

**Age-related changes in Bayesian belief updating
during attentional deployment and motor intention**

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Keywords

Cueing paradigm, spatial attention, feature-based attention, Bayesian modeling

Abstract

Predicting upcoming events using past observations is a crucial component of an efficient allocation of attentional resources. Therefore, the deployment of attention is sensitive to different types of cues predicting upcoming events. Here we investigated probabilistic inference abilities in spatial and feature-based attentional, as well as in motor-intentional subsystems, focusing specifically on the age-related changes in these abilities. In two behavioral experiments, younger and older adults (20 younger and 20 older adults for each experiment) performed three versions of a cueing paradigm, where spatial, feature, or motor cues predicted the location, color, or motor response of a target stimulus. The percentage of cue validity (i.e., the probability of the cue being valid) changed over time, thereby creating a volatile environment. A Bayesian hierarchical model was used to estimate trial-wise beliefs concerning the cue validity from reaction times and to derive a subject-specific belief updating parameter ω in each task version. We also manipulated task difficulty: participants performed an easier version of the task in Experiment 1 and a more difficult version in Experiment 2. Results from Experiment 1 suggested a preserved ability of older adults to use the three different cues to generate predictions. However, the increased task demands of Experiment 2 uncovered a difference in belief updating between the two age groups, indicating moderate evidence for a reduction of the ability to update predictions with motor intention cues in older adults. These results point at a distinction of attentional and motor intentional subsystems, with age-related differences tackling especially the motor-intentional subsystem.

Introduction

Predictions concerning upcoming events play an important role in modulating our responses. Especially when facing an uncertain and changing environment, our decisions and responses depend on one side on the prior beliefs that we created during our past experiences in the same or in a similar situation. On the other side, they depend on our ability to flexibly adapt to the ever-changing environment (Behrens, Woolrich, Walton, & Rushworth, 2007).

Previous research has shown that similar mechanisms modulate the deployment of attention (Vossel, Mathys, Daunizeau, Bauer, Driver, Friston & Stephan, 2014; Vossel, Mathys, Stephan, & Friston, 2015). Cueing paradigms, in which a cue predicts the location, a particular feature of a target, or the required motor response with a specific probability, are particularly useful to investigate the role of predictions for the attentional deployment (Posner, 1980; Rushworth, Ellison, & Walsh, 2001; Vossel et al., 2014; Dombert, Kuhns, Mengotti, Fink, & Vossel, 2016; Kuhns, Dombert, Mengotti, Fink, & Vossel, 2017). In these paradigms, validly cued targets induce faster responses, whereas slower responses are observed when predictions are violated, i.e., with invalidly cued targets. Moreover, reaction time (RT) differences between valid and invalid trials increase with increasing percentage of cue validity (%CV). Previous studies have shown that people are sensitive to changes in %CV, even when these changes are not explicitly signaled (Vossel et al., 2014; Dombert et al., 2016; Kuhns et al., 2017).

The present study aimed at investigating age-related differences in flexibly adapting to changes of probabilities (cue validity) in a volatile environment in different cognitive subsystems. We used three distinct cueing versions to isolate the processes involved in spatial attention, feature-based attention, and motor intention, and two different levels of task difficulty. These three attentional and motor intentional subsystems have been previously investigated in healthy young participants using functional MRI (fMRI; Dombert et al., 2016;

Kuhns et al., 2017) showing both common and differential neural correlates. However, these subsystems have never been directly compared in older adults.

Unsignaled changes in the %CV occurred during the experiments, creating a volatile environment. In volatile environments, when the %CV is changing unpredictably over time, people tend to infer cue validity from observations in past trials and this probabilistic inference process can be described using formal computational models such as the Hierarchical Gaussian Filter (Mathys, Daunizeau, Friston, & Stephan, 2011). This hierarchical Bayesian learning model provides formal rules on how probability estimates (here, of the probability that the cue will be valid in a given trial) are updated on a trial-by-trial basis after each new observation (trial). These update equations bear similarity to simpler reinforcement learning rules, where the updating of probabilities after new observations is affected by a prediction error term (i.e., the difference between the observed and predicted outcome) which is weighted by a learning rate. The learning rate thus determines how much the prediction error influences the updating of the probability estimate. A crucial difference between such models and the Bayesian model employed in the present study is that the learning rate in the latter model is not constant throughout the experiment. Instead, the learning rate changes over time depending on the next higher level in the hierarchy. In our specific case, trial-wise beliefs about the probability that the cue will be valid are influenced by higher-level beliefs about how fast this probability changes, or – in other words – how stable or volatile the environment is perceived. Accordingly, the participant's belief that the environment is highly volatile increases the updating about the probability of an outcome, whereas the updating is decreased with the belief that the environment is stable. It has been shown repeatedly that such volatility-based learning models outperform models with a fixed learning rate when probabilistic contexts change during the experiment (e.g., Behrens et al., 2007; Iglesias et al., 2013; Jiang, Beck, Heller, & Egner, 2015). In addition to this volatility-dependent hierarchical coupling in the Bayesian learning model, the trial-wise updates of beliefs about cue validity

and environmental volatility are affected by subject- and session-specific parameters which are estimated from the subject's observable responses.

In the present study, the Hierarchical Gaussian Filter (Mathys, Daunizeau, Friston, & Stephan, 2011) was applied to estimate trial-wise predictions about cue validity based on individual RTs and to deduct and compare subject-specific updating parameters.

Previous evidence suggests that older adults might show difficulties in reward-based learning when reward information is uncertain. However, they do not show the same level of impairment when the reward contingencies are entirely predictable, suggesting difficulties in dealing with probabilistic outcomes (for a review see Eppinger, Haemmerer, & Li, 2011). Along the same line, recent evidence points towards a reduced ability of older adults to use uncertainty to guide learning in a reward-based predictive inference task (Nassar et al., 2016). In Nassar et al.'s study, the participants had to estimate the location of a reward in a computer game in which a helicopter (non-visible to the participants for most of the trials) would drop bags of coins at different locations in every trial. The participants had to infer the position of the helicopter based on the position of the dropped bags on a trial-by-trial basis. The bags would drop in slightly different locations distributed around a mean determined by the helicopter position. The helicopter remained in the same location for most of the trials. However, in some trials it would abruptly change location. Therefore, participants' learning, estimated through computational modeling, would depend both on the trial-by-trial uncertainty concerning the precise position of the helicopter, and on the probability of change-points (trials in which the position of the helicopter would change abruptly).

To draw a parallel with the cueing paradigms used in the present study, the uncertainty described in Nassar et al.'s study can be considered analogous to the trial-by-trial estimates of the %CV, whereas the probability of change-points can be considered analogous to the changes in the %CV that determine the volatility of the environment. From these findings, we can hypothesize that the speed of updating concerning the trial-by-trial estimates of the %CV

will be reduced in older adults. However, given the fMRI findings of differential neural systems for updating in different attentional and motor intentional tasks (Dombert et al., 2016; Kuhns et al., 2017), it is also probable that such a reduction is not equally observed for the different cognitive systems.

Experiment 1

Materials and Methods

Participants

Initially, twenty-two older and twenty-two younger volunteers participated in the current study. Inclusion criteria were an age of 18-30 years for the younger group and of 50-75 years for the older group. All participants were right-handed, as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971), had a normal or corrected-to-normal vision and no history of neurological or psychiatric disorders. The group of older participants underwent the Mini-Mental State Examination (MMSE) to rule out general cognitive deficits (inclusion criterion: score ≥ 29 ; Folstein, Folstein, & McHugh, 1975). Two participants in each group had to be excluded from further analyses since the error rate in the experimental tasks deviated more than two standard deviations from the group mean (younger adults: one participant showed a mean error rate of 23% in the feature-based attention task, and the other participant of 20.5% in the motor task and 27.5% in the spatial attention task; older adults: one participant showed a mean error rate of 17% in the motor task, and one participant showed a mean error rate of 13.5% in the feature-based attention task). Hence, the final sample consisted of 20 older (9 females; age: 59 ± 6.8 (\pm SD) years; age range 50-71 years) and 20 younger participants (10 females; age: 23 ± 3.3 (\pm SD) years; age range 18-30 years). All participants gave written informed consent before participation. The study had been approved by the local ethics committee and was performed following the Code of Ethics of the World Medical Association (Declaration of Helsinki).

