

# Guessing, math, or something else? Lay people's processes for valuing annuities

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## RESEARCH ARTICLE

WILEY

# Guessing, math, or something else? Lay people's processes for valuing annuities

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## Abstract

Researchers have long been trying to understand why individuals dislike annuities. Here, we investigate if the process individuals use to assess the financial value of annuities may lead them to inaccurately value annuities. In Study 1, participants were asked to assess the monthly payments associated with a specific annuity lump sum or the annuity lump sum associated with a specific monthly payment. They were then asked to describe how they arrived at their answers. We find that when making this assessment, 42% of participants report attempts at using math, with some even describing mathematical formulas. Most other participants reported guessing instead. Reporting attempts at math is more common among participants with higher financial literacy and numeracy. Reported attempts at math, financial literacy, and numeracy predict arriving at more realistic financial values for annuities, as well as incorporating assessments of life expectancy in the math. Based on this process knowledge, we then designed an experiment in Study 2 and tested the effect of presenting information about life expectancy, providing feedback about payouts or their combination. We find that we can thereby change the assessed financial value of annuities and increase participants' interest in annuities, especially among participants that reported attempts at using math. Understanding the processes individuals use to assess the value of annuities informs theory and practice.

## KEYWORDS

annuity valuation, financial literacy, numeracy, valuation process

## 1 | INTRODUCTION

Annuities are financial products for which the buyer pays a premium, for example, a lump sum, and in return receives a monthly, guaranteed payouts from a specific age. Like a pension, the annuity pays as long as the annuitant lives. In case the annuitant dies, no payments are made to children or other heirs. Thereby, annuities insure against the risk of outliving one's financial resources in retirement (e.g., Mitchell et al., 1999).

According to expected utility theory, risk-averse individuals should annuitize all their wealth—assuming that annuities are fairly priced and that they are not worried about leaving money for their children or other heirs (Davidoff et al., 2005; Yaari, 1965). In reality, however, people are generally not in the habit of buying annuities—which is referred to as the so-called annuity puzzle (Friedman & Warshawsky, 1988).

Annuities may be perceived as a bad deal by people who do not expect to live long enough to run out of money (e.g., Mitchell

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et al., 1999). Additionally, people may not want to lock up all liquid wealth in annuities, so that there is money left to pass along to one's children after one's death (e.g., Inkmann et al., 2011; Lockwood, 2012) or to cover potentially large health and long-term care expenses (e.g., Davidoff, 2009; Poterba, 2006). People may also dislike annuities if they worry that the annuity provider might go bankrupt (Schulze & Post, 2010). People who think of annuities as an investment product rather than an insurance product may perceive annuities as risky due to the unknown payment duration (Brown et al., 2008). Annuities may also be aversive because they remind people of their limited life expectancy (Salisbury & Nenkov, 2016). Instead, people may prefer to stick with their default investment portfolio, that is, the investment mix a pension provider selected for people that do not make an active choice (Bateman et al., 2017; Hurwitz, Sade, & Winter, 2020).

Difficulties in computing the financial value of annuities may also play a role in disliking annuities (Shu et al., 2016). For example, in order to recognize that a lump-sum payment of \$500,000 equals roughly a lifelong monthly payout of \$2800 for a 65-year-old individual (see Section 2.1), at least three complex computational steps are needed: First, one would need to estimate maximum life expectancy (e.g., 110 years). Second, each monthly payout would need to be weighed with the probability of surviving until that particular month. Third, one would need to discount each monthly probability-weighted payout with an appropriate interest rate and add up those values. Not unsurprisingly, the literature has described annuities as “complex financial products that require the ability to ‘do the math’ to understand” (Shu et al., 2016), and more complex descriptions of annuities have been found to increase valuation mistakes (Brown et al., 2021).

Existing evidence suggests that annuities may seem less attractive because people tend to overestimate the monthly annuity payments associated with small lump sums (Goldstein et al., 2016) or evaluate small lump sums through different mental accounts (Hurwitz & Sade, 2021). Especially people with lower financial literacy and numeracy tend to make mistakes in computing the value of annuities (Bateman et al., 2018; Brown et al., 2017, 2021; McGowan et al., 2018). It has been speculated that people often do not do the math but rather guess—wrongly—at the number of years it takes for monthly payments to reach the value of the lump sum (Brown et al., 2017). Providing tables that show cumulative amounts of the monthly payments reached by specific ages tends to increase people's interest in annuities (Shu et al., 2016). Thus, whether people like annuities may depend on whether they are able to accurately assess the financial value of annuities by, for example, using a mathematical formula and accurate inputs in a formula (e.g., life expectancy).

One way to assess how people evaluate products is to ask them to describe what they did (e.g., Johnson et al., 2007; Read & Powell, 2002; Weber et al., 2007). Asking about thought processes has also led to insights about how people solve mathematical division and multiplication problems, so as to inform mathematics education (e.g., Hogan & Brezinski, 2003; LeFevre & Morris, 1999). An understanding of the process by which people assess inflation has also informed the design of inflation expectation surveys (Bruine de Bruin, van der Klaauw, et al., 2012). Although asking people to report their

thought processes has its merits, it can also impact processes and decisions. Wilson et al. (1993) find that individuals' choices for a poster change when being asked to think about the reasons for their choice beforehand.

## 1.1 | The current research

In the present paper, we aimed to understand the processes people use to assess the financial value of annuities and how these processes related to the accuracy of their assessments. In Study 1, we explored which processes participants report using to assess the financial value of annuities and whether attempts at math led to more accurate financial assessments of annuities. Specifically, participants were asked to assess the monthly payments associated with a specific annuity lump sum or to assess the annuity lump sum associated with a specific monthly payment. Participants were also asked to provide estimates of future life expectancy and the interest rate, to explore whether their assessments were realistic. To allow us to identify whether instructions to describe thought processes affected responses (Wilson et al., 1993), for example, due to social desirability (Fox et al., 2011; Krumpal, 2013) or ex post rationalization (Eyster et al., 2021), half of participants were asked to describe their thought processes as part of the instructions for the annuity valuation task and the other half received this request after they completed the task. If social desirability had affected responses and/or processes, we expected differences between those two groups of participants in the frequency of particular processes reported, annuity valuations, and accuracy. We thus then examined how commonly participants reported using math in each condition, as well as whether more accurate assessments of the financial value of annuities, were associated with attempts at math and assessments of life expectancy. We also examined whether responses varied with whether participants were asked to compute the lump sum versus lifetime monthly payout, with financial literacy and numeracy, as well as when the request for the description of the process is requested.

