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Healthy Aging Is Associated With Decreased Risk-Taking in Motor Decision-Making

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Healthy aging is associated with changes in both cognitive abilities, including decision-making, and motor control. Previous research has shown that young healthy observers are close to optimal when they perform a motor equivalent of economic decision-making tasks that are known to produce suboptimal decision patterns. We tested both younger (age 20–29) and older (age 60–79) adults in such a task, which involved rapid manual aiming and monetary rewards and punishments contingent on hitting different areas on a touch screen. Older adults were as close to optimal as younger adults at the task, but differed from the younger adults in their strategy. Older adults appeared to be relatively less risk-seeking, as evidenced by the fact that they adjusted their aiming strategy to a larger extent to avoid the penalty area. A model-based interpretation of the results suggested that the change in aiming strategy between younger and older adults was mainly driven by the fact that the first weighted monetary gains more than losses, rather than by a mis-estimation of one's motor variability. The results parallel the general finding that older adults tend to be less risk-seeking than younger adults in economic decision-making and complement the observation that children are even more risk-seeking than younger adults in a similar motor decision-making paradigm.

Public Significance Statement

This study investigated the behavior of younger and older adults in a task where observers are asked to point quickly to a target area, associated with monetary reward, while avoiding a nearby penalty area, associated with monetary punishment. Older observers tend to point further away from the penalty area, which can be interpreted as a sign of risk-avoidance. By modeling the behavior of an optimal observer in our task, we show that older adults, despite being more risk-avoidant than younger adults, are not less optimal at the task. Our investigation provides an innovative possibility to evaluate the integrity of the aging visuomotor system, further detailing the motor and cognitive changes associated with healthy aging.

Keywords: aging, decision-making, reward, motor control, aiming

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In recent years, a fruitful line of research has been developing, starting from the suggestion that human observers are close to optimal when confronted with the motor equivalent of a decision-making task (Trommershäuser, Maloney, & Landy, 2003a, 2003b). Rather than asking their participants to choose between options associated with a certain degree of monetary gain or loss, Trommershäuser and colleagues had their observers quickly aim with their finger to a target location associated with a monetary gain, while trying to avoid a nearby location associated with monetary loss. The observers consistently adapted their aiming location to the geometrical and value-based constraints of the task, achieving close to the maximum expected monetary gain allowed by their aiming imprecision. Multiple studies have replicated the original experiments, invariably finding close to optimal performance (Gepshtein, Seydell, & Trommershäuser, 2007; Trommershäuser, Gepshtein, Maloney, Landy, & Banks, 2005; Trommershäuser, Mattis, Maloney, & Landy, 2006), as long as the geometrical complexity of the target or penalty configuration was not excessive (Wu, Trommershäuser, Maloney, & Landy, 2006).

The fact that human observers are close to optimal in motor decisions under risk contrasts with the well-known discrepancies from normative behavior that are commonly observed in economic decisions under risk. When faced with an economic decision under risk, for instance when choosing between lotteries with different probabilities of gains and losses, human observers are known to deviate from expected utility, sometimes dramatically (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Maximizing ex-

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pected utility in a given choice requires comparing the expected utility associated with all options and picking the most advantageous one, regardless of the history of previous choices, and weighting gains and losses equally. Numerous deviations from this optimal behavior have been demonstrated. Human observers tend to base their choices on their current status, that is, a gain of $10 is valued more if the current amount of money gained is say $10 compared with the case where a gain of $10 is added on top of $100 worth of previous gains. Moreover, they generally show loss aversion, that is, the possibility that one lottery results in even a small loss makes it relatively unattractive. Human observers also tend to be differently risk-seeking when confronted with possible gains and losses. With the expected gain being equal, they tend to prefer a certain gain over an uncertain lottery, that is, they are risk-averse. However, with the expected loss being equal, they tend to prefer an uncertain lottery over a certain loss, that is, they are risk-seeking. Finally, human observers tend to weigh probability rather than use its normative value, so that low probabilities are treated as if they would be higher and high probabilities are treated as if they would be lower (see Barberis, 2013 for a recent review).

Some of these violations are not present in the case of motor decision-under risk. For instance, Wu, Delgado, and Maloney (2009) directly compared the choices of observers in a motor decision-under-risk task and in the corresponding economic lottery task. They were able to show that the probability weighting function that could be derived from the motor responses differed from the one derived from the lottery choices. The lottery choices implied overweighting of low probability and underweighting of high probability, the motor choices instead on average did not show any systematic discrepancy between implied and normative probabilities. Notice, however, that a direct comparison between motor decision-under-risk tasks and lottery tasks is not always straightforward. In motor tasks, there seem to be additional constraints not directly pertinent to the decision framework. Both for eye movements (Schütz, Trommershäuser, & Gegenfurtner, 2012; Stritzke, Trommershäuser, & Gegenfurtner, 2009) and for hand movements (Jarvstad, Hahn, Rushton, & Warren, 2013; Jarvstad, Hahn, Warren, & Rushton, 2014), human observers can be suboptimal because their RTs tend to be faster than what is required. This implies that they are less precise than they could be (Fitts, 1954). Moreover, the observer's precision can change in different conditions, making it difficult to estimate the performance of an optimal observer.

Healthy aging is associated with a significant decline in cognitive abilities that challenges decision-making (for review see Mata, Josef, & Lemaire, 2015). When faced with decisions which entail the risk of monetary loss, older adults are less efficient than younger adults because they tend to be excessively risk-averse (Rutledge et al., 2016; Tymula, Rosenberg Belmaker, Ruderman, Glimcher, & Levy, 2013), although this might be conditioned on the learning requirements of the task, as older adults can be less risk-averse than younger adults in tasks where learning favors a risk-averse strategy (Mata, Josef, Samanez-Larkin, & Hertwig, 2011).

Additional evidence suggests that specific aspects of reward processing might be impaired in older adults (see Mather, 2016). Older adults are generally sensitive to reward, as evidenced by imaging of the frontostriatal network (Samanez-Larkin, Worthy, Mata, McClure, & Knutson, 2014; Vink, Kleerekooper, van den Wildenberg, & Kahn, 2015) and of mesolimbic structures (Schott et al., 2007). In fact there is evidence that achieving immediate reward is prioritized in older adults compared with delayed reward in decision-making tasks (Worthy, Cooper, Byrne, Gorlick, & Maddox, 2014). Aging, however, seems to be associated with a decreased ability to use reward prediction error for learning reward contingencies (Samanez-Larkin et al., 2014; Schott et al., 2007; Vink et al., 2015) and with reluctance to switch decision strategy in response to prediction error (Eppinger, Walter, Heekeren, & Li, 2013). This deficit can be counteracted by the administration of levodopa, implying that changes in dopaminergic signaling are crucial in explaining the differential reward processing in older subjects (Chowdhury et al., 2013).

Besides changes in cognitive abilities, healthy aging is characterized by a general worsening of motor abilities (Spirduso, Francis, & MacRae, 2005). In particular rapid aiming movements appear to be slower and less precise in older adults, even though older adults' aiming performance can still improve with practice (Darling, Cooke, & Brown, 1989). As a consequence of degraded motor control, the execution of aiming movements relies to a larger extent on visual feedback in older adults compared with younger adults (Yan, Thomas, & Stelmach, 1998; Yan, Thomas, Stelmach, & Thomas, 2000), particularly in the case of highly trained movements (Seidler-Dobrin & Stelmach, 1998). Additional evidence suggests that older adults might be prone to large interference in dual tasks with both motor and cognitive requirements (Verhaeghen, Steitz, Sliwinski, & Cerella, 2003).

