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Age Related Differences in Loss Aversion - A Meta-analysis

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Abstract

Throughout lifetimes, individuals make decisions involving gains and losses. Loss aversion refers to the psychological tendency to overvalue losses over equivalent gains from a reference point, a concept essential for decision-making. The available literature on age and loss aversion yields mixed results. Hence, we conducted a meta-analysis by combining individual data sets. We performed a study-level random-effects meta-analysis (N = 20 data sets) and an individual-participant-level (IPD) meta-analysis, in a subset of data sets (n=1,565; 5 data sets) to model the relationship. We found a small and insignificant linear association between age and loss aversion. The individual-participant-level meta-analysis revealed a small effect characterized by a U-shaped relationship, with a decline in middle age. Incidentally, sex emerged as an explanatory variable for explaining heterogeneity in loss aversion. Overall, the meta-analysis motivates further empirical investigations on age-related changes in decision making across the lifespan.

Keywords: Loss aversion; Lifespan decision-making; Meta-analysis

Introduction

As individuals engage with the real world, they make a myriad of decisions that contain potential for both loss and gain. Kahneman and Tversky (1979) in Prospect Theory, noted that an individual overvalues losses over an equivalent gains, which translates to aversion for outcomes with losses. Throughout the lifespan, an individual makes variety of decisions that have inherent risks attached. Is it prudent to invest in this market? Will my business benefit from this venture? These decisions involve valuation of loss and gain. Considering literature that suggests changes in decision making across the life span (Tymula et al., 2013; Weller et al., 2011) and global changes in demographic profile coupled with the knowledge that the canonical models of human behaviour disproportionately rely on a typical young adult population, a sparse body of literature exists that has investigated age-related differences in loss aversion. Hence, we conducted a meta-analysis to address the question: are there age-related differences in loss aversion - a concept considered fundamental in decision making?

Brief Introduction of Loss Aversion

In Prospect theory, individual valuation of gain and loss in risky decision making involves a value-function, where it assumes an 'S' shaped function, as depicted in Figure 1. This value function denotes an asymmetry, which represents a disproportionate weighing of loss compared to an equivalent gain (Lejarraga and Hertwig, 2022). It is posited that the displeasure associated with a loss is greater than the pleasure accompanying a comparable gain. If a person is presented with an option to maintain the status quo or indulge in a gamble offering an equiprobable chance of loss and gain of equal magnitude, the most likely chosen option is to maintain the status quo (Levy, 1992). The tendency to reject choices involving potential losses has been referred to as loss aversion.

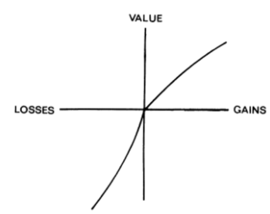

Figure 1: A hypothetical value function ; source: Kahneman & Tversky, 1979

Since its formulation, Prospect Theory (Kahneman and Tversky, 1979) has been accepted as an explanation to risky decision-making. Consequently, it has been applied to various disciplines, from international relations and policy decision-making (Levy, 1992) to business (J. Li et al., 2021). In comprehending the boundary conditions of loss aversion, beyond task-related characteristics (Mukherjee et al., 2025; Zeif and Yechiam, 2022), it is important to investigate individual differences-related effects. This is especially true given the global aging population. For instance, a United Nations report predicts an increase in the global population of individuals aged 65 and older. This suggests an increase in representation of these groups in crucial policy decisions for financial and health-related matters, reiterating the relevance of studying age-related differences in decision-making.

Age and Loss Aversion

Children-adolescent Population

Little appears to be certainly known about the existence, extent, or emergence of loss aversion. In one study, children aged above five years showed a strong tendency of loss aversion in choices (Steelandt et al., 2013), leading them to exchange their current outcomes only when the potential gain was greater than one times of the potential loss. It may be

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the case that adolescents share a similar pattern of loss aversion as those of young adults (Barkley-Levenson et al., 2013). Among the adolescent population, loss aversion may increase with age (Ernst et al., 2014). A study (Munro and Tanaka, 2014) conducted in rural Uganda among adolescents and their parents, found teenage children to have a higher loss aversion coefficient than their parents. It must be noted that the average age of parents was around 40-50 years, typically in middle adulthood. This finding resembles those found in later studies on decision-making preference (Tymula et al., 2013) and loss aversion (Blake et al., 2021; Guttman et al., 2021) that determine that loss aversion reduces in the middle age (around age 35 for Guttman et al., 2021) only to increase in later adulthood.

