Age dependent statistical learning trajectories reveal differences in information weighting

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Running Head: Statistical learning and information weightings

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Abstract

Statistical learning (SL) is a profound mechanism of learning that is already present during infancy. However, SL in the elderly has received far less attention and its relation to general cognitive function remains elusive. Here, we explore statistical learning in 40 healthy elderly and 40 young adults. The paradigm deployed tracks learning trajectories and shows age-related dependencies that are somewhat mediated by scores on a number of traditional cognitive assessments. Importantly, Bayesian models revealed differences in strategies between elderly and young adults when it comes to dealing with uncertainty. Computational models identify a possible explanation in the form of age-dependent differences in information weighting, in which young adults more readily change their behaviour, but exhibit greater frustration in response to erroneous predictions compared to the elderly. Taken together, the present pattern of results points towards age-related differences in information processing with lower but more balanced information weights in the elderly.

Keywords: Statistical Learning; Cognitive Assessment; Continuous Paradigm; Elderly

Introduction

Statistical learning (SL) is the ability to generate predictions based on extracted probabilistic dependencies in the environment. The majority of SL research has been concerned with early childhood development or young adults (see Krogh, Vlach, & Johnson, 2013; Daltrozzo & Conway, 2014 and Saffran & Kirkham, 2018 for reviews). This makes intuitive sense, as SL is a profound mechanism of learning that is already present in infancy (Roseberry, Richie, Hirsh-Pasek, Golinkoff, & Shipley, 2011; Saffran, Aslin, & Newport, 1996). SL in the elderly, however, has received far less scientific attention. Considering the world-wide increase in life-expectancy and age-of-retirement (WHO, 2015, 2017), it is important to further our understanding of fundamental mechanisms of learning in the elderly. Furthermore, despite SL's crucial involvement across sensory modalities (Creel, Newport, & Aslin, 2004; Kirkham, Slemmer, & Johnson, 2002; Moldwin, Schwartz, & Sussman, 2017 see Erickson & Thiessen, 2015 for a review), research attempting to link SL to traditional cognitive assessments has yielded conflicting evidence. Here, we aim to explore age-dependent differences in SL trajectories in elderly and young adults and a potential link to cognitive function.

SL in the elderly. Compared to young adults, no change in SL of deterministic sequences (e.g., 'B' always follows 'A') has been observed in the elderly (Cherry & Stadler, 1995; Daltrozzo & Conway, 2014; Frensch & Miner, 1994; D. V. Howard & Howard, 1989, 1992; Salthouse, McGuthry, & Hambrick, 1999). However, differences were observed when probabilistic sequences that are governed by an underlying transitional probability (TP) matrix (e.g., 'B' is most likely to follow 'A' and 'C' is less likely to follow 'A') were used. In this scenario, elderly showed overall poorer SL compared to younger adults as measured in serial reaction time tasks (Curran, 1997; Feeney, Howard, & Howard, 2002; D. V. Howard et al., 2004;

J. H. Howard & Howard, 1997). It is important to note that elderly participants respond slower, but not necessarily less accurately (Aizenstein et al., 2006). Indeed, performance differences may be the result of a difference in focus between elderly and young adults in a speed-accuracy trade-off (Forstmann et al., 2011; Salthouse, 1979). As a result, we focus here on age-dependent SL accuracy -rather than reaction time- in a probabilistic paradigm. Furthermore, rather than analyzing only overall SL performance, it has been suggested that learning trajectories (slopes) provide valuable insight into individuals' cognitive capacities and the time course of learning novel information (Kaufman et al., 2010; Misyak, Christiansen, & Tomblin, 2010; Siegelman, Bogaerts, Christiansen, & Frost, 2017). The analysis of learning trajectories can be particularly informative when the underlying TP matrix contains transitions where the most likely event is clear (high certainty), as well as transitions where the most likely next event is less pronounced (low certainty) (Shafir, Reich, Tsur, Erev, & Lotem, 2008). Having both low and high certainty states present in the TP matrix allows for the investigation of differences in participants' learning strategies and a potential link to cognitive function

SL and Cognitive Function. Much research is concerned with assessing cognitive function, both in the context of diagnosing cognitive impairment and classifying individuals' 'fitness-for-duty'. Cognitive function herby refers to performance on a specific test, or composite scores (e.g., BAC-SF in Keefe et al., 2004). Administering these tests often requires special training, good social skills, and a clear notion of which cognitive skill should be tested specifically. SL may provide a promising easy-to-administer alternative that targets an underlying learning mechanism. However, previous attempts to use SL as a measure of individual aptitude or to link it to various established measures of cognitive function have been plagued by a plethora of difficulties (Siegelman, Bogaerts, & Frost, 2017). These include low test-retest reliability (r = .44 in Kaufman et al., 2010), and low performance (21-47% at chance, see Siegelman, Bogaerts, and Frost, 2017 for a review). Importantly, many studies report little to no relationship to well established measures of cognitive function (e.g., r from -.06 to.19 in Feldman, Kerr, and Streissguth, 1995; Kaufman et al. 2010; Siegelman, Bogaerts, and Frost, 2017). The low correlations with measures of cognitive function could either be a symptom of the aforementioned methodological issues or indeed indicative that SL is mostly independent of other cognitive skills.

Based on Siegelman, Bogaerts, and Frost (2017) criticism of existing SL paradigms, a new auditory SL paradigm that focuses on learning trajectories was developed (Herff, Nur, Lee, Lee, & Agres, 2019). The paradigm shows high test-retest reliability in the elderly (r = .84), and correlated well with measures of cognitive function (r = .56). The auditory domain is a promising target to measure SL ability and link it to cognitive ability. This is because the auditory domain specializes in processing stimuli that unfold in time (Pérez-González & Malmierca, 2014) and relies heavily on extracting statistical information from the environment (Agres, Abdallah, & Pearce, 2018; Barascud, Pearce, Griffiths, Friston, & Chait, 2016; Sohoglu & Chait, 2016). However, similar to previous SL paradigms, many participants performed at chance level, and a relatively small sample size was used (n = 27). The authors suggested deploying more trials and modifying the task to be multi-modal. Consequently, we use Herff et al. (2019)'s SL paradigm, equipped with more trials (150 instead of 50), a multi-modal implementation (auditory-visual), and a new TP matrix that accommodates high and low certainty states to collect data from elderly and young adults.

Method

General Procedure

After providing informed consent, participants took part in a *cognitive assessment* (~30min), followed by the SL paradigm (~45min). The present data collection was part of a large EEG project collaboration between the Agency for Science, Technology and Research (A*Star) and the National University of Singapore (NUS). Analysis of the collected EEG data will be reported elsewhere.

Participants

Data of 40 young adults was recorded from the student population at the National University of Singapore (M_{age} = 21.4 SD_{age} = 2.7) and forty elderly were recruited (M_{age} = 66.7, SD_{age} = 4.2). Participants were required to have normal or corrected-to-normal hearing, to be literate in English, able to provide informed consent, and able to travel to the study site independently. Participation was reimbursed with SGD 40. The study was IRB approved (S-17-372).

Stimuli and Equipment

Statistical Learning Paradigm. The present study deployed a continuous SL paradigm designed to capture learning trajectories (Herff et al., 2019). In this paradigm, participants were presented with a long series of four states (sine waves at ~165 Hz (E3), 220 Hz (A3), ~294 Hz (D4), ~392 Hz (G4), each 500ms in duration). Every 7.5 to 11.5sec (15- 23 tones), the series stopped and participants were prompted to indicate which tone they thought would occur next. After a response, the sequence would continue. Here, the sequence is instantiated in both the acoustic, as well as in the visual modality. Four horizontally aligned circles on the screen were associated with the four sounds (lowest to highest pitch, left to right). On every event, a circle flashed as respective sound was played. After each stop in the sequence, participants indicated their response by clicking on the circle that they thought would occur next. In total, 150 responses (trials) per participant were collected.

Transitional Probability Matrix. The TP matrix governing the four states can be seen in Figure 1. The overall probability of each state is identical (25%). Two states (A,D, purple in Figure 1) are considered high certainty states, as the most likely next state is very evident with a 75% TP. The other two states (B,C, blue in Figure 1) are low certainty states, as the most likely next state is less evident with a 50% TP. For example, the most likely state after A is B, with a probability of 75% percent. The most likely state after B is D, with a probability of only 50% percent. The probability of repetition is zero throughout, and a response indicating repetition is considered a rule violation. *Cumulative Rule Violations* (CRV) as well *as Cumulative High Probability Pathway Choices* (CHPC) are two measurements of SL performance used here. CRV refers to the accumulated number of rule violations (responses indicating a repetition; red arrows in Figure 1) on a given trial. CHPC refers to the accumulated number of high probability responses (response identifying correctly the most likely next state; green arrows in Figure 1) on a given trial. Good performance is indicated by high CHPC and low CRV (Herff et al., 2019).