The aging-related changes in explicit and reward-based decision-making mentioned above and the aging-related changes in motor control raise the important question of whether and how aging affects motor decision-making under risk. We do not know whether the risk-averseness of older adults when faced with risky economic decisions (Rutledge et al., 2016; Tymula et al., 2013) also dominates motor decisions, and whether the worsening of aiming efficiency in older adults extends to the task-related strategies involved in the aiming-under-risk paradigm. Answering these questions will expand our understanding in at least two ways. First of all an original perspective on the complex changes related to functional aging is introduced. The task we are using has been devised within an explicit modeling framework, which allows for the comparison of visuomotor performance in different age groups against the behavior expected from an optimal observer. This provides an innovative possibility to evaluate the integrity of the aging visuomotor system, further detailing the motor changes associated with healthy aging. Considering that the global life expectancy is over 71 years, and over 80 years in many developed countries (WHO, 2016), and the fact that aging-related motor changes substantially contribute to falls causing serious injury (e.g., Alamgir, Muazzam, & Nasrullah, 2012), a more comprehensive investigation of sensorimotor performance in senior adults is definitely needed. Our results will, however, also be relevant to the debate concerning the similarities and differences between economic and motor decision-making (Jarvstad et al., 2013, 2014; Wu et al., 2009). There is evidence for age effects on economic decision-making (Hershey, Austin, & Gutierrez, 2015), but so far evidence from a comparable motor task is missing.

Our study is the first in which two groups of younger (age 20–30) and older (age 60–80) healthy observers were tested in a

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task closely modeled on the one introduced by Trommershäuser and colleagues (2003a, 2003b). Results showed that older adults tended to adjust their aiming position to a larger extent compared with younger adults to avoid hitting the penalty area, which could be interpreted as a sign of increased risk-averseness. A model-based interpretation of the pointing patterns supported the conclusion that the increased adjustment in aiming was due to an increased weighting of losses compared to gains in older adults, rather than to the overestimation of the motor imprecision.

Method

Participants

In total, 52 younger subjects (age range 18–30 years, $M = 22.5$, 44 women) and 34 older subjects (age range from 62–77 years, $M = 69.5$, 14 women) participated in our study. Recruitment of subjects was managed by calls for participation at the University of Giessen and in local newspapers. All subjects were paid for participation. Any history of ophthalmologic, neurological, or psychiatric disorders as well as medications presumed to interfere with sensorimotor functioning were screened out by a comprehensive interview protocol. All participants were right-handed assessed by Edinburgh Inventory (Oldfield, 1971) had normal or corrected-to-normal visual acuity, and were naive with respect to the purpose of the study. Informed consent was given by the participants according to the Declaration of Helsinki (World Medical Association, 2013). Method and procedures were approved by the local ethics committee.

Stimuli and Experimental Procedure

The stimuli and experimental procedure were designed to closely replicate the original paradigm by Trommershäuser, Maloney, and Landy (2003a, 2003b), the main difference being that instead of opting for a fixed deadline for aiming time, we adapted the deadline to the spontaneous aiming speed of each observer.

Observers were seated in front of a 21" ELO Touchscreen (ELO TouchSystems ET2125C, resolution of 1,280 × 960 pixel, refresh rate of 100 Hz) at a distance of approximately 35 cm. At the beginning of each trial the observer depressed a button located 14 cm in front of the screen with the index finger of their right hand. Depressing the button triggered the appearance of a fixation point. If the observer kept depressing the button for 2 s, the target circle and the penalty disk were presented. At this point the observer was required to tap on the panel within the target circle (see Figure 1). Pointing within the target circle before the time deadline was constantly associated with gaining 100 points, pointing within the penalty disk produced a loss of 0, 100, or 500 points depending on the penalty condition. The reward and penalty were added when observers pointed in the intersection of the circles, yielding 100, 0, or −400 points depending on the penalty condition. Pointing outside of both circles was neither awarded nor punished, pointing after the time deadline was punished with a loss of 700 points.

The target was a green circle whereas the penalty area was denoted by a red disk. Both had a diameter of 18 mm (approximately 3 deg of visual angle). The center of the target circle was randomly placed within an 88 × 88 mm square centered on the fixation point. The penalty disk occupied six possible positions relative to the target, with different levels of overlap (Figure 1B).

In the first 180 trials the observers practiced the task without reward. For the first 120 trials the observers practiced the task with a time deadline of 800 ms. A written feedback encouraged the observer to try to point faster in case the deadline was not met. From Trial 121 on, the time deadline was changed to the subject-specific value (80th percentile of the pointing time distribution between Trials 60 and 120). The experimental trials were organized in six blocks of 60 trials each. In each block the penalty condition (0, −100, or −500 points) was constant and the order of the blocks was randomized across observers. The relative position of the target and penalty stimuli was randomized across trials. In total, observers underwent 540 trials: 180 practice trials (30 repetitions for each penalty disk position) and 360 experimental trials (20 repetitions for each combination of penalty disk position and penalty condition). At the end of each trial observers received feedback indicating how many points they had gained or lost in the current trial. Additionally, as in the practice trials, they received a specific feedback if the pointing time exceeded the deadline. Stimuli were presented and responses collected using Matlab

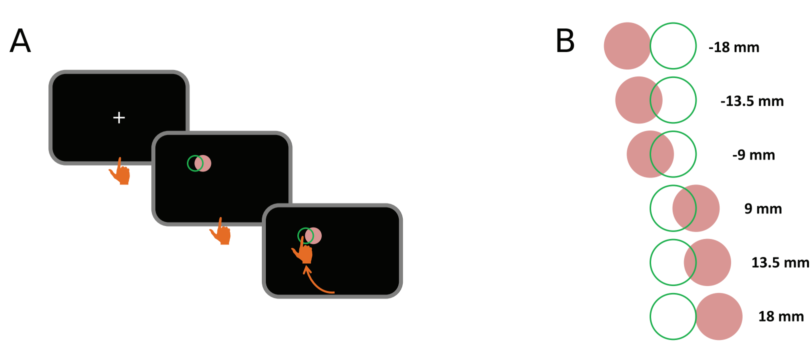

Figure 1. Experimental task (A) and relative position of target and penalty areas (B). Observers were required to point inside the green target circle while avoiding the penalty disk. Hitting the green circle was rewarded with 100 points whereas hitting the penalty disk was punished with the loss of 0, 100, or 500 points, depending on the experimental condition. Hitting over time was punished with a loss of 700 points. The penalty disk could occupy six possible positions relative to the target, here indicated by the millimeter distance between the circle centers. See the online article for the color version of this figure.

(MathWorks, Inc., Natick, MA) and the PsychToolbox (Brainard, 1997).

Optimal Pointing Computation

The computation of optimal pointing behavior in this task is in principle computationally very expensive, because it requires the simulation of large number of trials by a given observer. To simplify the problem we modeled each observers' behavior using a circular Gaussian distribution and we ignored any offset on the vertical axis. Under those assumptions the only determinants of optimal pointing behavior are the pointing imprecision, that is, the *SD* of the observer's movement end points, and the penalty condition, that is, the value of penalty relative to reward and the relative position of the two stimuli. Notice that because the arrangement of the six possible positions (Figure 1B) as well as the circular Gaussian distribution are symmetrical, only three optimal aiming points need to be computed for each combination of imprecision and penalty condition.

To allow for the rapid computation of optimal aiming point with arbitrary penalty values we constructed a grid of 1,000 × 1,000 cells, corresponding to the combinations of 1,000 *SD* levels (exponentially spaced between .16 and 116 mm, median 4.34 mm) and 1,000 penalty value levels (exponentially spaced between 1 and 1,57,000 points, median 393). We computed optimal aiming points for a randomly selected subset of cells (11,366 cells, i.e., 0.011% of the total).

Each optimal aiming point was computed by first simulating 100,000 samples from the circular Gaussian distribution, and evaluating for each penalty position condition the expected gain over a range of aiming values comprised between −586 and 586 mm. The procedure was iterated focusing in on the maximum gain location until a resolution of .003 mm was achieved. Particularly when simulating extremely high precisions, all of the 100,000 simulated points can be contained in an area smaller than the target area. This produces a gain profile that does not have a peak but an extended interval where gain is maximal. In the case that a constant maximum gain was observed over more than 30 samples, the optimal aiming point was computed as the average of those samples.

