

Age-related differences in the social associative learning of trust information

Kendra L. Seaman^{a,f,*}, Alexander P. Christensen^b, Katherine D. Senn^c, Jessica A. Cooper^d, Brittany S. Cassidy^e

^a Center for Vital Longevity, University of Texas at Dallas, Dallas, TX, USA

^b Department of Psychology and Human Development, Vanderbilt University, Nashville, TN, US

^c School of Social Work, University of North Carolina-Chapel Hill, Chapel Hill, NC, USA

^d Department of Psychiatry and Behavioral Sciences, Emory University School of Medicine, Atlanta, GA, USA

^e Department of Psychology, University of North Carolina at Greensboro, Greensboro, NC, USA

^f Department of Psychology, University of Texas at Dallas, Dallas, TX, USA

ARTICLE INFO

Article history:

Received 7 January 2022

Revised 23 January 2023

Accepted 24 January 2023

Available online 1 February 2023

Keywords:

Aging

Trust

Learning

Memory

ABSTRACT

Trust is a key component of social interaction. Older adults, however, often exhibit excessive trust relative to younger adults. One explanation is that older adults may learn to trust differently than younger adults. Here, we examine how younger ($N = 33$) and older adults ($N = 30$) learn to trust over time. Participants completed a classic iterative trust game with 3 partners. Younger and older adults shared similar amounts but differed in *how* they shared money. Compared to younger adults, older adults invested *more* with untrustworthy partners and *less* with trustworthy partners. As a group, older adults displayed less learning than younger adults. However, computational modeling suggests that this is not because older adults learn differently from positive and negative feedback than younger adults. Model-based fMRI analyses revealed several age- and learning-related differences in neural processing. Specifically, we found that older learners ($N = 19$), relative to older non-learners ($N = 11$), had greater reputation-related activity in metalizing/memory areas while making their decisions. Collectively, these findings suggest that older adult learners use social cues differently from non-learners.

© 2023 The Author(s). Published by Elsevier Inc.

This is an open access article under the CC BY-NC-ND license

(<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

1. Introduction

Trust is a key component of social interaction, cohesion, and subjective wellbeing (Poulin and Haase, 2015). While trust is critical for forming and maintaining social relationships, excessive trust could be problematic by making one more vulnerable to fraud, exploitation, and abuse. Studies examining adult age-related differences in trust behavior have shown that it tends to increase with age (Bailey et al., 2016, 2019; Webb et al., 2016). This change is

concerning because the growing size, affluence, and power of older adults compared to other age groups make them an appealing target for criminals. One potential explanation for older adults' excessive trust is that they may learn to trust differently than younger adults. This explanation, however, has been relatively untested (although see Suzuki et al., 2019).

Trust is often operationalized using the economic trust game (Berg et al., 1995). The participant, or investor, is given an endowment of \$X. They can choose how much of the endowment, if any, to share with a fictitious trustee. Any amount shared with the trustee is multiplied by some amount. Then, the trustee determines whether to split the benefits with the investor or keep all of it for themselves. If the trustee cooperates, there are gains for both the investor and trustee; if the trustee does not cooperate, the investor loses. Because of these stakes, the amount provided by the investor is considered an indication of trust. The amount shared by the trustee is considered a measure of their trustworthiness.

This study was preregistered Open Science Framework (<https://osf.io/b3au5>). An early version of this project was presented at the 2020 Scientific Research Network on Decision Neuroscience and Aging and Gerontological Society of America conferences. This manuscript is posted on the PsyArXiv preprint server (<https://psyarxiv.com/>).

* Corresponding author at: Center for Vital Longevity, University of Texas at Dallas, 1600 Viceroy Drive Suite #800, Dallas, TX 75235, USA, Phone: 972-883-3783.

E-mail address: kendra.seaman@utdallas.edu (K.L. Seaman).

thiness. In “one-shot” versions of this task, participants interact with a trustee only once. However, in iterative versions of this task (King-Casas et al., 2005), participants interact repeatedly with a trustee, giving them the chance to learn about a trustee through experience.

Prior studies have used both versions of the trust game to examine how trust differs between younger and older adults. Research using repeated versions of this game have found that compared to younger adults, older adults were more likely to invest with untrustworthy trustees (Bailey et al., 2016; Webb et al., 2016), ignore minor transgressions (Bailey et al., 2019), and persist with initial ratings of trustworthiness in the face of negative feedback (Suzuki, 2018). Collectively, these results suggest that older adults rely on initial information to make their trustworthiness judgments and fail to update these beliefs with experience. However, this possibility has not been tested empirically.

Recent studies have started using computational models to explore how trust develops with experience (Chang et al., 2010; Stanley, 2016). These models draw from standard reinforcement learning techniques to mathematically represent how people make decisions. Signals derived from these models can then be correlated with fMRI signals to uncover brain activity associated with these processes (O’Doherty et al., 2007). Prior studies using these techniques have revealed that midbrain dopaminergic neurons encoding various cortical regions reflect a learning signal – called reward prediction error or RPE – that allows organisms to update their encoded representations of value (O’Doherty et al., 2007; Schultz et al., 1997). The use of computational model-based fMRI has also uncovered a network of regions that encode reward and value – including the nucleus accumbens, medial prefrontal cortex, and posterior parietal cortex (Acikalin et al., 2017; Bartra et al., 2013; Clithero and Rangel, 2014). Activity in these regions is also involved in social valuation and learning (Chang and Sanfey, 2009; Delgado et al., 2005; Fareri et al., 2012), along with social-specific regions like the temporoparietal junction (TPJ) (Chang and Sanfey, 2009; Park et al., 2020).

Here, we use an extreme-group design to examine how age influences the development of trust with experience in an iterated trust game. Consistent with prior literature, our first hypothesis is that compared to younger adults, older adults will have less negative representations of untrustworthy partners. Our expectation is that older adults will give more to untrustworthy partners than younger adults. Our second hypothesis is that while both older and younger adults will change their representation of social value with experience, older adults will be more likely to change their representation based on positive (trustworthy) versus negative (untrustworthy) feedback. Our expectation is that there will be lower learning rates for losses compared to gains in older, but not younger, adults. These hypotheses were preregistered prior to data collection (<https://osf.io/b3au5>). In addition to these hypothesis-driven analyses, we conduct exploratory computational modeling and neuroimaging analyses to examine the cognitive and neurobiological mechanisms of how trust formation differs between young and older adults.

2. Method

2.1. Participants

Seventy-eight right-handed adults with no recent history of neurological problems were recruited from the University of North Carolina at Greensboro and the surrounding community. The younger participants were recruited from flyers posted in and around the university campus. The older participants were recruited from a lab-maintained database of older adults who had

expressed interest in participating in psychological research. Fifteen participants were excluded for various reasons described in the supplement (Section 5.1). These exclusions yielded an analyzed sample of 33 younger ($M_{age} = 22.45$ years, $SD = 3.62$, Age range = 19–32, 19 female) and 30 older ($M_{age} = 69.27$ years, $SD = 5.49$, Age range = 61–80, 21 female) adults. See Table S1 for descriptive and inferential statistics on demographics and cognitive ability measures. Younger and older adults had comparable years of education, but older adults reported higher socioeconomic status (MacArthur Scale of Subjective Social Status; e.g., Cundiff et al., 2013) relative to younger adults. Older adults had higher vocabulary scores (Zachary and Shipley, 1986), slower processing speed (Digit Comparison; Hedden et al., 2002), and a smaller working memory capacity (Digit Span; Wechsler, 1997) than younger adults.