In Study 2, we then cross-validated the so far correlational process knowledge evidence generated in Study 1 in a new sample. That is, we aimed to generate causal evidence that the self-reported processes discovered in Study 1 were indeed used by participants to value annuities. For that, we designed an experiment where participants were provided with information about future life expectancy (and in some conditions feedback on market annuity rates). Study 1 showed that participants who reported attempts at math used life expectancy in their computations. We then tested if providing information on future life expectancy changed participants' assessment of the financial value of annuities—in line with Study 1's process knowledge. That is, Study 2's intervention was designed to work only if the mathematical processes reported in Study 1 reflected what participants actually did when they valued annuities and thus providing a causal out of sample test of our initial findings. In addition, we tested if providing this information was useful to increase

participants' interest in annuities. The latter extension to Study 1 was included to understand if the process knowledge generated had the potential to design meaningful interventions that could be used on practice to stimulate interest in annuities. Overall, the analyses in this paper examined the following exploratory research questions:

RQ1: Do individuals report attempts at math when assessing the financial value of annuities, and does it vary with whether participants are asked to compute the lump sum versus lifetime monthly payout, with financial literacy and numeracy, as well with whether the request for the description of the process was received before or after the task? (Study 1)

RQ2: Are more accurate assessments of the financial value of annuities associated with attempts at math and estimates of future life expectancy and interest rates, even after accounting for whether participants were asked to compute the lump sum versus lifetime monthly payout, whether the request for the description of the process was received before or after the task, financial literacy and numeracy, and other demographics? (Study 1)

RQ3: Does providing participants with information about future life expectancy (vs. no information) change their assessments of the financial value of annuities and interest in annuities, and how does the effect vary with reported attempts at math? (Study 2)

## 2 | STUDY 1: ELICITING PROCESSES THAT INDIVIDUALS USE TO ASSESS THE FINANCIAL VALUE OF ANNUITIES

### 2.1 | Method

#### 2.1.1 | Procedure

##### *Assessment of the annuity value*

Participants completed an online survey, in which they were asked to assess the financial value of an annuity. They were randomly assigned to a *lump-sum* or *payout* condition. Participants in the *lump-sum* condition were asked how much of a lifetime payout per month someone aged 65 would get when having saved \$500,000. In the *payout* condition, participants were asked how much someone would need to have saved by age 65 to get a lifetime payout of \$2800 per month. All participants were told that they could take as much time as they wanted. The two conditions are roughly equivalent in that a lump sum of \$500,000 is approximately the amount needed to obtain a lifetime payout of \$2800 per month from retirement at age 65 and onward.<sup>1</sup> For our analyses, we converted participants' responses in both conditions to annuity rates based on the lump sum ( $P$ ) and payout ( $A$ ):

$$\text{Annuity rate} = \frac{A \cdot 12}{P}.$$

Because this variable tends to have large outliers (as in Brown et al., 2017), we analyzed next to the mean, the median of the annuity rates (in univariate analyses), or the logarithm of annuity rates (in regression models).

##### *Self-reported process of annuity value valuations*

After assessing the value of the annuity, participants were asked to describe in an open-ended text box how they generated their answer using standard instructions based on LeFevre et al. (1993) and Kuusela and Paul (2000) (i.e., we asked to “tell us how you came up with your answer” and to report “all of your thoughts that emerged when coming up with your answer”). Half of participants received the request for this description on the same screen as the annuity valuation task. The other half received it on the next screen, after they submitted their numerical estimate for the annuity valuation. Subsequently, participants were asked to self-classify their description of how they assessed annuity value (as in Johnson et al., 2007; Weber et al., 2007). Response options reflected the descriptions we uncovered when we asked participants in a pilot study how they assessed the value of annuities<sup>2</sup>: The number just popped up; I guessed; I did a calculation; and I used the internet to find the answer (e.g., an annuity calculator). Participants also had the option to indicate that none of the above applied. In addition, two research assistants independently read participants' responses and confirmed that there were no common processes that were missing from the provided options. Only selecting “I did a calculation” was counted as self-reporting an attempt at math.

Participants who checked the “I did a calculation” option were asked to further classify their attempt at math. In the *lump-sum* condition, the response options were the following: I divided 500,000 by the number of years to live and then by 10 (henceforth labeled “Rule 10”); I divided 500,000 by the number of years to live and then by 10 and made some adjustments (“Rule 10 with adjustments”); I divided 500,000 by the number of years to live and then by 12 (“Rule 12”); and I divided 500,000 by the number of years to live and then by 12 and made some adjustments (“Rule 12 with adjustments”). If a participant selected any of those options (vs. the again available option to indicate that none of the provided answers applied), we labeled the process used “Division Rule.” That is, the Division Rule was a summary category of processes that reflected similar attempts at math for which we could identify rather clearly the corresponding formula. In the *payout* condition, the response options were the following: I multiplied 2800 by 10 and then by the number of years to

<sup>1</sup>We took annuity quotes ([www.immediateannuities.com](http://www.immediateannuities.com)) 2 weeks before the survey was distributed. The quotes for a lump sum of \$500,000 were \$2850 for men and \$2717 for women, so on average \$2784.

<sup>2</sup>We performed a pretest with 10 university staff and faculty members. Participants saw either the lump-sum or a payout condition on a sheet of paper while the experimenter was present. After each participant filled in an estimate of a payout or lump sum, the experimenter handed another sheet of paper over to the participant with the question: How did you come up with this number? There are no right or wrong answers. Just tell me how you did it. From those responses, we selected the answer categories for Study 1 if they occurred more than once.

live; I multiplied 2800 by 10 and then by the number of years to live and made some adjustments; I multiplied 2800 by 12 and then by the number of years to live; and I multiplied 2800 by 12 and then by the number of years to live and made some adjustments. These processes are conceptually identical to the lump-sum condition but in reversed order (multiplication vs. division). For the sake of simplicity, we used the same labels as in the lump-sum condition ("Rule 10," ...) for each corresponding option in the payout condition and as overarching label again "Division Rule." In both conditions, the presented response options reflected descriptions provided by pilot study participants. Two research assistants confirmed that there were no additional commonly mentioned processes that were missing from the provided options. Because the two research assistants did not find additional processes, we used all subsequent analyses participants' self-classification.<sup>3</sup>

#### *Numeracy and financial literacy*

Next, we asked participants to complete an 8-item Objective Numeracy scale (Weller et al., 2013; e.g., "If the chance of getting a disease is 10%, how many people would be expected to get the disease out of 1000?") and a 5-item financial literacy scale (van Rooij et al., 2011; e.g., "Imagine that the interest rate on your savings account was 1 percent per year and inflation was 2 percent per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?"). We computed the number of correct answers for each. We also asked participants to assess their own numeracy on the 4-item Ability measure that is part of the Subjective Numeracy scale (Fagerlin et al., 2007; e.g., "Please check the box that best reflects how good you are at doing it: calculating a 15% tip"), with six response options varying from 1 (*Not at all good*) to 6 (*Extremely good*). We took the average of the responses to the four items (Cronbach's alpha = .91).

#### *Life expectancy and interest rate*

Next, we collected participants' estimates of life expectancy at age 65 for men and women and the interest rate on a 10-year U.S. treasury bond. Specifically, participants were asked, "How many more years do you think a male (female) person that is 65 years old today can expect to live?" and "What do you think is the current interest rate (yield) on a 10 year U.S. government bond?" Those parameters are used by actuaries to value annuities.

#### *Control variables*

Finally, we collected demographic control variables including gender, age, education, income, and savings as well as risk tolerance (1-item 10 point scale from Dohmen et al., 2011, asking "Are you generally a person who is willing to take risk?") and time preference (1-item 10 point scale from Falk et al., 2022, asking "Are you a person who is

generally willing to give up something today in order to benefit from that in the future or are you not willing to do so?") as the latter two variables are in theory relevant for decisions on annuities (e.g., Yaari, 1965).