Finally, we fixed the optimal aiming point in each grid cell through a biquadratic interpolation of the values of the nearest 300 cells for which an estimate was available. In all of the following analyses optimal aiming points were estimated for a given penalty value and imprecision, based on the closest grid cell.

Similar to previous reports using the same paradigm (e.g., Trommershäuser et al., 2003a) our observers exhibited a general rightward bias in their movement end points, which at least partly results from pointing with the right hand (Younger observers: 1.12 ± 1.5 mm, mean ± *SD*, Older observers: 1.59 ± 1.45 mm). If the observers had pointed at the locations computed after removing the rightward bias, they would have gained on average 970.7 points more over the −100 and −500 penalty conditions, that is 6.1% more points on average. A control experiment we conducted showed that asking observers to point with their left hand reduced the aiming bias by 78.7%. As this bias is most likely a simple motor error at the execution level, rather than a consequence of the aiming strategy, we felt confident in discounting it before evaluating the observers' behavior (Trommershäuser et al., 2003a). Before any further analysis and plotting, the average horizontal movement end point over all trials, excluding practice, 0-penalty trials and outlier end points, has been subtracted from the data for each observer. Notice that because our modeling of the data is based on predictions which are symmetric along the center of the target, a general bias results in poorer fits but the exact same configuration of best fitting parameters.

Modeling

The individual data were modeled in terms of the equivalent imprecision estimate and penalty value estimate that would have led to the observed movement end point pattern. Specifically, the two parameters characterizing the observer were defined as (a) the ratio between the equivalent imprecision and the observed pointing imprecision (b) the ratio between the equivalent penalty value and the nominal penalty value.

The parameter values were fitted to each observer's average pointing positions using unconstrained nonlinear optimization, as implemented by the *fminsearch* function in MATLAB. Optimal aiming points were computed using the grid algorithm described above. To establish whether each observer's data are reliably associated with the best fitting configuration of parameters, we repeated the fitting procedure 5,000 times after randomly resampling the movement end points of each observer in each condition. In the following we excluded data from the observers for whom, for any of the two parameters, the percentage of bootstrapped fits contained in an interval of .5 units centered on the value fit to the original sample was smaller than 40% (leaving 42 out of 52 observers in the younger group and 18 out of 34 observers in the older group). The same pattern of results was, however, obtained both when no observer was rejected and when we used rejection criteria as strict as 50%.

Intuitively, both increasing the value associated with penalty relative to gains and overestimating one's imprecision should produce overadjustment. The fact that the bootstrapping procedure revealed relatively stable fits suggests that the effect of the two parameters on the predictions cannot be completely equivalent. This conclusion is supported by the inspection of Figure 2, which illustrates the predictions associated with different configurations of parameters for one representative observer. For this example we imposed the Penalty Value Factor to be at different levels between .4 and 5.5 and for each level we optimized the Pointing Imprecision Factor alone. The fact that the trajectory of the points in Panel A is oblique indicates that the two parameters can, to a certain extent, be traded off against each other. Nonetheless, the predictions associated with the different parameter configurations are clearly not equivalent. A close inspection of Panel B shows that as the pointing imprecision factor decreases and the penalty value factor increases, the slope for both the −100 and −500 penalty conditions becomes steeper, but more so for the −100 condition, so that the difference between the two conditions becomes smaller. Ultimately, the fact that the residual errors increase if the parameter configuration is different from the best fit (Panel C) is a clear demonstration that different configurations of the parameters do not produce the same predictions.

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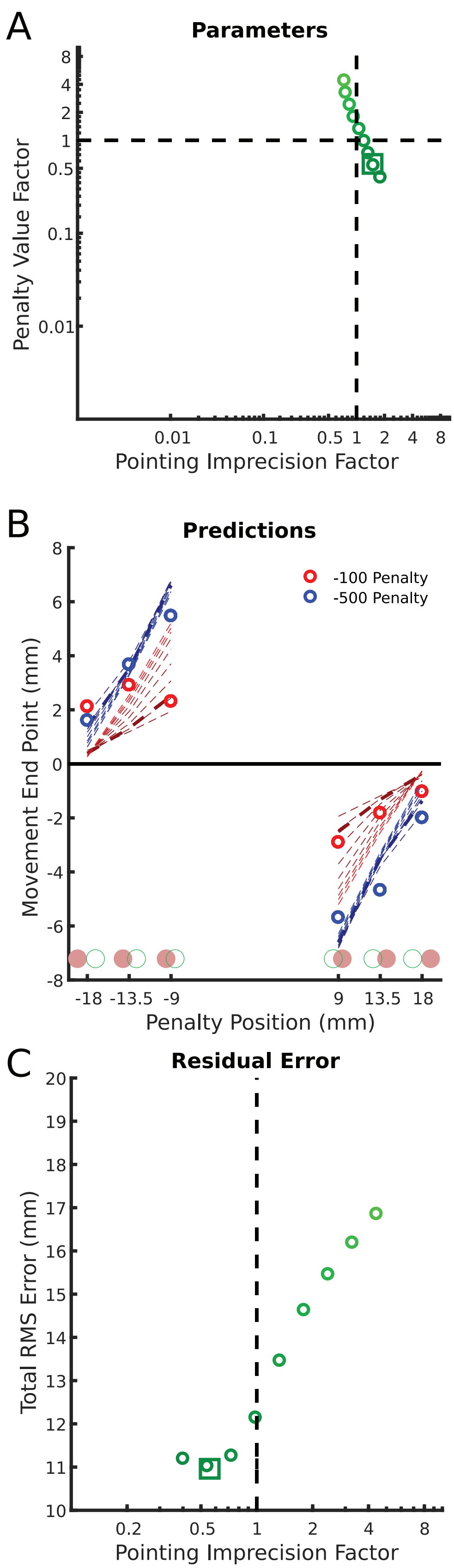

Figure 2. Different parameter configurations (A), corresponding predicted movement end points (B), and corresponding residual errors (C) for an example observer. Each circle in A represents a parameter configuration where the Penalty Value Factor was fixed and the Pointing Imprecision Factor was optimized. The square represents the best fit for this particular observer. Circles on Panel B represent the observed average Movement End Points for this example observer. The thin dashed lines represent the predictions associated with the parameter configurations plotted on Panel A, similarly coded by lightness (lighter lines correspond to higher Penalty Value Factor). The thicker lines represent the predictions associated with the best fit. Total residual errors on Panel C are color coded as on Panel A. The display sketches in Panel B are drawn as a reminder of the relative position of target and penalty areas, and are not drawn to scale. Notice that the different parameter configurations correspond to markedly different predictions and residuals increase as the parameter configuration diverges from the best fit. See the online article for the color version of this figure.

Results

General Performance

Information relative to the observers' general performance is reported in Table 1. The results show that the final score obtained by the older observers on average less than one-third of the score obtained by the younger observers. A glance at the probabilities of hitting the target, the penalty area and to respond overtime shows that the older observers' lesser score was mostly because of their increased probability of responding overtime. Indeed, older observers went overtime on average 13.1 more times compared with younger observers, which would imply a loss of 9,170 points only considering the 700 points subtracted for each trial. If one considers that each overtime response is also associated with a missed gain, it is clear that a large share of the 10,778 points that separate the young and old observers groups are associated to the overtime responses.