2.2. Social associative learning task

To quantify social associative learning, participants completed a repeated trust game (FeldmanHall et al., 2018; King-Casas et al., 2005) while undergoing functional magnetic resonance imaging (fMRI). On each trial (Fig. 1A), a participant was endowed with \$9 and saw a picture and a name to represent their partner for that trial. Next, participants chose how much (e.g., all [\$9], part [\$6 or \$3], or none [\$0]) of their endowment they wanted to share with that partner. The money participants chose to share with their partner was quadrupled (e.g., \$36, \$24, \$12). Then, the partner would choose to share either half of that quadrupled amount with the participant (e.g., return \$18, \$12, or \$6) or keep all the winnings (return \$0). The 3 partners systematically varied on their trustworthiness, defined here as their likelihood of sharing the quadrupled amount with the participant. Of the 3 partners, one partner was trustworthy (i.e., shares on 93% of trials), one was somewhat trustworthy (i.e., neutral and shares on 60% of trials), and one was untrustworthy (i.e., shares on 7% of trials). Participants played the trust game 15 times with each partner over the course of the task, for a total of 45 trials. Partners were interleaved in a random sequence. We expected that participants would continue to share with trustworthy partners and stop sharing with untrustworthy partners. The 45 trials were presented over 2 runs lasting approximately 6 minutes each. Timing for the trust game is described in the supplement (Section 5.2).

After the social associative learning task, participants completed a generalization task (e.g., FeldmanHall et al., 2018) in the scanner. Because the data from the generalization task are not relevant to the current hypotheses, the generalization task will not be further discussed.

2.3. Partner likability ratings

After the generalization task, participants indicated the extent they liked each of the 3 partners from the social associative learning task outside the scanner. On a computer, participants saw each of the partner faces from the task, one at a time, and indicated how much they liked each partner (“How much do you like this person?”) using a scale ranging from 1 (*extremely dislike*) to 7 (*extremely like*). The 3 partner faces were presented in a random order. We expected participants to like trustworthy partners and dislike untrustworthy partners.

2.4. Behavioral data analyses

Linear mixed-effects regression models were used to examine how people shared with the 3 partners over time. Full details on how the models were fit and specified can be found in the supplement (Section 5.3). We tested nested models regressing fixed

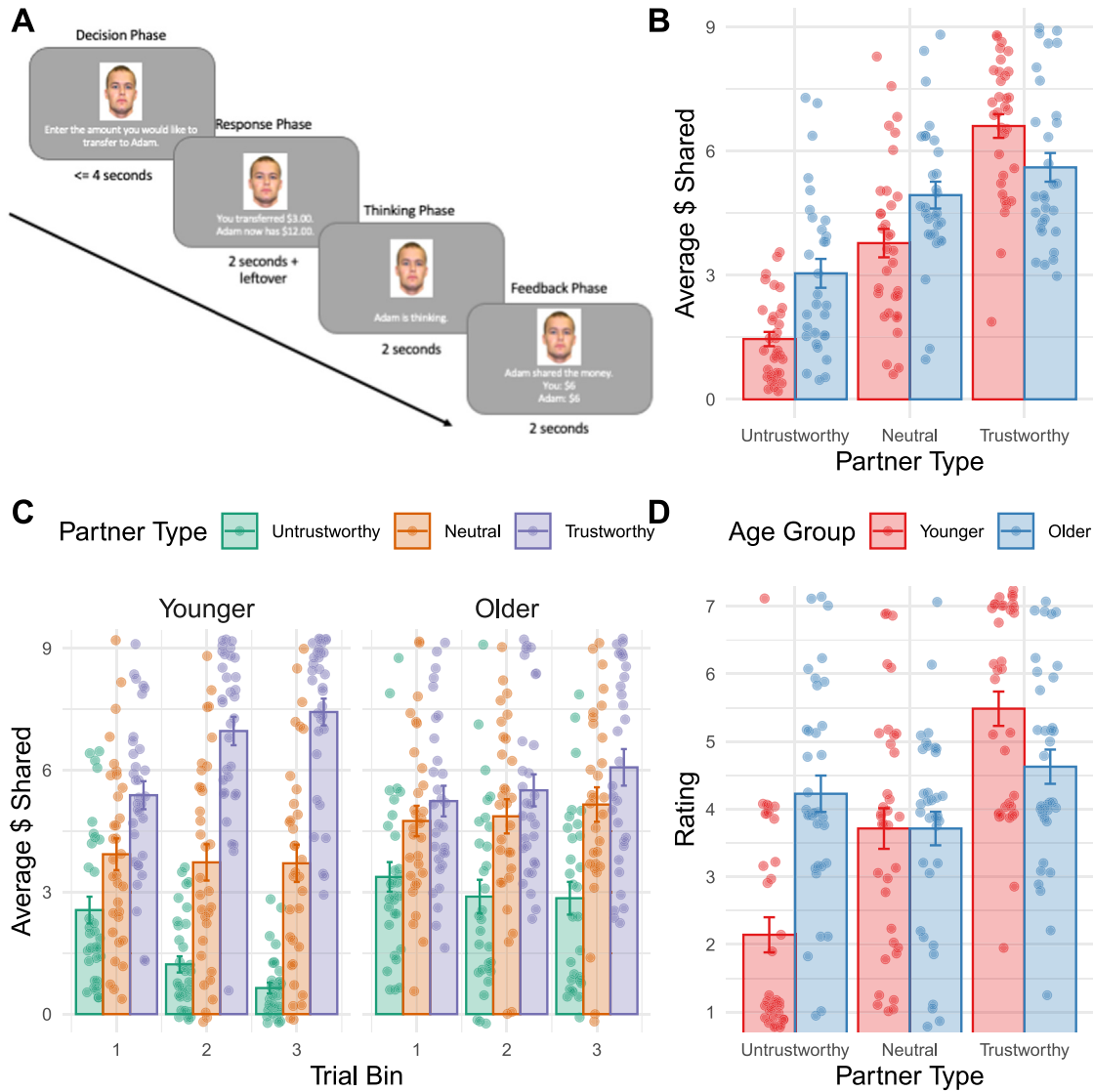


Fig. 1. Age-Related Differences in Trust Game Behavior. (A) The Trust Game full trial sequence when participants shared with partner. See Supplement (Section 5.2) for further details. (B) Average amount of money shared by Partner Type and Age Group. (C) Average amount of money shared by Partner Type and Age Group over 5-Trial Bin. (D) Post-experiment partner likeability ratings by Partner Type and Age Group. All dots represent individual means. All bars represent age group means and error bars are standard error.

effects of age group, partner trustworthiness, partner experience (i.e., the amount of experience with each partner as indexed by trial number), and all interaction terms on the amount shared by participants. The third model (Model 3) provided the best fit. Thus, all reported results are from Model 3.

