Imagining Personally-Relevant Outcomes Influences Perceived Risk of Viral Transmission for Older Adults

Alyssa H. Sinclair[1,2], Matthew L. Stanley[1,2], Shabnam Hakimi[1], Roberto Cabeza[1,2], R. Alison Adcock[1,2,3], & Gregory R. Samanez-Larkin[1,2]

[1]*Duke University, Center for Cognitive Neuroscience;* [2]*Duke University, Department of Psychology & Neuroscience;* [3]*Duke University, Department of Psychiatry & Behavioral Sciences*

Main Text Word Count: 2,363

Keywords: *COVID-19, aging, cognition, risk perception, episodic simulation, socioemotional selectivity, memory, decision-making*

Main

The COVID-19 pandemic has created a serious and prolonged public-health emergency. Older adults have been at significantly greater risk of hospitalization, ICU admission, and death due to COVID-19; as of February 2021, over 81% of COVID-19-related deaths in the U.S. occurred for people over the age of 65[1,2]. Converging evidence from around the world suggests that age is the most significant risk factor for severe COVID-19 illness and for the experience of adverse health outcomes[3,4]. Therefore, effectively communicating health-related risk information requires tailoring interventions to older adults' needs[5]. Using a novel informational intervention with a nationally-representative sample of 546 U.S. residents, we found that older adults reported increased perceived risk of COVID-19 transmission after imagining a personalized scenario with social consequences. Although older adults tended to forget numerical information over time, the personalized simulations elicited increases in perceived risk that persisted over a 1-3 week delay. Overall, our results bear broad implications for communicating information about health risks to older adults, and suggest new strategies to combat annual influenza outbreaks.

News and social media have repeatedly documented the risky behaviors of Americans throughout the pandemic, and recent survey evidence suggests that Americans tend to underestimate risk related to COVID-19 transmission[6]. As COVID-19 has spread, so too has misinformation about both the efficacy of different preventative behaviors (e.g., mask-wearing, hand-washing) and the risks of engaging in certain behaviors where the virus could be transmitted (e.g., grocery shopping, indoor dining, air travel). Unfortunately, those most at risk of severe illness and death due to COVID-19 (i.e., older adults) are also most susceptible to believing misinformation. Older adults are far more likely to believe and share false information from social media[7–9], and this problem is getting worse as increasing numbers of older adults become active on social media[10].

To combat COVID-19-related misinformation and to ensure that individuals who are most at-risk for severe illness (older adults) possess the information needed to make informed decisions, it is critical to develop interventions that meet the needs of older adults by (1) effectively conveying the risks of engaging in behaviors that could cause viral transmission, and (2) ensuring that risk information sticks over time. Here, we sought to develop an interactive intervention that would inform individuals about COVID-19-related risks and thereby improve downstream compliance with public health measures. Drawing on theoretical frameworks of aging and motivation, we designed our intervention to include elements that could optimize learning for older adults.

Past efforts to develop interventions for improving risk estimation have shown some success, but the effect sizes across interventions are typically small and the effects rapidly diminish over time[11–14]. Although older adults reliably self-report being more risk averse[15], their choice behavior is not always consistent with their stated preferences[16]. In some situations, older adults take more risks than younger adults[17]. Furthermore, older adults tend to seek out less information about risk[18], which can have negative consequences for their health-related decisions[19,20]. This problem may be exacerbated because older adults tend to be less successful at learning from numerical feedback[21,22].

However, personalized social information may help motivate older adults to improve risk literacy. Socioemotional Selectivity Theory (SST) posits that older adults are more motivated to make decisions that maximize emotional meaning, enhance social connections, and emphasize personally-relevant factors[23–25]. Prioritizing personally-relevant social connections is adaptive when one perceives limited time left in life; bolstering social connections can offer emotional rewards and the practical benefits of a support network[24,26]. Importantly, these motivational changes that occur later in life correspond to broad changes in decision-making, emotion regulation, learning, and information seeking[18,24].

Leveraging these theoretical insights from SST, we predicted that if older adults are more motivated to attend to personally-relevant social information, then they may be more responsive to an intervention that involves generating rich, personalized mental imagery about close others. Past studies have used mental imagery, termed *episodic simulation*, to enhance decision-making processes. Converging lines of research suggest that episodic simulation of the downstream outcomes of choices can improve decision making, including self-regulation[27–30]. Therefore, a personalized episodic simulation could influence beliefs about risk and enhance learning over time, particularly for older adults who are most at-risk.

In this large-scale, multi-session study, our primary objective was to investigate possible age-related differences with several strategies for communicating information about virus transmission risk. Our intervention involved presenting two kinds of information about risk: episodic and numerical information. We hypothesized that a personalized episodic simulation (relative to an impersonal or unrelated simulation) would facilitate learning, particularly among older adults, because this task connects risk information with personally-relevant social consequences. However, we expected that older adults would be less responsive to numerical information about risk. As a secondary, exploratory objective, we also investigated whether a personalized episodic simulation would motivate further information-seeking, encouraging ongoing learning after the intervention.