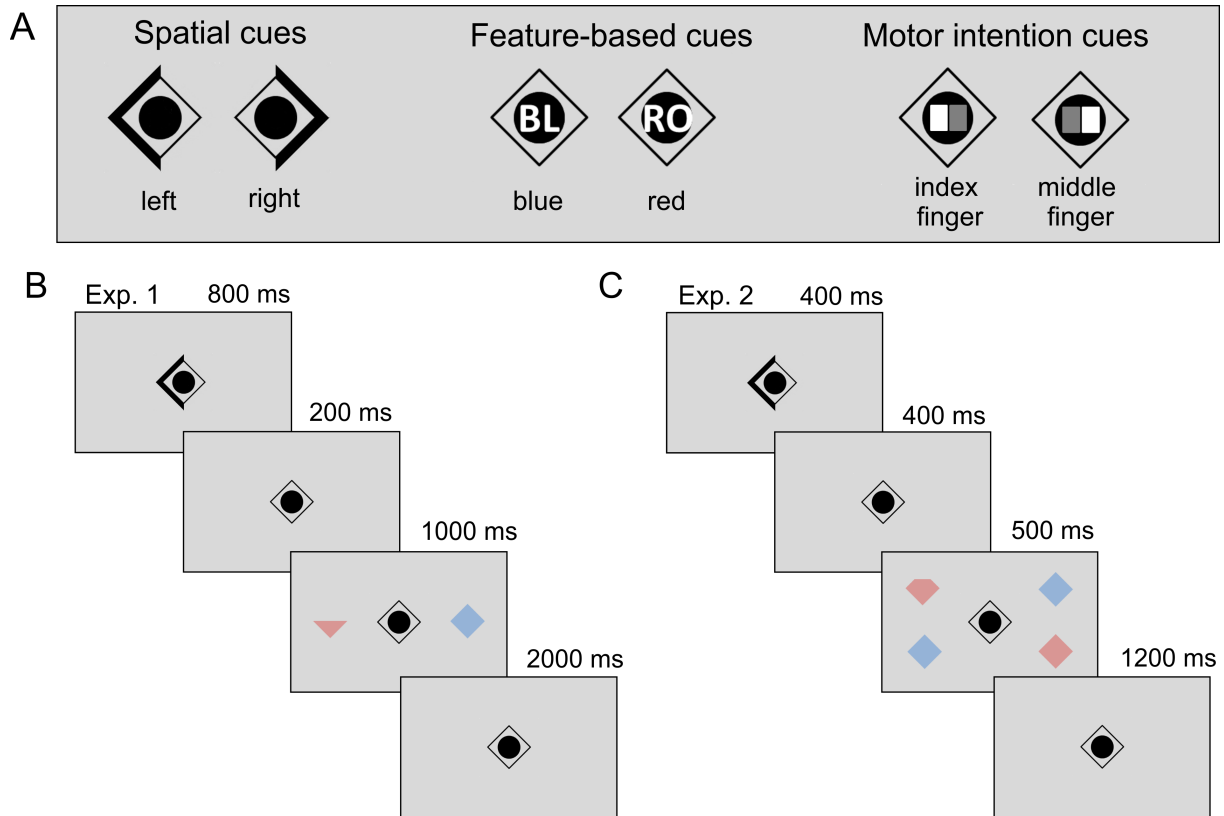
Stimuli and experimental paradigm

Three different cueing tasks (adapted from Dombert et al., 2016 and Kuhns et al., 2017) were presented consecutively on a laptop (resolution 1024 x 768, 60 Hz sampling rate) at a viewing distance of 52 cm.

At the beginning of each trial, the cue stimulus was shown for 800 ms. The cues in the three task versions contained either spatial or feature information about the upcoming target, or were preparatory for a motor response. In the spatial attention version, an arrowhead presented at the central fixation diamond pointed to the left or right side of the display, thereby indicating the most likely target location (Figure 1A). In the feature-based attention task, feature cues provided information about the most likely color of the target. These cues consisted of two-letter abbreviation of the color word in the center of the fixation diamond ('BL' or 'RO'; [i.e. 'BL', 'RE', in German, respectively]) (Figure 1A). This cue has been shown to elicit most effective cueing effects when compared to the presentation of the physical color or the whole color word (Dombert, Fink, & Vossel, 2016). Finally, in the motor intention task, the cue illustrated the two response buttons within the fixation diamond, with one being white and the other one being grey. Participants were asked to prepare the motor response corresponding to the white button, cueing either the right index or middle finger in preparation towards the upcoming target (Figure 1A).

After a 1000 ms stimulus onset asynchrony, the target display appeared for 1000 ms, consisting of one target stimulus, an upward or downward triangle located either on the left or right side of the fixation diamond (4.1° eccentric in each visual field, see Figure 1B), and a distractor stimulus (a diamond, located on the opposite side). When the distractor was red, the target was blue, and vice versa. Participants were asked to respond to upward or downward triangles by button presses with two different response buttons for their right index and middle finger. The response mapping (upward/downward triangle - index/middle finger) was

counterbalanced between participants. Participants were instructed to maintain central fixation and to respond as fast as possible to the target.



- insert Figure 1 here -

Figure 1. Experimental paradigm of Experiments 1 and 2. **A.** Three different cue stimuli were used for guiding spatial attention, feature-based attention, and motor intention. The spatial cue guided the attention towards one hemifield of the search display, whereas the feature cue was informative about the target color (RO for 'red' and BL for 'blue'). Motor responses were indicated by the salient white button cueing for index or middle finger response. **B.** Timeline of a valid trial for the spatial attention task in Experiment 1. **C.** Timeline of a valid trial for the spatial attention task in Experiment 2.

We counterbalanced the order in which the three different cueing tasks testing spatial attention, feature-based attention, or motor intention were administered across participants. In

each cueing task, the proportion of valid and invalid trials determining the validity of the cue information (%CV; i.e., the probability that the cue is valid) changed over the course of the experiment between levels of 50% and 80% (Figure 2B). Participants were informed about possible changes in %CV, but not about when they would occur or how high the %CV would be. A total of 200 trials per cueing version were shown, with alternating %CV blocks, each block consisting of 40 trials (Figure 2B). The position of the target, as well as its color, was counterbalanced across the cueing conditions and the %CV blocks. Following standard procedures in computational studies of trial-wise inference, target stimuli and trial sequence were identical between cueing versions. Halfway through each version, a one-minute break was introduced by displaying the word “Pause”. A practice session preceded each task of the experiment so that participants could get used to the fixation, manual response, and cueing conditions. The practice consisted of two separate, short runs; one run with a constant 80 %CV followed by a second run with changes in %CV. The total duration of the experiment (three runs with practice in between) amounted to approximately 70 minutes.

Behavioral data analysis

In a first step, we investigated the differences in general performance between the two age groups in the three different cueing tasks. We calculated each subject’s mean RT for correct trials across all cueing and %CV conditions and discarded responses deviating more than two standard deviations from the overall individual mean. Mean RT for each subject in each task version entered a 3×2 ANOVA with the within-subject factor *Task* (spatial attention/feature-based attention/motor intention) and *Age* (younger/older) as the between-subject factor. We performed a similar ANOVA on accuracy (% correct responses).

Moreover, we tested whether the participants showed general differences in cueing effects in the different versions of the task and between the two age groups. To account for the generally slower responses in older participants revealed by the first ANOVA, we

calculated normalized cueing effects by dividing the difference between valid and invalid RT by mean overall RT. These normalized cueing effects were analyzed with a 3 (*Task*: spatial attention/feature attention/motor intention) \times 2 (*Age*: younger/older) ANOVA. Besides, the normalized cueing effects were tested against zero with one-sample t-tests to ensure that the subjects paid attention to the cues. Results of the ANOVAs are reported after Greenhouse-Geisser correction at a significance level of $p < 0.05$. Post-hoc t-tests (with Bonferroni correction) were computed to interpret the significant effects when appropriate. Traditional frequentist analyses were integrated with their Bayesian counterparts computed in JASP (version 0.9.0.1), and Bayes factors (BF) are reported (BF_{10} for all comparisons and BF_{01} in those with $BF_{10} < 3$). The Bayes factor BF_{10} reflects the evidence for H_1 (i.e., the data from the two conditions/groups are different) compared with H_0 (i.e., the data from the two conditions/groups are not different). BF_{01} reflects the evidence in favor of the alternative hypothesis H_0 . $BF > 3$, > 10 , and > 30 indicate moderate, strong, or very strong evidence for a difference, respectively. $BF > 1$ but < 3 indicate anecdotal evidence and $BF = 1$ indicates no evidence in favor of one of the two hypotheses or, in other words, that H_1 and H_0 are equally likely (Wagenmakers et al., 2018).