2.5. Computational modeling

We used a series of computational learning models to understand how participants learned to trust. All models tested are fully described in the supplement (Section 5.4). We started with a model developed to represent how people make decisions during trust games (Fareri et al., 2012) and adapted this model to our task. In our model, the expected value of taking action a at time t and with partner i is calculated by multiplying the perceived probability of reciprocation, $p_i(t)$, by the amount of money they will receive if their partner reciprocates, $v_i(t)$, plus any money the participant retains $v_r(t)$.

$$EV_{ai}(t) = p_i(t) * v_i(t) + v_r(t)$$

Because the probability each partner will reciprocate is unknown, this value is learned using a simple value updating rule from reinforcement learning theory (Sutton and Barto, 1998). The model also considers differences in response to gains and losses by allowing the perceived probability that a partner will reciprocate to update with different learning rates in response to a gain (α_{gain}) or a loss (α_{loss}). Thus, the perceived probability p of partner i reciprocating at time t is:

$$p_i(t) = p_i(t-1) + \alpha_{gain} * \max(\gamma - p_i(t-1), 0) + \alpha_{loss} * \min(\gamma - p_i(t-1), 1)$$

where

$$\gamma = \begin{cases} 1 & \text{when partner shares} \\ 0 & \text{when partner keeps} \end{cases}$$

For this model, which we called the *gain-loss learning model*, and the following computational models, the learning rates (α_{gain} and α_{loss}) were constrained between 0 and 1. The probability of each potential action (share \$0, \$3, \$6, or \$9) was estimated by

placing the $EV_{ai}(t)$ into a softmax function with a free decision slope (β). Participant choices were fit using the `scipy.optimize` module in Python. The starting probability for all partners were initialized to chance ($p_i(0) = 0.5$).

We also tested a simplified model that updated the probability with a single learning rate parameter for gains and losses. This model assumes that participants update beliefs similarly when partners reciprocate (i.e., gains) and when they do not reciprocate (i.e., losses). Here, the perceived probability p of partner i reciprocating at time t is:

$$p_i(t) = p_i(t-1) + \alpha * (\gamma - p_i(t-1))$$

where

$$\gamma = \begin{cases} 1 & \text{when partner shares} \\ 0 & \text{when partner keeps} \end{cases}$$

In other words, this model only had one learning rate parameter (α) and all other modeling parameters were kept the same. We call this the *general learning model*.

These decision models were all compared to a model where each option was equally likely on each trial. We call this the *baseline model*. Models were compared by calculating the Akaike Information Criterion (AIC), (Akaike, 1974) and Bayesian Information Criterion (BIC), (Schwarz, 1978) for each model. Full explanation of models, including simulation studies, can be found in Supplement (Section. 5.4).

2.6. fMRI data acquisition

Whole-brain imaging was performed on a Siemens Magnetom Tim Trio 3T MRI scanner using a 16-channel head coil at the University of North Carolina at Greensboro-led Gateway MRI Center for Functional and Molecular Imaging in Greensboro, North Carolina. Stimuli were presented using a back projector and behavioral data were collected on a Dell laptop running Windows 10. The scanner was synced to the data collection equipment via scanner TTL.

Anatomical images were collected prior to the functional tasks in 1 run lasting 5 minutes and 21 seconds. These images were acquired with a high-resolution 3D magnetization prepared rapid gradient echo sequence (sagittal rotation; 192 slices, TR = 2300ms, TE = 2.26ms, TI = 900ms, flip angle = 8 degrees, 1.0mm isotropic voxels; with no fat suppression). Functional images reflecting brain activation during the social associative learning task were collected over 2 runs of using a fast field echo-planar sequence sensitive to blood oxygen level-dependent contrast (T2*; 32 slices with 4.0 mm thickness and no skip that were acquired in a descending order, TR = 2000ms, TE = 30ms; A/P phase encoding direction). The 2 functional runs had, respectively, 174 and 177 timepoints. Due to a software upgrade that had no impact on task trial timing, a subset of participants had 2 functional runs of 175 and 182 2000ms timepoints. At the beginning of each functional run, the scanner acquired and discarded 2 dummy scans.

2.7. fMRI data preprocessing

Results included in this manuscript come from preprocessing performed using FMRIPREP version 1.1.4 (Esteban et al., 2019), a Nipype (Gorgolewski et al., 2011) based tool, and denoised using “Denoiser.” See supplement (Section 5.5) for details.

2.8. Exploratory whole-brain analyses

To better understand age-related differences in how participants updated their beliefs about their partners, we conducted exploratory analyses to identify regions of the brain where younger

and older adults differed based on trial-wise estimates of perceived probability of reciprocation, $p_i(t)$, or reputation, and prediction error, $\gamma - p_i(t)$. Using the best-fitting model parameters for each individual in the gain-loss learning model, we estimated reputation and prediction error on each trial. We then used these trial-wise estimates as parametric modulators in whole-brain analyses.

Analyses focused on changes in brain activation during 2 different phases of the trial: the decision phase (reputation) and the feedback phase (prediction error). One older adult was excluded from the exploratory imaging analyses due to a scanner error affecting image quality. Using SPM12, A GLM model for each participant that incorporated all trials as events, a linear drift regressor for 2 concatenated runs, and trial-wise estimates as a parametric modulator computed parameter estimates (β) and t-contrast images (containing weighted parameter estimates) for each comparison at each voxel. Relevant parameter estimates were included in a group-level analysis, treating participants as a random effect. Because these analyses were exploratory, we thresholded the relevant comparisons to $p < 0.005$ ($k = 50$). Additional details can be found in the supplement (Section 5.6).

3. Results

3.1. Behavioral analyses

3.1.1. Overall partner effects

We fit a linear mixed effects model regressing amount shared on Age Group, Partner Type, Experience, and their interactions as fixed effects (see Table 1 for all model coefficient information and supplemental material for random effects information). See Table 1 for all model coefficient information. We characterized the overall effect of Partner Type (trustworthy, neutral, untrustworthy) on trust by Age Group (Fig. 1B). A main effect of Age Group showed that older adults ($M = 4.53$, 95% CI [4.10, 4.96]) shared more than younger adults ($M = 3.94$, 95% CI [3.52, 4.35]). People shared more to the trustworthy ($M = 6.10$, 95% CI [5.66, 6.55]) relative to the neutral ($M = 4.35$, 95% CI [3.87, 4.83]), $t = 6.14$, $p < 0.001$, and untrustworthy partners ($M = 2.24$, 95% CI [1.87, 2.62]), $t = 12.58$, $p < 0.001$. People also shared more to neutral relative to untrustworthy partner, $t = 9.42$, $p < 0.001$.

Age Group qualified significant contrast effects comparing sharing to the neutral and untrustworthy partners to the trustworthy partner. We characterized this interaction by comparing the shared amounts for each partner separately for younger and older adults. Younger adults shared more to the trustworthy ($M = 6.60$, 95% CI [5.98, 7.21]) partner relative to the neutral ($M = 3.77$, 95% CI [3.11, 4.43]), $t = 7.18$, $p < 0.001$, and untrustworthy ($M = 1.44$, 95% CI [0.92, 1.96]), $t = 12.17$, $p < 0.001$, partners, and shared more to the neutral relative to the untrustworthy partner, $t = 7.54$, $p < 0.001$. This pattern was muted among the older adults. Unlike younger adults, older adults shared similar amounts to the trustworthy ($M = 5.61$, 95% CI [4.96, 6.26]) and neutral ($M = 4.93$, 95% CI [4.24, 5.62]) partners, $t = 0.68$, $p < 0.57$. Like younger adults, older adults shared more to the trustworthy relative to the untrustworthy ($M = 3.04$, 95% CI [2.50, 3.59]) partner, $t = 5.77$, $p < 0.001$, and shared more to the neutral relative to the untrustworthy partner, $t = 5.82$, $p < 0.001$.

To better understand these effects, we also directly assessed age-related differences in the overall shared amount to each partner. Younger and older adults did not differ in their amounts shared to the trustworthy, $t = 0.99$, $p = 0.25$, and neutral, $t = 1.16$, $p = 0.16$, partners. Conceptually replicating related work (Castle et al., 2012), older adults shared more to the untrustworthy partner than did younger adults, $t = 4.25$, $p = 0.001$.