We recruited a nationally-representative online sample of 546 U.S. residents (stratified by age, gender, and race to approximate the demographic makeup of the nation) (Methods, *Participants*). Participants completed a survey about perceived risk (due to COVID-19) of engaging in various everyday activities in their local community (e.g., grocery shopping, dining inside a restaurant) (*Methods*, Survey). Next, we randomly assigned participants to complete one of three variants of the episodic simulation task (Methods, *Episodic Simulation Task*). In the Personal simulation condition, participants imagined a scenario in which they hosted a dinner party attended by four specific close others (e.g., friends, neighbors). In this scenario, a guest became seriously ill with COVID-19, exposed the other guests to the disease, and infected the host as well. In the Impersonal simulation condition, participants imagined a fictional character experiencing the same scenario. In the Unrelated (control) condition, participants imagined a scenario that was neither personalized nor related to COVID-19.

After the episodic simulation, participants completed the second half of the intervention, which presented numerical information about risk: All participants completed a risk estimation task that involved predicting and receiving feedback about the prevalence of COVID-19 cases in their local communities (Methods, *Risk Estimation Task*). To quantify the strength of this numerical risk intervention, we calculated *information prediction errors*, the discrepancy between predicted and actual risk values. If numerical risk information drives learning, then larger prediction errors (reflecting risk misestimation) should predict larger changes in perceived risk. Finally, after the two-part intervention, participants completed the survey of perceived risk again (regarding everyday activities) (Methods, *Survey*). To assess the immediate and long-lasting effects of the intervention, we assessed perceived risk both immediately after the intervention (Session 1) and after a delay of 1-3 weeks (Session 2).

We previously reported that the intervention effectively changed perceived risk[6]. Here, we tested whether the effects of the intervention differed across the lifespan. Using multiple linear regression, we predicted immediate post-intervention change in perceived risk (immediate post-intervention – baseline) from the variables *age* (continuous), *simulation condition* (Personal/Impersonal/Unrelated), average *prediction error,* and all interaction terms. As reported previously[6], we found a main effect of prediction error driving change in perceived risk (β = 0.22, t = 5.06, p < .001, 95% CI [0.14, 0.31]), demonstrating that numerical feedback improved the accuracy of risk perception. There was also an interaction between prediction error and simulation condition predicting change in perceived risk[6], such that learning from numerical information was enhanced when it was preceded by either the Personal or Impersonal simulation (Personal vs. Impersonal: β = -0.003, t = -0.04, p = .965, 95% CI [-0.12, 0.12], Personal vs. Unrelated: β = 0.17, t = 2.73, p = .007, 95% CI [0.05, 0.29]).

We found that the intervention produced immediate benefits for older and younger adults alike (Figure 1A, 1B; Figure 2A, 2B). Age was not significantly related to change in perceived risk at Session 1 (β = 0.01, t = 0.23, p = .791, 95% CI [-0.08, 0.10]), nor did age interact with prediction error (β = -0.04, t = -0.95, p = .343, 95% CI [-0.13, 0.05]) or simulation condition (Personal vs. Impersonal: β = 0.08, t = 1.19, p = .236, 95% CI [-0.05, 0.20], Personal vs. Unrelated: β = -0.06, t = -0.95, p = .340, 95% CI [-0.18, 0.06]). Overall, we found no significant age differences when perceived risk was assessed immediately after the intervention.

Next, we tested whether age was related to the longer-term effects of the interventions (Session 2). Using multiple linear regression, we predicted lasting change in perceived risk (delayed post-intervention – baseline) from the variables *age*, *simulation condition*, *prediction error*, and all interactions. We included a covariate for the duration of the delay period between sessions (ranging from 7-25 days). As in Session 1, there was no significant main effect of age on perceived risk at Session 2, $\beta = 0.02$, $t = 0.34$, $p = .731$, 95% CI [-0.07, 0.10]. However, there was an interaction between age and prediction error, such that effects of prediction error were not as evident in older adults after a delay, $\beta = -0.14$, $t = -3.12$, $p = .002$, 95% CI [-0.23, -0.05]. In other words, numerical information about risk did not effectively induce longer-term learning in older adults (Figure 1C, 1D).

We also found an interaction between age and simulation condition, such that older adults reported a greater increase in perceived risk in the Personal simulation condition (Personal vs. Impersonal: $\beta = 0.15$, $t = 2.35$, $p = .019$, 95% CI [-0.03, 0.28], Personal vs. Unrelated: $\beta = -0.12$, $t = -1.87$, $p = .062$, 95% CI [-0.24, 0.01]). Although this pattern of results is numerically consistent with the pattern in Session 1 (Figure 2A, 2B), the effect of the Personal simulation increasing perceived risk in older adults was enhanced over time (Figure 2C, 2D).

We hypothesized that the benefit of the Personal simulation for older adults may be enhanced after a delay because this condition could motivate individuals to independently seek out further information about local risk levels. To test this idea, we conducted an exploratory analysis in which we predicted post-intervention change in seeking information about local COVID-19 statistics (Session 2) from the variables *age*, *simulation condition*, *prediction error*, all relevant interaction terms, and the covariate for delay duration. There was an interaction between age and simulation condition predicting change in information seeking, such that older adults selectively increased information seeking during the weeks following the Personal simulation (Personal vs. Impersonal: $\beta = 0.25$, $t = 3.61$, $p < .001$, 95% CI [0.11, 0.38], Personal vs. Unrelated: $\beta = -0.16$, $t = -2.38$, $p = .018$, 95% CI [-0.29, -0.03]). Overall, for older adults the

Personal simulation was associated with increased information seeking about local risk levels, and longer-term increases in perceived risk (Figure 3A, 3B).

