not significant. There were also no significant differences between age groups or prior on sensitivity (β).

In a 2 (prior) x 2 (age group) x 2 (instruction group) repeated measures ANOVA on proportion of "positive" choices in the absence of any sensory information (0% coherence), the main effect of prior almost reached significance (p=.06), all other effects were not significant. A paired samples t-test revealed that proportion of "positive" choices was significantly higher for the Positive prior as compared to the Equal prior (MEqual=.49, MPositive=.52, SE=.015; t(133)=-2.08, p= .039).

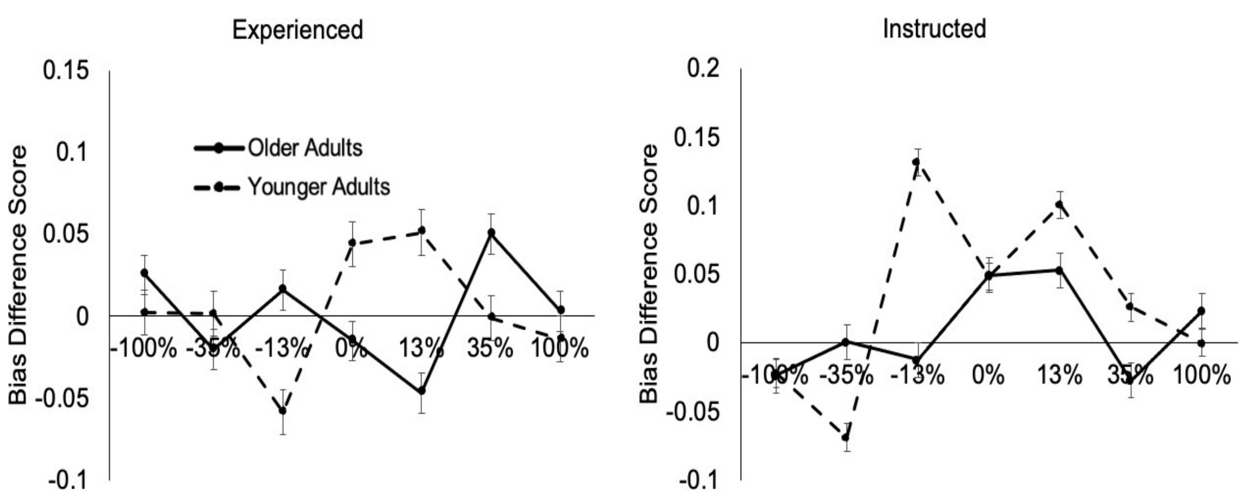

Figure 3.2 Bias Difference Score: To calculate the bias difference, we subtracted the proportion of positive choices for the Positive stimulus minus the proportion of positive choices for the Equal stimulus at each coherence level. Older adults (solid lines) and younger adults (dashed lines) are compared for each instruction condition.

For each instruction condition, we ran a 2 (age group) x 7 (coherence levels) repeated measures ANOVA on bias difference score. For the implicit group, there was an interaction between age group and coherence $F(6,444)=2.11$, $p=.05$ (Fig 3.2). Younger adults applied the bias differently for different coherence strengths ($p=.03$), while coherence did not affect older adults use of the bias ($p=.58$). Similarly for the explicit group, we found a significant main effect of coherence ($p=.003$) and an interaction with age group $F(6,318)=2.22$, $p=.04$ – younger adults applied the bias differently depending on coherence ($p<.001$), while coherence did not impact how older adults applied the bias ($p=.33$).

Performance

For the implicit group, there was a significant main effect of coherence on accuracy, such that participants were more accurate with higher coherences as compared to lower coherences ($F(2,154) = 257.92$, $p <.001$; Table 3.2). There was an interaction between age group and coherence $F(2,154)= 3.41$, $p=.03$, as well as a three-way interaction with prior $F(2,154)=4.81$, $p=.009$; on the hardest trials (13% coherence), older adults were slightly more accurate for Equal prior versus Positive prior trials (MEqual= .66 MPositive= .60 , SEC = .01; $p=.04$), but there were no differences in prior for the other coherences or age group.

For the explicit group, there were three significant main effects of coherence ($p <.001$), prior ($p <.001$), and age group ($p=.043$); participants were more accurate as dot-pair coherence increased and on Positive vs. Equal prior trials (MPositive=.83, MEqual=.79). Younger adults were more accurate as compared to older adults (MYounger=.84, MOlder =.79). There was also a three-way interaction between coherence, prior, age group ($F(2,106)=4.47$, $p=.01$); for both easy and difficult trials, older adults were more accurate with the Positive versus the Equal prior (MPositive=.66, MEqual=.60; 13% p=.001; MPositive=.96, MEqual=.93; 100% p=.006). In contrast, younger adults were more accurate with the Positive prior versus the Equal prior on the moderately easy trials (MPositive=.88, MEqual=.83; 35% p=.006).

Table 3.2.

Mean accuracy, separated by coherence, instruction and age groups.

Coherence	***Experienced***		***Instructed***	
	Older Adults	*Younger Adults*	*Older Adults*	*Younger Adults*
13%	.64 (.07)	.69 (.14)	.63 (.10)	.65 (.14)
35%	.82 (.12)	.83 (.15)	.78 (.12)	.83 (.13)
100%	.97 (.05)	.96 (.06)	.95 (.06)	.95 (.08)

For participants who "experienced" the priors, there were main effects of coherence (p<.001) and age group (p=.003) qualified by an interaction; younger adults were faster than older adults (MYounger= 1.79, MOlder=2.45), however only for moderately easy trials (35% coherence, p=.04) $F(3,231)=3.92$, p=.009. For the explicit group, there were significant main effects of coherence (p<.001), prior (p<.001), and age group (p<.001); younger adults were faster than older adults (MYounger= 1.56, MOlder=2.25), and reaction time decreased as coherence increased. Participants were faster with the Positive (M=1.87) versus Equal prior (M=1.95).