Table 1
Linear mixed effects model predicting amount shared

Predictors	Estimates	CI	p
(Intercept)	4.23	3.94–4.53	<0.001
Age Group	-0.30	-0.59 to -0.00	0.048
Partner Type [Neutral]	-1.75	-2.31 to -1.19	<0.001
Partner Type [Untrustworthy]	-3.86	-4.46 to -3.26	<0.001
Partner Experience	0.04	-0.11–0.20	0.581
Age Group * Partner Type [Neutral]	-1.07	-1.63 to -0.51	<0.001
Age Group * Partner Type [Untrustworthy]	-1.29	-1.90 to -0.69	<0.001
Age Group * Partner Experience	-0.05	-0.21–0.11	0.517
Partner Type [Neutral] * Partner Experience	-0.60	-0.95 to -0.26	0.001
Partner Type [Untrustworthy] * Partner Experience	-1.20	-1.47 to -0.93	<0.001
Age Group * Partner Type [Neutral] * Partner Experience	-0.39	-0.73 to -0.04	0.028
Age Group * Partner Type [Untrustworthy] * Partner Experience	-0.52	-0.79 to -0.25	<0.001
Observations	2777		
Marginal R ² / Conditional R ²	0.270 / 0.531		

Note. Random effects in Table S1

3.1.2. Partner effects with experience

The model also revealed age-related differences in how trust developed with experience with each partner (Table 1; Fig. 1C). To decompose this interaction, we first compared the relative strength of Partner Experience effects for each partner. A significantly positive Partner Experience slope for the trustworthy partner indicated that people shared more with this partner after having more experience with him, $b = 0.65$, $SE = 0.12$, $t = 5.31$, $p < 0.001$, 95% CI [0.40, 0.89]. A significantly negative Partner Experience slope for the untrustworthy partner indicated that people shared less with this partner after having more experience with him, $b = -0.55$, $SE = 0.10$, $t = 5.53$, $p < 0.001$, 95% CI [-0.76, -0.35]. The Partner Experience effect for the neutral partner was not significant, $b = 0.04$, $SE = 0.14$, $t = 0.30$, $p = 0.77$, 95% CI [-0.25, 0.33]. The relative strength of these effects varied by partner type. The Partner Experience effect was more positive for the trustworthy relative to the neutral, $t = 3.45$, $p = 0.003$, and untrustworthy, $t = 8.73$, $p < 0.001$, partners. It was also more positive for the neutral relative to the untrustworthy partner, $t = 3.52$, $p = 0.002$.

Age Group qualified significant contrast effects comparing Partner Experience effects on sharing to the neutral and untrustworthy partners relative to the trustworthy partner. Younger and older adults both had significant positive Partner Experience effects for the trustworthy partner (Younger adults: $b = 0.90$, $SE = 0.17$, $t = 5.38$, $p < 0.001$, 95% CI [0.56, 1.23]; Older adults: $b = 0.40$, $SE = 0.18$, $t = 2.24$, $p = 0.03$, 95% CI [0.04, 0.75]). Both younger and older adults also had non-significant Partner Experience effects for the neutral partner (Younger adults: $b = -0.09$, $SE = 0.20$, $t = 0.47$, $p = 0.64$, 95% CI [-0.49, 0.30]; Older adults: $b = 0.18$, $SE = 0.21$, $t = 0.85$, $p = 0.40$, 95% CI [-0.24, 0.60]). By contrast, whereas younger adults had a significant negative Partner Experience effect for the untrustworthy partner, $b = -0.83$, $SE = 0.14$, $t = 5.98$, $p < 0.001$, 95% CI [-1.10, -0.55]), the effect for older adults was only marginally negative, $b = -0.28$, $SE = 0.15$, $t = 1.95$, $p = 0.06$, 95% CI [-0.57, 0.01]).

Like the overall trust behavior shown by younger relative to older adults, the strength of older adults' Partner Experience effects was muted relative to younger adults. For younger adults, the Partner Experience effect was more positive for the trustworthy relative to the neutral, $t = 4.12$, $p = 0.002$, and untrustworthy, $t = 9.13$, $p < 0.001$, partners. It was also more positive for the neutral relative to the untrustworthy partner, $t = 3.14$, $p = 0.03$. For older adults, by contrast, the Partner Experience effect was not more positive for the trustworthy relative to the neutral partner, $t = 0.85$, $p = 0.96$, and not more positive for the neutral relative to the untrustworthy partner, $t = 1.88$, $p = 0.43$. It was, however, more positive for the trustworthy relative to the untrustwor-

thy partner, $t = 3.39$, $p = 0.01$. Collectively, these effects suggest that older adults displayed slower learning than younger adults. Note that these patterns also add nuance to the above-described patterns aggregated across trials because they suggest age-related differences in how much younger and older adults shared to the different partners based on their experience with them.

3.2. Computational modeling

Computational models allowed us to better understand how participants learned to trust. Fit statistics and parameter estimates for the computational models were averaged for each age group and are shown in Table S3. Both age groups' behavior was best fit by the *gain-loss learning* model (Younger adults: AIC = 87.11, BIC = 91.89, Older adults: AIC = 104.68, BIC = 109.42). There were no age-related differences in the gain or loss learning rates ($ps > 0.05$). At the individual level, approximately one-third of older adults ($N = 11$), were best-fit by the *baseline* model, suggesting that these individuals did not update their partners reputation based on their behavior.

3.3. Post-experiment partner likability

After the scanner tasks, participants indicated how much they liked each of the partners in the trust game (Fig. 1D). Main effects of age group, $F(68, 1) = 4.01$, $p = 0.049$, $\eta^2 = .017$, and partner, $F(2, 136) = 25.31$, $p < 0.001$, $\eta^2 = 0.207$, were qualified by an interaction between age group and partner type, $F(2, 136) = 15.57$, $p < 0.001$, $\eta^2 = 0.138$. A follow-up one-way ANOVA showed that younger adults clearly differentiated between different partner types, $F(2, 68) = 35.90$, $p < 0.001$, $\eta^2 = 0.426$. Trustworthy partners were liked more than neutral and untrustworthy, and neutral were liked more than untrustworthy ($ps < 0.001$). Older adults, however, did not differentiate between partner types, $F(2, 68) = 3.04$, $p = 0.055$, $\eta^2 = 0.059$. Pairwise comparisons showed that older adults only liked the trustworthy partner more than the neutral partner.