Adult Population

Loss aversion has been observed to increase with age (O'Brien and Hess, 2020). A study conducted in Pakistan (Hassan et al., 2014) and one in India (Arora and Kumari, 2015) found similar results of a positive linear relationship of loss aversion with age. A large sample study (Johnson et al., 2006) conducted on auto-buyers produced similar results of increasing loss aversion with age. In fact, older participants, residing in European countries like Germany, Switzerland and Austria as well as large samples of US households showed more loss aversion (Mrkva et al., 2020). It appears that loss aversion may decline in the middle age and rise as one ages and reaches older adulthood (Blake et al., 2021; Guttman et al., 2021).

On the contrary, another study (Seaman et al., 2018) found that loss aversion explained acceptance rates, with this influence greater for older adults than for younger adults, but age was not significantly related to loss aversion. Several other studies found a null effect (Barkley-Levenson et al., 2013; Y. Li et al., 2013; Viswanathan et al., 2015), or even a decline in loss aversion (Rutledge et al., 2016) with age.

Current Meta-analysis

Data Collection

Given the discrepant findings of individual studies, we conducted a meta-analysis. Papers were collected through a comprehensive review primarily on Scopus as the database. The following keywords were used on the database, "Age AND 'Loss aversion' AND Estimate OR Measure OR Parameter". The first search round produced 210 articles. We read the titles and abstracts of these 210 articles and the seemingly relevant articles were selected after removing duplicated search results. Further, we excluded the articles that did not measure both individual level age and loss aversion coefficients. Studies that assumed loss aversion as an explanatory variable, and those that measured loss aversion qualitatively or through riskless methods were removed from further analyses, bringing the count to 39 articles. Due to reasons such as poor documentation, contamination of files, absence of participant demographic information, large sample size in comparison to other studies, unreported group estimates and insufficient information, the total data file size culminated to 20 data sets. Hence, the study-level random-effect meta-analysis is based on a total of 20 data sets (see Table 1). Out of these 20 data sets, we could find raw data sets- with individual participant level loss aversion coefficient and age of participants - in 7 data sets. Out of these 7, only 5 had taken age as a continuous variable. Hence, the secondary approach of individual-participant-level (IPD) meta-analysis is based on data sets of 5 (n = 1,565) studies (see Table 2).

Study Characteristics

The accumulated data sets are heterogeneous as can be seen in Table 1. With a globally diverse participant pool, one study samples farmers, and some are based on professionals and teachers, and investors and others are classified as general. Across all studies the sample size varies from 34 to nearly 4500. Studies also vary on whether gambles were played hypothetically or in real. All these factors can become sources of between study heterogeneity.

With respect to loss aversion, a potential source of concern is the method of elicitation, with prior work (Gächter et al., 2022) which presents that lambda being elicited through risky measures such as lotteries is lower in magnitude than the lambda being measured through a riskless measure. In order to control for this heterogeneity, we took data sets (n=20) that elicit loss aversion through monetary risky items. Despite this, there remains heterogeneity as some data sets ask participants to choose between gamble style pairs of lotteries (Barkley-Levenson et al., 2013; Mrkva et al., 2020; Seaman et al., 2018) or through a questionnaire with options to choose among risky monetary items (Hassan et al., 2014). Even within the data sets that use pairs of lotteries, the specifications differ as some (Sun et al., 2021) ask participants to indicate a least acceptable amount of gain in a gamble with a specified loss amount, choose between sure payment and gamble (Lo Presti et al., 2022), choose between different gambles (Seaman et al., 2018), and accept-reject gambles with some specified gain and varying loss amounts(Mrkva et al., 2020).