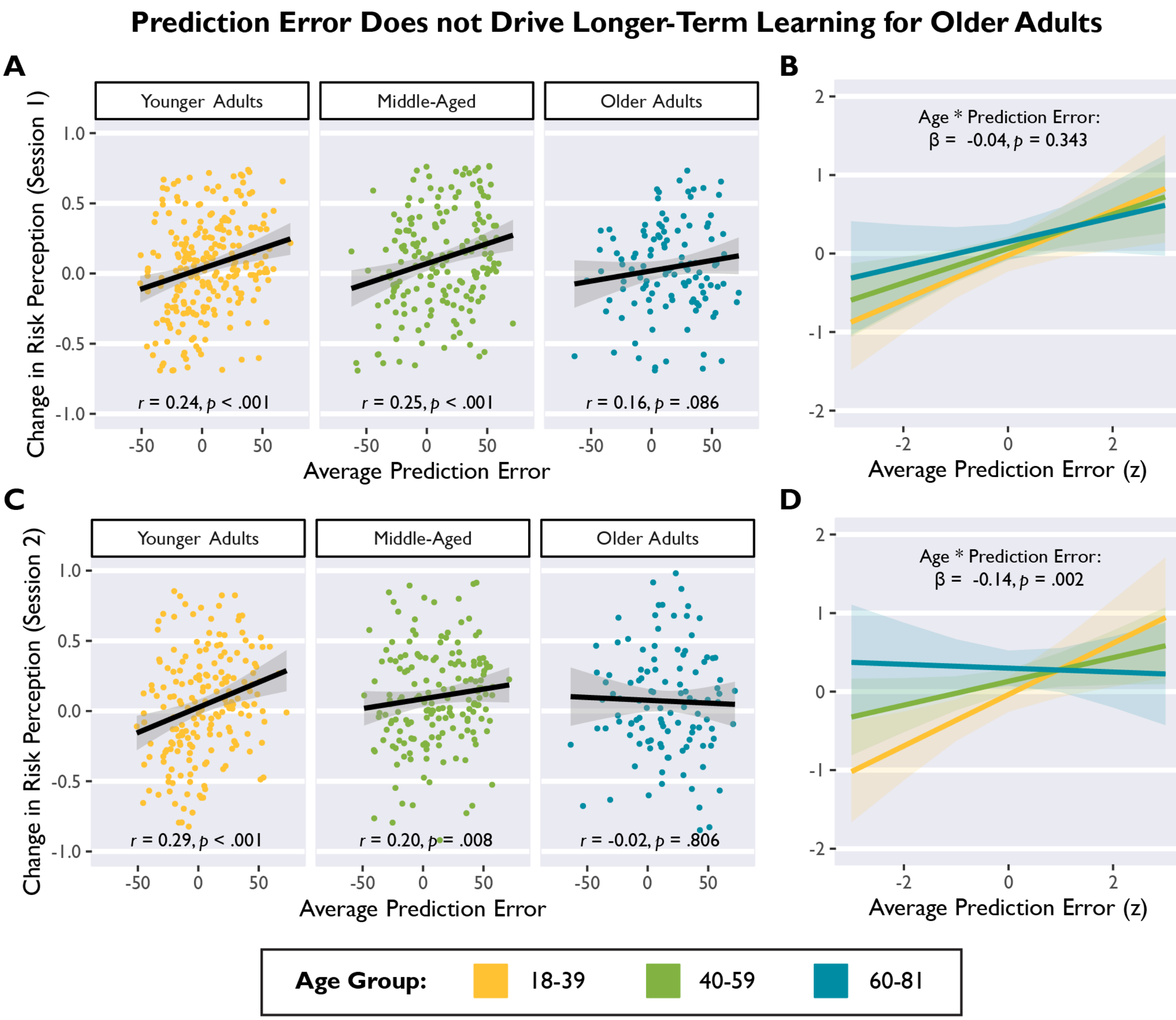

Figure 1. Comparing the effect of prediction error on change in risk perception across the lifespan. A) During Session 1 (immediately post-intervention), average information prediction error scores are positively associated with change in risk perception across all age groups. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the main effect of prediction error after controlling for simulation condition (standardized variables). C) During Session 2 (1-3 weeks post-intervention), older adults no longer showed an effect of prediction error on change in risk perception. D) Model-derived estimates corresponding to the raw data depicted in panel C, depicting the main effect of prediction error after controlling for simulation condition and delay duration (standardized variables). Points in panels A and C are jittered for visualization. Age groups are binned for visualization, but were included as continuous variables in statistical models.