3.4. Exploratory model-based fMRI analyses

Of interest in the exploratory model-based fMRI analyses was identifying age-related differences in brain activity corresponding with model parameters at 2 different times during each trial: when making a decision and when receiving feedback. During the decision phase, we examined brain activity related to probability of reciprocation, or reputation. During the feedback phase, we examined brain activity related to prediction error. Thus, we characterized age-related differences in brain activity emergent from the

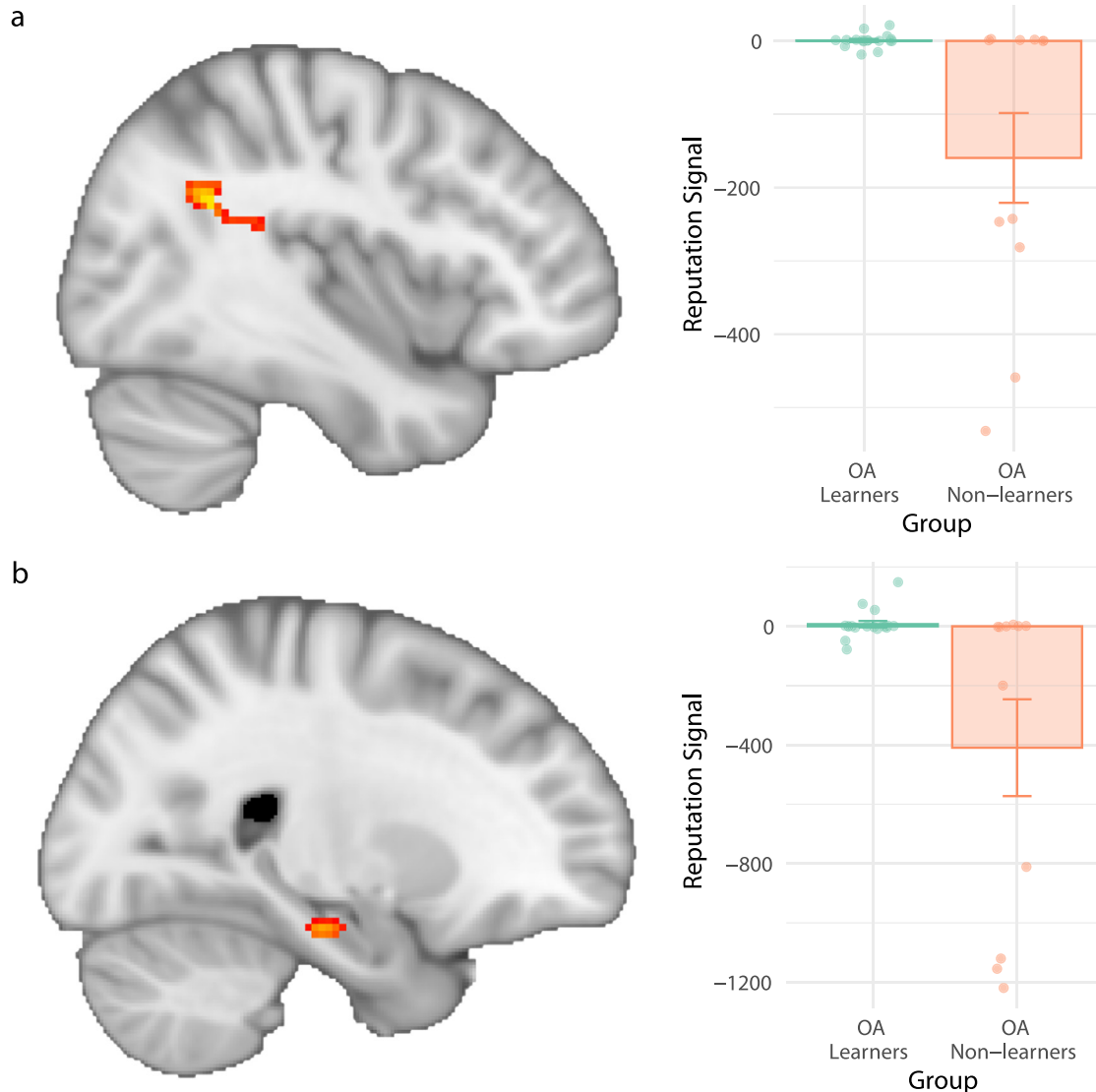


Fig. 2. Learning Differences in Reputation Signals during Trust Game. *Top:* Right angular gyrus. *Bottom:* Right parahippocampus. (A) *Left:* Learning difference (OA Learners > OA Non-learners) in reputation (predicted probability of reciprocation) representation during decision phase. *Right:* Learning difference in average parameter estimates in arbitrary units. (B) *Left:* Learning difference (OA Learners > OA Non-learners) in reputation representation during decision phase. *Right:* Learning difference in average parameter estimates in arbitrary units.

parametric modulators assessing reputation at the decision phase and prediction error during the feedback phase of trials using independent samples t-tests in SPM12. We also compared older adult learners (those best-fit by a learning model; $N = 19$) to non-learners (those best fit by the baseline model; $N = 11$). We made the decision to make this comparison to be consistent with work examining older adults with different behavior profiles (e.g., older adults with mild cognitive impairment vs. cognitively normal older adults) and because this split best reflects the fit versus non-fit dichotomy of the computational model.

3.4.1. Reputation prior to decision

Across all participants, as reputation increased, there was greater activity in the left middle occipital gyrus (Table S4A). This relation was stronger in younger than older adults in the right lingual gyrus. This relation was stronger in older than younger adults in the right inferior frontal gyrus relative to younger adults (Table S4B). This relation was stronger in older adult learners relative to non-learners in the bilateral angular gyrus and right medial

temporal lobe (Fig. 2; Table S4F), areas commonly associated with mentalizing and memory. These activations suggest a stronger relation between reputation signal and neural activation among older adults with good model fit versus not. Although we initially compared older adult learners to non-learners, we also explored brain regions whose activity positively related to reputation signal across older adults. No emergent activations emerged (Table S4e), suggesting a qualitative difference between some older adults and others.

3.4.2. Prediction error during feedback

Across all participants, prediction error positively related to activity in the striatum, insula, and frontal regions (Table S5A). No regions emerged in which this relation was stronger for younger relative to older adults (Table S5B). As prediction error increased, older adults had higher brain activation relative to younger adults across a wide variety of brain regions (Table S5C), including the left hippocampus. Comparing older adult learners to non-learners, we found no evidence of differential relations between prediction

error in brain activity (Table S5F). Prediction error more strongly positively related to activity in regions around the posterior lateral sulcus in non-learners relative to learners (Table S5G).

3.5. Exploratory correlations

We conducted an exploratory correlational analysis to better understand the relationship between sharing behavior and likeability ratings. This analysis was motivated by a post hoc hypothesis, is detailed in the supplement (Section 5.7), and is summarized here. A positive relation between sharing behavior and post-experiment partner likeability ratings emerged in younger adults ($r(97) = 0.720$, $p < 0.001$). This relation seemed weaker in older adults ($r(88) = 0.235$, $p = 0.026$). Correlation comparison suggested that older adults did not base their likeability ratings on their experience during the task as much as younger adults ($z = 4.51$, $p < 0.001$).

4. Discussion

Here, we examined adult age-related differences in learning to trust. Similar to prior studies, we found that both age groups learned from experience with partners: over time, they gave more money to trustworthy partners and less money to untrustworthy partner. However, these effects were blunted in older adults. Contrary to our predictions, age-related differences in learning to trust were not due to differences in updating in response to positive and negative feedback. Exploratory analyses revealed a number of potential alternate explanations, which we discuss below.

4.1. Positivity effect and asymmetric learning from gains and losses

Based on the positivity effect that has been observed in learning and memory (Carstensen, 2006), we predicted that older adults would be more likely to change their representation based on positive (trustworthy) versus negative (untrustworthy) feedback and that this would be demonstrated by lower learning rates for losses compared to gains in older, but not younger, adults. However, these predictions were not supported by our data. While the *gain-loss learning* model was the best-fitting model both at the group and individual levels, there was no significant difference between learning rates in either age group. This suggests that individuals in our sample show asymmetric learning from gains and losses, but there is no group-level asymmetry in learning rates for gains and losses and no effect of age on learning rate for either valence.