Table 3.3.

Mean reaction time, separated by coherence, instruction and age groups.

Coherence	***Experienced***		***Instructed***	
	Older Adults	*Younger Adults*	*Older Adults*	*Younger Adults*
0%	2.96 (2.61)	2.35 (2.05)	2.65 (2.33)	1.97 (1.70)
13%	2.85 (2.50)	2.03 (1.73)	2.52 (2.20)	1.76 (1.49)
35%	2.44 (2.09)	1.55 (1.25)	2.16 (1.84)	1.41 (1.14)
100%	1.54 (1.20)	1.23 (0.93)	1.61 (1.30)	1.05 (0.78)

<u>Confidence</u>

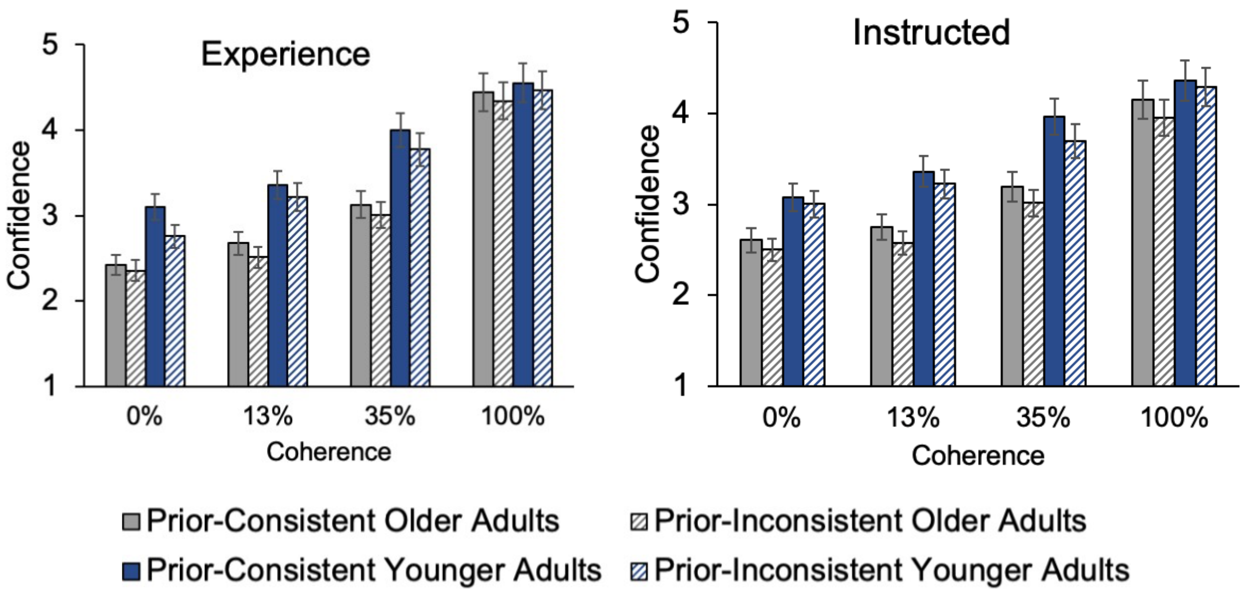

Figure 3.3: Mean confidence (correct answers only). Older adults are in gray, younger adults are in dark blue. Solid bars represent prior-consistent stimuli whereas dashed bars represent prior- inconsistent stimuli.

For the implicit "experience" group, there were main effects of coherence and prior-consistency (p's <.001) in which higher coherences were associated with higher confidence ratings, as well as when the stimulus was consistent with the prior (biased rightward) as opposed to inconsistent with the prior (leftward). There was an interaction between coherence and age group F (3,195) = 4.78, *p*=.0003 in which younger adults were more confident as compared to older adults for all but the easiest trials (100% coherence: *p*= 0.47).

Similarly for the "instructed" group, we found significant main effects of coherence and prior-consistency (p's <.001) on confidence, as well as a main effect of prior (*p*=.04). This was qualified by two interactions- one between prior and age group F (1,117) = 5.59, *p*=.02 in which younger adults were more confident for the Positive vs the Equal prior (MPositive = 3.60, MEqual=3.46, SE=.19, *p*=.003), but older adults' confidence was not impacted by the prior (MPositive = 3.09, MEqual =3.10, SE=.24, *p*=.85). An interaction between prior and prior-consistency *F(*1,117)= 5.39, *p*=.02 reveals that for prior-inconsistent stimuli, participants were more confident with Positive prior versus the Equal prior (MPositive =3.26,MEqual = 3.14, SE=.16; *p*=.008). However there were no differences in confidence between prior condition when stimuli were prior-consistent (MPositive =3.37, MEqual = 3.37, *p*=.94).

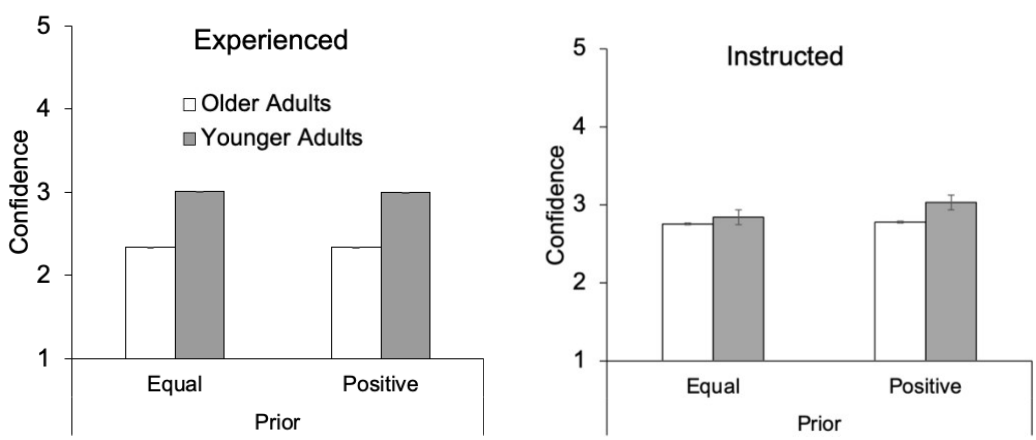

Figure 3.4 Mean confidence for 0% coherence trials. Separated prior condition, instruction, and age groups (older adults are white, younger adults are gray).