In order to conduct meta-analysis, we needed standardized effect size and standard error of Cohen's d for each data set. For data sets numbered 7-20 in Table 1, we have acquired the group statistics directly from the paper. Subsequent transformation to the group test statistics of t, f, Beta values or group means were done to convert to standardized measures. For the data sets numbered 1-6 , in each data set, individual loss aversion was regressed on age from the raw data set as their raw data were available. The resultant beta values were then transformed to required standardized measures. All 20 data sets (Table 1), therefore, inform the study-level random effect meta analysis. Since we could find individual level data for a subset of these data sets (Table 2) where age was available as a continuous variable (specifically 5, n=1,565), they were part of individual-participant level meta-analysis.

Table 1: Data sets in study level (n=20) meta-analyses, linked to source reference.

Data set	Method	N	Population	Payout
1. Richtmann et al., 2025	Gambles	178	German residents, Dresden/General	R
2. Kijima, 2019	Gambles	503	Farmers in Uganda	R
3. Karle et al., 2015	Gambles	73	General	R
4. Horn et al., 2023	Gambles	286	Prolific US/general	R
5. Lo Presti et al., 2022	Gambles	244	Italians from platform LimeSurvey/General	R
6. Sun et al., 2021	Gambles	237	Chinese fro platform/general	H
7. Barkley-Levenson et al., 2013	Gambles	34	Adolescents and adults/general	R
8. Guttman et al., 2021	Gambles	106	Volunteers recruited/general	R
9. Arora and Kumari, 2015	Gambles	457	Professionals, teachers from Punjab,India	H
10. Hassan et al., 2014	Risky investment items	391	Pakistani households, investors, employees	H
11. Seaman et al., 2018	Gambles	508	Online platform of Qualtrics/general	H
12. Blake et al., 2021	Gambles	1172	Online survey by market company	H
13. Y. Li et al., 2013	Gambles	336	From virtual lab	–
14. Ernst et al., 2014	Gambles	66	Adolescents by advertisements	R
15. Munro and Tanaka, 2014	Gambles	1289	Adults from a panel research/general	R
16. Munro and Tanaka, 2014	Gambles	412	Adolescents invited to participate	R
17. Mrkva et al., 2020(2A)	Gambles	4000–4500	American adults from an SBI data base	H
18. Mrkva et al., 2020 (2B)	Gambles	4000–4500	American adults from SBI data base	H
19. Mrkva et al., 2020(2C)	Gambles	4000–4500	American adults from SBI data base	H
20. Mrkva et al., 2020(2D)	Gambles	4000–4500	American adults from SBI data base	H

Results

Statistical Analyses

The variable of interest in all the data sets is the loss aversion coefficient. Prospect theory (Kahneman and Tversky, 1979) describes a value function, as detailed below in equation (1).

$$v(x) = \begin{cases} x^{\alpha}, & x \geq 0 \\ -\lambda |x|^{\beta}, & x < 0 \end{cases} \tag{1}$$

The value function denotes an asymmetry in valuing equal loss and gain from a common reference point. This asymmetry is denoted by the 'lambda' , which is the loss aversion coefficient. This 'lambda' parameter determines the steepness of the value function in the domain of loss. For the research question, minimally, we are concerned with the value of lambda and age of participants.

To assess between-study heterogeneity (for instance, I^2) and determine the relationship of age and loss aversion across datasets, we performed a random effects meta analysis.

Random effects meta analysis ensures that heterogeneity pertaining to sampling error is captured, along with heterogeneity introduced by the study level differences. Here, the underlying assumption is that the observed effect size of study k amounts to the true effect size of study k with some sampling error of k as depicted in equation (2).

$$\hat{\theta}_k = \theta_k + \epsilon_k \tag{2}$$

As shown in equation (3), this is a hierarchical model, where the true effect size is seen as emerging from an overarching distribution of true effect sizes with mean μ due to introduction of a second source of error, denoted by ζ_K, which refers to between-study level heterogeneity.

$$\theta_k = \mu + \zeta_k \tag{3}$$

Both these formulas, can be re-written as equation (4);

$$\hat{\theta}_k = \mu + \zeta_k + \epsilon_k \tag{4}$$

This shows that the observed effect sizes vary from their true effect due to sampling variation as well as between-study heterogeneity.