While these results were not predicted, they are consistent with at least 1 prior study showing no age-related differences in learning rates for gains and losses (Samaniez-Larkin et al., 2014). Although it is clear that older adults do not learn as well as younger adults (Mata et al., 2011), the extent to which this is driven by focusing on positive or negative feedback remains an open question. While the positivity effect suggests that older adults attend more to positive information, prior studies have shown that older adults learn equally well from positive and negative feedback (Samaniez-Larkin et al., 2014; Simon et al., 2010) or that older adults respond more to negative, compared to positive, feedback (Frank and Kong, 2008; Hämmerer et al., 2011). Our study makes an additional contribution to this growing literature.

4.2. Associative learning and social prediction error

Although both younger and older adults adjusted their behavior based on the behavior of the partners that they were interacting with, older adults did so to a lesser degree. This pattern is consistent with research showing age-related differences in

the development of trust across the adult life span (Bailey et al., 2016; Bailey and Leon, 2019; Rasmussen and Gutchess, 2019; Suzuki, 2016; Webb et al., 2016). One possible reason for this is the associative deficit hypothesis (Naveh-Benjamin, 2000), which would suggest that older adults may have had trouble learning to associate investors with their behaviors (Suzuki, 2016). Consistent with this explanation, studies using model-based fMRI have shown that older adults typically show a reduced learning signal, or reward prediction error, compared to younger adults (Chowdhury et al., 2013; Samaniez-Larkin et al., 2014). Thus, learning from this signal may be impaired (Suzuki et al., 2019).

However, unlike prior studies, we observed no age-related differences in updating based on positive and negative feedback. Further, across all participants we found prediction error signals in striatal, insular, and frontal regions, and any age-related differences we observed did not moderate these effects. This suggests that the majority of our participants, including older adults, encoded prediction errors in regions consistent with the broader literature on prediction errors (Daw et al., 2011; McClure et al., 2003), anticipating gains and losses (Knutson et al., 2003; Samaniez-Larkin et al., 2008), and subjective value (Bartra et al., 2013; Kable and Glimcher, 2007).

4.3. The role of memory

We found that older adult learners, relative to non-learners, had greater reputation-related activity in mentalizing/memory areas while making their decisions. This is consistent with a growing literature suggesting that explicit source memory is important for making good investment decisions in both younger and older adults (Murty et al., 2016; Rasmussen and Gutchess, 2019). This explanation is also consistent with the age-related differences observed in relations between average amount shared during the task and post-experimental likability ratings. Younger adults had a strong positive relation between the amount shared and their post-experiment ratings, suggesting that they retained explicit memories of each partner that they used to guide their post-experiment ratings. Older adults, on the other hand, had a weaker positive relation. This suggests that as a group, older adults did not retain explicit memories to the same extent as younger adults. It is possible the observed age group difference is due to the older non-learners using something else to guide their post-experiment ratings.

4.4. Over-recruitment and compensation

We observed several instances of increased recruitment of neural resources in older, but not younger, adults. For older adults, there was increased neural activity associated with reputation in the inferior frontal gyrus and with prediction error in many visual processing regions. While this age-related over-recruitment does not meet the formal definition of dedifferentiation (Koen and Rugg, 2019) or compensation (Cabeza and Dennis, 2012), it is consistent with studies observing increased recruitment of neural resources in older adults. The increased activity in visual processing regions during feedback is consistent with studies reporting increased recruitment of visual processing areas for faces in older, compared to younger, adults (D. C. Park et al., 2004; J. Park et al., 2012; Voss et al., 2008). Images of the partner were displayed along with feedback, so older adults may have attempted to associate this feedback with their visual representation of the partner. This additional recruitment may have allowed older learners to successfully update their representations of their partners. Although prediction error signals are commonly associated with midline structures like the nucleus accumbens, it is not uncommon to find prediction error signals in other brain regions. For instance,

multivoxel pattern analyses have shown that reinforcement signals can be decoded throughout the brain (Vickery et al., 2011). However, this is speculation and our notably unbalanced and underpowered analysis comparing older learners to older non-learners does not support this compensatory interpretation. As with the other exploratory analyses reported here, future studies are need to explicitly test any compensation interpretations.

4.5. Uncertainty and reliance on stereotypes

It is also noteworthy that older adults rated neutral partners significantly less likeable than trustworthy and quantitatively, if not significantly, less likeable than untrustworthy partners. The behavior of these neutral partners was relatively less predictable, increasing uncertainty about their actions. This type of uncertainty is thought to induce negative affect and lead to automatic stereotypic impression formation (FeldmanHall and Shenhav, 2019). Perhaps the lack of memory for trustworthiness of these partners led older adults to rely on these affective and stereotypic processes to make their likeability judgments. Given that all of the partners were younger men, and thus from a different age group, it is possible that the stereotypic processes would cause the lower likeability rating. Future work could examine if this same pattern holds for partners who are in the same in-group (e.g., older adults learning from older adult partners)

4.6. Conclusions

Although adult age-related differences in learning to trust are well-documented (Bailey and Leon, 2019), the underlying cognitive and affective mechanisms are not well understood. We did not find evidence supporting our predicted mechanism, that older adults would change their representations more in response to positive, compared to negative feedback. However, our exploratory analyses uncovered several other potential mechanisms that should be assessed in future work. A better understanding of how older individuals learn to trust is crucial given that they are often targeted by fraudulent schemes that take advantage of their excessive trust.

Disclosure statement

The authors report no conflicts of interest.

Data

Preregistration, synthesized behavioral data, and code used in the manuscript can be viewed at and downloaded from <https://osf.io/b3au5>. Neuroimaging data can be viewed on Neurovault (<https://identifiers.org/neurovault.collection:12828>).

Acknowledgements

This work was supported by a subaward from the Scientific Research Network on Decision Neuroscience and Aging, which is supported by the National Institute on Aging (NIA R24-AG054355). JAC was supported by K01MH126308. KLS was supported by T32-AG000029.

CRedit authorship contribution statement

Kendra L. Seaman: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization, Funding acquisition. **Alexander P. Christensen:** Software, Investigation, Data curation. **Katherine D. Senn:** Investigation. **Jessica A. Cooper:**

Methodology, Software, Formal analysis, Writing – review & editing, Funding acquisition. **Brittany S. Cassidy:** Conceptualization, Formal analysis, Investigation, Resources, Writing – original draft, Supervision, Project administration, Funding acquisition.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:[10.1016/j.neurobiolaging.2023.01.011](https://doi.org/10.1016/j.neurobiolaging.2023.01.011).