## 2.2 | Sample

The online survey was distributed to U.S. residents aged 45 to 60 by survey provider Qualtrics in February 2019. Retirement savings are of relevance to this age group. In total, 239 individuals completed the survey. Seven participants were removed from the lump-sum condition and three from the payout condition, because they entered "0" as their assessment of the annuity value.<sup>4</sup> The final sample of 229 participants included 77% women, 36% individuals with a college education, average annual income was \$46,135, and average savings were \$74,640. Table S1 shows descriptive statistics for the entire sample, as well as participants in the lump-sum and payout conditions.

## 2.3 | Results

### 2.3.1 | Do individuals report attempt at math when assessing the financial value of annuities, and does it vary with whether participants are asked to compute the lump sum versus lifetime monthly payout, with financial literacy and numeracy, with whether the request for the description of the process was received before or after the task? (RQ1)

Table 1 gives an overview of the different processes reported by participants.

According to Table 1, 42% of all participants reported attempts at math, 49% said that they guessed, 2% indicated using the internet to look up values, and 7% could not or were not willing to classify their process. Based on the follow-up question for those who reported attempts at math, we find that 26.6% indicated a version of the Division Rule (Rule 10, 12, ...) reporting statements in their text like, for example, "2800  $\times$  12 = 33600 so I figure you will live 15 years which equals 504000." For those who indicated a rule with adjustments, we find that typical adjustments made were—based on manually cross-checking with participants' text entries—rounding before a calculation (e.g., from 2.800 to 3.000) and/or adjusting the final result up or down in order to correct for suspected directional mistakes of their simple processes (e.g., "Estimated living to age 85, I roughed it to \$3000 a month and multiplied it by 12 months. And then roughed my answer by multiplying 20 years and put in a little

<sup>3</sup>Overall, the results of coding of the two research assistants were reliable in that both agreed in their categorization of text responses in 91% of all cases (Cohen's Kappa = .77). Coders' and participants' self-classifications agreed in 79% of all cases (Cohen's Kappa = .56). Potentially, in some cases, the text was too vague to be classified by the research assistant coders as a clear calculation or clear guess.

<sup>4</sup>When analyzing annuity rates (Section 2.4), those responses cannot be included as calculating an annuity rate in this case involves a division by zero. All results in this section (where it is technically possible to include also those responses hold) are available on request.

TABLE 1 Valuation processes in Study 1

General process	Text entry example	Fraction %			t-stat on mean difference between conditions	p-val	Mathematical process	Fraction %			t-stat on mean difference between conditions	p-val
		Full sample	Payout	Lump sum				Full sample	Payout	Lump sum		
Math	"Took the 500,000 and divided by 20 assuming the person lives 20 years then divided it by 12"	41.92	44.45	39.29	.789	.431	Rule 10	2.18	1.71	2.68	−.500	.618
							Rule 10 and adjustments	2.62	5.13	0.00	2.450	.015
							Rule 12	14.85	12.82	16.96	−.879	.380
							Rule 12 and adjustments	6.99	8.55	5.36	.944	.346
							No option fits	15.28	16.24	14.29	.409	.683
Guessing	"A complete guess"	49.34	47.87	50.9	−.457	.648						
Using the internet	"Google searched the question"	1.75	0.85	2.68	−1.051	.294						
No option fits	"People live longer"	6.99	6.84	7.14	−.090	.928						

Note: This table shows the distribution of valuation processes according to participants' self-classification for the full sample and by conditions. The entries "Rule ..." refer to participants' indicating that they divided the lump sum by the number of years to live and then by 10 or 12 (with potential adjustments) in case of the lump-sum condition. In the payout condition, the entries refer to approaches that multiplied the payout by 10 or 12 and the number of years to live. Fraction is the percentage of participants using an approach relative to the full sample or participants in each condition.



**TABLE 2** Characteristics of participants that report attempts at math in Study 1

	(1) Math	(2) Math	(3) Math	(4) Math	(5) Math	(6) Division
Age	−0.010 (0.007)	−0.014 <sup>*</sup> (0.007)	−0.009 (0.007)	−0.012 (0.007)	−0.013 <sup>*</sup> (0.007)	−0.023 <sup>**</sup> (0.010)
Gender	−0.028 (0.076)	0.003 (0.073)	0.005 (0.076)	−0.005 (0.077)	0.022 (0.074)	0.218 <sup>**</sup> (0.104)
Education high	0.121 <sup>*</sup> (0.068)	0.039 (0.068)	0.102 (0.068)	0.106 (0.068)	0.036 (0.067)	0.147 (0.093)
Income in \$'000	0.002 <sup>*</sup> (0.001)	0.001 (0.001)	0.001 (0.001)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
Savings in \$'000	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)
Risk tolerance	−0.001 (0.015)	−0.008 (0.014)	−0.000 (0.014)	−0.003 (0.015)	−0.007 (0.014)	0.014 (0.019)
Time preference	0.012 (0.015)	0.001 (0.015)	0.007 (0.015)	0.011 (0.015)	−0.000 (0.015)	0.033 <sup>*</sup> (0.020)
Lump-sum condition	−0.045 (0.064)	−0.050 (0.061)	−0.043 (0.063)	−0.047 (0.063)	−0.048 (0.061)	−0.067 (0.089)
Subj. numeracy		0.104 <sup>***</sup> (0.020)			0.093 <sup>***</sup> (0.022)	0.073 <sup>**</sup> (0.035)
Obj. numeracy			0.051 <sup>***</sup> (0.019)		0.025 (0.022)	−0.084 <sup>***</sup> (0.032)
Financial literacy				0.052 <sup>**</sup> (0.022)	0.009 (0.026)	0.145 <sup>***</sup> (0.039)
Observations	229	229	229	229	229	96
Pseudo R-squared	.039	.107	.061	.055	.113	.242

Note: This table presents the marginal effects from logistic regressions of a having reported attempts at math (0 = not reported, 1 = reported) in Models 1–5 and having reported the division rule (0 = not reported, 1 = reported) given that a math was reported in Model 6 on different sets of explanatory variables. Gender is a dummy variable (0 = male, 1 = female). Education is a dummy variable where a 1 indicates a level above the sample median (“Some college but no degree”) and 0 otherwise. Lump-sum condition is 0 for the payout condition and 1 for the lump-sum condition. Reported are marginal effects at means of independent continuous and discrete dummy variables. Standard errors are given in parentheses.

<sup>\*</sup>Statistical significance at the 10% level.

<sup>\*\*</sup>Statistical significance at the 5% level.

<sup>\*\*\*</sup>Statistical significance at the 1% level.

more to my answer”). Interestingly, participants who used a Rule 12 process (22%) applied a formula which is remarkably close to the way actuaries value annuities in case the interest rate was zero.<sup>5</sup>

Table 1 also contains statistics on the frequency of valuation processes reported within the *lump-sum* and *payout* conditions. Differences between the two conditions were not statistically significant, with one minor exception. In the payout condition, a few participants reported attempts at using the Rule 10 with adjustments ( $N = 6$ ), but none did so in the lump-sum condition ( $N = 0$ ).