Due to the diverse nature of the studies found through the systematic search, we decided to use random effects meta-analysis. The Restricted Maximum Likelihood Estimator was used to measure heterogeneity variance or τ^2, which reflects the variance of the distribution of true effect sizes, and the inverse-variance method was used to pool effect sizes.

$$\text{LossAversion}_{ij} = \beta_0 + \beta_1\,\text{Age}_{ij} + \beta_2\,\text{Age}_{ij}^2 + u_{0j} + \varepsilon_{ij} \tag{5}$$

Further, considering the non-linearity evident in our data set (see Figure 3), mixed non-linear models were performed on individual level data provided by a subset of the studies or data sets. A mixed model allows for the appropriate modeling of fixed and random effects. This model was chosen to control study-level heterogeneity in baseline loss aversion introduced by different studies while deriving the fixed effect of age on loss aversion.

In equations (5) loss aversion *ij* represents individual loss aversion for study *j*, βo is the intercept coefficient, $\beta 1$ represents the coefficient indicating fixed linear effect and $\beta 2$ represents the coefficient for the quadratic effect of age on loss aversion. The term *u0j* is the random intercept for study *j*, and *eij* stands for residual error term. These models account for study-specific baseline differences in loss aversion, which improves the generalization of the fixed effect of age on loss aversion.

Table 2: Data sets in individual-participant level (n=1,565) meta-analysis.

Data set	Risky decision task	Lambda estimation	Age
1. Karle et al., 2015	Choice between lottery and sure payment across two series of lotteries	Cut off values	18-35
2. Kijima, 2019	Choice between safe option and a risky option	Switch point	15-93
3. Seaman et al., 2018	Choice between a loss averse gamble and a gain seeking gamble	Switch point	20-81
4. Lo Presti et al., 2022	Choice between sure payment and a gamble	Switch point	18-82
5. Sun et al., 2021	State least amount of gain to switch from gamble A to B	Average of ratios	18-54

Model Results

Study-level Random Effect Meta-analysis As the procured data sets were heterogeneous, we ran a random effect meta-analysis. We found that the average effect of age on loss aversion is small and insignificant (estimate = 0.06 [-0.04; 0.17], zval = 1.17, p=0.24). The estimate of τ^2 that quantifies between-study heterogeneity was found to be 0.045 [0.02; 0.12]. This heterogeneity was substantial [I^2 = 87.4% [81.9%; 91.2%] with the test for heterogeneity being significant (Q(df = 19) = 150.31, p <0.00). In order to test for bias in the accumulated data sets, a funnel plot was generated. To test it statistically, Egger's regression-based test was run that reflected no evidence of bias in studies (z = 0.28, p = .78), suggesting that small study effect is unlikely to account for null results between the data sets. To make a robust case for heterogeneity based on the present meta-analysis evidence, we list the prediction interval as [-0.40; 0.52], as shown in Figure 2.

Individual-level (IPD) Meta-analysis Importantly, considering the non-linear patterns in the study-specific plot generated from the data set (see Figure 3), we decided to implement an individual-level (IPD) meta-analysis. Here, we pooled data from 5 studies (or data sets). Although, the number of studies is less, combining individual level data increases statistical power, that ensures the credibility of the results.

To test the significance of the possible non-linear trends (see Figure 3), we ran a Generalized Additive Model (GAM) as it permits non-linear smooth functions of predictor variables. The model found a significant non-linear effect (edf = 5.15 , Ref.df = 6.26, F = 4.07, p < 0.001). This motivated the investigation of a quadratic mixed effect model. This choice was adopted as theoretically, a curvilinear trajectory is consistent with trends observed in life-span perspective to other decision making processes (Tymula et al., 2013). Methodologically, a quadratic model facilitates interpretability, providing an age at which loss aversion is minimum or maximum through estimation of vertex.

Therefore, we implemented a mixed model on the entire data set (n= 1,565) with linear and non-linear specifications of raw age, while controlling for study-specific differences. This model, which we call model A, suggested a U-shaped relationship of modest effect between age^2 and loss aversion (see Figure 4) (beta = 0.0004, 95% CI [0.0001, 0.0008], t(1560) = 2.49, p = 0.01, R2 = 0.004)with vertex (45.65, 2.39) that proposed a lambda of 2.39 as the lowest at 45-46 years.