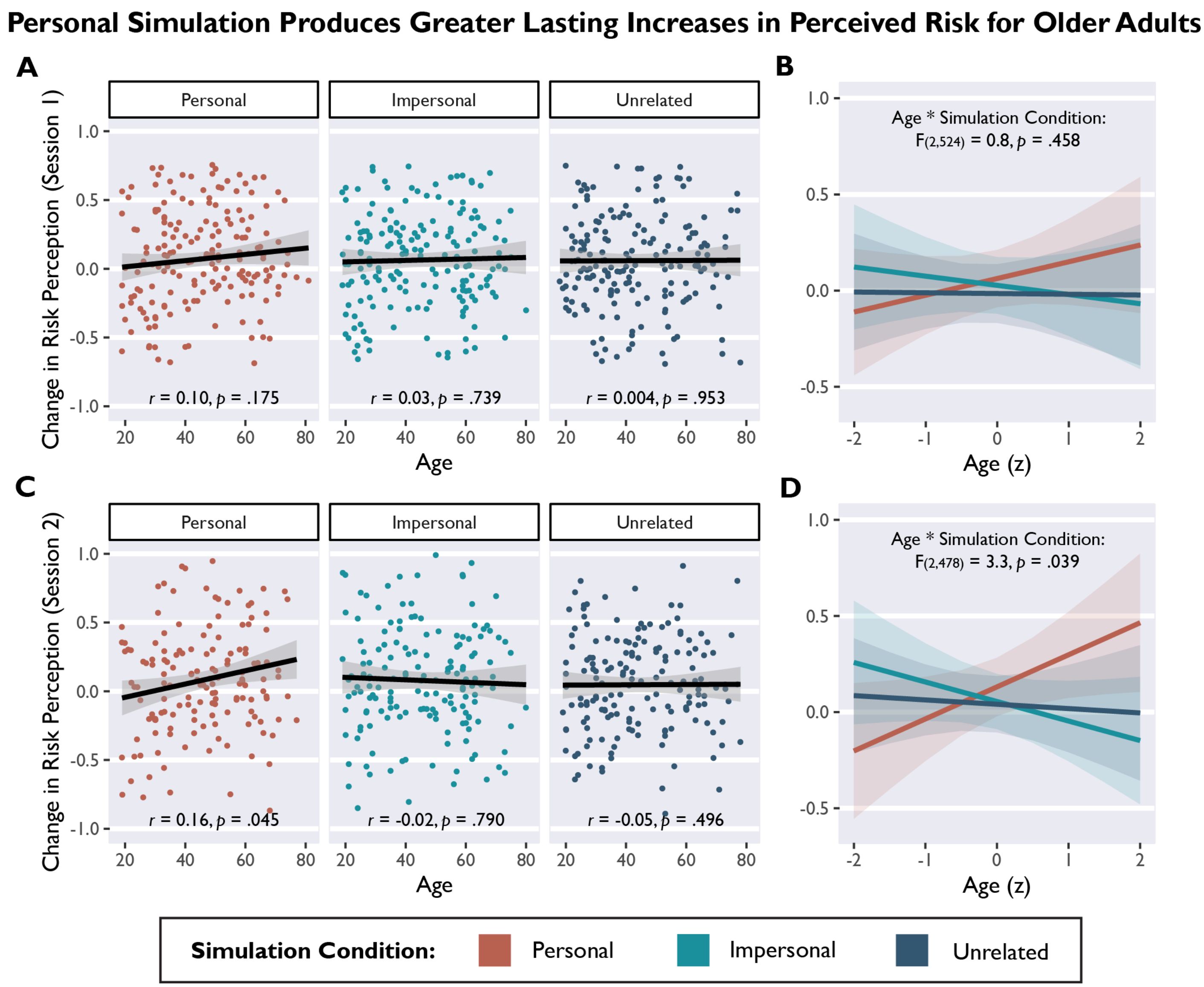

Figure 2. Comparing the effects of the three episodic simulation conditions (Personal, Impersonal, and Unrelated) on change in risk perception across the lifespan. A) During Session 1 (immediately post-intervention), there was no significant interaction between age and condition predicting change in risk perception. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the main effect of simulation condition after controlling for prediction error (standardized variables). C) During Session 2 (1-3 weeks post-intervention), the Personal simulation produced significantly greater lasting increases in perceived risk for older adults. D) Model-derived estimates corresponding to the raw data depicted in panel C, depicting the main effect of simulation condition after controlling for prediction error and delay duration (standardized variables). Points in panels A and C are jittered for visualization.