References

- Acikalin, M.Y., Gorgolewski, K.J., Poldrack, R.A., 2017. A coordinate-based meta-analysis of overlaps in regional specialization and functional connectivity across subjective value and default mode networks. *Front Neurosci* 11, 1. doi:[10.3389/fnins.2017.00001](https://doi.org/10.3389/fnins.2017.00001).
- Akaike, H., 1974. A new look at the statistical model identification. *IEEE Trans. Autom. Control* 19 (6), 716–723. doi:[10.1109/TAC.1974.1100705](https://doi.org/10.1109/TAC.1974.1100705).
- Bailey, P.E., Leon, T., 2019. A systematic review and meta-analysis of age-related differences in trust. *Psychol. Aging* 34 (5), 674–685. doi:[10.1037/pag0000368](https://doi.org/10.1037/pag0000368).
- Bailey, P.E., Petridis, K., McLennan, S.N., Ruffman, T., Rendell, P.G., 2019. Age-related preservation of trust following minor transgressions. *J. Gerontol. Ser. B* 74 (1), 74–81. doi:[10.1093/geronb/gbw141](https://doi.org/10.1093/geronb/gbw141).
- Bailey, P.E., Szczap, P., McLennan, S.N., Slessor, G., Ruffman, T., Rendell, P.G., 2016. Age-related similarities and differences in first impressions of trustworthiness. *Cognit. Emotion* 30 (5), 1017–1026. doi:[10.1080/02699931.2015.1039493](https://doi.org/10.1080/02699931.2015.1039493).
- Bartra, O., McGuire, J.T., Kable, J.W., 2013. The valuation system: A coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. *Neuroimage* 76, 412–427. doi:[10.1016/j.neuroimage.2013.02.063](https://doi.org/10.1016/j.neuroimage.2013.02.063).
- Berg, J., Dickhaut, J., McCabe, K., 1995. Trust, reciprocity, and social history. *Games Econ Behav* 10 (1), 122–142. doi:[10.1006/game.1995.1027](https://doi.org/10.1006/game.1995.1027).
- Cabeza, R., Dennis, N.A., 2012. Frontal lobes and aging: deterioration and compensation. *Principles of frontal lobe function* 2, 628–652.
- Carstensen, L.L., 2006. The influence of a sense of time on human development. *Science* 312 (5782), 1913–1915. doi:[10.1126/science.1127488](https://doi.org/10.1126/science.1127488).
- Castle, E., Eisenberger, N.I., Seeman, T.E., Moons, W.G., Boggero, I.A., Grinblatt, M.S., Taylor, S.E., 2012. Neural and behavioral bases of age differences in perceptions of trust. *Proc. Natl. Acad. Sci.* 109 (51), 20848–20852. doi:[10.1073/pnas.1218518109](https://doi.org/10.1073/pnas.1218518109).
- Chang, L.J., Doll, B.B., van 't Wout, M., Frank, M.J., Sanfey, A.G., 2010. Seeing is believing: trustworthiness as a dynamic belief. *Cognit. Psychol.* 61 (2), 87–105. doi:[10.1016/j.cogpsych.2010.03.001](https://doi.org/10.1016/j.cogpsych.2010.03.001).
- Chang, L.J., Sanfey, A.G., 2009. Unforgettable ultimatums? expectation violations promote enhanced social memory following economic bargaining. *Front Behav Neurosci* 3, 36. doi:[10.3389/fnbeh.2009.0036.2009](https://doi.org/10.3389/fnbeh.2009.0036.2009).
- Chowdhury, R., Guitart-Masip, M., Lambert, C., Dayan, P., Huys, Q., Düzel, E., Dolan, R.J., 2013. Dopamine restores reward prediction errors in old age. *Nat. Neurosci.* 16 (5), 648–653. doi:[10.1038/nn.3364](https://doi.org/10.1038/nn.3364).
- Clithero, J.A., Rangel, A., 2014. Informatic parcellation of the network involved in the computation of subjective value. *Soc Cogn Affect Neurosci* 9 (9), 1289–1302. doi:[10.1093/scan/nst106](https://doi.org/10.1093/scan/nst106).
- Cundiff, J.M., Smith, T.W., Uchino, B.N., Berg, C.A., 2013. Subjective social status: construct validity and associations with psychosocial vulnerability and self-rated health. *Int. J. Behav. Med.* 20 (1), 148–158. doi:[10.1007/s12529-011-9206-1](https://doi.org/10.1007/s12529-011-9206-1).
- Daw, N.D., Gershman, S.J., Seymour, B., Dayan, P., Dolan, R.J., 2011. Model-based influences on humans' choices and striatal prediction errors. *Neuron* 69 (6), 1204–1215. doi:[10.1016/j.neuron.2011.02.027](https://doi.org/10.1016/j.neuron.2011.02.027).
- Delgado, M.R., Frank, R.H., Phelps, E.A., 2005. Perceptions of moral character modulate the neural systems of reward during the trust game. *Nat. Neurosci.* 8 (11), 1611–1618. doi:[10.1038/nn1575](https://doi.org/10.1038/nn1575).
- Esteban, O., Markiewicz, C.J., Blair, R.W., Moodie, C.A., Isik, A.I., Erramuzpe, A., Kent, J.D., Gonçalves, M., DuPre, E., Snyder, M., Oya, H., Ghosh, S.S., Wright, J., Durnez, J., Poldrack, R.A., Gorgolewski, K.J., 2019. fMRIPrep: A robust preprocessing pipeline for functional MRI. *Nat. Methods* 16 (1), 111–116. doi:[10.1038/s41592-018-0235-4](https://doi.org/10.1038/s41592-018-0235-4).
- Fareri, D.S., Chang, L.J., Delgado, M.R., 2012. Effects of direct social experience on trust decisions and neural reward circuitry. *Front Neurosci* 6. doi:[10.3389/fnins.2012.00148](https://doi.org/10.3389/fnins.2012.00148).
- FeldmanHall, O., Dunsmoor, J.E., Tompary, A., Hunter, L.E., Todorov, A., Phelps, E.A., 2018. Stimulus generalization as a mechanism for learning to trust. *Proc. Natl. Acad. Sci.* 115 (7), E1690–E1697.
- FeldmanHall, O., Shenhav, A., 2019. Resolving uncertainty in a social world. *Nat Hum Behav* 3 (5), 426–435. doi:[10.1038/s41562-019-0590-x](https://doi.org/10.1038/s41562-019-0590-x).
- Frank, M.J., Kong, L., 2008. Learning to avoid in older age. *Psychol. Aging* 23 (2), 392–398. doi:[10.1037/0882-7974.23.2.392](https://doi.org/10.1037/0882-7974.23.2.392).
- Gorgolewski, K., Burns, C., Madison, C., Clark, D., Halchenko, Y., Waskom, M., Ghosh, S., 2011. Nipype: a flexible, lightweight and extensible neuroimaging data processing framework in python. *Front Neuroinform* 5, 13. doi:[10.3389/fninf.2011.00013](https://doi.org/10.3389/fninf.2011.00013).