An issue with model A is that it conflates within and between study differences. In order to disentangle these, we ran another quadratic mixed effect model, referred to as model B. In model B, we isolated the age-related variation among individuals within the same study by centering age around the mean of the specific study while controlling for between study mean age and study specific baselines. This model confirmed the presence of a small non-linear association between age and loss aversion at the level of within specific studies (beta = 0.0003, 95% CI [0.0000, 0.0007], t(1559) = 2.03, p = 0.043), an effect absent at between study-level (see Figure 5). In model B, the predicted minimum loss aversion is around 42 years of age. Hence, both the models A and B propose minimum loss aversion to be in mid-life. The different vertices observed in the two models is because the model A produced an estimate influenced by both within and between study variations whereas model B is reflective of age and loss aversion association within studies not confounded with systematic differences between studies.

Exploratory Sex Moderation Analysis To examine whether age-related trajectory of loss aversion differed for males (n=815) and females (n= 750), we ran a mixed effect model with sex along with its interaction with within-study linear and quadratic age specifications, while controlling for study-specific baseline. We found only an effect for sex, with females (beta = 0.31, 95% CI [0.06, 0.56], t(1557) = 2.43, p = 0.015, d= 0.16), exhibiting higher loss aversion than males (see Figure 6).

Discussion

The present study aimed to understand the relationship between age and loss aversion using meta-analysis at two levels. This dual set of results underscore the complexity of relationship between age and loss aversion, while also emphasizing the necessity to synthesize evidence across different levels.

Adding to the growing body of evidence on age-related differences in decision making, our study-level random effect meta-analysis found a small and insignificant estimate. This finding of a null association is important as it indicates that across diverse studies, loss aversion does not monotonically increase or decrease with age. It is likely that age alone is not a predictor of loss aversion. This finding was validated by an absence of small study effect using a funnel plot.

When we pooled individual level data, we found a small effect of a decrease in loss aversion for the mid-age relative to the younger and older adults in a U-shaped relationship. To delineate this relationship further, a closer examination re-