In addition, we used G*Power (<http://www.gpower.hhu.de>, Faul et al., 2007) to estimate the achieved power with a post-hoc analysis, based on the effect sizes of two previous studies investigating age differences during reward learning (Eppinger, Heekeren, & Li, 2015) and goal-directed spatial attention (Twedell, Koutstaal, & Jiang, 2017).

Bayesian modeling of trial-wise belief updating

To investigate age-related differences in belief updating under uncertainty during spatial attention, feature-based attention, and motor intention, a Bayesian hierarchical learning model was applied, estimating the individual trial-wise beliefs about cue validity (Mathys et al., 2011; Vossel et al., 2014). Single-trial RTs of each participant were used to derive learning

parameters for each task. Since the general speed of responding differed between the two age groups, these analyses were based on normalized RTs (i.e., RT divided by overall mean RT).

The model, applied separately in each participant to the three tasks, incorporates a *perceptual* and a *response* model (Figure 2A). While the perceptual model describes trial-wise updating of probability estimates based on the cue-target outcomes (observations), the response model is used to derive responses (i.e., RTs) based on these beliefs. For a more in-depth description of the model, please refer to Mathys et al. (2011). In what follows, we describe the model parameters as relevant for the present study.

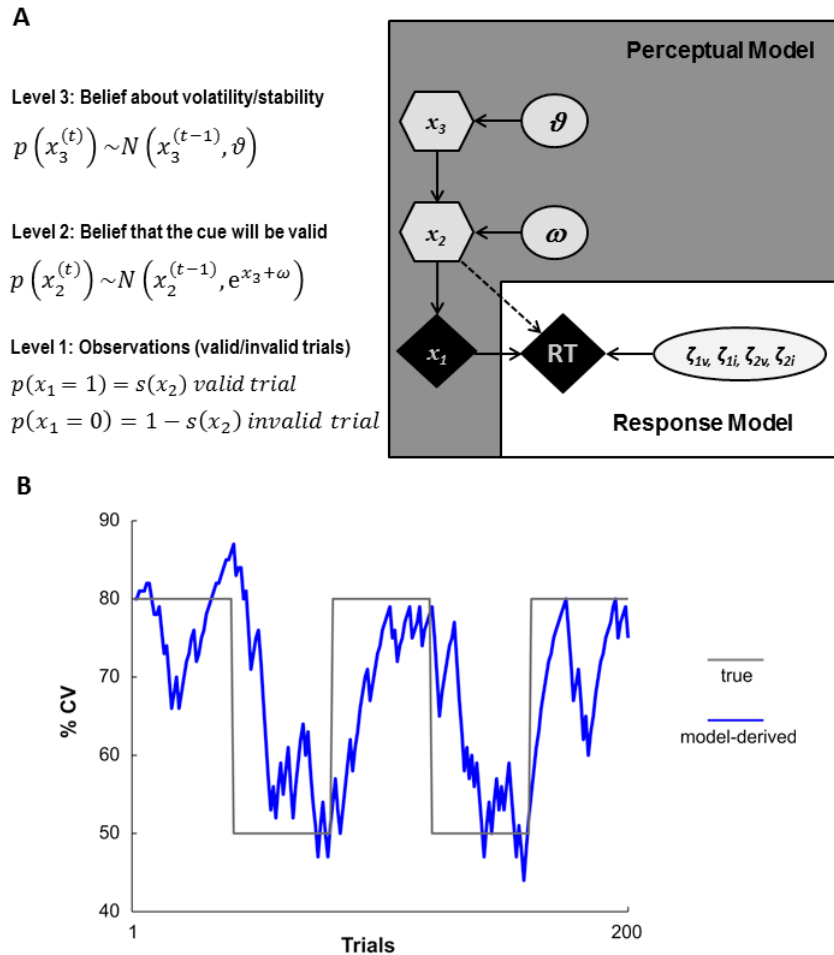


Figure 2. Illustration of the Bayesian hierarchical model for belief updating and example of the model output. **A.** The perceptual model (shown on the dark grey background) incorporates the three states (x_1, x_2, x_3). Higher levels are influenced by constant parameters ω and ϑ , which affect trial-wise changes on the respective level. Whereas the variables shown in diamonds and hexagons are quantities evolving with time (trials), circled variables are constants. Additionally, the quantities in the hexagons rely upon their previous states in a Markovian fashion. **B.** Percentage of cue validity (%CV) was manipulated over the course of the experiments, alternating between 80 and 50% (grey line). Here, trial-by-trial changes in $\hat{\mu}_1^{(t)}$ (i.e., the subject's belief that the cue is valid) over the course of 200 trials is shown. For this graph $\hat{\mu}_1^{(t)}$ was calculated for one subject to exemplify the model.

The perceptual model comprises three states denoted by x . The state $x_1^{(t)}$ at level 1 represents the environmental state of each trial t , which, in the present paradigm, consisted of either a validly or invalidly cued target (with $x_1^{(t)} = 1$ for valid and $x_1^{(t)} = 0$ for invalid trials). The distribution of the probability of a trial being valid (i.e., $x_1^{(t)} = 1$) is a Bernoulli distribution governed by the next higher state $x_2^{(t)}$. $x_2^{(t)}$ changes from trial to trial as a Gaussian random walk. How fast $x_2^{(t)}$ changes after new observations is determined by two quantities: $x_3^{(t)}$ (the state of the next upper level of the hierarchy) and a subject-specific updating parameter ω . The third state $x_3^{(t)}$ also changes as a Gaussian random walk, with the step size of the random walk being determined by a second fixed subject-specific parameter ϑ . Thereby, levels 2 and 3 of the model are hierarchically coupled Gaussian random walks that enable the flexible control of belief updating about cue validity in each trial in relation to beliefs about volatility (and subject-specific parameters). The subject-specific parameter ω determines the step-size of the random walk at the second level of the model, or in other

words, the speed of the belief updating about cue validity from trial-to-trial. ϑ determines the speed of the updating about the stability of cue validity (i.e., volatility, the third level of the model).

To infer the subject-specific beliefs about trial-by-trial cue validity and volatility from observable behavior (RTs), the perceptual model needs to be inverted; this yields the posterior densities of the hidden states $x^{(t)}$. In the following, the sufficient statistics of the subject's posterior belief are denoted by $\mu^{(t)}$ (mean), $\sigma^{(t)}$ (variance), and $\pi^{(t)} = \frac{1}{\sigma^{(t)}}$ (precision). As described in detail in Mathys et al. (2011), variational model inversion under a mean field approximation yields simple analytical update equations – where belief updating rests on weighted prediction errors. In this experiment, they provide us with the subject's estimate of the probability that the target appears at the cued location, the target color matches the cue, or that the target requires the cued motor response in a particular trial (note that this is an individualized approximate Bayes-optimality, in reference to the subject-specific values for the updating parameters ω and ϑ).