- Hämmerer, D., Li, S.-C., Müller, V., Lindenberger, U., 2011. Life span differences in electrophysiological correlates of monitoring gains and losses during probabilistic reinforcement learning. *J. Cogn. Neurosci.* 23 (3), 579–592. doi:[10.1162/jocn.2010.21475](https://doi.org/10.1162/jocn.2010.21475).
- Hedden, T., Park, D.C., Nisbett, R., Ji, L.-J., Jing, Q., Jiao, S., 2002. Cultural variation in verbal versus spatial neuropsychological function across the life span. *Neuropsychology* 16 (1), 65–73. doi:[10.1037//0894-4105.16.1.65](https://doi.org/10.1037//0894-4105.16.1.65).
- Kable, J.W., Glimcher, P.W., 2007. The neural correlates of subjective value during intertemporal choice. *Nat. Neurosci.* 10 (12), 1625–1633. doi:[10.1038/nn2007](https://doi.org/10.1038/nn2007).
- King-Casas, B., Tomlin, D., Anen, C., Camerer, C.F., Quartz, S.R., Montague, P.R., 2005. Getting to know you: reputation and trust in a two-person economic exchange. *Science* 308 (5718), 78–83. doi:[10.1126/science.1108062](https://doi.org/10.1126/science.1108062).
- Knutson, B., Fong, G.W., Bennett, S.M., Adams, C.M., Hommer, D., 2003. A region of mesial prefrontal cortex tracks monetarily rewarding outcomes: Characterization with rapid event-related fMRI. *Neuroimage* 18 (2), 263–272. doi:[10.1016/S1053-8119\(02\)00057-5](https://doi.org/10.1016/S1053-8119(02)00057-5).
- Koen, J.D., Rugg, M.D., 2019. Neural dedifferentiation in the aging brain. *Trends Cogn. Sci.* 23 (7), 547–559. doi:[10.1016/j.tics.2019.04.012](https://doi.org/10.1016/j.tics.2019.04.012).
- Mata, R., Josef, A.K., Samanez-Larkin, G.R., Hertwig, R., 2011. Age differences in risky choice: a meta-analysis. *Ann. N.Y. Acad. Sci.* 1235 (1), 18–29. doi:[10.1111/j.1749-6632.2011.06200.x](https://doi.org/10.1111/j.1749-6632.2011.06200.x).
- McClure, S.M., Berns, G.S., Montague, P.R., 2003. Temporal prediction errors in a passive learning task activate human striatum. *Neuron* 38 (2), 339–346. doi:[10.1016/S0896-6273\(03\)00154-5](https://doi.org/10.1016/S0896-6273(03)00154-5).
- Murty, V.P., FeldmanHall, O., Hunter, L.E., Phelps, E.A., Davachi, L., 2016. Episodic memories predict adaptive value-based decision-making. *J. Exp. Psychol. Gen.* 145 (5), 548–558. doi:[10.1037/xge0000158](https://doi.org/10.1037/xge0000158).
- Naveh-Benjamin, M., 2000. Adult age differences in memory performance: tests of an associative deficit hypothesis. *J. Exp. Psychol. Learn. Mem. Cogn.* 26 (5), 1170–1187. doi:[10.1037/0278-7393.26.5.1170](https://doi.org/10.1037/0278-7393.26.5.1170).
- O'Doherty, J.P., Hampton, A., Kim, H., 2007. Model-based fMRI and its application to reward learning and decision making. *Ann. N.Y. Acad. Sci.* 1104 (1), 35–53. doi:[10.1196/annals.1390.022](https://doi.org/10.1196/annals.1390.022).
- Park, B., Fareri, D., Delgado, M., Young, L., 2020. The role of right temporoparietal junction in processing social prediction error across relationship contexts. *Soc. Cogn. Affect. Neurosci.* nsaa072. doi:[10.1093/scan/nsaa072](https://doi.org/10.1093/scan/nsaa072).
- Park, D.C., Polk, T.A., Park, R., Minear, M., Savage, A., Smith, M.R., 2004. Aging reduces neural specialization in ventral visual cortex. *Proc. Natl. Acad. Sci.* 101 (35), 13091–13095. doi:[10.1073/pnas.0405148101](https://doi.org/10.1073/pnas.0405148101).
- Park, J., Carp, J., Kennedy, K.M., Rodrigue, K.M., Bischof, G.N., Huang, C.-M., Rieck, J.R., Polk, T.A., Park, D.C., 2012. Neural broadening or neural attenuation? Investigating age-related dedifferentiation in the face network in a large lifespan sample. *J. Neurosci.* 32 (6), 2154–2158. doi:[10.1523/JNEUROSCI.4494-11.2012](https://doi.org/10.1523/JNEUROSCI.4494-11.2012).
- Poulin, M.J., Haase, C.M., 2015. Growing to trust: evidence that trust increases and sustains well-being across the life span. *Social Psychol. Personal. Sci.* 6 (6), 614–621. doi:[10.1177/1948550615574301](https://doi.org/10.1177/1948550615574301).
- Rasmussen, E.C., Gutchess, A., 2019. Can't read my broker face: learning about trustworthiness with age. *J. Gerontol. Ser. B* 74 (1), 82–86. doi:[10.1093/geronb/gby012](https://doi.org/10.1093/geronb/gby012).
- Samanez-Larkin, G.R., Hollon, N.G., Carstensen, L.L., Knutson, B., 2008. Individual differences in insular sensitivity during loss anticipation predict avoidance learning. *Psychol. Sci.* 19 (4), 320–323. doi:[10.1111/j.1467-9280.2008.02087.x](https://doi.org/10.1111/j.1467-9280.2008.02087.x).
- Samanez-Larkin, G.R., Worthy, D.A., Mata, R., McClure, S.M., Knutson, B., 2014. Adult age differences in frontostriatal representation of prediction error but not reward outcome. *Psychobiology (Austin, Tex.)* 14 (2), 672–682. doi:[10.3758/s13415-014-0297-4](https://doi.org/10.3758/s13415-014-0297-4).
- Schultz, W., Dayan, P., Montague, P.R., 1997. A neural substrate of prediction and reward. *Science* 275, 8.
- Schwarz, G., 1978. Estimating the dimension of a model. *Ann. Stat.* 6 (2), 461–464. doi:[10.1214/aos/1176344136](https://doi.org/10.1214/aos/1176344136).
- Simon, J.R., Howard Jr., J.H., Howard, D.V., 2010. Adult age differences in learning from positive and negative probabilistic feedback. *Neuropsychology* 24 (4), 534–541. doi:[10.1037/a0018652](https://doi.org/10.1037/a0018652).
- Stanley, D.A., 2016. Getting to know you: general and specific neural computations for learning about people. *Soc. Cogn. Affect. Neurosci.* 11 (4), 525–536. doi:[10.1093/scan/nsv145](https://doi.org/10.1093/scan/nsv145).
- Sutton, R.S., Barto, A.G., 1998. *Reinforcement learning: An introduction*. MIT press, Cambridge, MA.
- Suzuki, A., 2016. Persistent reliance on facial appearance among older adults when judging someone's trustworthiness. *J. Gerontol. B Psychol. Sci. Soc. Sci.* 73 (4), 573–583. doi:[10.1093/geronb/gbw034](https://doi.org/10.1093/geronb/gbw034).
- Suzuki, A., 2018. Persistent reliance on facial appearance among older adults when judging someone's trustworthiness. *J. Gerontol. Ser. B* 73 (4), 573–583. doi:[10.1093/geronb/gbw034](https://doi.org/10.1093/geronb/gbw034).
- Suzuki, A., Ueno, M., Ishikawa, K., Kobayashi, A., Okubo, M., Nakai, T., 2019. Age-related differences in the activation of the mentalizing- and reward-related brain regions during the learning of others' true trustworthiness. *Neurobiol. Aging* 73, 1–8. doi:[10.1016/j.neurobiolaging.2018.09.002](https://doi.org/10.1016/j.neurobiolaging.2018.09.002).
- Vickery, T.J., Chun, M.M., Lee, D., 2011. Ubiquity and specificity of reinforcement signals throughout the human brain. *Neuron* 72 (1), 166–177. doi:[10.1016/j.neuron.2011.08.011](https://doi.org/10.1016/j.neuron.2011.08.011).
- Voss, M.W., Erickson, K.I., Chaddock, L., Prakash, R.S., Colcombe, S.J., Morris, K.S., Doerksen, S., Hu, L., McAuley, E., Kramer, A.F., 2008. Dedifferentiation in the visual cortex: An fMRI investigation of individual differences in older adults. *Brain Res.* 1244, 121–131. doi:[10.1016/j.brainres.2008.09.051](https://doi.org/10.1016/j.brainres.2008.09.051).
- Webb, B., Hine, A.C., Bailey, P.E., 2016. Difficulty in differentiating trustworthiness from untrustworthiness in older age. *Dev. Psychol.* 52 (6), 985–995. doi:[10.1037/dev0000126](https://doi.org/10.1037/dev0000126).
- Wechsler, D., 1997. *Wechsler Memory Scale, Third Edition The Psychological Corporation*, San Antonio, TX.
- Zachary, R.A., Shipley, W.C., 1986. *Shipley institute of living scale: revised manual*. West. Psychol. Services.