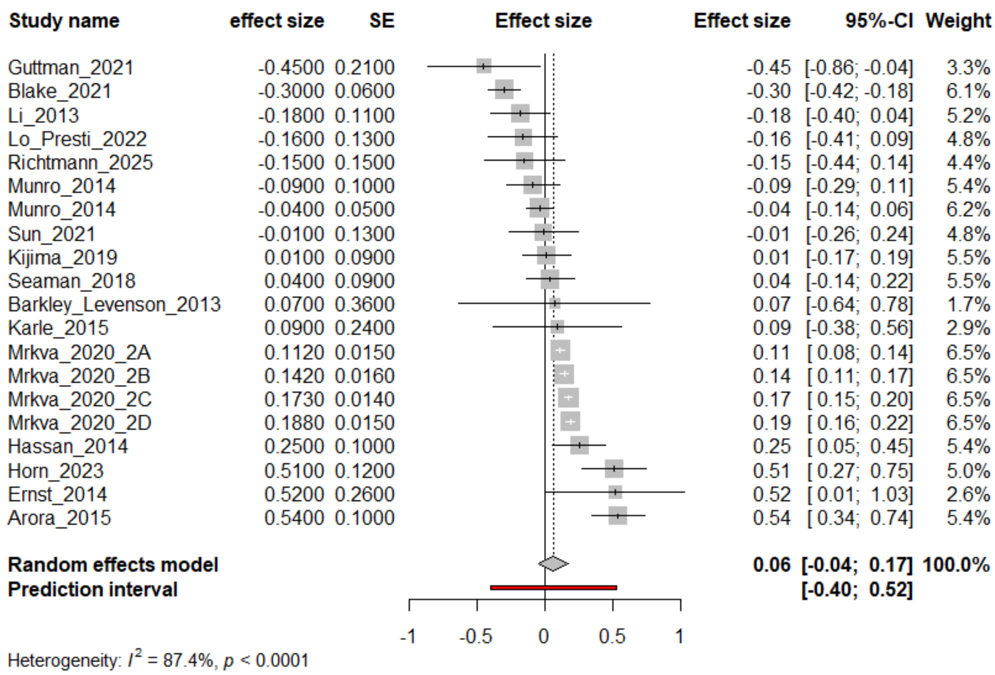

Figure 2: Forest plot of random effect meta-analysis

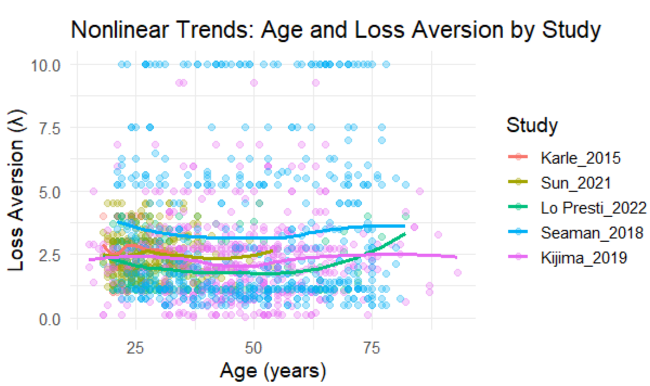

Figure 3: Study-specific curves of age and loss aversion

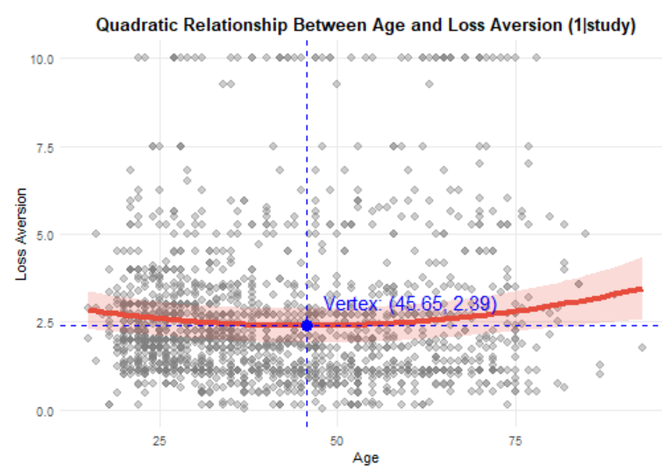

Figure 4: U-shaped curve between age and loss aversion

vealed that the relationship existed within specific datasets. This result of a non-linear trajectory corroborates the findings of previous work (Blake et al., 2021; Guttman et al., 2021). An intuitive explanation of the results is provided by western developmental psychology literature (Stott, 1974). These explanations must be interpreted with caution as they may not be generalizable to diverse population groups. The common understanding is that adolescence is a tumultuous period characterized by uncertainty related to one's identity, resources and social support. This may reinforce salience to loss. On the other hand, middle adulthood is marked by cognitive maturity, expanding assets and social relationships that provide a better bargaining power to individuals. Upon reaching the fag end of life, defined by diminishing physical and financial agility, individuals may orient towards preservation against losses. These lifespan related motivational changes appear to explain some of our finding but it remains unclear to what extent these developmental changes are fundamentally related to loss aversion, and more broadly to asymmetric valuation of

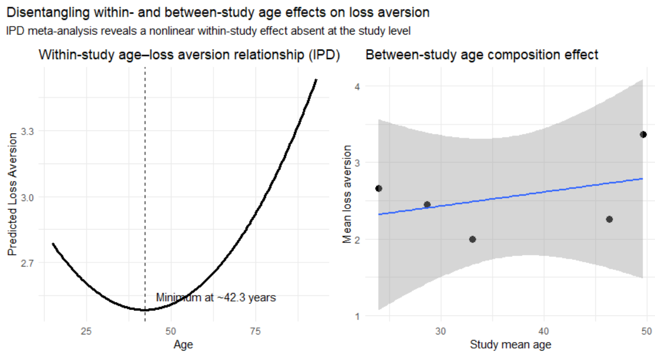

Figure 5: Within and between study effect of age on loss aversion

loss relative to gain. Additionally, in exploratory analyses, we found that inclusion of interaction term with sex attenuated the significance of age. It demonstrated that females have higher loss aversion than males. This evidence aligns with prior literature suggesting greater willingness to take risk among men (Byrnes et al., 1999; Powell and Ansic, 1997). Recent studies have attributed sex differences in risk attitude to differences in loss aversion (Booij et al., 2010; Dawson, 2023) beyond mere differences in utility curvature. It is noteworthy that weakening of the curvilinear trend suggested that sex influences baseline levels of loss aversion while the broader curvilinear trend remained similar across the sexes.