How the hidden beliefs translate into observable behavior (RTs) is expressed in the response model. In previous work (Dombert et al., 2016; Kuhns et al., 2017), a response model in which RTs were directly governed by the estimated cue validity before the observation of the trial outcome $\hat{\mu}_1^{(t)}$ described the data most plausibly and this response model was also applied in the present experiments. Here, it is assumed that the RT in a given trial is a linear function of the estimated probability that the cue will be valid $\hat{\mu}_1^{(t)}$. $\hat{\mu}_1^{(t)}$ is derived from a sigmoid transformation of the value of $\mu_2^{(t-1)}$ from the previous trial. In valid trials, a high probability estimate results in faster responses, while the opposite effect (slower responses with higher cue validity estimates) should occur in invalid trials. Two response model parameters ζ_1 and ζ_2 parameterize the intercept and the slope of the linear function for valid and invalid trials, respectively:

$$RT^{(t)} = \begin{cases} \zeta_{Iv} - \zeta_{2v}\hat{\mu}_1^{(t)} & \text{for } x_1^{(t)}=1 \text{ (i.e. valid trial)} \\ \zeta_{Ii} + \zeta_{2i}\hat{\mu}_1^{(t)} & \text{for } x_1^{(t)}=0 \text{ (i.e. invalid trial)} \end{cases}$$

The subject-specific parameters of the perceptual model (ω and ϑ) and the response model on the basis of trial-wise RT were estimated using a variational Bayesian estimation, as implemented in the HGF toolbox (<http://www.translationalneuromodeling.org/tapas/>) running on MATLAB® (2012b, The MathWorks, Inc., Natick, Massachusetts, United States). Variational Bayes is an iterative scheme, which can be regarded as an extension of the expectation-maximization algorithm yielding approximate posterior probability densities over the model parameters.

Of primary relevance for the present study were the model parameters ω and ϑ of the perceptual model, since they influence the learning about cue validity and volatility. For completeness, we also report the estimated response model parameters in the Supplementary materials and analyzed the ζ_2 parameter in relation to task and group effects. ζ_2 is a potentially interesting parameter, since it quantifies how much RTs change with changes in the estimated cue validity. ζ_1 just determines the absolute level of RTs and was not analyzed any further.

Besides these estimates of the free model parameters, variational Bayes yields estimates of the (negative) free-energy F as a lower bound on the log-model evidence, a measure that takes into account model accuracy and complexity (Friston et al., 2007). While the absolute level of the log-model evidence is not very meaningful, the values can be used to compare alternative models of the same data: the relative differences between log evidence values of different models of the same data (summed over individual subjects in a fixed-effects approach; Stephan et al., 2009) can be expressed as (log) Bayes factors (BF) and posterior probabilities (PP) of the model given the observed data. To this end, we compared model evidence for the hierarchical Bayesian learning model in each task and group to an alternative

model in which RTs were governed by a constant level of cue predictability (estimated from the data) so that no learning of the changing cue predictability levels occurred.

Results

Behavioral data

An overview of mean RTs and accuracy in the three versions of the cueing tasks for each age group is given in Table 1.

Table 1. Behavioral data for Experiment 1. Mean RTs (\pm SEM) and mean accuracy (\pm SEM), for spatial attention, feature-based attention, and motor intention, separately for younger and older adults.

Task	Mean RT (ms)		Accuracy (%)	
	Younger	Older	Younger	Older
<i>Spatial attention</i>	507 (± 16)	655 (± 19)	97.6 (± 0.3)	98.3 (± 0.3)
<i>Feature-based attention</i>	502 (± 17)	648 (± 16)	96.5 (± 0.5)	98.0 (± 0.3)
<i>Motor intention</i>	486 (± 18)	607 (± 16)	96.0 (± 0.5)	98.0 (± 0.4)

The ANOVA on accuracy with the within-subject factor *Task* (feature-based attention/spatial attention/motor intention) and the between-subject factor *Age* (younger/older) yielded a main effect of *Task* ($F_{(1.8,68.1)} = 5.91$, $p = 0.006$, $\eta_p^2 = 0.13$; $BF_{10} = 7.2$ compared to the null model). Post-hoc paired samples t-tests (Bonferroni corrected threshold: $p = 0.017$) comparing the tasks revealed better performance in the spatial attention task ($97.9 \pm 0.2\%$; mean \pm SEM) compared to the motor intention task ($97 \pm 0.36\%$; $t_{(39)} = -2.92$, $p = 0.006$; $BF_{10} = 6.6$) and compared to the feature-based attention task ($97.3 \pm 0.34\%$; $t_{(39)} = -2.89$, $p = 0.006$; $BF_{10} = 6.1$). The performance in the motor task and the feature-based attention task did not differ ($t_{(39)} = -0.88$, $p = 0.38$; $BF_{01} = 4.1$). The main effect of the between-subject factor *Age* was significant ($F_{(1,38)} = 7.96$, $p = 0.008$, $\eta_p^2 = 0.17$; $BF_{10} = 6.2$ compared to the null model), indicating higher accuracy for older than younger participants ($98 \pm 0.35\%$ vs. $97 \pm 0.35\%$). The interaction *Age* \times *Task* was not significant ($F_{(1.8,68.1)} = 2.4$, $p = 0.1$, $\eta_p^2 = 0.06$; $BF_{01} = 1.6$ compared to the model including the two main effects).

The ANOVA on individual mean RT (across all conditions) revealed a significant main effect of *Task* ($F_{(1.9,72.9)} = 9.74$, $p = 0.0002$, $\eta_p^2 = 0.2$; $BF_{10} = 124$ compared to the null model). Post-hoc paired samples t-tests (Bonferroni corrected threshold: $p = 0.017$) comparing the tasks revealed significantly faster RTs in the motor intention task (546 ± 15 ms; mean \pm SEM) as compared to the spatial attention (581 ± 17 ms; $t_{(39)} = -4.4$, $p = 0.00007$; $BF_{10} = 343$) and the feature-based attention task (575 ± 16 ms; $t_{(39)} = 3.18$, $p = 0.003$; $BF_{10} = 11.9$). The mean RT in the feature-based attention task and the spatial attention task did not differ ($t_{(39)} = -0.88$, $p = 0.38$; $BF_{01} = 4.8$). Additionally, the between-subject factor *Age* was significant ($F_{(1,38)} = 39.67$, $p = 0.0000002$, $\eta_p^2 = 0.5$; $BF_{10} = 44291$ compared to the null model), indicating generally slower RTs for the older participants (636 ± 15 ms vs. 498 ± 15 ms). The interaction *Age* \times *Task* was not significant ($F_{(1.9,72.9)} = 1.58$, $p = 0.21$, $\eta_p^2 = 0.04$; $BF_{01} = 2.4$ compared to the model including the two main effects).

The ANOVA on normalized cueing effects yielded no significant main effect of *Task* ($F_{(2,75.3)} = 1.35$, $p = 0.27$, $\eta_p^2 = 0.03$; $BF_{01} = 3.9$ compared to the null model) or *Age* ($F_{(1,38)} = 0.21$, $p = 0.65$, $\eta_p^2 = 0.006$; $BF_{01} = 3.3$ compared to the null model), nor an interaction between *Task* \times *Age* ($F_{(2,75.3)} = 0.34$, $p = 0.71$, $\eta_p^2 = 0.01$; $BF_{01} = 5.7$ compared to the model including the two main effects). We additionally performed one-sample t-test against zero to investigate whether younger and older adults show significant cueing effects in all task versions. Indeed, all t-tests were significant (all $ps < 0.005$), showing that both age groups were using the cues during the three tasks versions.

The main focus of our study was the assessment of trial-wise inference on cue validity using Bayesian modeling. For this reason, we analyzed the task- and subject-specific parameters ω and ϑ which determine the speed of the trial-wise updating of the belief that the cue will be valid (ω) and the belief about the volatility of cue validity (ϑ). The ANOVA with the within-subject factor *Task* (feature-based attention/spatial attention/motor intention) and the between-subject factor *Age* (younger/older) on the updating parameter ω did not reveal any significant main effect (*Task*: $F_{(2,75.1)} = 0.25$, $p = 0.78$, $\eta_p^2 = 0.007$; $BF_{01} = 10$ compared to the null model; *Age*: $F_{(1,38)} = 3.3$, $p = 0.08$, $\eta_p^2 = 0.08$; $BF_{01} = 1.6$ compared to the null model) or interaction (*Task* \times *Age*: $F_{(2,75.1)} = 0.06$, $p = 0.94$; $\eta_p^2 = 0.002$; $BF_{01} = 7.1$ compared to the model including the two main effects). The ANOVA on the parameter ϑ quantifying updating about volatility did also not reveal any significant main effect (*Task*: $F_{(1,38.3)} = 1.28$, $p = 0.27$, $\eta_p^2 = 0.03$; $BF_{01} = 3.8$ compared to the null model; *Age*: $F_{(1,38)} = 0.73$, $p = 0.4$, $\eta_p^2 = 0.02$; $BF_{01} = 3.4$ compared to the null model) or interaction (*Task* \times *Age*: $F_{(1,38.3)} = 0.87$, $p = 0.36$, $\eta_p^2 = 0.02$; $BF_{01} = 3.6$ compared to the model including the two main effects). The descriptive data of the response model parameters and the results of frequentists and Bayesian ANOVAs on the parameter ζ_2 are shown in the Supplementary Materials (Table S1 and S1).