Next, we analyzed how participants' financial literacy, numeracy, and other characteristics relate to reporting attempts at math in the annuity valuation task. Note that participants' subjective numeracy, objective numeracy, and financial literacy were positively and strongly significantly correlated. The correlation coefficients between subjective and objective numeracy were .37 ( $p < .01$ ), between subjective numeracy and financial literacy .39 ( $p < .01$ ), and between objective numeracy and financial literacy .52 ( $p < .01$ ). Thus, when including all three measures jointly in multivariate analyses, the correlation might

create multicollinearity issues. Additional tests, however, revealed that such issues were not present.<sup>6</sup>

We ran logistic regressions of a dummy variable indicating having reported attempts at math (=1) or not (=0) on different sets of variables. Table 2 displays the regression results.

Consistently across models, greater subjective numeracy, greater objective numeracy, and greater financial literacy predicted a higher likelihood of reported attempts at math. All three measures were positively related to the likelihood of attempts at math when included separately in a model (see Table 2, Models 2–4). When we included the three measures jointly in the regression (Model 5), only subjective numeracy remained significant because of the high correlation among those three variables. Subjective numeracy was a strong predictor of reporting the Division Rule (Table 2, Model 6), that is, attempts at math for which we could

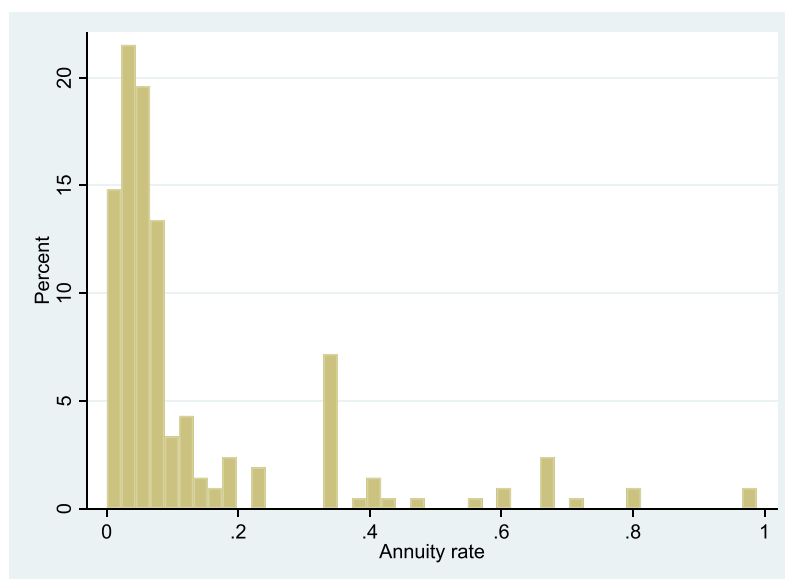
<sup>5</sup>Ignoring (for simplicity) within years discounting as well as assuming a flat interest rate term structure, the actuarial valuation formula for an annuity paying at the beginning of a month is given by  $P = (A \cdot 12) \sum_{t=0}^{T-x-1} \frac{t^p x}{(1+r)^t}$ , with  $P$  being the lump-sum premium,  $A$  the monthly payout,  $p_x$  the probability of an individual aged  $x$  today to survive to age  $x + t$ ,  $T$  the maximum possible age assumed, and  $r$  the annual interest rate. In case the interest rate is zero, the formula simplifies to  $P = (A \cdot 12) \sum_{t=0}^{T-x-1} t^p x = (A \cdot 12) \cdot \text{life expectancy at age } x$ .

<sup>6</sup>We also performed a factor analysis on the three measures. The analysis resulted in one factor with an Eigenvalue greater than one explaining 98.9% of the variance. In addition, we used the resulting Bartlett factor scores as weights to construct a composite measure of participants' sophistication. Using this composite measure in our models produced virtually the same results. In addition, in all linear models except one, VIF values were smaller than 10. High VIF values were found only in case of continuous interactions (see Tables S3–S5). In addition, we checked if our sample size was sufficient given the number of predictors included in the regression models based on the procedure of Stevens (2002, p. 143). For two models (Models 6 in Tables 2 and 4), this was not the case. In response, we estimated those models as well with reduced sets of predictors finding no substantial changes in coefficient magnitudes, sign, and significance (results available upon request).

**TABLE 3** Annuity rates and distance from market benchmark in Study 1

Variable		All participants	Condition: Payout given		
			No calculation	Any calculation	Division rule
Annuity rate	Mean	45.64	58.27	29.85	21.47
	Median	.11	.22	.07	.06
	Std	208.70	258.27	122.08	98.65
Correct $\pm 2\%$	Fraction	0.19	0.15	0.23	0.33
Observations		117	65	52	33
		All participants	Condition: Lump sum given		
			No calculation	Any calculation	Division rule
Annuity rate	Mean	1.16	1.84	.11	.09
	Median	.05	.04	.05	.05
	Std	11.33	14.54	0.20	0.18
Correct $\pm 2\%$	Fraction	0.35	0.29	0.43	0.46
Observations		112	68	44	28

Note: This table shows descriptive statistics for the annuity rates that participants estimated in the two valuation conditions as well as the fraction of participants whose estimates were within a 2-percentage point range around the annuity market benchmark rate of 6.7% (correct  $\pm 2\%$ ).

**FIGURE 1** Distribution of annuity rates in Study 1. Note that this figure shows the distribution of annuity rates in Study 1. The annuity rate is defined as the annual amount of annuity payouts (A/12) divided by the lump-sum premium  $P$ . For generating this histogram, 20 observations have been removed as annuity rates of those respondents were too large ( $\gg 1$ ) to allow creating a meaningful figure. [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com/doi/10.1002/bdm.2316)]

identify the corresponding formula.<sup>7</sup> Among the control variables, older age was in some models negatively related with having reported attempts at math.

Finally, we tested whether the request for participants to provide a description of their process impacted the processes used. For this purpose, we compared means and medians of a number of variables

between those participants who saw the text entry field on the same screen as the task and those who only saw it on the following screen. The latter group thus did not know when solving the task that they would be asked to indicate how they did it. Within each valuation task condition (lump sum or payout), we compared the following variables: valuation task duration in seconds, text length in characters, and percentage having reported attempts at math. We did not find significant differences between those variables (see Table S2). These results suggested that regardless of whether participants were aware that they need to report on their process or not, they used on average the same processes.

<sup>7</sup>Note, in this model, objective numeracy predicts negatively having applied the Division Rule. This effect is caused by the high correlation between the sophistication measures. When each one is included separately, subjective numeracy and financial literacy positively and significantly predict the use of the Division Rule, while the coefficient for objective numeracy is not significant.



### 2.3.2 | Are more accurate assessments of the financial value of annuities associated with attempts at math and estimates of future life expectancy and interest rates, even after accounting for whether participants were asked to compute the lump sum versus lifetime monthly payout, whether the request for the description of the process was received before or after the task, financial literacy and numeracy, and other demographics? (RQ2)

Table 3 gives descriptive statistics for annuity rates that participants estimated in the two valuation conditions; Figure 1 plots their distribution.

Participants' estimates included large outliers—mean and median annuity rates differed strongly. By cross-checking with the written text, we identified some outliers to be typos (e.g., in the text, a participant wrote \$4166 but entered \$41,166 in the valuation field), others were potential typos (e.g., a participant stated having used the Division Rule but entered an annual amount), and others seemed to be clear guesses. We did not correct potential typos to avoid researcher-driven bias, especially in cases where the response could have been a typo (monthly vs. annual) or a true valuation mistake. Rather, as noted above, we dealt with outliers by analyzing the median of the annuity rates (in univariate analyses) or the logarithm of annuity rates (in regression models).