We analyzed 0% coherence trials separately for each instruction group with a 2 (age group) x 2 (Prior) repeated measures ANOVA. For the implicit group, there was a significant main effect of age ($F(1,77)=8.61, p=.004$) in which older adults were underconfident (M=2.44, SE= .15) as compared to younger adults (M=3.11, SE= .15). For the "instructed" group, there was a main effect of prior ($p=.004$) qualified by an interaction between prior and age group $F(1,53)=5.41$, $p=.02$. Younger adults were more confident for the Positive prior (vs. Equal Prior) on trials with no orientation information ($p=.003$), while older adults' confidence was not affected by Prior condition ($p=.59$, Fig. 3.3).

Linear Ballistic Accumulator Model

Table 3.4.

Estimated parameters from LBA model

	Older Adults		**Younger Adults**	
	Equal	*Positive*	*Equal*	*Positive*
s	0.21	0.24	0.38	0.44
A	1.38	1.21	1.05	0.80
Ter	0.25	0.14	0.16	0.16
b	1.03	1.05	0.74	0.93
$v_{0\%}$	0.49	0.50	0.48	0.49
$v_{13\%}$	0.57	0.59	0.68	0.77
$v_{35\%}$	0.70	0.77	0.94	1.12
$v_{100\%}$	1.31	1.22	1.34	1.60

*Note***.**Variables are : s (drift rate variability), A (start point noise), Ter(nondecision time), b (response threshold), v0% , v13%, v35%, v100% (drift rate estimates per coherence).

Starting point noise, A, was smaller for the Positive prior versus the Equal prior ($F(1,130)=9.20$, $p=.003$) and for younger adults versus older adults ($F(1,130)=6.32$, $p=.01$). For response threshold (b) , there were main effects of prior ($F(1,130)=7.13$, $p=.009$) and age group

($F(1,130)=5.70$, $p=.02$). The response threshold was higher for the Positive versus Equal prior and this was driven by the younger adults. An interaction indicated that the prior ($F(1,130)=5.63$, $p=.02$) affected younger adults ($p=.002$) but not older adults threshold setting ($p=.76$). Nondecision time (Ter) was bigger for the "Equal" versus "Positive" prior ($F(1,130)=4.35$, $p=.04$). This was driven primarily by the older adults ($p=.057$).

For drift rates, a significant main effect of coherence was found as hypothesized ($F(3,390)= 112.79$, $p<.001$). Participants had better accumulation rates as for the Positive prior (M=.89) versus the Equal one (M=.82)($F(1,390)= 4.88$, $p=.028$). Younger adults showed better accumulation rates (M=.95) as compared to older adults (M=.77) ($F(1,130)= 8.05$, $p=.008$). There was an interaction between prior and age group ($F(1,130)=4.68$, $p=.028$) and simple effects showed that the prior was significant for younger adults ($p =.007$) versus older adults ($p=.96$). There was an interaction between coherence and age group ($F(3,390)=3.14$, $p=.025$) and simple effects showed that the effect of age was significant for trials with some ambiguity (13%, 35%), but not for the easiest or hardest trials (100%, 0%). There was also a 3-way interaction between coherence, instruction group, and age group on drift rate ($F(3,390)= 2.67$, $p=.047$). The effect of age was significant for those in the "instructed" group for all but the hardest trials (0% coherence, $p=.95$). For those in the "experience" group, the effect of age was significant for trials with some ambiguity (13%,35%). There was another 3-way interaction between coherence, prior, and age group on drift rate ($F(3,390)= 4.14$, $p=.007$). Simple main effects show that the effect of prior for younger adults is significant for all but the hardest trials ($p=.90$); for older adults, the effect of prior is only observed at 35% coherence trials.

<u>HMeta D' Model</u>

A repeated measures ANOVA revealed a significant main effect of coherence, such that d' was significantly higher for stimuli with high dot pair coherence than low dot-pair coherences, $F(2,260) = 396.63$, $p < .001$. There was a significant interaction between coherence, age group, and instruction group $F(2,260) = 5.33$, $p = .005$. In the "experienced" group, both age groups performed similarly except for the hardest trials in which the younger adults showed better sensitivity ($p = .025$). In the "instructed" group, the younger adults showed better sensitivity than older adults for moderately ambiguous stimuli (35%) ($p = .024$), but not the other stimuli (Fig 3.5A). Figure 3.5B presents the average estimated Meta-d' for both instruction groups at each coherence level. A repeated measures ANOVA revealed a significant main effect of coherence, such that Meta-d' was significantly higher for stimuli with high dot pair coherence than low dot pair coherences, $F(2,260) = 33.59$, $p < .001$. No other effects or interactions were significant.

Figure 3.5C presents the average estimated M-ratio for both instruction groups at each coherence level. A repeated measures ANOVA revealed a significant main effect of coherence, such that M-ratio was significantly higher for stimuli with high dot pair coherence than low dot pair coherences, $F(2,260) = 13.54$, $p < .001$. There was also a main effect of instruction group, where those who were explicitly instructed of the priors showed higher M-ratios as compared to those who experienced the priors $F(1,130) = 5.14$, $p = .02$. An age group and instruction group interaction was nearly significant ($p = .06$); in the "experience" group, younger adults were more metacognitively efficient as compared to older adults (MYounger = .96, MOlder = .69, $p < .001$), but there were no age differences in metacognitive efficiency in the "instructed" group (MYounger = 1.01, MOlder = 1.31, $p = .39$).