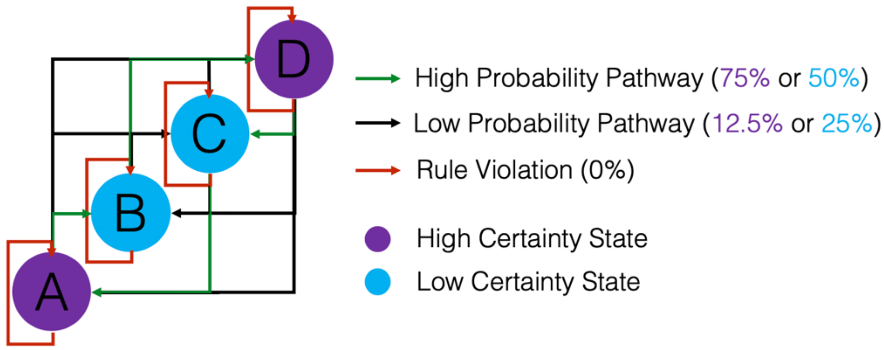

Figure 1: Schematic representation of the TP matrix. The two main measures of SL performed used here, are Cumulative Rule Violations (CRV, accumulation of response associated with a red arrow), and Cumulative High Probability Choices (CHPC, accumulation of responses associated with a green arrow). Because the most likely next state is clearer (75%, purple) in state A and D compared to states B and C (50%, blue), states A and D are considered high certainty states, and states B and C are considered low certainty states.

Cognitive Assessment. A battery of cognitive tests was administered that comprises the Rey Auditory Verbal Learning Test (RAVLT) (Rey, 1958), Digit Span task (backwards and forwards), Verbal Fluency task (see Randolph, Braun, Goldberg, & Chase 1993), Symbol Digit Modality Test (Smith, 1982) in written (DSW) and verbal (DSV) form, and Colour Trails Test (D'Elia, Satz, Uchiyama, & White, 1996). All assessors were formally trained and the tests were administer as described in the *Neuropsychological Assessments Training Manual for Assessors* (Yu, 2018). A short summary of each test follows below.

RAVLT. The test consists of multiple parts. In part one, participant listen to a 15 item word list (List-A). This is repeated five times, and the number of correct recalls is counted after each iteration. In the models and Figure 4, this is coded as *RAVLT1* to *RAVLT5*. In the second part, the participant listens to a different 15 item word list (List-B), and the number of correctly recalled items is coded as *RAVLTB*. Afterwards, participants are asked to recall the items from List-A again and the number of correctly recalled items is coded as *RAVLTRECA*. After a delay, filled with the Digit Span Test and Color Trail test (see below), the RAVLT continues to assess delayed recognition and required participants to recall the items of List-A. The number of correctly recalled items is coded as *RAVLTDelayedRacall*. In this final part, participants listen to a list of 50 items. The list contains the 15 items of List-B, and it is the participants' task to identify words that have been presented before. The number of correctly recognized words is coded in models and Figure 4 as *RAVLTRecognition*. This test assesses verbal memory in terms of recognition as well as recall.

Digit Span Task. This tasks consists of two parts. In the first part, participants are asked to listen to short sequences of numbers and repeat them afterwards. The tasks consists of two items for each string length. If both strings are not correctly repeated, the task stops and the total number of recalled strings is coded as *DigitSpanFWD*. Afterwards, the same task is repeated with different numbers. This time, however, participants are required to repeat the numbers backwards. The number of correctly recalled string is coded as *DigitSpanBWD*.

Colour Trails Test. The tests consists of two parts. In part one, participants are asked to connect numbered circles in ascending order on a sheet of paper. In the second part, participants are asked to connect numbers and letters, by alternating between numbers (in ascending order) and letters (in alphabetic order). The tests assesses visual attention and task switching capability. Time to completion is measured separately for the two parts and are included in the models as well as Figure 4 as *ColorTrail1* and *ColorTrail2*.

Verbal Fluency task. This task requires participants to name as many animals as possible in 60 seconds. The number of different animals names is coded as *SemanticFluencyAnimals* in the models and Figure 4. The tests assesses linguistic store and retrieval.

Symbol Digit Modality Test. This test consists of two parts. In the first part, participants are provided with a visual key that links the numbers 1 to 9, to nine different visual symbols. Participants then have 90 seconds to associate the correct number to a list of symbols by writing the number next to the symbol. The number of correctly linked symbols is coded as *DigitSymbolWritten*. In the second part, participants are provided with a new response sheet and repeat the task, however, this time they speak out the number, rather than writing them on the sheet. The number of correctly linked symbols in the second part is coded as *DigiSymbolVerbal*. The tests assess association memory, divided attention, and visual scanning.

Results

Overall SL Performance. A total of 12.000 responses were collected, evenly distributed across the four states (A = 25.57%, B = 25.92%, C = 24.02%, D = 24.48%). We used a simulation-based approach to assess chance and ideal performance (see Supplement S0). The results are summarized in Table 1. Overall learning trajectories can be seen in Figure 2.

Table 1. SL Performance Summary

Age Group	*N*	*Above Chance in CHPC*	*Below Chance in CRV*	*Ideal Performance Range*
Young Adults	40	36	38	15
Elderly	40	32	32	7

Note. Above chance CHPC, and below chance CRV indicate successful learning of the TP matrix.

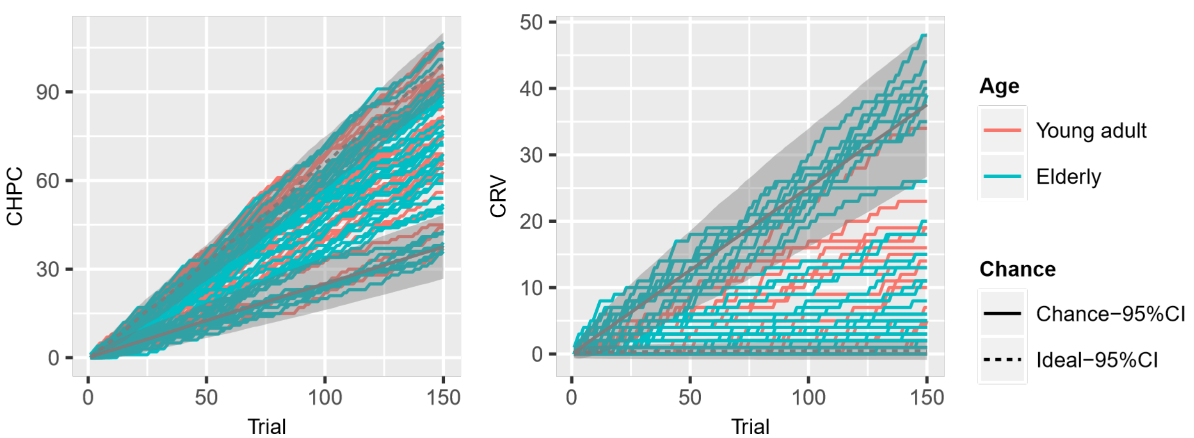

Figure 2: Overall performance in the SL task. The left panel shows cumulative high probability choices (CHPC) responses and the right panel shows cumulative rule violations (CRV). The grey bands represent 95% CIs.

Statistical Learning, Age, and Certainty. A generalized Bayesian mixed effects model predicted the responses that lie on the high probability pathway. The model was provided with a fixed effect for *Trial* (1-150, representing the learning trajectory over the course of the experiment), *Age* (elderly vs young adult), *Certainty* (high-certainty state vs. low-certainty state), as well as all interactions. The model was also provided with random effects for *Participant* and the precise *Sequence* listened to. Further information about the models can be found in Supplement S1. We report coefficient estimates (β), estimated error in the coefficients, as well as evidence ratios for the individual hypotheses. For convenience, we denote effect with "*" that can be considered 'significant' at an $\alpha = .05$ level. This corresponds to odds ratios >= 19 (odds 95/.05 = 19).