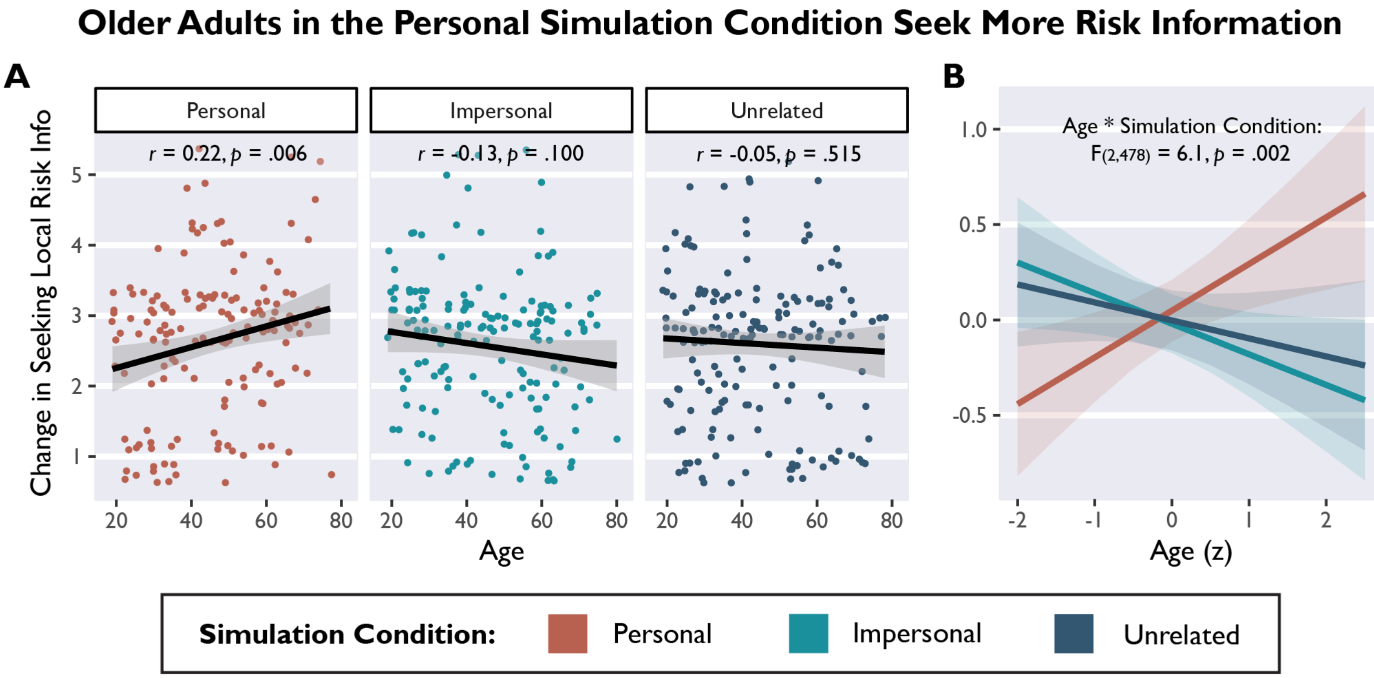

Figure 3. Comparing the effect of age and the three episodic simulation conditions (Personal, Impersonal, and Unrelated) on change in COVID-19 risk-related information seeking. A) Older adults in the Personal simulation condition increased independent information seeking about local risk statistics during the post-intervention delay period. Raw data points are jittered for visualization. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the effect of age on change in information seeking after controlling for prediction error and delay duration (standardized variables).

The COVID-19 pandemic has presented staggering new social and health-related challenges. In particular, older adults have been disproportionately impacted by the pandemic: Older adults are at significantly greater risk of severe illness, hospitalization, and death due to COVID-19[3]. Compounding these health concerns, older adults may prioritize information differently when considering health-related risk information[18–20,31], and they are more susceptible to misinformation[7–9]. In this high-stakes context, it is crucial to develop interventions that convey information about health risks in a manner that is tailored to the needs of older adults.

Here, we investigated the age-related effects (both immediate and longer-term) of several strategies for conveying information about risk. As reported previously, our novel informational intervention was effective for both older and younger adults alike[6]. Immediately after the intervention, older adults reported changes in perceived risk that were comparable to those reported by younger adults. However, age differences emerged over time: Although younger adults successfully retained learning after a delay of 1-3 weeks, older adults were more likely to lose the benefits of the intervention over time if the information was poorly matched to their emotional and cognitive processing characteristics. Here we showed that numerical information about risk (quantified as information prediction errors) effectively drove longer-term learning in younger adults, but not older adults. This is consistent with prior evidence that, relative to younger adults, older adults learn more slowly from prediction errors[32,33]. Crucially, older adults reported greater long-lasting increases in perceived risk only when they imagined the possible outcomes of risky decisions that affected themselves and close others. Imagining an impersonal or unrelated scenario did not influence perceived risk in older adults, either immediately or after a delay.

In an additional exploratory analysis, we also found that for older adults only, the personalized episodic simulation was associated with increased information-seeking about risk. That is, during the post-intervention delay period (1-3 weeks), older adults reported having actively consumed more information about local COVID-19 risk levels relative to their pre-intervention habits. This finding suggests that the personalized episodic simulation helped motivate ongoing learning and cultivate a habit of information-seeking. In contrast, the personalized episodic simulation did not increase information-seeking in younger adults. Overall, our results suggest that including a personalized imagination exercise can enhance the efficacy of interventions that target older adults, facilitating longer-term learning and better health-related decision making.

Taken together, these results suggest that certain strategies are more effective for promoting longer-term retention of information in older adults. Although older adults may be more prone to forgetting numerical information, a personalized episodic simulation can enhance lasting learning and information-seeking behaviors over time. Our results are generally consistent with the fundamental tenets of Socioemotional Selectivity Theory, which posits that older adults are more motivated to reinforce social connections and seek information that is personally-relevant or emotionally meaningful[18,23,24]. Imagining a personalized scenario that connects information with existing semantic and episodic memories may be an effective way to make risk information more memorable for older adults. Personalized interventions situate risk information in context, drawing on social connections to enhance salience.

Throughout the course of the COVID-19 pandemic, Americans have underestimated the risk of engaging in many different everyday activities[6]. On average, our intervention encouraged older adults to be more risk averse, reporting greater subjective perceived risk of engaging in various everyday activities (e.g., dining in a restaurant). In the context of the COVID-19 pandemic, instilling caution and risk-averse attitudes offers clear benefits for public health, especially for at-risk groups like older adults. However, in other contexts, an overall increase in risk-aversion may not be a desirable outcome. Future research may investigate whether personalized episodic simulations can *bidirectionally* improve the accuracy of risk-related beliefs in older adults, simultaneously counteracting both underestimation and overestimation.