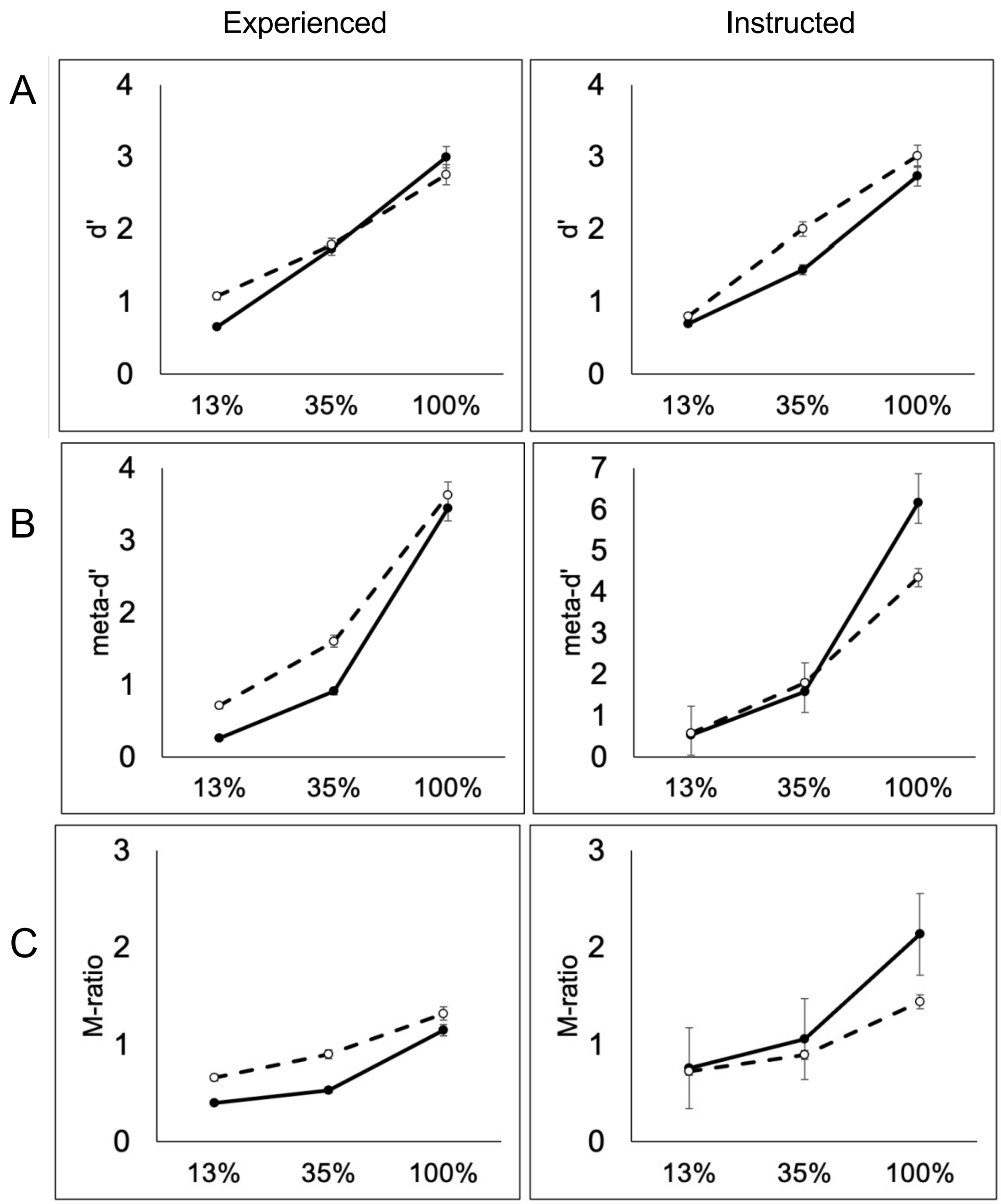

Figure 3.5: Performance and metacognitive measures using HMeta-D. Abs. value of coherence levels (including both positive and negative), but only for Positive prior trials. A: d' is type 1 performance in orientation discrimination task. B) Meta-d' is estimated metacognitive sensitivity C) M-ratio is a relative measure of metacognitive efficiency. Older adults (solid lines) and younger adults (dashed lines) are compared between instruction group (experience on left, instructed on right).

Discussion

We investigated differences between younger and older adults in how they learn base-rate priors and their metacognitive abilities when priors are either learned implicitly through experience or explicitly through instruction. Both older and younger adults showed use of the bias when no sensory information was available. Younger adults strategically applied the bias for stimuli with weaker sensory information, while older adults applied the bias the same regardless of dot-pair coherence. For the group that experienced the priors, there were no significant differences in accuracy between the younger and older adult participants. Younger adults exhibited faster response times compared to older adults, but only for stimuli of moderate difficulty. Participants were more confident for prior-consistent stimuli, indicating the prior that they implicitly learned also affected confidence. Younger adults were more confident compared to older adults for all but the easiest trials. In contrast, in the explicit group, the younger adult participants demonstrated higher accuracy and lower reaction times compared to the older adults. Younger adults exhibited greater confidence when the prior information was positive as opposed to equal, whereas older adults' confidence levels were not influenced by the type of prior. For trials with no orientation signal, younger adults displayed higher confidence levels for the positive prior condition compared to the equal prior condition, while older adults' confidence remained unaffected by the prior condition.