Median annuity rates of 11% (payout condition) and 5% (lump-sum condition) estimated by participants were economically reasonable. Both values were close to the value an annuity calculator ([www.immediateannuities.com](http://www.immediateannuities.com)) gave at the time of the survey, which was 6.7% (=average of male and female rates). The difference in medians was significant at the 1% level ( $Mdn_{lump-sum} = .11$  vs.  $Mdn_{payout} = .05$ ,  $\chi^2 = 30.11$ ,  $p < .01$ ).<sup>8</sup> Participants in the condition with payouts estimated higher annuity rates than the market offers, while participants in the lump-sum condition estimate lower rates.

Next, we analyzed how the valuation result was related to participants' financial literacy and numeracy, reporting attempts at math, and estimates of future life expectancy and the interest rate. We ran several OLS regression models of the log annuity rate on different sets of covariates. Results are shown in Table 4.

Models 1 and 2 showed that variables capturing participants' sophistication (subjective numeracy and financial literacy) and potentially related to sophistication (higher education and higher income) predicted smaller annuity rates. As the overall sample mean of the annuity rate was higher than the market rate of 6.7% (cf. Table 3), this finding implied that higher sophistication was related to more realistic results in the valuation task. In Model 3, where we included all demographic characteristics and sophistication variables jointly, only the coefficients for income and financial literacy remained statistically significant due to the correlation between the variables.<sup>9</sup>

Models 4 and 5 demonstrated that whether a participant had reported attempts at math or not did not explain annuity rates estimated.<sup>10</sup> Neither did having applied the Division Rule or any variant of the Division Rule (results available on request). Potentially, a formula alone was not sufficient to value an annuity properly—as a participant needed to integrate into the formula an accurate estimate for life expectancy and an interest rate (if it was unequal to zero).

Next, we examined the role of perceived life expectancy and interest rates in participants' assessed values of annuities. Based on the survey questions that elicited participants' estimates for life expectancy from age 65 onward, we found an average of 17.9 and 21.6 years, respectively. These estimates were reasonably close to their empirical counterparts, which were 18–19.2 years for men and 20.6–21.6 years for women.<sup>11</sup> In contrast, participants' estimate for the interest rate on a 10-year T-bond was on average 1.6%, while on the day the survey was in the field, the interest rate was actually much higher at 2.7%.<sup>12</sup> Based on reading participants' text responses, we found that a number for life expectancy was explicitly mentioned as a component in the math in 27% of the responses (e.g., “Figured a person might live to be about 80 ....” and “... If you lived another 30 years ....”). However, almost no participant took an interest rate into account for discounting or compounding future payments. An interest rate was mentioned only in 2.6% of all responses and then in vague statements like, for example, “Adjusted slightly for interest income.”

In Models 4 and 5, we then included perceived life expectancy and interest rates as main effects and in Model 6 as interactions with reporting attempts at math. Models 4 and 5 showed that estimates for life expectancy at age 65 and the interest rate were not related to annuity rates. But when interacting these valuation parameters with an indicator for having reported attempts at math (Model 6), the main effect for life expectancy as well as the interaction term were significant. Specifically, for participants who reported having guessed, perceived life expectancy played no statistically significant role in the valuation process. However, for participants who reported math, the interaction with life expectancy term's negative sign showed that such participants not only used a formula that is similar to an actuarial valuation but integrated valuation parameters in an economical meaningful way. The higher a participant estimated life expectancy, the lower the estimate for the annuity rate became as monthly payments have to last for longer periods. The interaction term with the interest rate was not significant, perhaps because very few participants thought about an interest rate in the first place (Table 4, Model 6).

Next, we analyzed the accuracy of participants' assessments. Specifically, we examined the dispersion of participants' assessments around an objective benchmark and how it related to the valuation process used (guessing, math, or Division Rule). Using a

<sup>10</sup>In Models 4–6, we use as the measure of life expectancy participants' estimate for females. Results hold as well if we include male life expectancy (available on request).

<sup>11</sup>At the time of the survey, the latest (end of 2016) OECD statistics reported estimates of 18 (male) and 20.6 years (female) (<https://data.oecd.org/healthstat/life-expectancy-at-65.htm>), while the Social Security Administration reported estimates of 19.2 years (male) and 21.6 years (female) (<https://www.ssa.gov/OACT/population/longevity.html>).

<sup>12</sup><https://www.treasury.gov/resource-center/data-chart-center/interest-rates/pages/textview.aspx?data=yield>

<sup>8</sup>The difference in means is significant at the 5% level ( $M_{lump-sum} = 45.34$ ,  $SD = 19.29$  vs.  $M_{payout} = 1.16$ ,  $SD = 1.07$ ,  $t(227) = 2.25$ ,  $p = .03$ ).

<sup>9</sup>When including three sophistication measures separately in Model 3, each coefficient is statistically significant at the 5% (subjective and objective numeracy) or 1% level (financial literacy).

**TABLE 4** Explaining the valuation result in Study 1

	(1) Annuity rate	(2) Annuity rate	(3) Annuity rate	(4) Annuity rate	(5) Annuity rate	(6) Annuity rate
Gender	−0.069 (0.339)		−0.240 (0.339)		−0.286 (0.340)	−0.171 (0.343)
Age	−0.035 (0.033)		−0.027 (0.033)		−0.029 (0.034)	−0.024 (0.034)
Education high	−0.633** (0.314)		−0.450 (0.319)		−0.425 (0.322)	−0.413 (0.322)
Income in \$'000	−0.009** (0.005)		−0.008* (0.005)		−0.008* (0.005)	−0.008* (0.005)
Savings in \$'000	−0.000 (0.001)		0.000 (0.001)		0.000 (0.001)	0.000 (0.001)
Risk tolerance	−0.003 (0.065)		0.013 (0.064)		0.001 (0.065)	−0.017 (0.065)
Time preference	0.001 (0.067)		0.025 (0.067)		0.038 (0.068)	0.054 (0.068)
Lump-sum condition	−1.736*** (0.286)	−1.674*** (0.278)	−1.730*** (0.281)	−1.626*** (0.288)	−1.680*** (0.282)	−1.574*** (0.284)
Subj. numeracy		−0.182* (0.102)	−0.113 (0.110)		−0.143 (0.113)	−0.131 (0.112)
Obj. numeracy		−0.107 (0.098)	−0.089 (0.102)		−0.106 (0.103)	−0.082 (0.103)
Financial literacy		−0.206* (0.117)	−0.200* (0.118)		−0.198* (0.118)	−0.223* (0.118)
Exp. years to live 65+, female				−0.001 (0.016)	−0.006 (0.016)	0.020 (0.020)
Interest rate on 10-year T-bond (%)				−0.137 (0.090)	−0.126 (0.089)	−0.116 (0.107)
Math				−0.080 (0.292)	0.330 (0.304)	1.994** (0.793)
Math × exp. years to live 65+						−0.077** (0.035)
Math × interest rate						0.000 (0.190)
Constant	1.191 (1.836)	0.064 (0.420)	1.620 (1.831)	−1.176*** (0.414)	2.111 (1.905)	1.088 (1.951)
Observations	229	229	229	229	229	229
Adjusted R-squared	.154	.178	.181	.121	.184	.196

Note: This table presents the results from OLS regressions of the log of the annuity rate on different sets of explanatory variables. Gender is a dummy variable (0 = male, 1 = female). Education is a dummy variable where a 1 indicates a level above the sample median ("Some college but no degree") and 0 otherwise. Lump-sum condition is 0 for the payout condition and 1 for the lump-sum condition. Math is a dummy variable (0 = not reported, 1 = reported). Standard errors are given in parentheses.