Trial ($\beta_{Trial} = .14$, $EE_{\beta Trial} = .05$, $Odds(\beta_{Trial} > 0) = 579.65$*) predicted the probability of high probability pathway responses, indicating that learning took place. *Age* ($\beta_{Age} = -.31$, $EE_{\beta Age} = .09$, $Odds(\beta_{Age} < 0) = > 9999$*) also carried predictive value, with young adults overall being more likely to produce high probability pathway responses. The low *Certainty* states led to overall fewer high probability pathway responses ($\beta_{LowCertainty} = -.61$, $EE_{\beta LowCertainty} = .07$, $Odds(\beta_{LowCertainty} < 0) = > 9999$*), indicating that participants were able to discern the differences between states in the TPs. The *LowCertainty x Trial* interaction ($\beta_{LowCertainty\ x\ Trial} = -.31$, $EE_{\beta LowCertainty\ x\ Trial} = .07$, $Odds(\beta_{LowCertainty\ x\ Trial} < 0) = > 9999$*) predicted reduced high probability pathway responses in low certainty states as the experiment progresses. This can be seen in Figure 3 in the positive slope for the high certainty states and the negative slope for the low certainty states. *The Trial x Certainty x Age* interaction showed ($\beta_{LowCertainty\ x\ Trial\ x\ Age} = .15$, $EE_{\beta LowCertainty\ x\ Trial\ x\ Age} = .05$, $Odds(\beta_{LowCertainty\ x\ Trial\ x\ Age} > 0) = 733.69$*) that young adults decrease stronger in the probability of high probability pathway responses in low certainty states compared to the elderly as the experiment progresses. In Figure 3, this can be seen in the difference in slope between the left and right panel in the low certainty (blue) lines. Importantly, the *Trial x Age* interaction did not carry predictive value ($\beta_{Trial\ x\ Age} = -.03$, $EE_{\beta Trial\ x\ Age} = .03$,

$Odds(\beta_{Trial\ x\ Age} < 0) =$ 3.88). This means that learning trajectories in high certainty states were comparable between the two age groups, as can be seen in Figure 3 by the similar slope between the red lines (high certainty state) in the left and right panel.

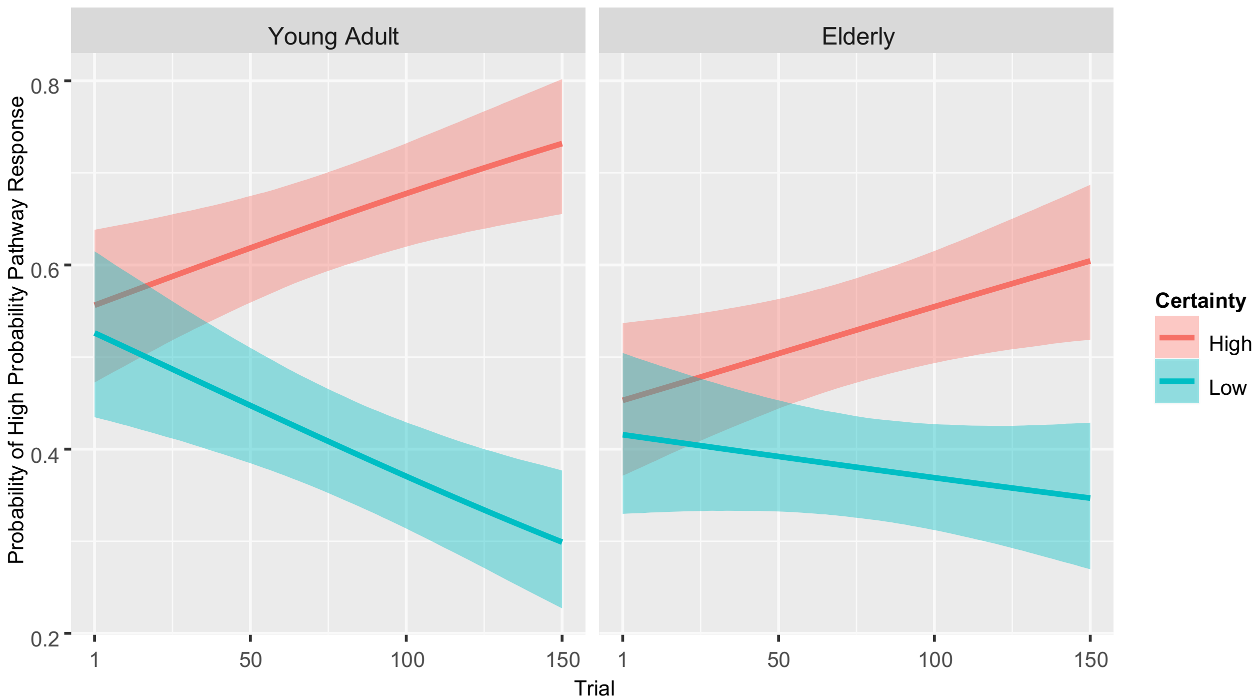

Figure 3. Effects of age and certainty state on SL. Both age groups show clear learning trajectories. Young adults show a higher intercept at the beginning of the experiment compared to elderly participants. Learning trajectories (slopes) are comparable between the two age groups on high certainty states (red lines). Interestingly, both groups appear to underestimate the probability of the most likely response in the low certainty states (blue lines). This is particularly pronounced in the young adults who over the course of the experiment, produce increasingly fewer responses that lie on the high probability pathway in low certainty states. The bands indicate 95%CIs.

For CRV, we combined the data from high and low certainty states, as both have 0% TPs of repeating states. *Age* (β_{Age} = .34, $EE_{\beta Age}$ = .14, $Odds(\beta_{Age} > 0)$ = 136.40*) predicted the probability of rule violations, with elderly (M = 0.0972, SD = 0.2963) on average showing more rule violations than young adults (M = 0.0463, SD = 0.2102). Both *Trial* (β_{Trial} = -.03, $EE_{\beta\,Trial}$ = .03 $Odds(\beta_{Trial} > 0)$ = 5.61) as well as the *Trial**Age* interaction ($\beta_{Age\ x\ Trial}$ = .1, $EE_{\beta\,Age\ x\ Trial}$ = .04, $Odds(\beta_{Age\ x\ Trial} < 0)$ = 1.60) did not show an effect. This is most likely due to the overall small number of rule violations straight from the beginning (see Supplement S1 for a summary and the risk ratios of the SL, age, and certainty models).

SL and Cognitive ability. Figure 4 provides an overview of the magnitudes of the correlation values between SL as measured by CHPC and CRV by the end of the experiment, and all cognitive assessments conducted. The dendrogram is the result of hierarchical clustering of these magnitudes. Supplement S2 contains the full correlation matrix.