Using parameter estimates from the LBA, we replicated past findings that older adults show greater response caution (higher threshold levels) as compared to younger adults. Threshold values were lower for the Equal versus Positive prior and this was driven by the younger adults, suggesting that they only show greater response caution to Positive prior trials. This is similar to Thakur et al 2021 findings that both explicit and implicit learners use starting point (or boundary setting) in learning a general bias. Starting point noise (A) and non-decision time (Ter) were greater for older adults as compared to younger, replicating previous findings (Garton et al 2019), and also providing support for modeling aging cognition with increased neural noise. Similarly, Forstmann et al. (2011) found larger variability in the start points of evidence accumulation for older than younger adults in their LBA parameter estimates from a speed/accuracy manipulation task, and they concluded that older adults were “less proficient at controlling their bias or response caution settings”.

CHAPTER 4

Neural substrates of perceptual decision-making and implicit learning of Bayesian priors

Introduction

Investigating the underlying neural circuits supporting implicit learning of biases might augment our understanding of the mechanisms behind impaired decision-making observed in some neurological disorders, like Parkinson's Disease. Some areas like dorsolateral prefrontal cortex (dlPFC), lateral occipital cortex, anterior Insula, and frontal gyri have a role in evidence accumulation in the decision-making process (Imani et al., 2021; H R Heekeren et al., 2004). Given that evidence accumulation is influenced by dot-pair coherence, activation in these regions may fluctuate depending on task difficulty. Research on Parkinson's disease has also identified the cerebellum and basal ganglia as critical supporting areas for implicit learning (Pascual-Leone et al., 1993).

We predict we will see increased activation in areas involved in changing decision boundaries such as the premotor area, striatum, basal ganglia, thalamus, dorsolateral prefrontal and dorsal anterior cingulate (Imani et al., 2021). We predict there will be a positive correlation between striatal activity and implicit learners' ability to discriminate the priors. The striatum and basal ganglia are more involved in starting point or decision boundary changes, which may be the mechanism driving implicit learning of priors. Additionally, we expect to see activation in the pre- supplementary motor cortex, representing motor planning before a perceptual decision (Forstmann et al., 2008).

Past research has studied how explicit cues impact perceptual decision-making. Using the change in LBA response bias as a covariate, they found that an explicit and reliable cue was associated with activation in the OFC, hippocampus, and bilateral putamen (Forstmann et al., 2010). The cue is first processed by the OFC which sends excitatory input to the striatum and releases the thalamus and premotor areas from inhibition (Ideda et al 1996; Mink 1996, lehg et al 2007). However it is unknown if implicit, experience-based learning also utilizes the OFC, hippocampus, and putamen.

Methods & Materials

Participants

Data were collected from 21 undergraduate students (18-32 years old) at University of California, Los Angeles (UCLA) using a shared pool of psychology research subjects ("SONA") for course credit or $20 (Table 4.1 for participant demographics). Participants were eligible if they met the following requirements: not colorblind, have normal or corrected-to-normal vision, did not have an active medical, neurological, or psychiatric diagnosis and are not taking chronic medications that could affect sensory processing, movement, or cognition. All participants gave informed consent that was approved by the Institutional Review Board of the University of California.

Table 4.1.

Participant descriptive statistics.

	Mean (SD) or % (N=21)
Average age	20.8 (3.3) years; range:18-32 years
Gender	17 Female / 4 Male
Race/Ethnicity	44% Asian, 26% White 4% Other, 22% Hispanic 4% Black

fMRI Task

Participants completed the perceptual decision-making task described in Study 2 with slight changes in order to optimize it for fMRI scanning. Each trial began with a fixation point (400ms) with a jittered intertrial interval (M=4 seconds), followed by the Glass pattern which remained until a keypress. Participants heard audio feedback for incorrect choices or no sound for correct choices. There were no metacognitive judgements after each orientation decision. Participants completed three runs of the task. Participants were given 10-15 black and white practice trials before stepping into the scanner. All participants learned the priors implicitly and were not explicitly instructed of them or that they existed in the task. As in Study 2, one color stimulus was biased (e.g., oriented rightward 75% of the time) and the other color stimulus was unbiased (e.g., oriented rightward 50% of the time). Color and the biased orientation direction were counterbalanced, so I refer to the stimulus biased rightward as "Positive" and the unbiased stimulus as "Equal".

fMRI Data Acquisition, and Analyses

Scanning was performed using a 3-Tesla Siemens Trio MRI machine at the UCLA Brain Mapping Center. All participants were screened for metal with a metal detector prior to entering the scanning suite. Outside of the scanner, participants completed a post-task questionnaire assessing awareness of the priors.

In order to minimize participant fatigue, we will break up the task with the anatomical structural scan. We will use a magnetization prepared rapid gradient echo (MPRAGE) for image registration. According to previous works, a total of 34 structural images will be collected using a T2*-weighted bandwidth matched scan, with a TR of 5000 ms and TE of 33 ms, voxel size of 1.6 x 1.6 x 4 mm, matrix size of 128 x 128, field of view 200. During the functional runs we will collect 34 T2*- weighted echoplanar functional images (EPIs) with a TR of 2000 ms, TE of 30 ms, voxel size of 3.1 x 3.1 x 4.00 mm, matrix size of 64 x 64, field of view of 200 (Wagshal et al., 2014).

Functional MRI data was preprocessed and analyzed using the FMRIB Software Library, using FSL FEAT (Smith et al., 2004). After removing the first couple volumes, preprocessing steps included: brain extraction tool (BET) to remove any non brain areas from the images, motion correction with MCFLIRT (FMRIB Linear Image Restoration Tool with Motion Correction), spatial smoothing with a 5mm Gaussian kernel, temporal filtering (using cutoffcalc FSL tool), and mean intensity normalization. Participants' functional images will be registered to their anatomical scan (from MPRAGE), and to the FSL Montreal Neurological Institute (MNI) template.