\*Statistical significance at the 10% level.

\*\*Statistical significance at the 5% level.

\*\*\*Statistical significance at the 1% level.

logit model, we regressed a measure of accuracy, that is, a dummy variable of having estimated an annuity rate within a 2-percentage points range around the market rate (=1) or not (=0) on participant characteristics and the process reported.<sup>13</sup> Results in Table 5 showed that demographic characteristics did not correlate with accuracy. When included separately, objective numeracy and financial literacy (Columns 1–3) positively predicted accuracy, while when included jointly (Column 4), they were not significant likely due to their correlation (Section 2.4). Having reported math or not was in no model significantly related to accuracy (Columns 1–4).

It seems that reports of having attempted math and integrating life expectancy into a formula predicted the valuation results directionally (i.e., higher life expectancy was related to lower annuity

rates; see Table 5) but not necessarily the accuracy. These results suggested that what is necessary to get an accurate result is not only mathematical reasoning and using the right formula but also the right ingredients for a formula (i.e., a realistic number for life expectancy<sup>14</sup>).

Potentially, only sophistication in combination with math leads to higher accuracy. To investigate this possibility, we interacted sophistication measures with having reported math or not. To do so, we selected financial literacy, as among the three measures, its coefficient's statistical significance was the largest ( $p = .025$ ; Column 3) and interacted it with having reported math or not. Moreover, to facilitate

<sup>13</sup>This result holds if we use instead of the average male–female annuity rate male or female annuity rates as well as an interval range of 1 percentage point.

<sup>14</sup>Note that the mean of life expectancy does not differ by having reported attempts at math or not (male:  $M_{no\ math} = 17.39$ ,  $SD = 9.03$  vs.  $M_{math} = 18.67$ ,  $SD = 8.58$ ,  $t(227) = -1.08$ ,  $p = .283$ ; female:  $M_{no\ math} = 21.35$ ,  $SD = 9.69$  vs.  $M_{math} = 21.92$ ,  $SD = 8.13$ ,  $t(227) = -0.46$ ,  $p = 0.643$ ).

**TABLE 5** Explaining accuracy in Study 1

	(1) Correct ±2%	(2) Correct ±2%	(3) Correct ±2%	(4) Correct ±2%	(5) Correct ±2%	(6) Correct ±2%	(7) Correct ±2%	(8) Correct ±2%
Gender	0.057 (0.070)	0.079 (0.071)	0.078 (0.071)	0.089 (0.071)	0.067 (0.070)	0.055 (0.070)	0.054 (0.070)	0.056 (0.071)
Age	−0.001 (0.007)	0.001 (0.007)	−0.002 (0.007)	−0.001 (0.007)	−0.001 (0.007)	−0.003 (0.007)	−0.001 (0.007)	−0.001 (0.007)
Education high	−0.023 (0.065)	−0.007 (0.063)	−0.009 (0.063)	−0.023 (0.065)	−0.014 (0.066)	−0.011 (0.065)	−0.025 (0.066)	−0.026 (0.066)
Income in \$'000	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Savings in \$'000	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Risk tolerance	0.010 (0.013)	0.012 (0.013)	0.009 (0.013)	0.010 (0.013)	0.008 (0.013)	0.009 (0.013)	0.007 (0.013)	0.007 (0.014)
Time preference	0.001 (0.014)	−0.000 (0.014)	0.004 (0.014)	0.000 (0.014)	0.003 (0.014)	0.003 (0.014)	0.003 (0.014)	0.004 (0.014)
Lump-sum condition	0.161 <sup>***</sup> (0.055)	0.164 <sup>***</sup> (0.055)	0.161 <sup>***</sup> (0.055)	0.162 <sup>***</sup> (0.055)	0.161 <sup>***</sup> (0.059)	0.128 <sup>**</sup> (0.059)	0.160 <sup>***</sup> (0.058)	0.156 <sup>***</sup> (0.060)
Subj. numeracy	0.032 (0.021)			0.016 (0.023)				
Obj. numeracy		0.039 <sup>**</sup> (0.017)		0.022 (0.020)				
Financial literacy			0.050 <sup>**</sup> (0.021)	0.032 (0.025)	0.046 <sup>**</sup> (0.021)	−0.002 (0.027)	0.040 <sup>*</sup> (0.021)	0.033 (0.023)
Exp. years to live 65+, female	−0.002 (0.003)	−0.001 (0.003)	−0.002 (0.003)	−0.001 (0.003)	−0.002 (0.003)	−0.005 (0.004)	−0.002 (0.003)	−0.001 (0.003)
Interest rate on 10-year T-bond (%)	0.009 (0.019)	0.009 (0.019)	0.009 (0.019)	0.008 (0.019)	0.009 (0.019)	−0.003 (0.022)	0.006 (0.018)	0.010 (0.020)
Math	0.071 (0.060)	0.074 (0.058)	0.073 (0.058)	0.056 (0.060)	0.079 (0.061)	−0.489 <sup>**</sup> (0.199)		
Math × exp. years to live 65+						0.011 (0.007)		
Math × interest rate						0.018 (0.039)		
Math × fin. literacy						0.114 <sup>***</sup> (0.041)		
Division rule							0.143 <sup>**</sup> (0.069)	0.110 (0.122)
Division × exp. years to live 65+								−0.002 (0.008)
Division × interest rate								−0.022 (0.049)
Division × fin. literacy								0.042 (0.046)
Constant					−0.005 (0.392)	0.309 (0.401)	0.009 (0.387)	−0.006 (0.389)
Observations	229	229	229	229	229	229	229	229
Pseudo R-squared	.063	.073	.075	.082				

TABLE 5 (Continued)

	(1) Correct ±2%	(2) Correct ±2%	(3) Correct ±2%	(4) Correct ±2%	(5) Correct ±2%	(6) Correct ±2%	(7) Correct ±2%	(8) Correct ±2%
Adjusted R-squared					.031	.064	.042	.034

Note: This table presents in Models 1–4 the marginal effects from logistic regressions of having estimated an annuity rate within an interval of  $\pm 2$ -percentage points around the market benchmark rate (=1) or not (0) on a having reported attempts at math (0 = not reported, 1 = reported) and different sets of explanatory variables. Gender is a dummy variable (0 = male, 1 = female). Education is a dummy variable where a 1 indicates a level above the sample median (“Some college but no degree”) and 0 otherwise. Lump-sum condition is 0 for the payout condition and 1 for the lump-sum condition. Reported are marginal effects at means of independent continuous and discrete dummy variables. Models 5–8 show results from corresponding models estimated with OLS. Models 7 and 8 use as a measure of attempts at math an indicator variable for the division rule (0 = not reported, 1 = reported). Standard errors are given in parentheses.