We proceeded to further analyze the proportion of target hit trials as a function of the penalty position and penalty condition (see Figure 3). To analyze the data statistically, we recoded the penalty position in terms of distance and side, and we submitted the proportion of target hits to a mixed 4-way analysis of variance (ANOVA) with Penalty Distance (0, 13.5, and 18 mm), Penalty Side (Penalty disk on the Left vs. on the Right) and Penalty Condition (0, −100, and −500) as within-observer factors and Age Group (Younger vs. Older) as between-observer factor. All effects and interactions involving factors with more than two levels are Greenhouse-Geisser corrected. This yielded a significant main effect of Penalty Condition ($F(1.667, 140.034) = 33.789$, $p < .001$, $\eta_p^2 = .287$), a significant main effect of Penalty Side ($F(1, 84) = 44.612$, $p < .001$, $\eta_p^2 = .347$), a significant main Penalty Side × Age Group interaction ($F(1, 84) = 5.092$, $p = .027$, $\eta_p^2 = .057$), a significant main effect of Penalty Distance ($F(1.585, 133.163) = 79.338$, $p < .001$, $\eta_p^2 = .486$), a significant Penalty Condition × Penalty Side interaction ($F(1.781, 149.573) = 16.362$, $p < .001$, $\eta_p^2 = .163$), a significant Penalty Condition × Penalty Side × Age Group interaction ($F(1.781, 149.573) = 4.864$, $p = .012$, $\eta_p^2 = .055$), a significant Penalty Condition × Penalty Distance interaction ($F(3.267, 275.220) =$

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Table 1
Performance Statistics (Overall Number and Percentage of Trials Where the Target Area Was Hit, Where the Penalty Area Was Hit, and Where RT Exceeded the Deadline and Final Score, for the Two Groups of Observers

		Target hit		Penalty hit		Overtime			Final score	
Group	Statistic	Mean	*SD*	Mean	*SD*	Mean	*SD*	Group	Mean	*SD*
Young	*N*	303.2	39.6	24.1	10.8	15.7	19.5	Young	15528.8	16946.7
	p(%)	84.2	11.0	6.7	3	4.3	5.4	Old	4750	15863.9
Old	*N*	290.7	42.3	20	8.5	28.8	20.2			
	p(%)	80.8	11.8	5.5	2.4	8	5.6			

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20.238, $p < .001$, $\eta_p^2 = .194$) and a significant Penalty Side × Penalty Distance interaction ($F(1.582, 132.866) = 10.189$, $p < .001$, $\eta_p^2 = .108$). All remaining main effects and interactions were not significant (all *p*s > .05).

The general pattern of results is that the target circle was missed more often (the probability of hitting the target decreased from 86.9 to 78.6%) when the penalty circle was on the left side of the target and more so when hitting the penalty circle was associated with a loss of points. This tendency is even more strongly present in older adults. This result can be explained by the fact that in general our observers had a rightward aiming bias, and the older adults both had a numerically larger bias and tended to adjust to a larger extent (see below). Avoiding the penalty disk required a rightward shift when the disk was to the left of the target. This shift summed to the general aiming bias and led the observers to miss the target. When the penalty circle was on the right side, the general bias and the aiming adjustment counteracted each other, so that the observers hit the target more often.

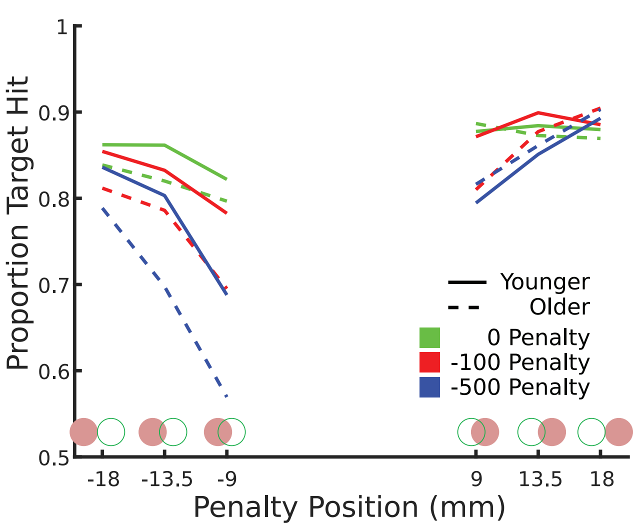

Figure 3. Proportion of target hits as a function of penalty disk position and penalty condition. Notice that in general the observers missed the target more often when the penalty circle was on the left side of the target (negative penalty position values). This is because of the fact that in this case the general rightward aiming bias and the task-related adjustment to avoid the penalty go in the same direction, whereas they cancel out to a certain degree when the penalty disk is located to the right of the target. See the online article for the color version of this figure.

The average pointing time across experimental blocks and as a function of the experimental condition and the individual probability of overtime are depicted in Figure 4. The data in Figure 4A show that pointing times decrease for both groups through the experiment, indicating that learning dominates over fatigue, and that older adults are on average slower than younger adults by 117 ms. This was confirmed by a repeated-measure ANOVA with Trial Block as a within-observer factor and Age Group as a between observer factor. Both the effect of Trial Block ($F(3.101, 260.517) = 31.872$, $p < .001$, $\eta_p^2 = .275$) and the effect of Age Group ($F(1, 84) = 68.541$, $p < .001$, $\eta_p^2 = .449$) were significant, but their interaction was not ($F(3.101, 260.517) = .966$, $p = .461$, $\eta_p^2 = .011$).

The pointing time data are presented as a function of the experimental condition in Panel B. Besides the general slower responses in older adults, it appears that the observers were slower in the conditions which were associated with the higher probability of being penalized, that is, when the distance between the penalty and target areas was small and when the penalty value was high. Pointing times were also larger when the penalty disk was on the right of the fixation point (albeit by mere 3.4 ms on average) and more so when the penalty value was high. Again, this could be because of the rightward bias leading to a higher likelihood of penalty hits when the penalty area was on the left. Like in the case of the proportion of target hits, we analyzed the pointing times with a mixed 4-way ANOVA with Penalty Distance (0, 13.5, and 18 mm), Penalty Side (Penalty disk on the Left vs. on the Right) and Penalty Condition (0, −100, and −500) as within-observer factors and Age Group (Younger vs. Older) as between-observer factor. This yielded a significant main effect of Penalty Condition ($F(1.871, 157.175) = 32.389$, $p < .001$, $\eta_p^2 = .347$), a significant main effect of Penalty Side ($F(1, 84) = 40.850$, $p < .001$, $\eta_p^2 = .327$), a significant main effect of Penalty Distance ($F(1.692, 142.094) = 60.505$, $p < .001$, $\eta_p^2 = .419$), a significant Penalty Condition × Penalty Side interaction ($F(1.915, 160.831) = 6.372$, $p = .003$, $\eta_p^2 = .071$), a significant Penalty Condition × Penalty Distance interaction ($F(5.658, 307.240) = 5.735$, $p < .001$, $\eta_p^2 = .064$) and again a significant main effect of Age Group ($F(1, 84) = 59.561$, $p < .001$, $\eta_p^2 = .415$). All remaining main effects and interactions were not significant (all *p*s > .05).

Finally, as evidenced in Panel C, the older observers are generally more likely to point overtime compared with younger adults, $t(84) = 3.022$, $p = .003$. Given that both groups of observers had the same decrease in pointing time over the course of the experiment, it appears unlikely that this was because of an additional