We performed first level analysis of data from single subjects using a general linear model (GLM) with corrections for local autocorrelations (Woolrich et al., 2001). We analyzed data from correct and incorrect trials separately. We convolved model regressors with a canonical double- gamma hemodynamic response function, for each subject's fMRI data. We included 16 regressors of interests for different combinations of the following trial types: correct/incorrect, Positive Prior/Equal Prior, Prior-Consistent direction/Prior-inconsistent direction, hard trials/easy trials. Motion parameters were included as nuisance regressors. We used the FMRIB Local Analysis of Mixed-Effects module in FSL for each contrast of interest. Z statistic images were thresholded using cluster-corrected statistics with a height threshold of $Z > 2.3$ and a cluster probability threshold of $P < 0.05$, whole-brain corrected using the theory of Gaussian random fields (K. J. Friston et al., 1994).

fMRI Preprocessing

Results included in this manuscript come from preprocessing performed using fMRIPrep 22.0.2 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on Nipype 1.8.5 (K. Gorgolewski et al. (2011); K. J. Gorgolewski et al. (2018); RRID:SCR_002502).

Anatomical data preprocessing

A total of 1 T1-weighted (T1w) images were found within the input BIDS dataset.The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al. 2010), distributed with ANTs 2.3.3 (Avants et al. 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a Nipype implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white- matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 6.0.5.1:57b01774, RRID:SCR_002823, Zhang, Brady, and Smith 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 7.2.0, RRID:SCR_001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017). Volume-based spatial normalization to one standard space (MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.3.3), using brain-extracted versions of both T1w reference and the T1w template. The following template was selected for spatial normalization: ICBM 152 Nonlinear Asymmetrical template version 2009c [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym].

Functional data preprocessing

For each of the 3 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated by aligning and averaging 1 single-band references (SBRefs). Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 6.0.5.1:57b01774, Jenkinson et al. 2002). The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for head-motion. These resampled BOLD time-series will be referred to as preprocessed BOLD in original space, or just preprocessed BOLD. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary- based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in Nipype (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (CompCor, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the preprocessed BOLD time-series (using a discrete cosine filter with 128s cut-off) for the two CompCor variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, a mask of pixels that likely contain a volume fraction of GM is subtracted from the aCompCor masks. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's aseg segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the k components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. Additional nuisance timeseries are calculated by means of principal components analysis of the signal found within a thin band (crown) of voxels around the edge of the brain, as proposed by (Patriat, Reynolds, and Birn 2017). The BOLD time-series were resampled into standard space, generating a preprocessed BOLD run in MNI152NLin2009cAsym space. First, a reference volume and its skull-stripped version were generated using a custom methodology of fMRIPrep. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).

Many internal operations of fMRIPrep use Nilearn 0.9.1 (Abraham et al. 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in fMRIPrep's documentation.

Results

I used Quickpsy to plot the psychometric functions for each participant below (Fig 4.1). Only three participants (10-12) demonstrated sensitivity to the priors and coherence. The following analyses will be centered on these participants. Accuracy increased and reaction time decreased as coherence increased and participants were more accurate for the Positive versus Equal prior (Table 4.2).

Table 4.2

Performance measures for participants 10-12.

	Accuracy		Reaction Time	
Coherence	*Equal*	*Positive*	*Equal*	*Positive*
0%	-	-	1.17 (.04)	1.25 (.04)
13%	.55 (.019)	.65 (.04)	1.22 (.05)	1.19 (.04)
35%	.62 (.018)	.86 (.03)	1.01 (.04)	1.01 (.04)
100%	.70 (.017)	.98 (.01)	.84 (.03)	.80 (.03)

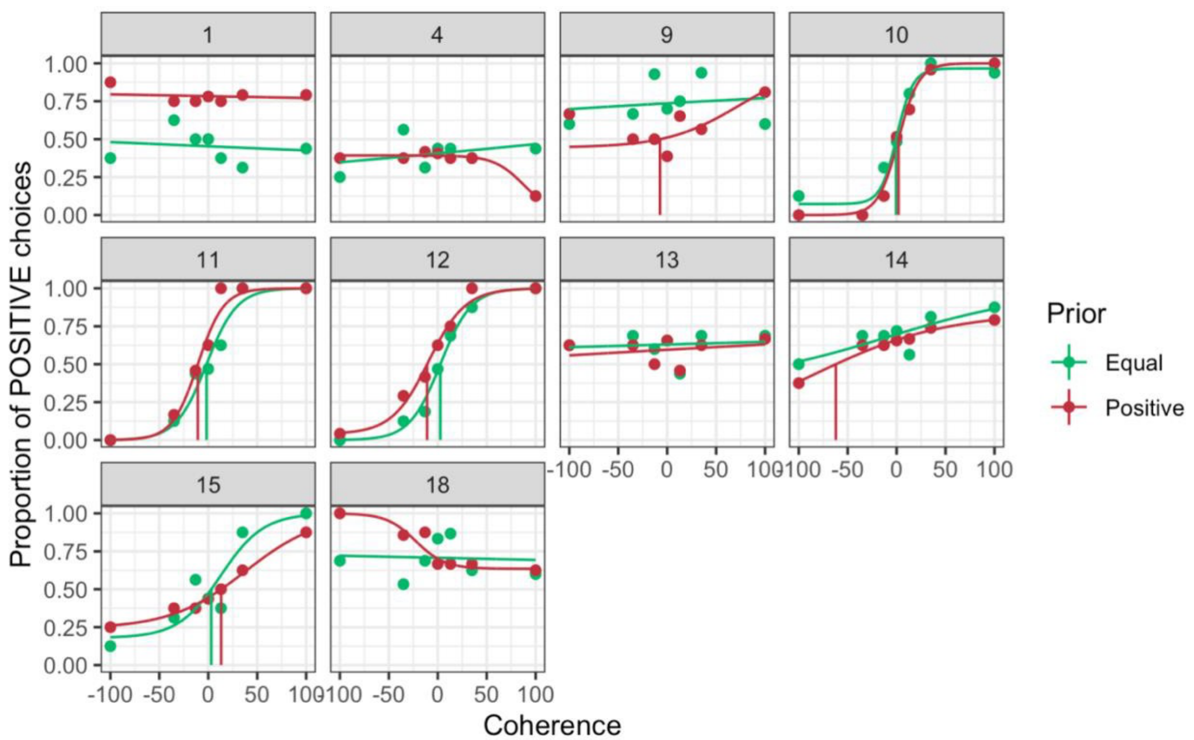

Figure 4.1: Psychometric curves per participant. On the X-axis, positive dot-pair coherences are the varying difficulties of rightward trials while negative coherences correspond to varying

difficulties in leftward trials. On the y-axis, the proportion of Positive, or rightward, choices the participants made for each of these stimuli.