Although we conducted our study in the context of the COVID-19 pandemic, our findings may be broadly relevant to other health-related challenges. For example, annual influenza outbreaks pose a recurring health risk for older adults. Relative to their younger counterparts, older adults are far more likely to experience severe health complications due to the seasonal flu, and they are far more likely to die because of it[34]. The seasonal flu vaccination is a readily available and effective means of reducing health-related complications and death in older adults. Personalized episodic simulations that target risk beliefs about the seasonal flu might encourage older adults to get the vaccine each year. Incorporating personalized and socially-relevant elements could also improve communication of information about health-related decisions (e.g., regarding lifestyle changes or medical procedures) for older adults. Future research can further explore these possibilities to apply episodic simulation to improve other health-related outcomes.

Methods

This study is part of a larger project on risk perception during the COVID-19 pandemic. Other results from this larger project have been previously reported elsewhere[6]. The study was approved by the Duke University Health System IRB (Protocol #00101720). The design of the intervention was pre-registered, and age-related analyses were included under planned exploratory analyses (https://osf.io/6fjdy). Data and code necessary to reproduce analyses are provided online via the Open Science Framework (https://osf.io/35us2/).

Participants

We recruited a nationally-representative sample of 816 current U.S. residents via Prolific (stratified by age, gender, and race to approximate the demographic makeup of the nation). We excluded 88 participants for the following preregistered reasons: missing COVID-19 statistics for their location (27), failing an attention check (27), or providing off-topic or excessively short responses to the Episodic Simulation task (e.g., answering a prompt for 2-3 sentences with only a few words). Additionally, 189 participants completed a control condition (Unguided Exploration) that was discussed in a previous report[6] but was not relevant to the present analyses. After these exclusions, the final sample consisted of 546 participants.

Procedure

Survey. To assess subjective **perceived risk**, we asked participants to rate the riskiness (due to COVID-19) of engaging in 15 different activities in their local community, using a 5-point Likert-type scale (*1 = Not at all risky*, *5 = Extremely risky*). Activities included picking up takeout, grocery shopping (indoors, masked), exercising in a gym (indoors, no mask), dining in a restaurant (indoors, no mask), and going to a bar or club (indoors, no mask). We averaged ratings for the 15 items to calculate a composite score of perceived risk. Participants completed this subjective risk assessment three times: before the intervention, immediately after the intervention (Session 1), and 1-3 weeks after the intervention (Session 2). We calculated within-subjects change scores (post-intervention – baseline) for each testing session, to assess the effect of the intervention on risk perception. To assess independent information seeking, we also asked participants to report how much their COVID-related media consumption habits had changed during the post-intervention delay period. Participants rated change in information seeking about local COVID-19 risk statistics on a 5-point Likert scale (*1 = Much less than usual*, *5 = Much more than usual*).

Episodic Simulation Task. The Episodic Simulation task involved guided imagination through one of three scenarios that illustrated the potential consequences of risky decisions. During the simulation, participants were instructed to visualize events and details, then type responses in a text box. Participants were randomly assigned to one of three episodic simulation conditions in a between-subjects design: The Personal simulation (Session 1: n = 181, Session 2: n = 158), Impersonal simulation (Session 1: n = 180, Session 2: n = 166), or Unrelated simulation (Session 1: n = 185, Session 2: n = 173). In the Personal simulation, participants imagined themselves hosting a dinner party in their home, with four specific close others (e.g., friends or neighbors) as guests. Participants identified each guest by first name and/or relationship (e.g., “My sister Maria”), then visualized the guests and the setting (e.g., the dining room) in as much detail as possible. In this scenario, a guest began exhibiting symptoms of COVID-19 during dinner. The guest later confirmed a diagnosis and was hospitalized. The host then informed the other dinner party guests of the exposure, and eventually also became ill with COVID-19. The Impersonal simulation depicted a fictional character and his friends undergoing the same scenario. The Unrelated simulation described a scenario that was thematically related (a story about rabbits falling ill after eating rotten vegetables), but did not include any personalized or COVID-related elements. Full text for all simulation conditions is provided in Supplemental Material (*Episodic Simulation Text*).

Risk Estimation Task. After the Episodic Simulation, participants completed the Risk Estimation task, which involved estimating numerical risk levels in their local community. Participants received a brief tutorial about risk and probability, then were instructed to think about events of seven different sizes (5, 10, 25, 50, 100, 250, and 500 people) that could happen in their location. For each event size, participants estimated the probability (*0% = Impossible … 100% = Definitely*) that at least one of the people attending the event was infected with COVID-19. After estimating the risk levels for all event sizes, participants received veridical feedback about actual risk probabilities. Actual risk values were calculated based on the prevalence of active COVID-19 cases in each participant's county of residence[35]. We calculated *information prediction error* as a measure of misestimation, the average discrepancy between estimated and actual risk values across event sizes[6].