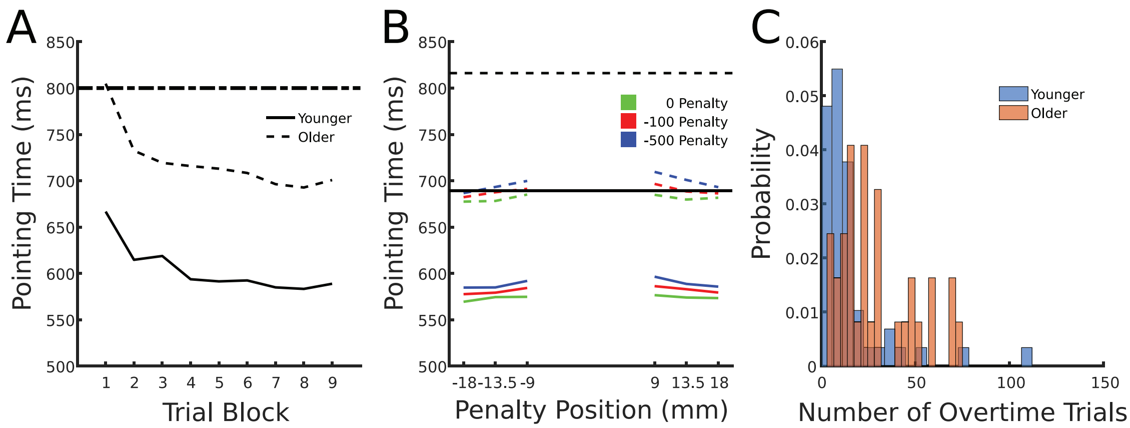

Figure 4. Pointing time as a function of trial block (A), pointing time as a function of experimental condition (B), and histograms (empirical density functions) of the individual number of overtime trials (C). Data in A are average pointing times over blocks of 60 trials. The individual deadline was established in Block 2 (when the fixed deadline of 800 ms, dashed line was used). Blocks 7–9 were run on a different day. Notice that the 800 ms deadline was close to the average spontaneous pointing time of the older observers. Data in B indicate that pointing times tended to be longer for the most risky conditions, that is, with highest possible loss and smallest target area. The black horizontal lines represent the average individual deadlines for the two groups. Notice that the average deadline for older adults was higher than the initial 800 ms deadline. The histograms in C show that the whole distribution is shifted to higher values for older adults, excluding that the higher overtime rate is determined by a few outlier observers. In general the results suggest that the initial 800 ms deadline was more demanding for the older adults, pushing them to respond faster in the practice trials and resulting in more challenging individual deadlines. See the online article for the color version of this figure.

vulnerability to fatigue in older adults. More likely, the 800 ms deadline that was used in the early practice blocks was more demanding for the older adults, as evidenced by the fact that the individual deadlines were in fact slightly longer on average, meaning that they were already closer to their speed limit as the individual deadline was established.

The average pointing imprecision is depicted in Figure 5. Despite the fact that the time constraints were more demanding for

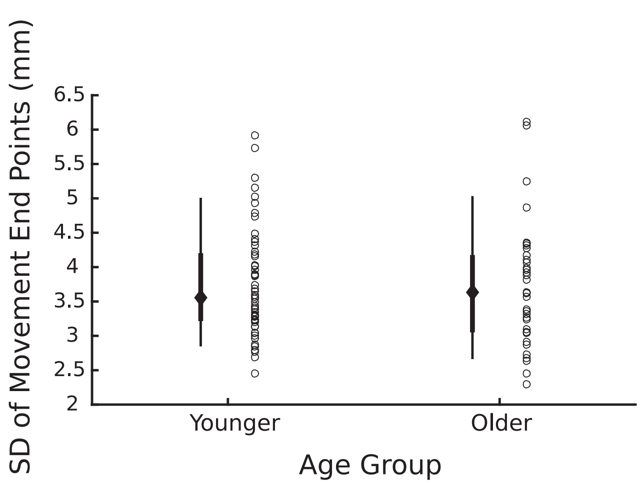

Figure 5. Pointing Imprecision in the two age groups. Each point represents the average value for an observer. The box plots represent median, interquartile interval and the interval between the 9th and 91st percentile of the distribution. Overall the pointing imprecision was comparable across age groups.

older adults, the pointing precision did not differ across groups ($t(84) < 1$). Based on with Fitt' s law (1954), one would expect pointing imprecision to increase given a stricter speed requirement, nonetheless, it appears that the titration of the pointing time deadline was sufficient to equalize pointing performance across groups in terms of movement end point precision. This ensured that the different strategies we observed in younger and older adults were not determined by different a priori probabilities of hitting the target or penalty areas.

Aiming Strategy: 0-Penalty Condition

In one of the three penalty conditions the observers did not lose any points if they hit the penalty disk. In this case the optimal strategy is simply to aim for the center of the target stimulus while ignoring the penalty. The actual movement end points of the observers show a tendency to avoid the penalty disk even if it was irrelevant (see Figure 6). This tendency was evident also in the practice session, which was conducted at the beginning of the first session, before the observers were informed about the possible task-relevance of the penalty disk.

We included the 0-penalty condition in our paradigm mainly to exactly replicate the methods of Trommershäuser, Maloney, and Landy (Trommershäuser et al., 2003a, 2003b). Not having this condition could have constituted a confounding factor in case we had failed to replicate their results. Notice, however, that because the optimal strategy in this condition is independent both from the observer's precision and from the position of the penalty disk, the data do not allow for an interpretation of the observer's strategy in terms of reward sensitivity and precision estimation. In the remainder of the article we concentrate on the −100 and −500 penalty

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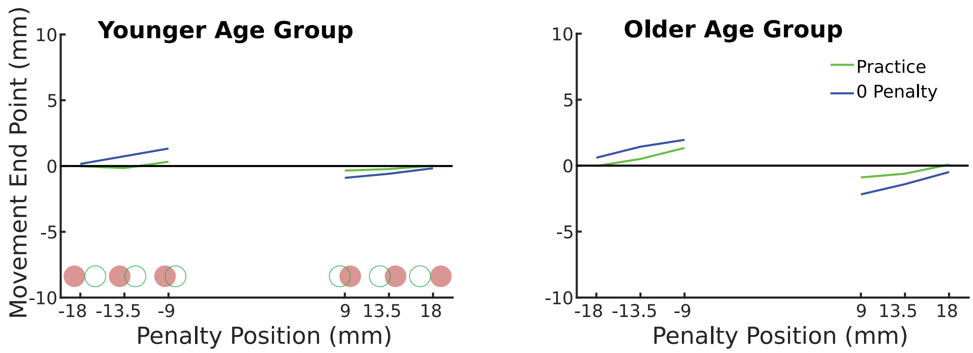

Figure 6. Average movement end points in the practice trials with fixed deadline (green) and in the trials where the no penalty was applied (blue) as a function of the position of the penalty disk. Data for the younger and older age groups are presented in the left and right panels, respectively. Movement end points tended to be shifted to the right (positive values) when the penalty disk was on the left size (negative values, see icons in left panel) and vice versa. This indicated that the observers spontaneously avoided the penalty disk even if it was not relevant for the task, and even before experiencing any monetary loss. The circles in the left panel are drawn as a reminder of the relative position of target and penalty areas, and are not drawn to scale. See the online article for the color version of this figure.

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conditions, where the optimal strategy depends both on penalty value and on aiming precision.

Aiming Strategy Under Risk

The general observed aiming strategy, compared with the general optimal strategy, in the presence of nonzero penalty (i.e., under risk) is illustrated in Figure 7. Both the younger and the older observers pointed away from the center of the target area to avoid hitting the penalty disk. They did so to a larger extent when the target and disk area were nearer and when the penalty in terms of points was larger. This strategy qualitatively matches the optimal strategy, although quantitative deviations from optimality are evident in both groups. In particular we can observe that generally speaking the observers overcompensated when the penalty area was far from the target and undercompensated when it was near.

Differential strategies are more evident if one considers separately the slope of the adjustment as a function of penalty-target distance and its overall extent. The individual values of the slope adjustment are illustrated in Figure 8. The values represent the amount to which the movement end point changes as a function of the distance between the target and penalty areas. A repeated-measure ANOVA with Penalty Level as a within-subject factor and Age Group as a between-subjects factor showed that the aiming point changed more in the −500 Points Penalty condition ($F(1, 84) = 35.01$, $p < .001$, $\eta_p^2 = .294$), but there was no evidence for a difference of slope between the age groups ($F(1, 84) = .026$, $p = .873$, $\eta_p^2 < .001$) and the interaction was also not significant ($F(1, 84) = 1.519$, $p = .221$, $\eta_p^2 = .018$).