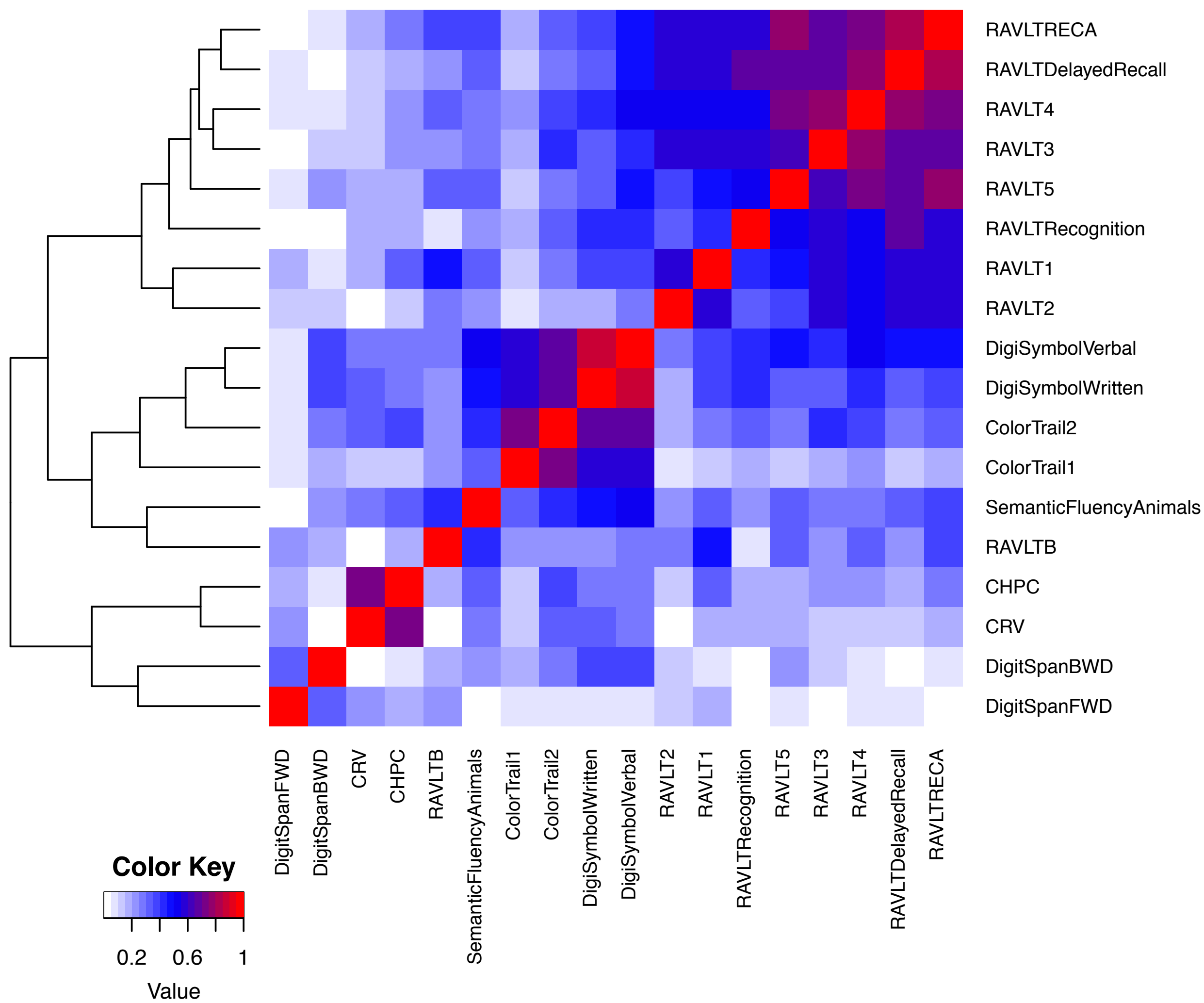

Figure 4: Hierarchical clustering of the magnitudes of the correlation coefficients of SL and all cognitive assessment. Even though both digit span tests are clustered the closest to CRV and CHPC, a step-wise regression revealed that *RAVLT1 and DigitSymbolWritten* carry the most predictive value for SL.

Figure 4 shows that SL and most cognitive assessments tend to be clustered in two distinct groups of measurements. This, combined with the overall low correlations (all $r < .33$, see Supplement S2) points towards SL being distinct to the construct targeted by most cognitive assessment tests. However, this does not exclude the possibility that there are individual cognitive assessments that relate to SL. To address this, a step-wise regression (both-ways, ΔBIC

penalty term) was performed to reveal the best predictors for CHPC and CRV. For CHPC, the *RAVLT1* and for CRV, the *DigiSymbolWritten* test were the only surviving predictor.

Consequently, we deployed linear Bayesian mixed effects models predicting CRV and CHPC scores. The models were provided with a fixed factor for *Age*, *Trial,* as well as the *RAVLT1* and *DigiSymbolWritten* scores. All interaction terms were fully parameterized, with the exception of *RAVLT1* and *DigiSymbolWritten* interaction terms as they are of no interest to the present design. We found for both cognitive assessments, *RAVLT1* ($\beta_{Trial\ x\ RAVLT1}$ = 1.01, $EE_{\beta\ Trial\ x\ RAVLT1}$= .09, $Odds(\beta_{Trial\ x\ RAVLT1} > 0)$ = > 9999*) and *DigiSymbolWritten* ($\beta_{Trial\ x\ DSW}$ = .74 , $EE_{\beta\ Trial\ x\ DSW}$= .10 , $Odds(\beta_{Trial\ x\ DSW} > 0)$ = > 9999*), that larger scores predicted steeper statistical learning trajectories. Furthermore, the models showed that this effect is stronger in the elderly compared to the young adults ($\beta_{Trial\ x\ RAVLT1\ x\ Elderly}$ = .78, $EE_{\beta\ Trial\ x\ RAVLT\ x\ Elderly\ 1}$= .12, $Odds(\beta_{Trial\ x\ RAVLT1\ x\ Elderly} > 0)$ = > 9999* ; $\beta_{Trial\ x\ DSW\ x\ Elderly}$ = .40, $EE_{\beta\ Trial\ x\ DSW\ x\ Elderly}$ = .15, $Odds(\beta_{Trial\ x\ DSW\ x\ Elderly} > 0)$ = 231.26*). This can also be seen in Figure 5 in the larger difference between the two colored lines in the elderly compared to the young adults (see Supplement S2 for the full models).

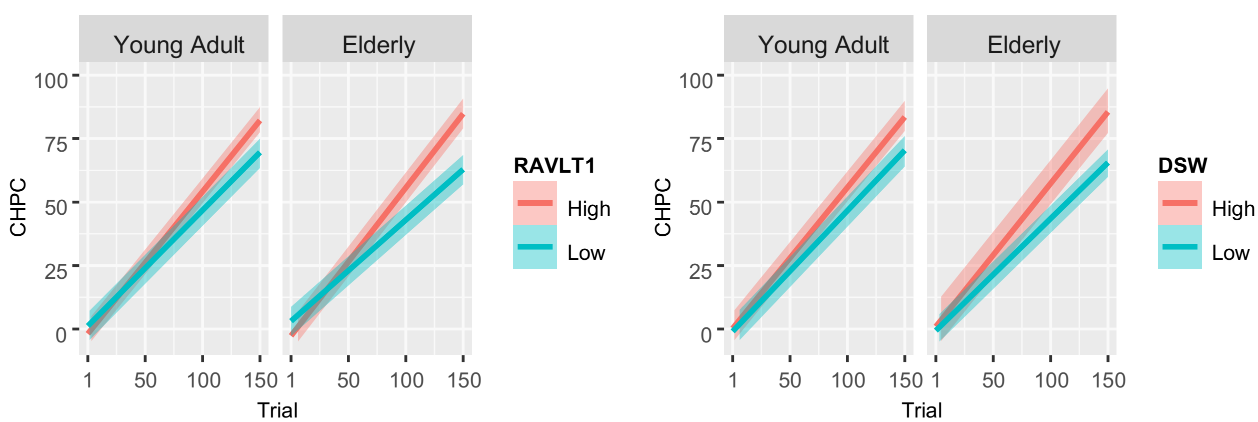

Figure 5. Marginal effects plots of Age, SL, and cognitive assessment scores. Both age groups show higher predicted CHPC values with high RAVLT1 (2.14) and high DSW (2.64, red lines) compared to low RAVLT1 (-

2.35) and low DSW scores (-2.08, blue lines). The larger distances between the red and the blue lines in the elderly compared to the young adults visualizes the three-way interaction. The bands represent 95% CIs.

Statistical Learning Mechanisms. To explain the age dependent differences in low and high certainty states (see Figure 3), we deployed three cognitive models. The first model assessed whether participants predominantly used the outcome from their last response to the same state when forming a prediction. This would be problematic for SL paradigms in general, because such paradigms assume that participants continuously sample information from the sequence, not only when they are prompted to respond. Fortunately, we found evidence that participants did not predominantly rely on the information of their last prediction ($\beta_{LastPredHPP\ x\ LastPredCorrect}$ = -.05, $EE_{LastPredHPP\ x\ LastPredCorrect}$ = .15, $Odds(\beta_{LastPredHPP\ x\ LastPredCorrect} < 0)$ = 1.80). This behavior did not differ between age groups ($\beta_{LastPredHPP\ x\ LastPredCorrect\ x\ Elderly}$ = - .25, $EE_{LastPredHPP\ x\ LastPredCorrect\ x\ Elderly}$ = .20, $Odds(\beta_{LastPredHPP\ x\ LastPredCorrect\ x\ Elderly} < 0)$ = 8.88), and therefore does not explain the age-dependent behavior towards low certainty states (see Supplement S3.1 for the full model).