To further investigate the relationship between age and model-based updating parameters in the group of older adults, we performed correlations between age and values of parameters ω and ϑ in the three versions of the tasks in this group of participants. We found a trend towards significance for a negative correlation between age and ω in the feature-based attention task ($r = -0.47$, $p = 0.037$; $BF_{01} = 0.47$), suggesting that the values of ω tended to be more negative – indicating slower updating – with higher age. No other significant results were found ($ps > 0.5$). When considering the parameter ϑ , no significant correlations with age were found ($ps > 0.2$).

Figure 3 shows observed RT costs in relation to predicted RTs costs for different values of estimated cue validity $\hat{\mu}_1^{(t)}$ (binned in higher or lower/equal to 0.7).

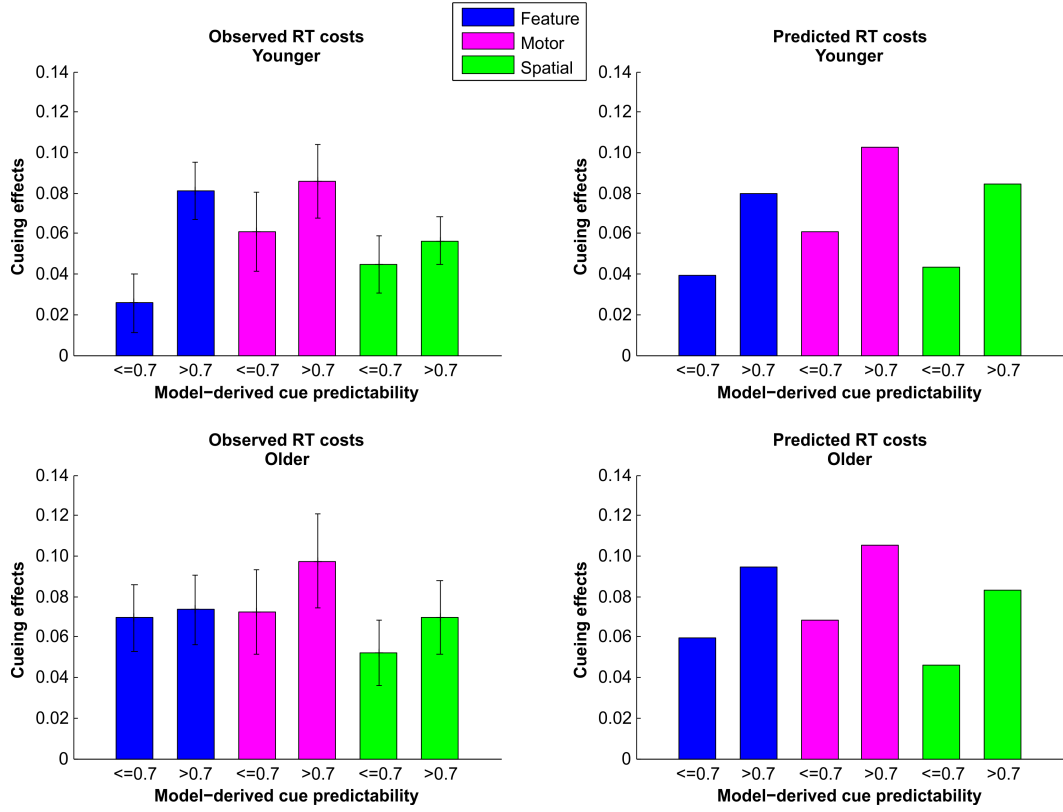


Figure 3. Observed and predicted pattern of RT costs from the Bayesian hierarchical model in Experiment 1. RT costs were calculated by subtracting normalized RTs of invalid trials from valid trials, and they are shown in relation to the participants' trial-by-trial estimate of the cue predictability $\hat{\mu}_1^{(t)}$ for all three tasks versions and the two age groups, binned in cue validity higher or lower/equal to 0.7. Error bars indicate SEM.

Formal model comparison between the Bayesian learning model and an alternative model without learning of the changing cue predictability levels yielded strong evidence in favor of the Bayesian model for all but one model comparison (younger adults: feature-based attention: BF = 13.78, PP = 1.0; motor intention: BF = 2.61, PP = 0.93; spatial attention: BF =

27.44, PP = 1.0; older adults: feature-based attention: BF = 13.56, PP = 1.0; motor intention: BF = 20.77, PP = 1.0; spatial attention: BF = 29.70, PP = 1.0).

Post-hoc power analyses performed on the effect sizes of the age \times condition interaction of two independent studies resulted in a power of 99% ($\eta_p^2 = 0.24$, Eppinger et al., 2015) and 98% ($\eta_p^2 = 0.21$, Twedell et al., 2017).

Discussion

The first experiment was designed to explore putative age-related differences in the ability to use trial-by-trial observations to estimate the cue validity, i.e., to update predictions concerning upcoming stimuli. In addition, we tested whether the attentional deployment and the updating behavior differed between three different versions of the cueing paradigm, namely the spatial attention, the feature-based attention, and the motor intention tasks.

We found no evidence of age-related differences in belief updating abilities. None of the learning parameters from the Bayesian learning model analyzed showed group differences between older and younger participants. There was also no evidence of differences in updating between the three different tasks. As for the attentional deployment, measured from the normalized cueing effects, we again did not find any age-related differences, nor differences in the different tasks. In contrast, we observed age-related differences in the general performance, with older participants being more accurate but slower in reacting than the younger participants, indicating a speed-accuracy trade-off. Also, we found a higher accuracy for the spatial task, compared with the feature-based and the motor intention tasks, and faster RTs for the motor intention task, compared with the spatial and the feature-based tasks. Although the reaction to the target involves motor preparation across conditions, the motor-intentional cue allows building a representation of the movement at an earlier stage, and this might explain these RT differences.

Experiment 2

The results of Experiment 1 revealed comparable abilities to infer cue validity in older and younger adults across different cueing conditions in a simple task setting. Besides, older adults were more accurate (although slower) than younger adults, indicating that they used a more conservative strategy to perform the task. Also, the presence of the speed-accuracy trade-off in older adults might complicate the interpretation of modeling results, based only on the trial-by-trial pattern of RTs.

When investigating age-related differences, it is essential that the tasks engage the cognitive resources of the participants. If the tasks are too easy, this might conceal age-related differences by not fully engaging participants' capacities. Therefore, Experiment 2 employed more difficult versions of the cueing tasks to investigate whether increased task difficulty may uncover age-related decline in belief updating in any of the three attentional-intentional domains. These versions were more similar to the ones used in previous neuroimaging studies with younger participants (Dombert et al., 2016; Kuhns et al., 2017).

We exacerbated the task by shortening the cue and target appearance time, as well as the time window to respond to the target. In addition, the target stimuli and search display were made more complex, the latter by adding two distractor stimuli.