Notice that the intercept values in the fits do not have a real meaning, because at a distance of 0 the target and penalty areas

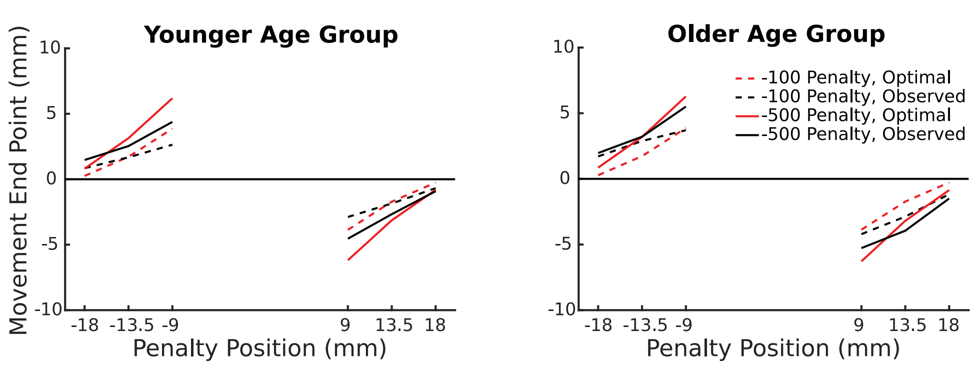

Figure 7. Movement end points in the trials with −100 points penalty (dashed lines) and −500 points (solid lines) as a function of the position of the penalty disk. The average observed movement end points are drawn in black. For comparison the corresponding average optimal aiming points are drawn in red. Data from the younger and older observer groups are presented in the left and right panels, respectively. Both groups of observers shifted their aiming points away from the penalty disk as it approached the center of the target circle, and did more so when the penalty was larger, qualitatively in accordance with the optimal pointing strategy. See the online article for the color version of this figure.

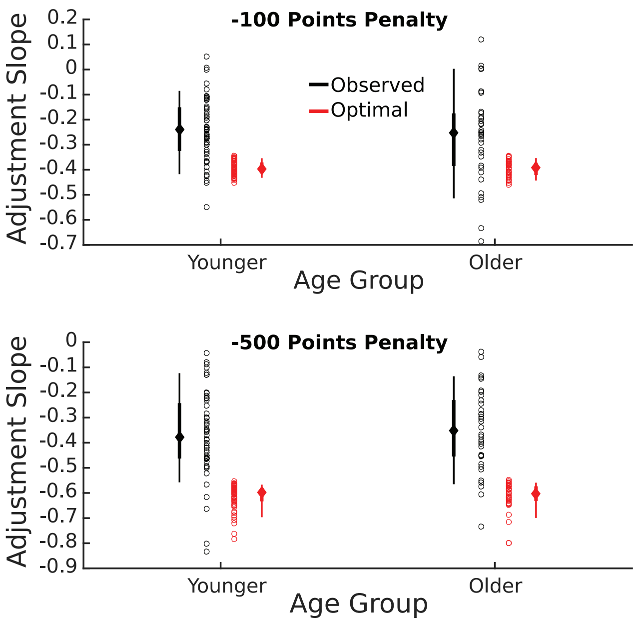

Figure 8. Individual adjustment slope. The circles indicate by how many mm the movement end point of a given observer changes by each mm displacement of the penalty disk. Data are shown separately for the two age groups (left and right) and for the different penalty conditions (upper and lower panels). Optimal slope values are drawn in red. In general the slopes are comparable across age groups and are smaller than optimal. See the online article for the color version of this figure.

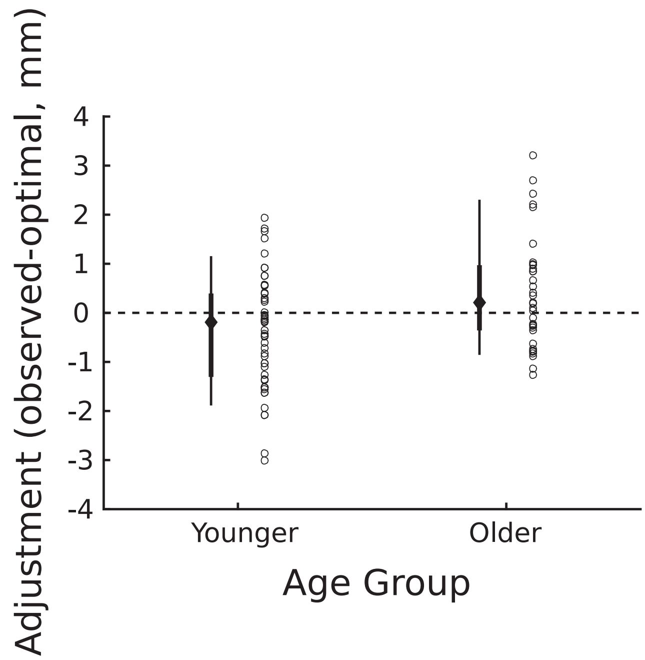

Figure 9. Discrepancy from optimal adjustment. A value of 0 indicates optimal adjustment. Values larger than 0 indicate overadjustment, values under 0 indicate underadjustment. Albeit among large interindividual differences, the overall pattern indicates a slight tendency to underadjustment among the younger observers and to overadjustment among the older observers. The values plotted in this figure can be compared to Figure 7, where the movement end points are further displaced from 0 relative to the predicted aiming points in the case of the older observers (right panel) compared to the younger observers (left panel).

perfectly overlap and the optimal behavioral strategy would change completely. In fact one would have to aim more or less in the middle of the screen with penalty −100, when all areas yield a gain of 0, and far enough in any direction from the penalty and target areas with penalty −500. Instead we proceeded to analyze the overall discrepancy between the observers' aiming strategy and the corresponding optimal strategy (see Figure 9). The results indicate that the younger group of observers tended to adjust their aiming points slightly less than they should have (−0.379 ± 1.138 mm, mean ± *SD*), whereas the older observers tended to slightly overadjust (0.401 ± 1.139 mm). In fact the adjustment was statistically larger in the older age group compared to the younger age group, $t(84) = 3.11$, $p < .003$. Notice that the same information is encoded as the difference between the absolute observed and optimal values in Figure 7.

Efficiency

In general we observed that the aiming strategy of the observers takes into account both the value of the penalty and the geometrical configuration of the stimuli, as would be expected from an optimal observer. In the following we quantify the performance of the observers and compare it to the performance of a hypothetical optimal observer. We define efficiency as the ratio between the number of points gained by each observer per trial (excluding overtime penalty) and the average amount of points gained by the optimal observer in a simulation of 100,000 trials per condition. The overall efficiency estimates are very close to 100% (see Figure 10), indicating that observers were successful in adapting their behavior to the task constraints. Notice, however, that failing completely to adjust to the task requirements does not imply an efficiency of 0% and relatively large under- or over-adjustment still yields relative good efficiency (see Figure 11). The efficiency

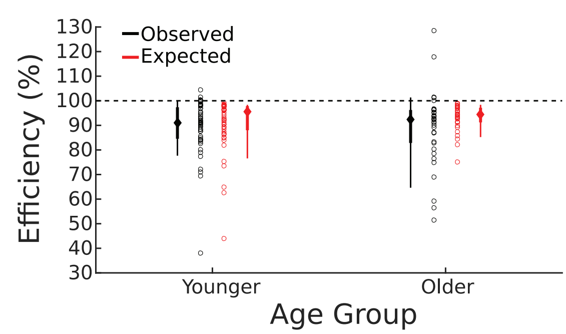

Figure 10. Efficiency, that is, ratio between the total amount of points and the score warranted by optimal behavior. The efficiency computed based on the observer's final score is drawn in black. The efficiency computed based on the score expected given the observer's pointing strategy is drawn in red. Trials where the observers did not meet the time deadline are not considered in the computation. Notice that while the expected gain cannot be larger than the optimal one, the stochastic nature of the task allows the observed efficiency to be higher than 100%. See the online article for the color version of this figure.