The second model assessed potential differences between young adults and elderly when dealing with different probabilities. The model assesses whether information is differently sampled based on the Δ-difference between believed probabilities (as measured by the responses) and real probabilities (as shown in the sequences), and further, whether this difference occurs at the lower or upper end of the probability spectrum. In other words, do participants more strongly adjust their predictions when they are further away from the true probabilities (e.g., Δ = .5 with $P_{Perceived}$ = .25 and P_{Real} = .75 vs. Δ = .25 with $P_{Perceived}$ = .5, P_{Real} = .75), and is this difference shaped depending on whether it occurs towards the low or the high end of the probability spectrum (e.g., $\Delta = .2$ with $P_{Perceived} = .3$, $P_{Real} = .5$ vs. $\Delta = .2$ with $P_{Perceived} = .55$, $P_{Real} = .75$)? We observe that both age groups deploy a learning mechanism whereby they adjust their behaviour more strongly, the further they are off ($\beta_{ActualMinusResponseProbs} = 2.20$, $EE_{ActualMinusResponseProbs} = .18$, $Odds(\beta_{ActualMinusResponseProbs} > 0) = > 9999$*). The interaction term reveals that the young adults adjust their behaviour more readily the further they are off compared to the elderly ($\beta_{ActualMinusResponseProbs\ x\ Elderly} = -.71$, $EE_{ActualMinusResponseProbs\ x\ Elderly} = .24$, $Odds(\beta_{ActualMinusResponseProbs\ x\ Elderly} > 0) = 733.69$*). Both groups also adjust their behaviour depending on where on the probability spectrum the incongruence between believed and real probability occurs, with stronger behavioural changes towards the higher end ($\beta_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs} = .43$, $EE_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs} = .24$, $Odds(\beta_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs} > 0) = 25.47$*). However, we found no evidence that this incongruency mechanism differs between the age groups ($\beta_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs\ x\ Elderly} = -.34$, $EE_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs\ x\ Elderly} = .32$, $Odds(\beta_{ActualMinusResponseProbs\ x\ StateSpecificReponseProbs\ x\ Elderly} < 0) = 5.84$). As a result, this model does not explain the age-dependent differences in low certainty responses shown in Figure 3 either (see Supplement S3.2 for the full model).

The third model is the most parsimonious explanation, and simply assesses the weights that young and elderly attach to positive (e.g., B follows A) and negative (e.g., B does not follow A) observations. Effectively, this cognitive model simplifies statistical learning to a continuous sampling of information with a 'positive' weight that reflects increasing the likelihood of making a particular choice when the specific transition is observed in the sequence, and a 'negative' weight that reflects decreasing the likelihood of making the particular choice when the specific transition is not observed. Since the Bayesian models provide slope coefficients of behavioural change in both age groups at two different TPs for the high probability pathway, we have two equations for each age group with two unknowns each. As a result, we can use Gaussian elimination (see Supplement A3.3) to obtain the weights that elderly ($PositiveWeight_{Elderly} = .27$, $PositiveWeight_{Elderly} = -.37$) and young adults ($PositiveWeight_{YoungAdults} = 45$, $PositiveWeight_{YoungAdult} = -.79$) attach to continued sampling of positive and negative observations in a simplified decision-making model. The resulting weights are seen in Figure 6.

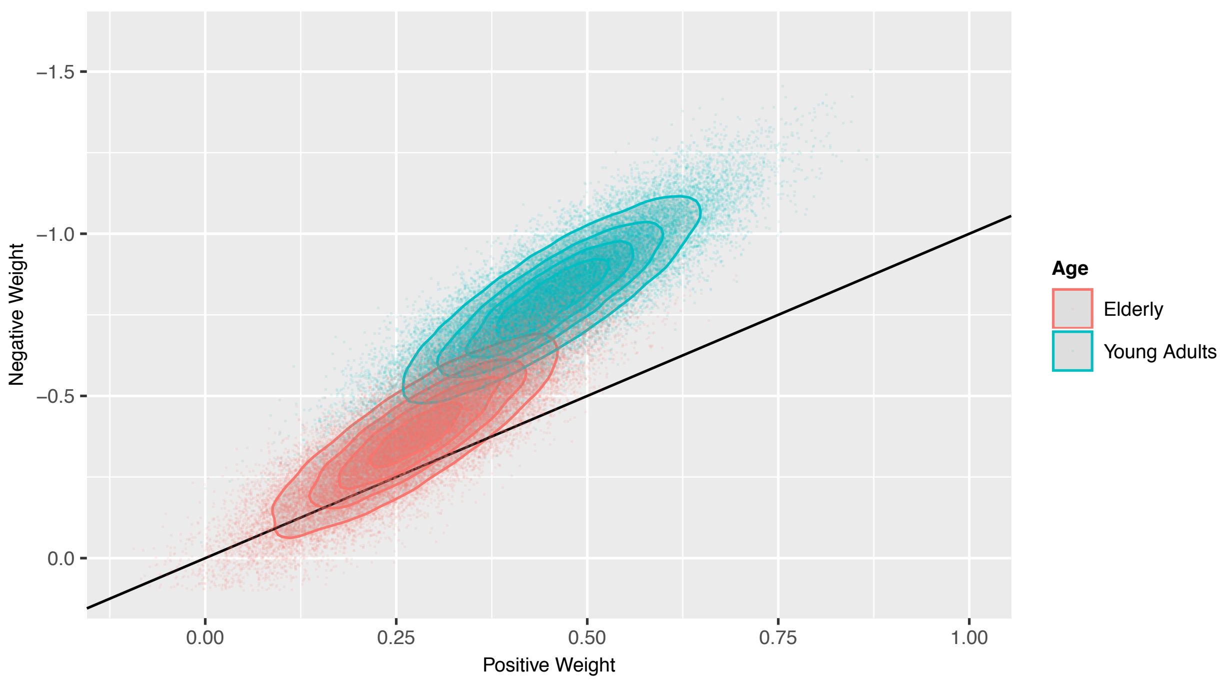

Figure 6. Estimated weights distribution to positive and negative observations in both age groups. Positive weights indicate predicted change providing the same answer, given it was correct. Negative weights indicate predicted change providing the same answer, given it was incorrect. Both groups show clear signs of learning by using both positive and negative observations. This is indicated by the non-zero weights on both axes for both groups, and by the fact that in both groups, positive weights all fall within the range of positive numbers (increase in probability to provide the same response), and negative weights all fall within the range of negative numbers (decrease in probability to provide the same response. Young adults show larger sways in their predictions as shown by the larger weights on both axes compared to the elderly. Both young adults and elderly weight negative observations stronger than positive, however, this is substantially more pronounced in the young adults who strongly use negative information in the process of forming future predictions.

To obtain the weights distribution in Figure 5, the information weights for both groups were calculated after each iteration of the Bayesian Model. Since the model ran on 10.000 iterations, with 1000 warmups on four cores, Figure 6 uses the data of a total of 36.000 posterior distributions. A Hotelling T^2 test using 10.000 permutations shows a significant difference between the information weights distributions of elderly, as well as young adults ($t^2(2,71997) = 112447.7$, $p = < .0001$) in the present study. Further support was found by calculating Kullback-Leibler divergence on the probability density functions of elderly and young adults' information weights. The divergence between the elderly and the young adults' information weights ($D_{KL}(PDF_{Elderly} \parallel PDF_{YoungAdults}) = 3.1054$), is substantially larger compared to the Kullback-Leibler divergence distribution obtained from 10.000 random permutations of the Age group vector ($D_{KL\text{-}Mean}(PDF_{GroupA} \parallel PDF_{GroupB}) = .00012$, $D_{KL\text{-}SD}(PDF_{GroupA} \parallel PDF_{GroupB}) = .00008$). In summary, we found strong support that the elderly and the young adult cohort operate on different information weights. This can also be seen in Figure 7.