Statistical Analysis

Statistical analyses were conducted using multiple linear regression in R (v4.0.3). Continuous variables were standardized before submission to multiple linear regression. Factor variables for conditions were effect-coded. Visual inspection of histograms indicated that several variables exhibited high kurtosis, with some extreme values at both tails of the distribution. As a result, residuals from fitted models were larger for values at the tails. To correct for high kurtosis and meet the assumption of normality, we winsorized extreme values to the 5th and 95th percentiles. The variable for change in perceived risk (Session 1) was winsorized. As previously reported, winsorization improved model fits but did not change the statistical significance of our findings[6]. Additionally, we log-transformed the variable for actual risk (i.e., local case prevalence) to account for skew. Other variables were not transformed because distributions were approximately normal. Figures were produced using the *ggplot2*[36] and *sjPlot*[37] packages.

Acknowledgements: The study was funded by discretionary funding and an U.S. National Institute on Aging grant awarded to GSL (R01-AG058574). AS is supported by an NSF Graduate Research Fellowship and an NSERC Canada Postgraduate Scholarship.

Author Contributions: AS, SH, MS, and GSL designed the studies. AS, SH, and MS created stimuli and survey materials. AS performed data collection. AS analyzed data with input from SH, MS, RAA, RC, and GSL. AS and MS drafted the paper, with input from SH, RAA, RC, and GSL. All authors approved of the final version.

Competing Interests Statement: The authors have no competing interests to report.

References

1. CDC. COVID Data Tracker. *Centers for Disease Control and Prevention* https://covid.cdc.gov/covid-data-tracker (2021).
2. Honein, M. A. Summary of Guidance for Public Health Strategies to Address High Levels of Community Transmission of SARS-CoV-2 and Related Deaths, December 2020. *MMWR Morb. Mortal. Wkly. Rep.* **69**, (2020).
3. Chen, Y. *et al.* Aging in COVID-19: Vulnerability, immunity and intervention. *Ageing Res. Rev.* **65**, 101205 (2021).
4. Stratton, C., Andersen, L., Proulx, L. & Sirotich, E. When apathy is deadlier than COVID-19. *Nat. Aging* **1**, 144–145 (2021).
5. Inouye, S. K. Creating an anti-ageist healthcare system to improve care for our current and future selves. *Nat. Aging* **1**, 150–152 (2021).
6. Sinclair, A. H., Hakimi, S., Stanley, M., Adcock, R. A. & Samanez-Larkin, G. Pairing Facts with Imagined Consequences Improves Pandemic-Related Risk Perception. *PsyArXiv* (2021) doi:10.31234/osf.io/53a9f.
7. Brashier, N. & Schacter, D. Aging in an Era of Fake News. *Curr. Dir. Psychol. Sci.* **29**, 316–323 (2020).
8. Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B. & Lazer, D. Fake news on Twitter during the 2016 U.S. presidential election. *Science* **363**, 374–378 (2019).
9. Guess, A., Nagler, J. & Tucker, J. Less than you think: Prevalence and predictors of fake news dissemination on Facebook. *Sci. Adv.* **5**, eaau4586 (2019).
10. Pew Research Center. Share of U.S. adults using social media, including Facebook, is mostly unchanged since 2018. *Pew Research Center* https://www.pewresearch.org/fact-

tank/2019/04/10/share-of-u-s-adults-using-social-media-including-facebook-is-mostly-unchanged-since-2018/ (2019).

11. Jacklin, R., Sevdalis, N., Darzi, A. & Vincent, C. A. Efficacy of cognitive feedback in improving operative risk estimation. *Am. J. Surg.* **197**, 76–81 (2009).
12. Lermer, E., Streicher, B., Sachs, R., Raue, M. & Frey, D. Thinking Concretely Increases the Perceived Likelihood of Risks: The Effect of Construal Level on Risk Estimation. *Risk Anal.* **36**, 623–637 (2016).
13. Lustria, M. L. A. *et al.* A Meta-Analysis of Web-Delivered Tailored Health Behavior Change Interventions. *J. Health Commun.* **18**, 1039–1069 (2013).
14. Torgerson, C. J., Porthouse, J. & Brooks, G. A systematic review and meta-analysis of randomised controlled trials evaluating interventions in adult literacy and numeracy. *J. Res. Read.* **26**, 234–255 (2003).
15. Josef, A. K. *et al.* Stability and change in risk-taking propensity across the adult life span. *J. Pers. Soc. Psychol.* **111**, 430–450 (2016).
16. Mamerow, L., Frey, R. & Mata, R. Risk taking across the life span: A comparison of self-report and behavioral measures of risk taking. *Psychol. Aging* **31**, 711–723 (2016).
17. Mata, R., Josef, A. K., Samanez-Larkin, G. R. & Hertwig, R. Age differences in risky choice: a meta-analysis. *Ann. N. Y. Acad. Sci.* **1235**, 18–29 (2011).
18. Löckenhoff, C. E. & Carstensen, L. L. Socioemotional Selectivity Theory, Aging, and Health: The Increasingly Delicate Balance Between Regulating Emotions and Making Tough Choices. *J. Pers.* **72**, 1395–1424 (2004).

19. Meyer, B. J. F., Russo, C. & Talbot, A. Discourse comprehension and problem solving: Decisions about the treatment of breast cancer by women across the life span. *Psychol. Aging* **10**, 84–103 (1995).