Whole-brain neural activation during Positive prior trials that were prior-consistent and had little sensory information (0% and 13% coherences) revealed paracingulate gyrus, inferior frontal gyrus (IFG), precentral gyrus, postcentral gyrus, and lateral occipital cortex (Figure 4.2).

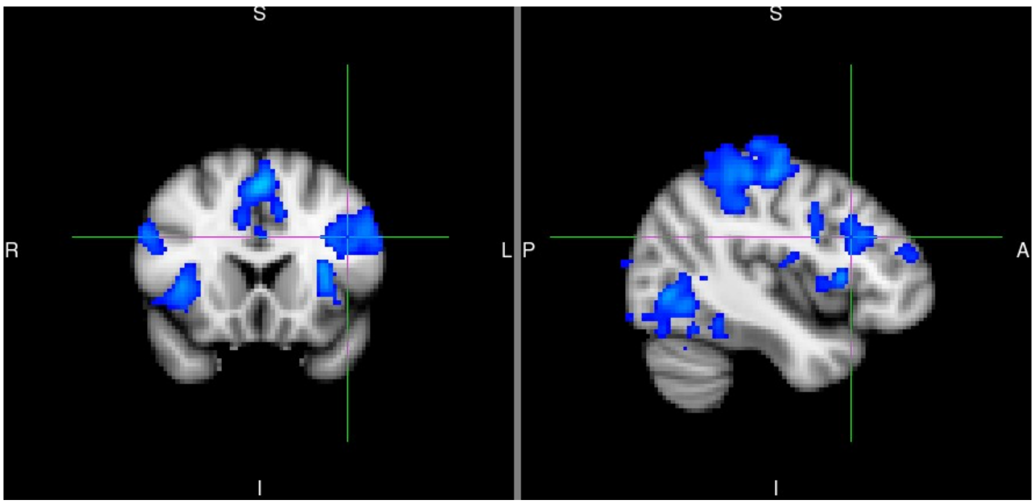

Figure 4.2 Whole-brain neural activation during Positive Prior trials that are prior-consistent with little sensory information. Whole-brain activation during positive prior trials that were prior-consistent and had very little sensory information (0%, 13%) revealed activation of the paracingulate gyrus, inferior frontal gyrus (IFG), precentral gyrus, postcentral gyrus, and lateral occipital cortex.

For Equal prior trials that were prior-consistent and had very little sensory information, whole brain analyses revealed activation in the subcortical regions like the putamen, caudate, and thalamus (Figure 4.3). Whole brain activation was qualitatively greater for the Equal, versus

Positive prior. Though we predicted subcortical activation for Positive prior trials, it's possible that participants are implementing a general, rather than stimulus-specific, bias.

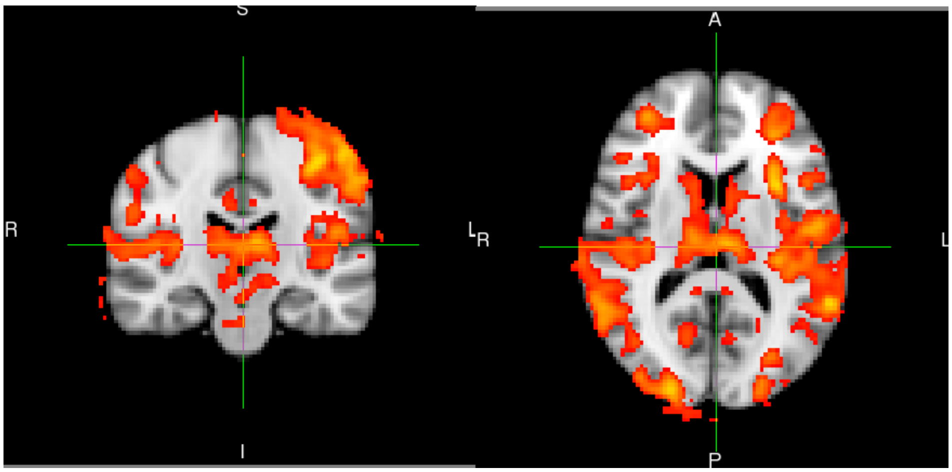

Figure 4.3 Whole-brain neural activation during Equal Prior trials. Whole-brain activation during Equal prior trials that were prior-consistent and had very little sensory information (0%, 13%) revealed activation of paracingulate gyrus, caudate, thalamus, and putamen.

Discussion

In Study 3, I presented preliminary data from subjects performing the perceptual decision- making task during fMRI. One stimulus was biased towards an orientation while the other stimulus was equally balanced. Participants were not explicitly instructed of the priors and needed to learn them implicitly through experience. Unfortunately, most participants did not show sensitivity to dot-pair coherence or prior condition and accuracy was low overall. Since these analyses are only centered on three participants, conclusions are limited. Consistent with previous findings, we found activation in cortical and subcortical structures for prior-consistent information in perceptual-decision making but we did not observe an action-selection circuit between the OFC, hippocampus, and putamen (Forstmann et al., 2010).