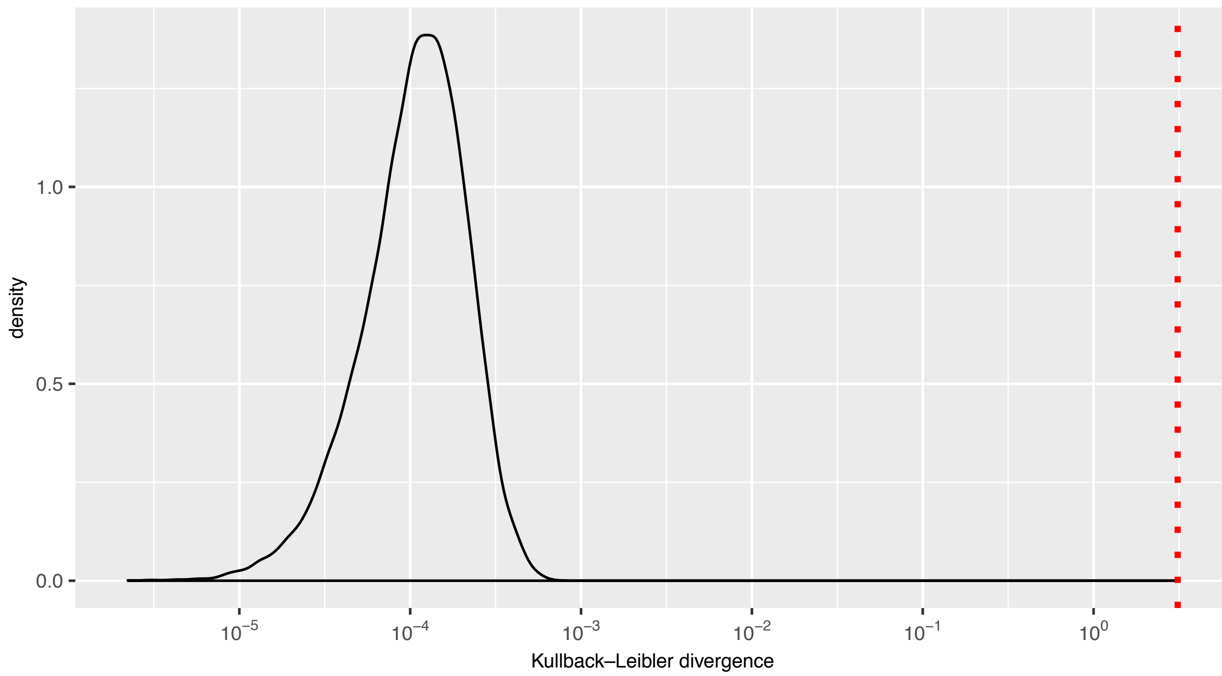

Figure 7. Kullback-Leibler divergence between the probability density functions of the information weights of elderly and young adults. The dotted red-line indicates the Kullback-Leibler divergence observed between the information weights of the young adults and the elderly cohort in the present study. The distribution in black can be used to assess divergence values that could occur by chance. The distribution was obtained by 10.000 iterations of calculating the divergence after shuffling the Age group vector. The x-axis is log scaled.

Discussion

We investigated differences in SL trajectories between elderly and young adults, and both groups learned the underlying statistical structure. In addition, scores on some traditional cognitive assessments mediated learning trajectories. Both age groups showed similar learning trajectories of the most likely next event when the transition was likely (high certainty). When it came to dealing with less certain transitional probabilities, learning trajectories diverged between age groups. To explain these findings, we deployed three cognitive models. We found that elderly and young adults use similar strategies, however young adults are more willing to change their behaviour and strongly weight negative observations in their decision making process.

SL Performance and Age. Many SL paradigms suffer from overall low performance (Siegelman, Bogaerts, & Frost, 2017). Following previous suggestions (Herff et al., 2019), we deployed more trials and multi-modal stimuli, and found clear signs of learning in the majority of participants in both age groups. Overall, more young adults learned the most likely next event and responded around ideal performance as compared to the elderly. This is in line with previous studies that also showed age-related decline in SL of probabilistic stimuli (Curran, 1997; Feeney et al., 2002; J. H. Howard & Howard, 1997). Trial-wise analysis, however, revealed that young adults show more high probability responses initially, but the learning trajectories over time are comparable between the groups. This could be indicative of a more conservative strategy deployed by the elderly, such as a stronger 'prior' inclination towards equiprobable responses in the beginning. If elderly deployed a different strategy compared to the young adults, then the low certainty states may reveal further insight.

Certainty States. Within the high certainty states, learning trajectories between the two age groups were not significantly different from one another. However, when faced with less certain transitional probabilities, the response pattern in the elderly stayed relatively constant and close to the actual underlying transitional probability throughout the experiment. Young adults, on the other hand, showed an initial strong tendency towards the most likely event, followed by a rapid decay in the probability of responding with the next most likely state (see Figure 3). To find a parsimonious explanation we deployed three cognitive models that further explored underlying learning mechanisms.

Learning Mechanisms. We found evidence that both age groups draw information from the continuous sequence, rather than only from the last time they provided a response specific to the current state. Both groups also adjust their behaviour to a greater degree, the further their own beliefs differ from the actual underlying probabilities. However, young adults do this faster. In addition, participants were more willing to adjust their behaviour at the higher end of the probability spectrum. For example, if participants were 20% off from the true underlying probability when the true probability is 50%, responses would shift more slowly towards the true probability compared to when they were 20% off from a 75% target. Importantly, these learning mechanisms do not explain the age-dependent differences observed in the low certainty responses. The observed difference between groups seems to be due to contrasting approaches in information weighting between the young and elderly participants.

There is ample evidence that correct predictions are intimately tied with internally generated rewards (Fisker, Berkes, Orbán, & Lengyel, 2010) that increase the probability of the same prediction in the future, similar to a Bayesian observer. However, the decrease in probability caused by an erroneous prediction may not be identical to the increase in probability caused by a correct prediction. With the data collected here, we were able to calculate the weights that young adults and elderly attach to positive and negative transitional observations. Young adults attached larger weights to both types of observations compared to the elderly, which could be the mechanism by which the younger adults initially show faster behavioural changes. Most importantly, young adults strongly weight information of negative observations over positive ones when it comes to formulating future predictions. The elderly also rely on negative information more than on positive, but to a substantially lesser extent. Indeed, the elderly participants here appear close to equi-weighting for positive and negative information.

Overweighting negative observations appears sensible out of an evolutionary perspective, as it allows rapid discarding of impossible or unlikely –and therefore unreliable– outcomes. However, it would also lead to a drift away from the true underlying transitional probabilities. The decrease over time of high probability choices in the low certainty states could be an example of this. Interestingly, the lower but more balanced weights in the elderly –in the long run– would yield more accurate yet slower behavioural changes. This fits the general observation that elderly weight accuracy over speed (Forstmann et al., 2011; Salthouse, 1979). We hope this finding will motivate future research to explore differences in information weighting.

SL and Cognitive Ability. In both age groups we found evidence that higher cognitive assessment scores predict steeper learning trajectories. Importantly, this effect was exacerbated in the elderly. Specifically, while elderly with high cognitive assessment scores show similar SL performance compared to young adults with high cognitive assessment scores, elderly with low cognitive assessment scores show lower SL performance compared to young adults with matched scores. A possible explanation could be that low cognitive assessment scores in the elderly may be indicative of age-related cognitive decline that affects various functions in the brain, whereas low scores in a younger population are less likely to be indicative of functional impairments. The two most promising predictors of SL were the RAVLT 1 as well as the Digit Symbol (written) Modality test. This makes intuitive sense, as the Digit Symbol Modality test was designed to capture associative learning, and RAVLT tests auditory memory, and clearly both memory and associative learning are related to the present paradigm.

However, clustering based on the correlation magnitudes and overall low correlations suggest that SL ability and traditional cognitive assessments –at large– most likely target different underlying constructs. This is line with previous literature that suggests that SL and general cognitive function are largely independent (Feldman, Kerr, and Streissguth, 1995; Kaufman et al. 2010; Siegelman, Bogaerts, and Frost, 2017). Furthermore, compared to the other effects found in the present analysis, the link between cognitive assessment and SL is low in magnitude. Indeed, the maximum correlation of $r = .33$ is in line with previous studies that also show low correlations between SL and cognitive assessments (Feldman et al., 1995). This suggests that the high correlations found in a study that used a previous iteration of the present paradigm may have been an artefact of low sample size and performance (Herff et al., 2019). Clearly, further research is needed to explore the potential link between SL and general cognitive function. Furthermore, it is worth noting that by deploying a multi-modal paradigm, there is the possibility that our pattern of results was evoked by differences in cross-modal integration between elderly and young participants. Currently we do not have the data to further explore this possibility, so future research is required.

Conclusion

The paradigm deployed here tracked learning trajectories and revealed differences between elderly and young adults in behaviour when it comes to dealing with uncertainty. A possible explanation was found in the form of age-dependent differences in information weighting, in which young adults are generally more readily adjust their behaviour, but are also more irritated by erroneous predictions compared to the elderly. The weights deployed by young adults favour rapid behavioural adaptation, whereas the weights used by the elderly favour more precise behavioural adaptation over the course of time. We hope that future research using this paradigm will provide precise estimates of individuals' information weighting of positive and negative predictive outcomes.

Author contributions

S.A.H. developed the paradigm, and designed, coded, as well as prepared the experiment. K.A.R helped develop the experimental design and paradigm. Data collection was performed or supervised by S.A.H. and S. Z. Data was analysed and interpreted by S.A.H. The manuscript was written by S.A.H. with S.Z., R.Y, and K.R.A providing comments. The project and collaboration was initiated by K.R.A and R.Y. R.Y provided lab space and equipment. All authors approved of the final version of this manuscript.