Materials and Methods

Participants

Twenty-one older and twenty-two younger participants, who had not participated in Experiment 1, participated in Experiment 2. Two participants from the young age group and one subject in the older group had to be excluded due to a error rate in the experimental tasks that deviated more than two standard deviations from the group mean (younger adults: one participant showed a mean error rate of 26% in the feature-based attention task and of 40% in the motor task, and the other participant showed a mean error rate of 51.5% in the motor task;

older adults: one participant showed a mean error rate of 58.5% in the feature-based attention task and of 48% in the spatial attention task). Therefore, the final sample comprised twenty older participants (10 females; age: 61 ± 8.2 (SD) years; age range 50-77 years) and twenty younger participants (10 females; age: 26 ± 3.3 (SD) years; age range 19-30 years). The group of younger adults in Experiment 2 differed from the one of Experiment 1 by age ($t(38) = -2.13$, $p = 0.04$), with participants of the younger group being slightly younger in Experiment 1 than in Experiment 2 (23.4 ± 0.75 vs. 25.7 ± 0.75 years; mean \pm SEM). No differences in age were found between older participants in Experiment 1 and Experiment 2 (59 ± 1.5 vs. 61.4 ± 1.8 years; $t(38) = -1.02$, $p = 0.31$). The inclusion criteria matched those of Experiment 1.

Stimuli and experimental paradigm

Experiment 2 used the same cue stimuli for the three task versions and manual responses towards target stimuli as Experiment 1. However, the cue and target presentation were shortened to 400 ms and 500 ms, respectively, and the intertrial interval was reduced (1200 ms vs. 2000 ms in Experiment 1) (see Figure 1C). The complexity of the search display was increased, containing three distractor diamonds and one target diamond peripherally arranged in the corners of an imaginary rectangle centered on the fixation diamond (4.1° eccentric in each visual field). The target diamond had a missing corner in its upper or lower half and participants were asked to indicate which corner was missing. The response mapping was counterbalanced across participants. Each hemifield always contained one red and one blue diamond with counterbalanced positions across %CV blocks and valid and invalid trials, resulting in an equal number of diagonally and horizontally arranged trials. All other aspects of the task including the trial sequence and %CV manipulation were kept constant with regard to Experiment 1.

Behavioral data analysis and Bayesian modeling

The same analyses as in Experiment 1 were performed.

Eye movement recording and analysis

Previous evidence showed that age correlates with increased difficulty in voluntary saccade control (Peltsch, Hemraj, Garcia, & Munoz, 2011). Since we introduced additional distractor stimuli to make the task more complex, eye movements were recorded to control for fixation ability. An EyeLink® 1000 MR-compatible eye-tracker system (SR Research Ltd.) was employed at a sampling rate of 500 Hz. A 9-or 5 point calibration was performed, followed by a validation to ensure that errors were $<1^\circ$. Data were processed using the ILAB toolbox (Gitelman, 2002) in MATLAB (The MathWorks, Inc., Natick, Massachusetts, United States). The time between cue and target onset was analyzed for the amount of time spent in a predetermined fixation zone of 1.5° around the central fixation diamond. Consequently, the percentage of fixation time within the central ROI was compared using independent samples t-tests for each task, between the age groups.

Results

Behavioral data

Table 2 provides the mean RTs and accuracy in the three experimental conditions for each age group.

Table 2. Behavioral data for Experiment 2. Mean RTs (\pm SEM) and mean accuracy (\pm SEM), for spatial attention, feature-based attention, and motor intention, separately for younger and older adults.

Task	Mean RT (ms)	Accuracy (%)
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	Younger	Older	Younger	Older
<i>Spatial attention</i>	662 (± 21)	809 (± 26)	93.4 (± 0.5)	84.8 (± 2.7)
<i>Feature-based attention</i>	653 (± 22)	824 (± 22)	93.0 (± 1.1)	84.4 (± 2.3)
<i>Motor intention</i>	603 (± 22)	803 (± 23)	92.2 (± 1.0)	84.4 (± 2.2)

The 3 (*Task*: feature-based attention/spatial attention/motor intention) \times 2 (*Age*: younger/older) ANOVA on accuracy revealed a significant main effect of *Age* ($F_{(1,38)}=12.1$, $p = 0.001$, $\eta_p^2 = 0.24$; $BF_{10} = 19.6$ compared to the null model). In contrast with the results of Experiment 1, the younger participants were more accurate than the older participants in Experiment 2 ($93 \pm 1.7\%$ vs. $84 \pm 1.7\%$). Neither a main effect of *Task* ($F_{(1.9,71.6)} = 0.52$, $p = 0.59$, $\eta_p^2 = 0.01$; $BF_{01} = 7.8$ compared to the null model) nor a significant *Task* \times *Age* interaction were found ($F_{(1.9,71.6)} = 0.18$, $p = 0.82$, $\eta_p^2 = 0.005$; $BF_{01} = 7.1$ compared to the model including the two main effects).

The same ANOVA on mean RTs revealed a significant main effect of *Task* ($F_{(1.77,67.4)} = 8.75$, $p = 0.0007$, $\eta_p^2 = 0.19$; $BF_{10} = 45$ compared to the null model). Post-hoc paired samples t-tests (Bonferroni corrected threshold: $p = 0.017$) comparing the tasks revealed that RTs in the motor intention task (703 ± 22 ms) were significantly faster than in the spatial attention task (736 ± 20 ms; $t_{(39)} = -3.8$, $p = 0.001$; $BF_{10} = 55$) and in the feature-based attention task (738 ± 20 ms; $t_{(39)} = 3.6$, $p = 0.001$; $BF_{10} = 32$). There was no difference in mean RTs between the spatial attention task and the feature-based attention task ($t_{(39)} = 0.22$, $p = 0.83$; $BF_{01} = 5.7$). A main effect of *Age* ($F_{(1,38)} = 32.5$, $p = 0.000001$, $\eta_p^2 = 0.46$; $BF_{10} = 6733$ compared to the null model) was found, with slower RTs for older compared with younger participants (812 ± 21 ms vs. 639 ± 21 ms). In addition, the *Task* \times *Age* interaction ($F_{(1.77,67.4)} = 3.97$, $p = 0.028$, $\eta_p^2 = 0.1$; $BF_{01} = 0.44$ compared to the model including the two main effects) was

significant. Post-hoc independent samples t-tests (Bonferroni corrected threshold: $p = 0.017$) comparing tasks between the age groups indicated that younger participants were significantly faster in all tasks (feature-based attention: $t_{(38)} = -5.55$, $p = 0.000002$, $BF_{10} = 5808$; motor intention: $t_{(38)} = -6.3$, $p = 0.0000002$, $BF_{10} = 49778$; spatial attention: $t_{(38)} = -4.3$, $p = 0.0001$, $BF_{10} = 218$). In order to test for differences between task versions within the two age groups, we calculated post-hoc paired samples t-tests (three tests per age group; Bonferroni corrected threshold: $p = 0.017$). Results revealed faster RTs in younger participants for the motor intention task (603 ± 22 ms) compared with the spatial attention task (662 ± 21 ms; $t_{(19)} = -4.78$, $p = 0.0001$; $BF_{10} = 221$) and with the feature-based attention (653 ± 22 ms; $t_{(19)} = 3.34$, $p = 0.003$; $BF_{10} = 12$). There was no difference between the spatial attention task and the feature-based attention task ($t_{(39)} = -0.59$, $p = 0.56$; $BF_{01} = 3.7$). No differences were found between task versions within the group of the older participants.

The ANOVA on normalized cueing effects yielded no significant main effect of *Task* ($F_{(1.9,73.1)} = 0.05$, $p = 0.95$, $\eta_p^2 = 0.001$; $BF_{01} = 11.3$ compared to the null model), nor a *Task* \times *Age* interaction ($F_{(1.9,73.1)} = 0.06$, $p = 0.93$, $\eta_p^2 = 0.002$; $BF_{01} = 7$ compared to the null model). However, there was a significant main effect for *Age* ($F_{(1,38)} = 5.7$, $p = 0.02$, $\eta_p^2 = 0.13$; $BF_{01} = 0.4$ compared to the model including the two main effects), with higher normalized cueing effects for younger than older adults (0.11 ± 0.01 ms vs. 0.07 ± 0.01 ms). We additionally performed one-sample t-test against zero to investigate whether younger and older adults show significant cueing effects in all task versions. Indeed, all t-tests were significant (all $ps < 0.005$), showing that both age groups were using the cues during the three tasks versions.

As in Experiment 1, the subject-specific updating parameter ω was compared in an ANOVA with the within-subject factor *Task* (spatial attention/feature-based attention/motor intention) and the between-subject factor *Age* (younger/older). The main effects of *Task* ($F_{(2,75)} = 0.21$, $p = 0.81$, $\eta_p^2 = 0.006$; $BF_{01} = 10.5$ compared to the null model) and *Age* ($F_{(1,38)} = 2.4$, $p = 0.13$, $\eta_p^2 = 0.06$; $BF_{01} = 2.15$ compared to the null model) were not significant.