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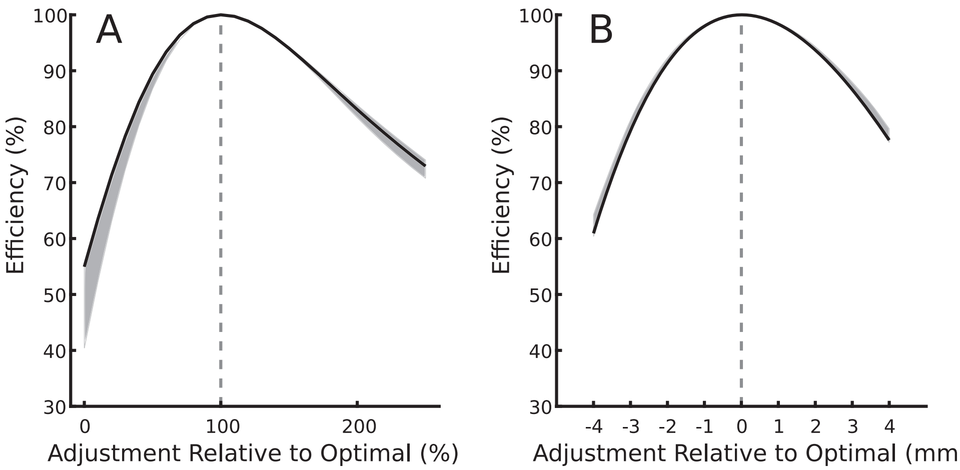

Figure 11. Expected efficiency as a function of the amount of adjustment to the task demand. The value of adjustment is defined both as a ratio of the optimal adjustment (A) and as the shift in the direction of the required shift (B). The black line represents the median of the distribution across observers and the boundaries of the gray areas represent the 9th and 91st percentiles. Notice that an adjustment of 0 in A, which stands for the strategy of always aiming at the center of the target circle independently of the penalty position and condition, still yields an efficiency of at least 40% for most observers. Adjusting twice as much as an optimal observer is still associated with efficiency over 80%. A comparison of Figure 9 and Panel B confirms that the pointing strategies of most observers were compatible with quite high efficiency.

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values do not seem to differ between the two groups of observers. Given the highly skewed distribution of the efficiency measure, rather than using parametric tests we submitted them to a Wilcoxon's rank sum test. The median value of efficiency was not statistically different between the age groups ($Z = -.234$, $p = .814$). Notice that the statistical test was performed on the expected efficiency, computed simulating 100,000 trials for each of the 12 conditions using the average movement end points of the observer in each condition. The expected efficiencies are a better measure of the optimality of the observers' behavior compared with the observed efficiencies as they are less subject to stochastic variations and when computing them we discounted the confounding effects of general horizontal and vertical aiming biases.

Model-Based Interpretation of the Aiming Strategy

Taken at face value the results seem to indicate that both young and old observers are quite efficient at this task, coherent with previous reports (Gepshtein et al., 2007; Trommershäuser et al., 2005, 2003a, 2003b, 2006). However, the reason for the residual suboptimality in younger and older adults might be qualitatively different, as suggested by the fact that younger observers tend to underadjust their aiming to avoid the penalty area whereas older observers tend to overadjust.

Formally, the behavior of an optimal observer in this task is determined by the estimate of its pointing precision and by the relative value attributed to gains and losses. One way to interpret suboptimal behavior in a given observer is to assume that it originates from a wrong estimation of pointing precision, to a wrong interpretation of monetary risk or to a combination of both factors. In the following we fit each observer's average pointing locations using a model that assumes optimal behavior but where two free parameters control the estimate of pointing variability and the ratio between penalty and gain value, respectively. Notice that this approach is similar to the one used for instance by Wu and colleagues (2006), who computed the equivalent imprecision which would have justified the observed aiming strategy assuming optimality.

To fit each observer's data we used two parameters defined as (a) the ratio between the equivalent imprecision and the observed pointing precision (b) the ratio between the equivalent value of the penalty and the nominal value. Generally speaking setting both parameters to 1 produces optimal pointing, values larger than one are associated with overadjustment and values smaller than 1 are associated with underadjustment. Modifying the two parameters independently, however, has a complex pattern of nonlinear effects on the predicted movement end points in the different conditions.

The fits for individual observers are presented in Figure 12. Looking at the data it is easy to notice that there is an excess of younger observer who were assigned a low penalty value parameter, whereas the distribution of the pointing imprecision factor is largely overlapping between the two age groups. This was confirmed by statistical analysis. A Wilcoxon's rank sum test comparing the two age groups was significant in the case of the penalty value factor ($Z = 2.669$, $p < .008$) but not in the case of the pointing imprecision factor ($Z = .589$, $p = .556$). This indicates that the residual suboptimality in the younger observers, which manifests itself in their tendency to underadjust in the presence of the penalty circle, is because of the fact that they tend to weight losses less than they weight gains, when performing the pointing-under-risk task. This tendency is, however, not present in the older group. Performing Wilcoxon signed-ranks test for each parameter individually showed that the median value differed from 1 only in the case of the penalty value factor in the younger age group ($Z = 3.407$, $p < .001$). The same test did not yield significant results in

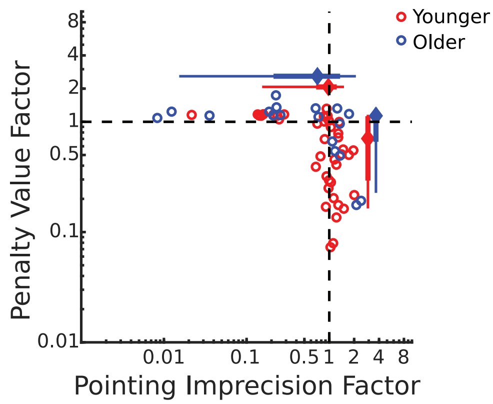

Figure 12. Model fitting results. Circles indicate the combination of parameter fits for each individual in the two groups. The distribution of the fitted values largely overlap between groups in the case of the pointing imprecision factor, whereas proportionally more young observers show low fits for the penalty value factor. The data suggest that younger observers tend to attribute a smaller weight to losses as compared to gains relative to older adults. Notice that the modeling results are in agreement with the observation that younger adults adjust their aiming strategy less than older adults when the target and penalty areas are close. See the online article for the color version of this figure.

the case of the penalty value factor in the older age group (Z = .370, p = .711), nor in the case of the pointing imprecision factor both in the younger (Z = .667, p = .504) and older (Z = .936, p = .349) age groups.

Discussion

Our study is the first, to our knowledge, to test the impact of aging on rapid aiming under risk. A number of key findings emerged from the analysis of our data.

1. Older adults can achieve a level of precision in rapid aiming comparable with the one of younger adults, if they are allowed to be slower.

2. Generally speaking both younger and older adults are able to adapt their aiming behavior to the task demands and achieve close to optimal performance.

3. Residual discrepancies in the aiming strategies suggest that older adults are relatively more risk-averse than younger adults, adapting their aiming strategy to a larger extent to avoid the penalty area.

4. The model-based interpretation of the movement end point patterns in older and younger adults suggests that age-related changes in risk-averseness are due to the fact that younger adults overweight gains as compared with losses, rather than to differences in the implicit estimation of aiming imprecision.

Our findings show that the results from the aiming-under-risk paradigm can be fruitfully interpreted beyond the assessment of optimality. Optimality in risky choices is a very important concept as it offers a normative benchmark that can be used to interpret results from very different paradigms. Optimal integration of sensory information with learned motor outcomes appears to be a basic feature of human motor control (e.g., Körding & Wolpert, 2004). Beyond aiming, optimality can be evaluated in paradigms where observers perform saccadic eye movements (Schütz et al., 2012; Stritzke et al., 2009), whole-body movements (O'Brien & Ahmed, 2013), as well as in tasks where observers steer vehicles in a virtual environment (Dunning, Ghoreyshi, Bertucco, & Sanger, 2015). Computing optimality can even be successfully used to compare results across species (Balci, Freestone, & Gallistel, 2009). Moreover, the same framework can be used to evaluate perceptual judgments under risk (Landy, Goutcher, Trommershauser, & Mamassian, 2007; Warren, Graf, Champion, & Maloney, 2012; Zhang, Morvan, & Maloney, 2010) and the performance in tasks where perceptual and motor noise have to be taken into account at the same time (Tassinari, Hudson, & Landy, 2006). Our results, however, showed that remarkably similar levels of efficiency at the motor-decision-under-risk task can correspond to qualitatively different strategies, as observers can exceed both in being risk-seeking, which is predominantly the case for younger adults, and risk-avoidant, which seems to be the case for older adults. Furthermore, our model-based analysis showed that relatively subtle differences in aiming strategy can be reconducted to specific parameters that define the problem of rapid aiming under risk. While both overweighting the value of losses compared with gains and underestimating one's precision generally increase an observer's tendency to avoid the penalty area, the model-based analysis of the movement end point patterns indicated that many younger observers tended to underweight the value of losses, while correctly estimating their aiming inaccuracy.