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Supplemental Material

Supplement S0 Assessing chance and ideal performance

In total, 36 young adults and 32 elderly showed CHPC values that are significantly above chance. A total of 38 young adults and 32 showed CRV significantly below chance. To obtain a conservative approximation of what constitutes chance performance, we simulated 10,000 observers providing random responses (25% for each state) and constructed a 95% CI around the resulting CHPC and CRV. Participants that fell within the 95% CI by the end of the study were considered to be perform at chance level. The probabilistic nature of the present paradigm makes the assessment of 'ideal' performance non-trivial. To address this, we simulated 10,000 ideal observers. At the end of each trial, each ideal observer randomly generated a response based on the exact TPs observed up to the respective trial. The distribution of ideal observer responses was then used to construct a 95% CI for both CHPC. The same procedure was used for CRV, except that ideal observers were provided with a weak prior towards providing equiprobable responses. This step was necessary to avoid a flat 0 band for CRV. Based on this methodology, 15 out of the 40 young adults showed CHPC values comparable to those of ideal observers by the end of the experiment, and 7 out of 40 showed CRV values comparable to those of ideal observers. Of the elderly, 8 out of 40 showed CHPC values, and 4 out of 40 showed CRV values, that are comparable to those of ideal observers.

Supplement S1 – Statistical Learning, Age, and Certainty Models

The Bayesian models used here always attempt the maximal random effect structure as justified by the experimental design whilst avoiding singular fits (see Barr, Levy, Scheepers, & Tily, 2013). All continuous predictors were scaled ($M = 0$, $SD = 1$). The models were provided with weakly informative priors ($t(3,0,2)$ see Gelman et al., 2013). Every model ran here consists of 4 chains, 1000 warmups, and 10,000 iterations implemented in the R environment using the brms package (Bürkner, 2017, 2018).

The tables below report the mean point estimates of the Risk Ratios in the posterior for each predictor. The model coefficients reported in-text are the natural logarithms of the risk ratios reported here. The tables were prepared using the *tab_model* function of the *sjPlot* package (see https://cran.r-project.org/web/packages/sjPlot/index.html) in the R-environment.

Table S1.1: High probability Pathway response model

	High Probability Pathway Response		
Predictors	*Risk Ratios*	*CI (50%)*	*CI (95%)*
Intercept	1.47	1.40 – 1.54	1.27 – 1.69
Trial	1.15	1.11 – 1.19	1.05 – 1.26
CertaintyLow	0.54	0.52 – 0.57	0.47 – 0.62
Elderly	0.73	0.69 – 0.78	0.62 – 0.87
Trial.CertaintyLow	0.73	0.70 – 0.77	0.64 – 0.84
Trial.Elderly	0.97	0.95 – 0.99	0.91 – 1.04
CertaintyLow.Elderly	1.27	1.22 – 1.31	1.15 – 1.39
Trial.CertaintyLow.Elderly	1.16	1.12 – 1.20	1.05 – 1.28
Random Effects			
σ^2	0.00		
τ_{00}	0.25		
ICC	0.00		
$N_{Participant}$	80		
$N_{Sequence.}$	150		
Observations	12000		
Marginal R^2 / Conditional R^2	0.055 / 0.163		

Table S1.2: Rule Violation Response Model

	Rule Violation		
Predictors	*Risk Ratios*	*CI (50%)*	*CI (95%)*
Intercept	0.15	0.14 – 0.16	0.12 – 0.18
Trial	0.97	0.95 – 0.99	0.91 – 1.03
Elderly	1.41	1.29 – 1.54	1.07 – 1.84
Trial.Elderly	1.01	0.99 – 1.04	0.94 – 1.09
Random Effects			
σ^2	0.02		
τ_{00}	0.04		
ICC	0.34		
$N_{Participant}$	80		
$N_{Sequence.}$	150		
Observations	12000		
Marginal R^2 / Conditional R^2	0.004 / 0.101		

Supplement S2: Statistical Learning and Cognitive Assessment

Table S2.1. Model summary of the Statistical Learning and Cognitive Assessments models.

	CHPC			CRV		
Predictors	*Estimates*	*CI (50%)*	*CI (95%)*	*Estimates*	*CI (50%)*	*CI (95%)*
Intercept	37.87	36.96 – 38.80	35.21 – 40.65	4.57	3.99 – 5.18	2.79 – 6.31
Trial	22.26	22.19 – 22.33	22.06 – 22.46	2.03	1.99 – 2.07	1.91 – 2.15
Elderly	-0.50	-1.32 – 0.17	-3.90 – 1.62	0.50	-0.11 – 1.16	-1.28 – 2.78
DSW	1.41	0.70 – 2.23	-0.47 – 3.98	-0.83	-1.35 – -0.34	-2.37 – 0.55
RAVLT 1	0.97	0.34 – 1.68	-0.73 – 3.33	-0.24	-0.70 – 0.21	-1.64 – 1.16
Trial.Elderly	-0.67	-0.77 – -0.57	-0.97 – -0.38	0.80	0.74 – 0.86	0.62 – 0.98
Trial.DSW	0.74	0.67 – 0.80	0.54 – 0.93	-0.19	-0.23 – -0.15	-0.31 – -0.07
Elderly.DSW	0.61	-0.08 – 1.45	-1.48 – 3.91	-1.25	-2.10 – -0.53	-4.08 – 0.64
Trial.RAVLT1	1.01	0.95 – 1.07	0.83 – 1.20	0.28	0.24 – 0.32	0.17 – 0.40
Elderly.RAVLT1	0.64	-0.00 – 1.39	-1.26 – 3.24	-1.18	-1.84 – -0.57	-3.30 – 0.46
Trial.Elderly.DSW	0.40	0.29 – 0.50	0.10 – 0.69	-1.24	-1.30 – -1.17	-1.42 – -1.06
Trial.Elderly.RAVLT1	0.78	0.70 – 0.86	0.55 – 1.01	-1.27	-1.32 – -1.22	-1.41 – -1.13
Random Effects						
σ^2	101.46			33.10		
τ_{00}	518.28			30.11		
ICC	0.16			0.52		
N	80 $_{\text{ParticipantID}}$			80 $_{\text{ParticipantID}}$		
Observations	12000			12000		
Marginal R^2 / Conditional R^2	0.786 / 0.945			0.284 / 0.804		

Table S2.2 Statistical Learning and Cognitive Assessment Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. CHPC																	
2. CRV	-.75** [-.83, -.63]																
3. R1	.33** [.12, .51]	-.26* [-.45, -.04]															
4. R2	.15 [-.07, .36]	.01 [-.21, .23]	.60** [.44, .72]														
5. R3	.25* [.03, .44]	-.14 [-.34, .09]	.57** [.40, .70]	.56** [.39, .70]													
6. R4	.24* [.03, .44]	-.15 [-.36, .07]	.55** [.38, .69]	.55** [.38, .69]	.75** [.63, .83]												
7. R5	.15 [-.07, .36]	-.14 [-.35, .08]	.41** [.21, .58]	.40** [.20, .57]	.57** [.41, .70]	.65** [.50, .76]											
8. RB	.16 [-.06, .37]	-.04 [-.26, .18]	.47** [.28, .63]	.26* [.04, .46]	.15 [-.07, .36]	.29** [.08, .48]	.23* [.01, .43]										
9. RRecall	.25* [.03, .45]	-.16 [-.37, .06]	.58** [.42, .71]	.60** [.44, .72]	.65** [.50, .76]	.74** [.62, .83]	.72** [.60, .81]	.32** [.11, .51]									
10. DSFWD	.21 [-.01, .41]	-.16 [-.37, .06]	.20 [-.02, .40]	.14 [-.08, .35]	.03 [-.19, .25]	-.07 [-.29, .15]	.06 [-.16, .28]	.26* [.04, .45]	.01 [-.21, .23]								
11. DSBWD	.11 [-.11, .32]	-.04 [-.25, .19]	.11 [-.12, .32]	.12 [-.10, .33]	.11 [-.11, .33]	.04 [-.18, .26]	.19 [-.03, .39]	.19 [-.03, .40]	.09 [-.13, .30]	.33** [.11, .51]							
12. CT1	-.10 [-.31, .12]	.08 [-.14, .29]	-.08 [-.29, .14]	.07 [-.15, .29]	-.13 [-.34, .09]	-.19 [-.39, .03]	-.11 [-.32, .11]	-.20 [-.40, .02]	-.10 [-.31, .12]	.10 [-.12, .31]	-.16 [-.36, .06]						
13. CT2	-.25* [-.44, -.03]	.23* [.01, .43]	-.24* [-.44, -.02]	-.25* [-.45, -.03]	-.39** [-.56, -.19]	-.35** [-.53, -.15]	-.22* [-.42, -.00]	-.16 [-.37, .06]	-.24* [-.43, -.02]	-.11 [-.32, .11]	-.23* [-.43, -.01]	.51** [.33, .66]					
14. RRecallD	.22 [-.00, .42]	-.16 [-.37, .06]	.62** [.47, .74]	.60** [.44, .73]	.66** [.52, .77]	.79** [.68, .86]	.64** [.48, .75]	.21 [-.01, .41]	.83** [.74, .88]	-.08 [-.30, .14]	-.03 [-.24, .19]	-.09 [-.30, .13]	-.27* [-.46, -.05]				
15. RRecog	.19 [-.03, .39]	-.16 [-.37, .06]	.38** [.18, .55]	.35** [.14, .53]	.59** [.43, .72]	.63** [.48, .75]	.51** [.32, .65]	.08 [-.14, .30]	.62** [.46, .74]	.04 [-.18, .26]	.01 [-.21, .23]	-.16 [-.37, .06]	-.35** [-.53, -.14]	.67** [.53, .78]			
16. SFW	.28* [.07, .47]	-.24* [-.44, -.03]	.33** [.12, .51]	.21 [-.01, .41]	.27* [.06, .46]	.25* [.03, .44]	.31** [.10, .50]	.43** [.23, .59]	.38** [.18, .56]	.05 [-.17, .27]	.25* [.03, .44]	-.32** [-.51, -.11]	-.36** [-.54, -.15]	.33** [.12, .51]	.25* [.03, .44]		
17. DSW	.29** [.08, .48]	-.32** [-.51, -.11]	.34** [.13, .52]	.18 [-.04, .38]	.27* [.05, .46]	.41** [.21, .58]	.34** [.13, .52]	.25* [.04, .45]	.39** [.18, .56]	.10 [-.12, .31]	.40** [.20, .57]	-.53** [-.67, -.35]	-.49** [-.64, -.31]	.35** [.14, .53]	.40** [.20, .57]	.50** [.31, .65]	
18. DSV	.29* [.07, .48]	-.31** [-.50, -.10]	.41** [.21, .58]	.26* [.04, .45]	.40** [.20, .57]	.52** [.34, .66]	.43** [.24, .60]	.30** [.09, .49]	.51** [.32, .65]	.09 [-.13, .30]	.36** [.15, .53]	-.52** [-.66, -.34]	-.47** [-.63, -.28]	.46** [.27, .62]	.43** [.23, .59]	.52** [.34, .67]	.88** [.82, .92]