However, a significant *Task* \times *Age* interaction ($F_{(2,75)} = 4.33$, $p = 0.017$, $\eta_p^2 = 0.1$; $BF_{10} = 6.6$ compared to the model including the two main effects) was observed. Post-hoc independent samples t-tests (Bonferroni corrected threshold: $p = 0.017$) showed that the learning parameter ω in the motor intention task tended to be reduced in older compared with younger adults ($t_{(38)} = 2.49$, $p = 0.019$, $BF_{10} = 3.2$; see Figure 4). Thus, younger participants tended to be faster than the older participants in updating their beliefs about cue validity in the motor intention task. No significant differences were found between younger and older adults in the learning parameter ω in the spatial attention task ($t_{(38)} = -1.6$, $p = 0.12$, $BF_{01} = 1.2$) and in the feature-based attention task ($t_{(38)} = 1.6$, $p = 0.12$, $BF_{01} = 1.2$). No significant differences were found between task versions for each of the two groups.

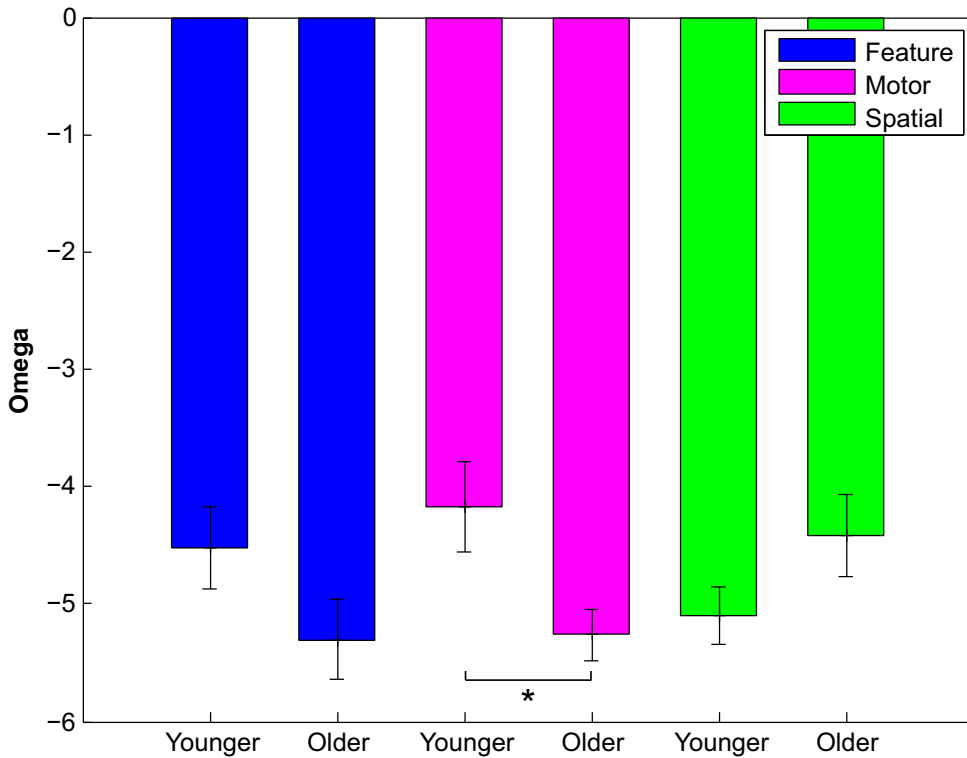


Figure 4. Results from the Bayesian hierarchical Model in Experiment 2. Between-group comparison of the individual updating parameter ω for spatial attention, feature-based

attention, and motor intention. Less negative values of ω indicate faster updating. In the motor intention task, younger participants are significantly more flexible in their tendency to adapt their predictions, as opposed to older adults.

The ANOVA on ϑ parameter (updating of volatility) did not reveal any significant main effect (*Task*: $F_{(1.1,43)} = 0.77$, $p = 0.4$, $\eta_p^2 = 0.02$; $BF_{01} = 6.1$ compared to the null model; *Age*: $F_{(1,38)} = 0.26$, $p = 0.61$, $\eta_p^2 = 0.007$; $BF_{01} = 3.9$ compared to the null model) nor a *Task* \times *Age* interaction ($F_{(1.1,43)} = 1.34$, $p = 0.26$, $\eta_p^2 = 0.03$; $BF_{01} = 0.94$ compared to the model including the two main effects). The descriptive data of the response model parameters and the results of frequentists and Bayesian ANOVAs on the parameter ζ_2 are shown in the Supplementary Materials (Table S1 and S2).

In order to further investigate the relationship between age and model-based updating parameters in the group of older adults, we performed correlations between age and values of parameters ω and ϑ in the three versions of the tasks in this group of participants. We found no evidence for correlations between age and learning parameters in the three tasks (ω : $ps > 0.2$; ϑ : $ps > 0.6$; all $BF_{10} < 1$).

Figure 5 shows observed RTs cost in relation to predicted RTs costs for different values of $\hat{\mu}_1^{(t)}$ (binned in higher or lower/equal to 0.7).

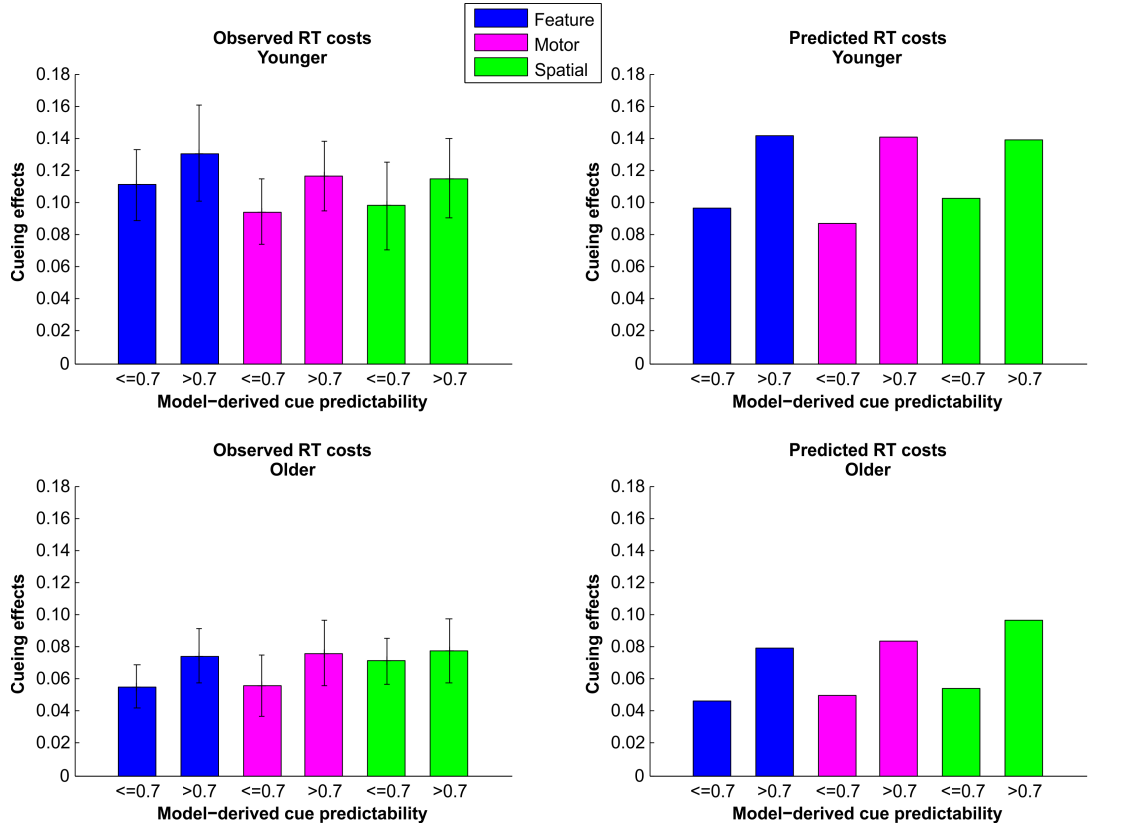


Figure 5. Observed and predicted pattern of RT costs from the Bayesian hierarchical model in Experiment 2. RT costs were calculated by subtracting normalized RTs of invalid trials from valid trials, and they are shown in relation to the participants' trial-by-trial estimate of the cue predictability $\hat{\mu}_1^{(t)}$ for all three tasks versions and the two age groups, binned in cue validity higher or lower/equal to 0.7. Error bars indicate SEM.