Our study exemplifies some of the differences between tasks formulated in terms of motor decision making and in terms of lottery choices. In particular, some of the suboptimality in the performance of our observers, both young and old, was because of factors that do not have a direct equivalent in lottery-based paradigms. First of all, our observers showed a rightward bias in their movement end points, which cost them on average at least 5% of their score. Second, they showed a tendency to slightly increase their pointing time when the risk associated with a given trial was high. Our paradigm involves very high penalties for trials in which observers respond overtime, which is meant to discourage them from trading response speed against precision. Future studies might use pointing time as an additional dimension to evaluate optimality and to compare performance between younger and older adults. This will require the measurement of individual speed–accuracy trade-off functions and possibly the use of reduced overtime penalties. We anticipate that observers will prove to be quite ineffective in achieving optimality when response speed control becomes relevant (Jarvstad et al., 2013, 2014; Schütz et al., 2012; Stritzke et al., 2009).

Our findings are highly relevant to our understanding of whether changes in cognitive and motor abilities associated with aging are necessarily detrimental. Among obvious interindividual differences, aging is characterized by decline in sensorimotor abilities (e.g., Seidler et al., 2010; Spirduso et al., 2005). Some aspects of sensorimotor decline are directly challenging for performance in the aiming-under-risk task, if anything because older adults are expected to be slower and less precise (Darling et al., 1989). Although the older observers were still more likely to produce

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overtime response than younger observers, probably because they had difficulties meeting the deadline we initially imposed to all observers, the aiming performance was comparable. Titrating the time deadline to each observer's spontaneous aiming speed abolished age-related differences in aiming precision. This indicates that there is no hard limit to aiming precision in healthy elderly observers, but speed can still be traded off for precision (Fitts, 1954). This result is also consistent with the observation that human observers can flexibly and efficiently adapt to changes in the instructed speed when pointing under risk (Dean, Wu, & Maloney, 2007).

Once the conditions for a fair comparison between younger and older adults were established, that is, once basic sensorimotor impairments were discounted, our results showed that older observers were not less optimal in their aiming strategy than younger observers. This result is not trivial, because there is evidence that some degree of learning is required for optimal behavior in the aiming-under-risk task (Neyedli & Welsh, 2013) and older adults have difficulties in using reward prediction error for learning strategies in economic decision-making (Samanez-Larkin et al., 2014; Schott et al., 2007; Vink et al., 2015). While our results suggest that older adults can adapt their motor behavior as quickly as younger adults in response to the reward contingencies, a definitive answer could only be provided by a specifically designed study. Our paradigm involved a relatively large number of geometrical arrangements that were randomly interleaved between trials, and the event of hitting the penalty circle was quite rare. This makes it difficult to investigate the reward-based changes in aiming strategy through the trials.

Another question for which our paradigm cannot provide a definite answer is whether the relative change in the weighting of gains and losses associated with aging is because of an absolute increase in the weighting of gains, an absolute decrease in the weighting of losses or a combination of both. This question is particularly intriguing since Rutledge and colleagues (2016) found specific changes in the sensitivity to gains associated with aging in their decision-making task. While separately assessing the sensitivity of motor choices to losses and gains is possible in specifically designed paradigms (e.g., Chapman, Gallivan, Wong, Wispinski, & Enns, 2015), obtaining absolute weights appears harder. Attempts have been made at defining nonmonetary costs when studying motor control as a decision-making process. These could be used as an independent "currency" that could be traded for achieved monetary gains and avoided monetary losses (e.g., Braun, Nagengast, & Wolpert, 2011; Rigoux & Guigon, 2012; Todorov, 2004). However, motor costs are likely changing with aging as well, which is likely to limit their usefulness as a reference nonmonetary value across age groups.

Our study focused exclusively on the measurement and modeling of the movement end points in terms of the optimal aiming strategy. However, one could argue that at least some of the differences in aiming between the age groups are because of a differential sensitivity to distractor saliency, rather than to differences in motor decision-making. Indeed, some evidence exists showing that older adults show larger saccadic curvature toward distractor stimuli, which can be interpreted as a sign of less efficient inhibition of the distractor location (Campbell, Al-Aidroos, Pratt, & Hasher, 2009). Movement curvature toward distractors has also been observed in the case of manual reaching (Moher, Anderson, & Song, 2015), although the amount of curvature might not be related to distractor saliency (van Zoest & Kerzel, 2015). The fact that older adults showed larger avoidance of the penalty stimulus in our paradigm, which would imply if anything that the distractor position was more efficiently inhibited, and the fact that salient distractor effects are most prominent in the curvature of the aiming movement rather than in the movement end points, makes it rather unlikely that excessive sensitivity to distractor saliency plays a large role in our results. Nonetheless, measuring the curvature of aiming trajectories in the aiming under risk paradigm might provide valuable insights in the age-related changes at the interface of bottom-up saliency and motor decision making.

One possible reason for the differential strategy that we observed in younger and older adults might have to do with the fact that the net score achieved by the older adults was on average lower compared with the younger observers, although this seems unlikely because the current score was not communicated to the participant during the experiment. We propose that our finding of an age-related switch from risky to risk averse strategy in the pointing-under-risk task nicely complements the observation that children tend to favor risk-seeking strategies in this task, to the point of performing suboptimally (Dekker & Nardini, 2016). Taken together, our results and those of Dekker and Nardini (2016) suggest the intriguing possibility of a lifelong trajectory of the predominant strategy in this task, from suboptimal risk-seeking in children, to close to optimal risk-seeking in younger adults, to close to optimal risk-averseness in older adults. It is possible that this trajectory continues beyond the age range that we investigated, which would mean adults older than 80 years could show even larger risk-averseness, to the point of being suboptimal, although that would require quite extreme aiming strategies.

In summary, our results contribute to our understanding of optimal decision-making in two crucial respects. First, they highlight that optimality in decision-making should not be considered as a coherent concept, but that it can be determined by multiple factors. So far, in particular differences between economic decision-making and sensorimotor decision making have been emphasized (Jarvstad et al., 2013, 2014). However, we show that even within the same task, different strategies can result in similar optimal behavioral decisions. This suggests a comprehensive evaluation of decision-making needs to take into consideration a complexity of parameters inherent in a specific task. Furthermore, our insights into age-specific contributions to optimality add to the emerging focus on differential aging processes. Established theories of age-related functional changes are dominated by the assumption of a general decline with increasing age (e.g., Baltes, Staudinger, & Lindenberger, 1999; Craik & Byrd, 1982; Hasher & Zacks, 1988; Salthouse, 1996). Our data provides further evidence that differentiation between specific vulnerabilities and preserved resources is needed. Various submechanisms contribute to aging processes and call for detailed investigation to improve our understanding of decline and stability (Cabeza, Nyberg, & Park, 2005).

To conclude, our study offers a relatively reassuring view of the effects of aging, compared with the studies that focused on economic decision-making (e.g., Rutledge et al., 2016; Tymula et al., 2013). If the general motor slowing associated with aging is discounted, healthy older adults can be as efficient in the pointing-under-risk task as young observers. While older adults might differ

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from younger adults in the way their motor decisions are influenced by the risk of monetary loss, the strategy they choose can be as adaptive as the one favored by younger observers.

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