20. Willis, S. L., Dolan, M. M. & Bertrand, R. M. Problem solving on health-related tasks of daily living. in *Processing of medical information in aging patients: Cognitive and human factors perspectives* 199–219 (Lawrence Erlbaum Associates Publishers, 1999).

21. Eppinger, B., Hämmerer, D. & Li, S.-C. Neuromodulation of reward-based learning and decision making in human aging. *Ann. N. Y. Acad. Sci.* **1235**, 1–17 (2011).

22. Nassar, M. R. *et al.* Age differences in learning emerge from an insufficient representation of uncertainty in older adults. *Nat. Commun.* **7**, 11609 (2016).

23. Carstensen, L. L. Social and emotional patterns in adulthood: Support for socioemotional selectivity theory. *Psychol. Aging* **7**, 331–338 (1992).

24. Carstensen, L. L., Fung, H. H. & Charles, S. T. Socioemotional Selectivity Theory and the Regulation of Emotion in the Second Half of Life. *Motiv. Emot.* **27**, 103–123 (2003).

25. Charles, S. T. & Carstensen, L. L. Emotion Regulation and Aging. in *Handbook of emotion regulation* 307–327 (The Guilford Press, 2007).

26. Antonucci, T. C. & Jackson, J. S. Social support, interpersonal efficacy, and health: A life course perspective. in *Handbook of clinical gerontology* 291–311 (Pergamon Press, 1987).

27. Benoit, R. G., Paulus, P. C. & Schacter, D. L. Forming attitudes via neural activity supporting affective episodic simulations. *Nat. Commun.* **10**, 2215 (2019).

28. Gaesser, B. & Schacter, D. L. Episodic simulation and episodic memory can increase intentions to help others. *Proc. Natl. Acad. Sci.* (2014) doi:10.1073/pnas.1402461111.

29. Peters, J. & Büchel, C. Episodic Future Thinking Reduces Reward Delay Discounting through an Enhancement of Prefrontal-Mediotemporal Interactions. *Neuron* **66**, 138–148 (2010).

30. Schacter, D. L., Addis, D. R. & Buckner, R. L. Episodic simulation of future events: Concepts, data, and applications. in *The year in cognitive neuroscience 2008* 39–60 (Blackwell Publishing, 2008).

31. Samanez-Larkin, G. R. & Knutson, B. Decision making in the ageing brain: Changes in affective and motivational circuits. *Nat. Rev. Neurosci.* **16**, 278–289 (2015).

32. Eppinger, B., Schuck, N. W., Nystrom, L. E. & Cohen, J. D. Reduced Striatal Responses to Reward Prediction Errors in Older Compared with Younger Adults. *J. Neurosci.* **33**, 9905–9912 (2013).

33. Samanez-Larkin, G. R., Worthy, D. A., Mata, R., McClure, S. M. & Knutson, B. Adult age differences in frontostriatal representation of prediction error but not reward outcome. *Cogn. Affect. Behav. Neurosci.* **14**, 672–682 (2014).

34. Monto, A. S. *et al.* Influenza control in the 21st century: Optimizing protection of older adults. *Vaccine* **27**, 5043–5053 (2009).

35. Chande, A. *et al.* Real-time, interactive website for US-county-level COVID-19 event risk assessment. *Nat. Hum. Behav.* 1–7 (2020) doi:10.1038/s41562-020-01000-9.

36. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*. (Springer-Verlag New York, 2016).

37. Lüdecke, D. *sjPlot: Data Visualization for Statistics in Social Science*. (2021).

Figure Legends

Figure 1. Comparing the effects of prediction error on change in risk perception across the lifespan. A) During Session 1 (immediately post-intervention), average information prediction error scores are positively associated with change in risk perception across all age groups. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the main effect of prediction error after controlling for simulation condition (standardized variables). C) During Session 2 (1-3 weeks post-intervention), older adults no longer showed an effect of prediction error on change in risk perception. D) Model-derived estimates corresponding to the raw data depicted in panel C, depicting the main effect of prediction error after controlling for simulation condition and delay duration (standardized variables). Points in panels A and C are jittered for visualization. Age groups are binned for visualization, but were included as continuous variables in statistical models.

Figure 2. Comparing the effects of the three episodic simulation conditions (Personal, Impersonal, and Unrelated) on change in risk perception across the lifespan. A) During Session 1 (immediately post-intervention), there was no significant interaction between age and condition predicting change in risk perception. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the main effect of simulation condition after controlling for prediction error (standardized variables). C) During Session 2 (1-3 weeks post-intervention), the Personal simulation produced significantly greater lasting increases in perceived risk for older adults. D) Model-derived estimates corresponding to the raw data depicted in panel C, depicting the main effect of simulation condition after controlling for prediction error and delay duration (standardized variables). Points in panels A and C are jittered for visualization.

Figure 3. Comparing the effects of age and the three episodic simulation conditions (Personal, Impersonal, and Unrelated) on change in COVID-19 risk-related information seeking. A) Older adults in the Personal simulation condition increased independent information seeking about local risk statistics during the post-intervention delay period. Raw data points are jittered for visualization. B) Model-derived estimates corresponding to the raw data depicted in panel A, depicting the effect of age on change in information seeking after controlling for prediction error and delay duration (standardized variables).