Note. CHPC = Cumulative High Probability Pathway Correct; CRV = Cumulative Rule Violations. R1-5 = RAVLT scores of the first to the fifth attempt. RB = RAVLT B – List scores. RRecall = RAVLT Recall Score. DSFWD = Digitspan forward score. DSBWD = Digitspan backwards score. CT1 = Color Trail 1 time. CT2 = Color Trail 2 time. RRecallD = RAVLT delayed recall score. RRecog = RAVLT Recognition Score. SFA = Semantic Fluency animal score. DSW = Digit symbol written modality score. DSV = Digit symbol verbal modality score. A * indicates $p < .05$, a ** indicates $p < .01$.

Supplement S3. Explanatory Cognitive Models

Table S3.1 Last State Specific Response Model

	Correct		
Predictors	*Risk Ratios*	*CI (50%)*	*CI (95%)*
Intercept	1.16	1.11 – 1.21	1.03 – 1.31
LastPredHPP	1.53	1.45 – 1.61	1.32 – 1.78
LastPredCorrect	0.97	0.89 – 1.06	0.75 – 1.26
Elderly	0.72	0.68 – 0.77	0.61 – 0.85
CertaintyLow	0.65	0.63 – 0.68	0.58 – 0.73
LastPredHPP.LastPredCorrect	0.95	0.86 – 1.05	0.71 – 1.27
LastPredHPP.Elderly	1.19	1.11 – 1.28	0.97 – 1.47
LastPredCorrect.Elderly	1.18	1.05 – 1.33	0.84 – 1.66
LastPredHPP.CertaintyLow	0.78	0.73 – 0.83	0.64 – 0.94
LastPredCorrect.CertaintyLow	0.96	0.86 – 1.06	0.71 – 1.28
Elderly.CertaintyLow	1.15	1.09 – 1.21	0.99 – 1.33
LastPredHPP.LastPredCorrect.Elderly	0.78	0.68 – 0.89	0.53 – 1.15
LastPredHPP.LastPredCorrect.CertaintyLow	1.19	1.06 – 1.34	0.84 – 1.69
LastPredHPP.Elderly.CertaintyLow	1.15	1.05 – 1.26	0.88 – 1.50
LastPredCorrect.Elderly.CertaintyLow	1.05	0.91 – 1.20	0.71 – 1.55
LastPredHPP.LastPredCorrect.Elderly.CertaintyLow	0.90	0.77 – 1.06	0.56 – 1.44
Random Effects			
σ^2	0.00		
τ_{00}	0.25		
ICC	0.00		
$N_{Participant}$	80		
Observations	11360		
Marginal R^2 / Conditional R^2	0.064 / 0.115		

Note. *LastPredCorrect* codes whether the last particular transition was encountered, the participant made a correct prediction, regardless of whether that prediction was a high probability response or not. *LastPredHPP* codes whether the last time a participant encounter a particular transition, they made a high probability response.

Table S3.2. Delta Probability Model

	Correct		
Predictors	*Risk Ratios*	*CI (50%)*	*CI (95%)*
Intercept	0.24	0.22 – 0.26	0.19 – 0.30
StateSpecificResponseProbs	11.15	9.94 – 12.50	7.99 – 15.60
ActualMinusResponseProbs	8.98	7.93 – 10.17	6.28 – 12.92
Elderly	1.38	1.24 – 1.54	1.01 – 1.90
StateSpecificResponseProbs.ActualMinusResponseProbs	1.54	1.30 – 1.81	0.96 – 2.45
StateSpecificResponseProbs.Elderly	0.45	0.39 – 0.53	0.28 – 0.71
ActualMinusResponseProbs.Elderly	0.49	0.42 – 0.58	0.30 – 0.79
StateSpecificResponseProbs.ActualMinusResponseProbs.Elderly	0.71	0.57 – 0.89	0.38 – 1.33
Random Effects			
σ^2	0.00		
τ_{00}	0.25		
ICC	0.00		
$N_{Participant}$	80		
Observations	11360		
Marginal R^2 / Conditional R^2	0.041 / 0.097		

Note. *StateSpecificResponseProbs* refers to the probability of following the high probability pathway for that particular state that a participant has shown to that point in the experiment. *ActualMinusResponseProbs* simply refers to the difference between the actual transition probability of the high probability pathway for a given state minus the *StateSpecificResponseProbs*.

S3.3 Estimating the Weights

Because the Bayesian models provide us with the slope coefficients of behavioural change in both age groups at two different transitional probabilities for the high probability pathway, we have two equations for each age group with two unknowns each. The probabilities are determined by the underlying transitional probabilities. In high certainty states, a high probability pathway state will occur next 75% of the time, whereas in 25% of the time it will not. In the low certainty states, both high and low probability pathway states will follow at 50% of the time. The response changes can be directly taken from the Bayesian model. Because these models use a linear combination of the coefficients for the predictions, the learning trajectory-related coefficients are added up to obtain the measure of behaviour change in both age groups and both certainty states. As a result we can use the two equations concerned with young adults (i and ii) to estimate the weights for the young adults, and we can use the two equations concerned with the elderly (iii and iv) to estimate the weights for the elderly on the latent variable that underpins the model predictions. We can determine the information weights for each iteration of the model. Below is an example for the best model coefficients.

$i)\ PositiveWeight_{YoungAdults} * .75 + NegativeWeight_{YoungAdults} * .25 = \beta_{Trial} = .14$

$ii)\ PositiveWeight_{YoungAdults} * .5 + NegativeWeight_{YoungAdults} * .5 = \beta_{Trial} + \beta_{Trial\ x\ CertaintyLow} = -.17$

$iii)\ PositiveWeight_{Elderly} * .75 + NegativeWeight_{Elderly} * .25 = \beta_{Trial} + \beta_{Trial\ x\ Elderly} = .11$

$$iv)\ PositiveWeight_{Elderly} * .5 + NegativeWeight_{Elderly} * .5$$
$$= \beta_{Trial} + \beta_{Trial\ x\ Elderly} + \beta_{Trial\ x\ CertaintyLow} + \beta_{Trial\ x\ CertaintyLow\ x\ Elderly} = -.05$$

$PositiveWeight_{YoungAdults} = 45$

$NegativeWeight_{YoungAdult} = -.79$

$PositiveWeight_{Elderly} = .27$

$NegativeWeight_{Elderly} = -.37$