Formal model comparison between the Bayesian learning model and an alternative model without learning of the changing cue predictability levels yielded strong evidence in favor of the Bayesian model for all model comparisons (younger adults: feature-based attention: BF = 80.47, PP = 1.0; motor intention: BF = 21.34, PP = 1.0; spatial attention: BF = 83.97, PP = 1.0; older adults: feature-based attention: BF = 10.70, PP = 1.0; motor intention: BF = 15.38, PP = 1.0; spatial attention: BF = 6.21, PP = 1.0).

Eye movement data

A total of 19 of the 120 datasets (one for each of the three task versions for the younger and older adults) had to be discarded from further analysis due to poor tracking quality and technical difficulties. Independent samples t-tests on the percentage of fixation time in the cue-target period were conducted for each task version, between age groups. In the feature-based attention task, five datasets of older participants could not be included. Analysis showed significantly higher fixation time in younger adults ($99 \pm 0.3\%$; mean \pm SEM) compared to older adults ($98 \pm 0.2\%$; $(t_{33}) = 2.6$, $p = 0.01$). In the motor intention task, datasets of five younger and four older adults did not enter the analysis. Again, younger participants had a significantly better fixation performance ($99 \pm 0.2\%$) than the older group ($98 \pm 0.3\%$; $t_{29} = 3$, $p = 0.005$). As for the spatial attention task, five datasets from older adults had to be discarded. The remaining participants showed no significant differences ($t_{33} = 0.7$, $p = 0.49$) in fixation time (younger: $99 \pm 0.4\%$; older: $98 \pm 0.2\%$). Despite the differences between age groups in some of the task versions, mean fixation values showed that also older adults were able to keep good fixation during the task.

Discussion

In Experiment 2, we employed a more difficult version of the cueing paradigm used in Experiment 1, with the aim of challenging the participants' ability to infer the cue validity and updating their beliefs in a volatile environment. Age-related differences were found in both behavioral performances and the model parameters. Younger participants were faster and more accurate in their responses than older participants, suggesting that the difficult version of the paradigm challenged more the latter group. This was also reflected in the results of the cueing effects, where younger participants showed higher cueing effects than older participants, suggesting that the former group was more sensitive to the cue information and showed stronger orienting towards the cues. Besides, age-related and task differences where

found when analyzing the subject-specific updating parameter ω . More specifically, younger participants showed a tendency (or moderate evidence) towards faster belief updating in the volatile environment in the motor intention task than older participants. Whereas probabilistic inference abilities did not differ with age in Experiment 1, increased task demands in Experiment 2 unraveled moderate evidence of a slowing of belief updating with motor intention cues for older participants.

Concerning task differences, similarly to Experiment 1, the motor intention task induced faster RTs than the spatial and the feature-based attention tasks. The same pattern was found for RTs in the group of the younger participants, whereas no difference in RTs between tasks was found for the group of the older participants.

General discussion

Using three different versions of a cueing paradigm and two task difficulty levels, we investigated age-related changes in the ability to use recent observations and environmental cues to infer the probability of upcoming events for an efficient attentional deployment. Formal computational modeling with a generic Bayesian learning scheme allowed us to characterize individual updating of beliefs concerning the occurrence of upcoming events in a volatile environment when different stimulus properties were predicted by spatial, feature, or motor cues. The results highlighted a significant interaction between task and age group in the more difficult task version (Experiment 2). Post-hoc analyses pointed towards a tendency (or moderate evidence) of a reduced ability to update predictions in older participants in the more difficult version of the motor intention task, i.e., when the finger required for the response was cued.

Previous fMRI studies (Dombert et al., 2016; Kuhns et al., 2017) used the same three versions of the task in healthy young participants and showed that probabilistic inference for spatial attention, feature-based attention, and motor intention engages different brain regions.

Results showed that a common node located in the left anterior intraparietal sulcus was involved in inferring trial-wise cue validity during spatial and feature-based attention (Dombert et al., 2016). However, distinct correlates were found for spatial attention and motor intention (Kuhns et al., 2017). Whereas for spatial attention the activity of the right temporo-parietal junction was modulated by trial-wise estimates of the cue being valid (see also Vossel et al., 2015 and Dombert et al., 2016), the same process for motor cues was supported by the left angular gyrus and anterior cingulate cortex. The difference in the neural substrates of probabilistic inference processing can explain the selective age-related differences in belief updating abilities in the motor intention task. Indeed, there is evidence that the functionality of the prefrontal cortex is reduced with aging (for a review see Hedden and Gabrieli, 2004), and previous studies also point to a decline of anterior cingulate cortex function and volume with age (Pardo et al., 2007; Mann et al., 2011).

Differently from previous findings showing generalized difficulties in older adults with reward-based probabilistic learning (Eppinger, Haemmerer, & Li, 2011; Nassar et al., 2017), the present results yielded moderate evidence of reduced probabilistic belief updating in older adults only when motor cues are used to predict the appearance of the target and only in the more difficult version of the task. Conversely, no differences were found for the spatial attention and feature-based attention tasks. The lack of evidence for a reduction of probabilistic belief updating abilities found in our group of older adults in two out of the three subsystems investigated could be due to the different nature of the tasks, tackling attentional systems and not the reward system. In line with our results, previous studies reported preserved cueing effects in older adults for endogenous attention (Tellinghuisen, Zimba, & Robin, 1996; Curran, Hills, Patterson, & Strauss, 2001; Tales, Muir, Bayer, & Snowden, 2002), despite slower latencies for early visual ERP components, i.e., N1 and P1, as well as later components such as the P3, in older compared with younger adults (Curran et al., 2001).

Using a cueing task with spatial cues predicting the hand needed for the response, Sterr and Dean (2008) found an absence of validity effects (difference in RTs between validly and invalidly cued responses) in a group of older adults compared with younger participants. In addition, they found differences in ERP components, such as the foreperiod contingent negative variation and the lateralized readiness potential, between the two age groups indicating reduced lateralized motor preparation in the group of older participants. These results suggested differences in processing of motor cues with healthy aging, in line with the present results. However, in the abovementioned study, no manipulation of the cue predictability during the task was performed. It is indeed by manipulating the cue predictability over time that allowed us to unveil age-related differences in the updating of predictions.

Some limitations of the present results should be mentioned. The present group of older adults included participants below 60 years old (>50 years), possibly constraining our results in term of age-related differences that could be detected. Also, the sample size of the two groups may only be suited to detect medium-to-strong age-dependent effects. Previous studies investigating age \times condition interactions during reward learning (Eppinger et al., 2015) or goal-directed spatial attention (Twedell et al., 2017) reported relatively large effect sizes; post-hoc power analyses based on these studies yielded an achieved power of 99% and 98% for our sample size, respectively. Therefore, it is possible that smaller age-related differences might have remained undetected. To overcome this limitation and to help with the interpretation of null findings, we provided Bayesian counterparts of traditional frequentist analyses. Our interest was focused on exploring age-related differences in the perceptual model parameters ω and ϑ . Whereas for ϑ Bayesian analyses indicated evidence against a main effect of age, the results were less conclusive for ω , with Bayesian analyses indicating no clear evidence against a main effect of age. However, the evidence of an age-related

difference for the parameter ω in the motor intention task in Experiment 2 was the strongest, suggesting that age-related changes are occurring in the motor intention subsystem.

In conclusion, by combining the analysis of behavior with a formal computational model, the present work provides new insights into age-related changes in the efficiency of probabilistic inference in the motor-intentional subsystem as well as into the mechanisms that support such inference processes within attentional subsystems.

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