\*Statistical significance at the 10% level.

\*\*Statistical significance at the 5% level.

\*\*\*Statistical significance at the 1% level.

calculation and interpretation of interaction terms, we estimated the interaction models with OLS.

First, Column 5 reproduced the corresponding logit model of Column 3 with results being consistent. Column 6 then showed that based on the significant interaction term, the combination of math and having high financial literacy increased accuracy. In other words, being smart enough to use a formula and to understand how to use it was required to derive accurate valuation results.

Columns 7 and 8 showed corresponding results when we used, instead of having reported math per se, the indicator variable for having used a formula that is close to the actuarial formula, the Division Rule. In this specification, the dummy variable for having used such a formula was itself already significant—consistent with the results in Section 2.4 where we found that the use of such a formula was already an indicator of a higher level of sophistication and thus potentially lead to more accurate valuation results. Indeed, the interaction (Column 8) of having used the advanced formula and financial literacy was now not significant anymore.

Finally, we tested whether the request for participants to provide a description of their process impacted the annuity rates estimated and accuracy, that is, if social desirability impacted processes used by participants. Following Fox et al. (2011), we compared means and medians of the annuity rates as well as accuracy between participants that saw the request to report on their process on the same screen as the valuation task versus those who saw it on the subsequent screen. We did not find significant differences between those groups (see Table S2).

## 2.4 | Discussion of Study 1

The literature on annuities showed that individuals have difficulties to valuing them and that higher financial literacy and numeracy corresponded to valuations that are closer to realistic market prices (Bateman et al., 2018; Brown et al., 2017, 2021; McGowan et al., 2018). With Study 1, we first wanted to investigate if individuals report attempts at math when valuing an annuity, and if doing so

varies with viewing annuities from a lump-sum versus payout perspective, with financial literacy and numeracy, and with when the request to report on the process is shown (RQ1). In addition, we were interested in whether reported attempts at math, higher financial literacy and numeracy, estimates for future life expectancy and the interest rate, and viewing annuities from a lump-sum versus payout perspective relate positively more accurate annuity valuations (RQ2).

We find that 42% of participants report attempts at math, while the remaining participants seem to have guessed.<sup>15</sup> The frequency of reporting attempts at math is not related to being asked to assess the lump sum associated with a given payout or the payout associated with a given lump sum. Neither is it related to when the request to report on the process is shown. For participants who report math, their formula is sometimes close to the way that actuaries perform valuations, taking an estimate of future life expectancy, but ignores the interest rate. When calculating, some participants adjust numbers, for example, by rounding before a calculation (e.g., from 2800 to 3000) to probably ease calculation. Doing so is in line with the evidence on simplification strategies found in the literature on mathematics education (see, e.g., Campbell, 1995).

Participants who reported attempts at math are characterized by having higher financial literacy and numeracy. This finding is in line with Sinayev and Peters (2015) in that higher numeracy predicts using more sophisticated strategies but not in line with Cokely and Kelley (2009). The latter finds that when being confronted with tasks that require to calculate expected values, participants with higher cognitive abilities make more choices consistent with expected value calculation but rarely make such calculations and instead apply smart heuristics. We cannot perfectly explain whether the differences between the tasks across both studies yielded such different results. Potentially, the math applied in our case (e.g., the

<sup>15</sup>Reporting to having guessed is not likely to reflect a lack of participants' motivation while participating in the survey but indeed having guessed (see additional analyses in Supporting Information S1).

Division Rule) is a smart heuristic and math at the same time. Our finding that older age is often negatively related with attempts at math is consistent with an age-related decline of crystallized intelligence (e.g., Bruine de Bruin et al., 2007, 2014; Bruine de Bruin, Parker, & Fischhoff, 2012) and motivation to use numbers (Bruine de Bruin et al., 2015).

For those who reported attempts at math, longer estimated life expectancy at age 65 is associated with lower estimates of annuity payouts. Annuity valuations do not depend on when participants were asked to report about their process but did differ between with viewing annuities from a lump-sum versus payout perspective. Participants in the payout condition estimate higher annuity rates than those in the lump-sum condition.

We further find that reporting attempts at math per se does not result in higher accuracy, that is, estimating annuity rates that are close to market rates. We only find evidence for a positive relation for valuation accuracy and attempts at math for participants who have high financial literacy or used more advanced formulas (which itself is predicted by higher literacy). It seems thus that for achieving accurate valuations, it is not mathematical reasoning per se that is important but being able to identify the right formula (e.g., as in Foltice & Langer, 2017) and also use the right parameters in the formula, that is, a correct estimate of the life expectancy at age 65.

Finally, we do not find evidence that the mere act of asking participants to describe their thought processes affects thought processes reported nor other variables, for example, due to social desirability (Fox et al., 2011; Krumpal, 2013) or ex post rationalization (Eyster et al., 2021). That is, we do not find differences in the fraction of participants that reported attempts at math, the task duration, text length entered and annuity rates estimated, and accuracy between the half of participants that were asked to describe their thought processes as part of the instructions (and thus might have felt a need to report or use more sophisticated processes) and the other half that received this request after they completed the task (and thus could not anticipate being asked to report on their thoughts). Moreover, the evidence on the relations between attempts at math, financial literacy and numeracy, estimates for life expectancy at age 65, and annuity valuations is consistent with participants not only reporting attempts at math but also actually using math in combination with estimates of future life expectancy to assess the financial value of an annuity.

However, this evidence is still correlational and not causal. Potentially unobserved factors could have driven our findings. That is, instead through attempts at math valuation, results and accuracy might have been caused by unknown factors that are positively correlated with financial literacy, numeracy, and reporting attempts at math. We still thus lack causal evidence on whether some participants use math to value annuities. As estimates for life expectancy at age 65 play a central role in the attempts at math reported (e.g., by using the Division Rule), providing information on life expectancy in an experiment might be a promising candidate to gather causal evidence on whether or not a formula is used.

### 3 | STUDY 2: EXPERIMENTAL EVIDENCE

#### 3.1 | Development of the experiment and predictions

The aim of the experiment was to study if providing information on about future life expectancy (vs. no information) to participants causally changes their assessments of the financial value of annuities and thereby interest in annuities and how the effect varied with reported attempts at math. That is, first, we wanted to cross-validate our process evidence from Study 1. Second, we wanted to test if the process knowledge generated had helped to design meaningful interventions that could be used on practice to stimulate interest in annuities.

Study 1 showed that participants were on average in their assessment of life expectancy close to realistic estimates. For the experiment, thus, we needed to provide a numerical value that was smaller or larger than this value in order to be able to change annuity valuations.

At the same time, we aimed at increasing participants' interest in annuities—which posed some extra difficulty. On the one hand, if we provided a lower number than actual life expectancy, then in a payout condition, estimated annuity lump sums will decrease, and the annuity would have looked more attractive (the prediction for a lump-sum condition is identical). But, in practice, such a manipulation would add little value: As soon as participants received feedback on actual annuity lump sums (e.g., when looking up annuity rates on a website), they would experience a negative surprise in that actual annuity rates are worse than they expected and lose their interest in annuities. If we provided, on the other hand, higher number than actual life expectancy, then participants would be likely to view annuities as even more expensive (high lump sums needed) and lose their interest as well.