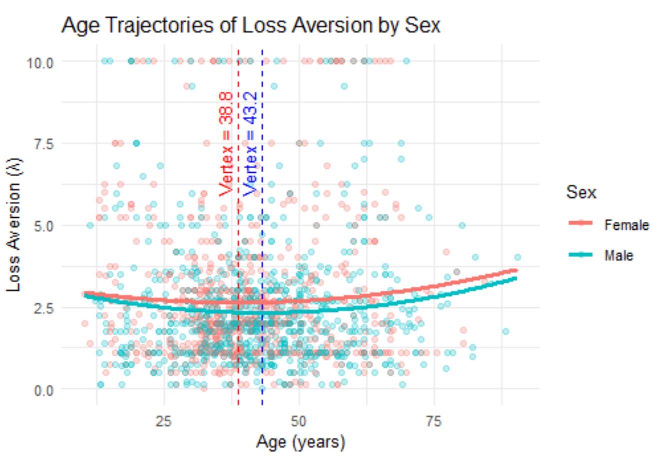

Figure 6: Exploratory sex-specific age trajectories

When these findings are taken together, they suggest that the U-shaped relationship between age and loss aversion is most robust only in the more constrained within-study model with an effect of modest magnitude. It connotes that other factors, when allowed to vary between studies, may gain prominence over age in systematically explaining the variance in loss aversion.

The current study should not be interpreted as a case to rule out age-related differences in decision making across the lifespan (Tymula et al., 2013), but rather to indicate the necessity of meta-studies to establish which kind of decision making is fairly robust or variable across lifespan.

In addition to the theoretical contribution, the present study illustrates methodologically the complementary value of conducting both levels of meta-analysis. Study-level random-effect meta-analysis is the predominant practice, as it allows for greater inclusion of studies, but it precludes findings non-linear relationship, due to reliance on group-level statistics that in our case assume linearity. On the other hand, an individual-level meta-analysis, although constrained by the number of studies because it relies on availability of individual-level data, permits the detection of non-linear patterns and decomposition of phenomenon as existing within or between diverse datasets. This inconsistency in results by the two kinds of meta-analysis is less a discrepancy but a demonstration of how different levels of meta-analysis shape what kind of theorization is possible.

Limitations and Future Directions

Importantly the findings should be interpreted with the caveat that there is substantial heterogeneity, indicated by the high I^2 value. It may pertain to different population characteristics, sample sizes, or even the way lambda is operationalized. In Tables 1 and 2, we have highlighted that datasets differ in their method of elicitation and estimation of loss aversion, which also denote different reference points. This implies that the interpretation of lambda (Abburu et al., 2025) may not be wholly equivalent across datasets. For us, it is important to note that this heterogeneity is relevant for between study meta-analysis. The IPD meta-analysis mitigates this issue by estimating within study relationship between age and loss aversion, thereby holding the specific operationalization of loss aversion and other contextual factors constant within each dataset.

Upon availability, future work must incorporate datasets that measure loss aversion in a consistent manner on a large sample. The study also urges researchers to distribute focus to individuals across different ages beyond the disproportionately overrepresented narrow student population.

Although age was the focus of the paper, we found sex to be a reliable variable in the exploratory analyses. The modest number of studies in the IPD analyses and the increased complexity of this model necessitate future work to more thoroughly understand sex-related differences in loss aversion which have been scarce in the literature.

Also, as loss aversion is linked to economic behaviours of saving (Bowman et al., 1999) and performance in the market (Bouteska and Regaieg, 2020), policy makers may utilize the findings to better guide financial decision making for individuals at different stages of life.

The present study motivates expansion of theoretical models with a focus on non-linearity and lifespan approaches to understand how decisions are taken at different stages of life, which in turn will enhance decision theory.

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