We predicted that implicit learners would implement the bias by changing decision boundaries, as in previous research (Thakur et al., 2021). Changes in threshold boundaries are associated with activation in the premotor area, striatum, basal ganglia, thalamus, dorsolateral prefrontal and dorsal anterior cingulate (Imani et al., 2021). For the Equal prior trials that were prior-consistent but very difficult (0% and 13% coherence), we found activation in the premotor area, putamen, thalamus, and caudate. Activation for the same type of trials for Positive priors (prior-consistent and difficult), whole brain activation was less overall and we did not observe any changes in basal ganglia or striatum as we predicted. We expected to see striatal areas involved in motor planning and action preparation (Utter & Basso, 2008).

Data collection is still ongoing due to multiple setbacks in the COVID-19 pandemic. Participants' poor accuracy in the task is a limitation of study and perhaps future research could augment pre-scanner training or split it into multiple training sessions with hundreds of trials. Multivoxel pattern analyses could train decoders to classify motion direction and color of individual stimuli in the brain during random dot motion to investigate if there is any evidence for implicit representations of these priors in the brain. Further research on the neural correlates of implicit learning and decision-making can augment understanding of the decision-making mechanisms altered in clinical patient populations and may provide insight into how the brain learns and decides in the absence of conscious knowledge.

CHAPTER 5

Concluding Remarks

In these studies, I investigated the differences between explicit instruction of priors and implicit learning of priors through experience in perceptual decision-making and metacognition. In everyday life, people pick up on statistical regularities in the environment over time- for example, a baby learning English will implicitly learn that some syllables are more likely to follow others and taxi drivers might implicitly know what sort of obstacles (wildlife, people crossing) are likely to occur at which intersections. People without experience might be explicitly instructed of these statistical regularities (e.g., through a grammar lesson or through road signs)- but how this differs from implicitly learning them, particularly on decision-making and metacognition, is understudied. Implicit versus explicit learning of priors has been termed the "experience-description" gap (FitzGerald et al., 2010; Garcia et al., 2021, 2023). Explicit descriptions of priors have affected participants' performance in perceptual decisions, while more optimal decisions were made when information was implicit and low-level (e.g., perception and sensorimotor control; Girshick et al., 2011; Knill & Richards, 1996; Körding & Wolpert, 2004).

Study 1 demonstrated that when sensory information was poor, the explicit group applied the priors more (versus higher coherences) and were more confident when stimuli were prior-consistent versus inconsistent. In contrast, the group who learned priors implicitly applied them when there was no sensory signal, but not for other coherences, and confidence ratings were only impacted by coherence and not prior-consistency. Metacognitive efficiency did not differ between the two instruction groups, so when the explicit group gave higher confidence ratings to prior-consistent stimuli, this was not accompanied by a boost in accuracy. Those in the explicit instruction group showed different drift rates per prior for each coherence level, possibly reflecting a top-down attentional affect that increases evidence accumulation rates.

In Study 2, both younger and older adults performed this perceptual-decision making task however with different prior conditions that created a global bias. Explicit instruction of priors boosted younger adults' performance as compared to older adults, while age groups performed similarly in the implicit group. Older adults' confidence was not impacted by prior condition, but it was impacted by explicit instruction of priors. Age differences in decision-making were likely driven by different mechanisms- older adults had greater starting point noise and longer nondecision time for the Equal prior; whereas younger adults utilized threshold setting and drift rate differences. For the biased prior, implicit younger adults were more metacognitively efficient than older adults, but there were no age differences found in the explicit group. Past research on metacognitive efficiency across the lifespan found that older adults exhibited a decline in perceptual, but not memory, metacognitive efficiency compared to younger adults, even when task performance was controlled to ensure similar levels of accuracy (Palmer et al 2014). Further research in metacognitive monitoring can elucidate how metacognitive deficits result in difficulties in controlling behavior (Koriat & Goldsmith, 1996). Findings from this research could help us understand aging-related conditions like Alzheimer's disease that are often accompanied by metacognitive impairments, which can contribute to non-adherence to treatment and compromised decision-making abilities (Cosentino, 2014).

In Study 3, younger adults performed this task (without the confidence ratings) while in the fMRI scanner. The priors were not explicitly provided to the participants. Unfortunately, most participants showed no sensitivity to coherence or prior condition, and overall accuracy was low. Because these analyses only focus on three subjects, the findings are limited. We identified activity in cortical and subcortical areas for prior-consistent information consistent with earlier findings, like activation of sensory integration areas (e.g., LOC) and frontoparietal networks involved in evidence accumulation. For the unbiased prior, areas like the thalamus, caudate, paracingulate gyrus show that perhaps implicit learning is occurring during these trials. We did not observe the orbitofrontal-hippocampal-putamen circuit as past research has, though that experiment utilized explicit biases (Forstmann et al., 2010) that are more likely to rely on the hippocampus.

These studies have several limitations that limit our conclusions. Study 1 and 2 were conducted online, so the participant's environment could not be fully controlled. To mitigate this, questions in the post-task questionnaire aimed to identify relevant environmental information like size of screen, distance from screen, and distractions occurring in the background. Participants found performing hundreds of trials to be tedious, which led to some dropouts and computer errors. It is unclear if our findings generalize to other types of decision-making, but misuse of prior probability information and different effects of explicit descriptions versus experience is also prevalent in higher-level decision-making (Tversky & Kahneman, 1992; Hertwig & Erev, 2009).

Future research should investigate how our findings from this perceptual decision-making task compare to performance in higher-level tasks or everyday life metacognitive monitoring performance. Through computational modelling we found that older and younger adults are likely utilizing different decision-making mechanisms when applying the prior, so further research could investigate the neural correlates that support behavior and if they differ with age. Aging is associated with reduced white matter integrity in fronto-striatial tracts that connect pre-supplementary motor area to the striatum (Garton et al.., 2019), important for threshold setting in decision making, suggesting that they may be recruiting areas that are usually spared in aging, like those used for implicit learning.

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