In consequence, we combined in the experiment the provision of a higher number than actual life expectancy (vs. no information) with immediate feedback (vs. no feedback) on annuity market rates. That is, first, we aimed to decrease annuity valuations and then by giving immediate feedback on market rates creating a positive surprise that was supposed to increase interest in annuities.

In particular, we used a two-by-two design. That is, we randomly assigned participants to one of the following four conditions: control and no feedback given; control and feedback given; life expectancy information and no feedback given; and life expectancy information and feedback given.

We expected that, first, compared with a control condition without information on life expectancy, subjects seeing on a higher number than actual life expectancy will estimate lower annuity rates. Second, we expected that giving feedback on market annuity rates increased interest in annuities irrespective of providing life expectancy information (as Study 1 valuations on average were too pessimistic). Third, we expected that compared with a control condition without information on life expectancy, giving feedback on market

**TABLE 6** Interest in annuities in Study 2

		Feedback condition		Difference	N
	Life expectancy condition	No feedback	Feedback		
Interest in annuities	Full sample	3.57	4.21	0.64	232
	Control	3.67	4.13	0.45	113
	Information	3.47	4.29	0.82	119
N		118	114		

Note: This table shows the mean interest in annuities in Study 2 for different conditions. Conditions differ by whether participants received a life expectancy information or not during the valuation task (control and information) and whether participants received feedback on market annuity rates before the indicated their interest in annuities. Interest in annuities are responses to the question “In general, how likely is it that you will be buying an annuity? (select 7 if you already own an annuity)” measured on a 7-point Likert scale from 1 (*Extremely unlikely*) to 7 (*Extremely likely*).

annuity rates increased interest in annuities stronger when subjects are provided a higher number than actual life expectancy. Fourth, we expected that our manipulations were ineffective for those who report no attempts at math as those participants used no formula that integrated life expectancy information.

## 3.2 | Method

### 3.2.1 | Procedure

#### *Experimental design*

Participants were randomly assigned to one of four conditions varying if information on life expectancy was provided or not and if feedback on market annuity rates was given or not. All participants started again by assessing the value of annuities and subsequently self-classifying the process they used for that task (instructions were identical to Study 1). Because Study 1 showed that the lump-sum condition and the payout condition yielded similar results, Study 2 only included the condition in which participants were asked to assess payouts associated with a provided lump sum of \$500,000.

In the instruction text for the annuity valuation, a random 50% of the sample was provided with a number higher than actual life expectancy through adding (similar as in Hurwitz, Mitchell, & Sade, 2022) the following sentence to the generic text all participants in Study 1 saw: “Note, 25 percent of the U.S. population live up to age 90 (that is another 25 years after age 65).” The numbers used were based on estimates of the distribution of number of years to live after age 65 (average of male and female) using U.S. mortality data (Milevsky, 2020). Thus, participants were not deceived. The other 50% of participants did not receive such additional information.

After all participants submitted their estimates for the annuity payouts, 50% of participants in each of the conditions (control and life expectancy information) received feedback on market annuity rates by being shown the following message: “You estimated that a person aged 65 will receive a lifetime payout of \$ <own estimate shown here> per month if s/he has saved \$500,000. Currently, U.S. insurance

companies offer lifetime payouts of about \$2,800 per month for a person that has saved \$500,000.”

Then, interest in annuities was elicited by asking all participants to respond to the following question “In general, how likely is it that you will be buying an annuity? (select 7 if you already own an annuity)” measured on a 7-point scale from 1 (*Extremely unlikely*) to 7 (*Extremely likely*). Next, participants responded to that same set of survey questions as in Study 1 (demographics, life expectancy, numeracy, ...).

#### *Additional control variables*

To test in additional checks if providing information on life expectancy affects interest in annuities through alternative mechanisms (other than through a formula), we also elicited participants' confidence in their numerical estimate right after the valuation task based on the 1-item scale of Gamble et al. (2015) (“How confident are you about this answer?” with seven response options varying from 1 (*Not confident at all*) to 7 (*Extremely confident*). Providing life expectancy as a valuation input might potentially increase confidence in the estimate derived. Being more confident could change participants' interest in annuities (see, e.g., Ben-David et al., 2018). In addition, after the question on interest in annuities, we elicited mortality salience with the 1-item scale used in Salisbury and Nenkov (2016) (“To what extent have you been thinking about death in the past several minutes while filling out the survey?” with seven response options varying from 1 (*Not at all*) to 7 (*A lot*). Providing information on how long people live might increase mortality salience and thus in turn reduce interest in annuities (Salisbury & Nenkov, 2016).

### 3.2.2 | Sample

The online survey was distributed by Qualtrics in August 2019 to a sample with the following criteria: U.S. resident, aged 45–60 (as in Study 1), and not having participated in Study 1. We received in total 232 complete responses. In terms of demographic characteristics, the sample was very similar to Study 1 with the difference that 54% were female (77% in Study 1). Table S6 shows descriptive statistics for the sample.



### 3.3 | Results

#### 3.3.1 | RQ3: Does providing participants with information about future life expectancy (vs. no information) change their assessments of the financial value of annuities and interest in annuities, and how does the effect vary with reported attempts at math?

First, we tested whether providing information on life expectancy affected participants' estimated life expectancy. Compared with the no information control group, male life expectancy increased by 3.4 years, and female life expectancy increased by 4.1 years. These increases were statistically significant (male:  $M_{\text{control}} = 16.60$ ,  $SD = 8.33$  vs.  $M_{\text{life expectancy information}} = 20.03$ ,  $SD = 8.78$ ,  $t(230) = 2.97$ ,  $p = .003$ ; female:  $M_{\text{control}} = 19.91$ ,  $SD = 9.53$  vs.  $M_{\text{life expectancy information}} = 23.98$ ,  $SD = 8.99$ ,  $t(230) = 3.34$ ,  $p = .001$ ).

Participants' estimated annuity rates (see details in Table S6) differed between the control and the life expectancy information conditions. Note that, in Table S6, we merged the feedback and no feedback conditions, as feedback on payouts was only given after the valuation result was entered by a participant and thus could not have impacted the valuation. In particular, annuity rates decreased when providing information on life expectancy. Like in Study 1, mean annuity payouts and the corresponding rates were impacted by outliers. Therefore, the difference in mean annuity rates (18.0%) was not statistically significant ( $M_{\text{control}} = 0.34$ ,  $SD = 2.32$  vs.  $M_{\text{life expectancy information}} = 0.16$ ,  $SD = 1.10$ ,  $t(230) = 0.76$ ,  $p = .45$ ), but the difference in medians (0.8%), which is a more robust and reliable measure in this case, was significant ( $Mdn_{\text{control}} = .05$  vs.  $Mdn_{\text{life expectancy information}} = .04$ ,  $\chi^2 = 6.88$ ,  $p = .009$ ). We concluded from these tests that providing information on life expectancy number reduced participants' estimated annuity rates.

Table 6 shows participants' interest in annuities in the different experimental conditions.

Comparing participants that received no feedback on annuity market rates with participants that received feedback irrespective of the life expectancy information condition (Table 6, line: full sample) showed that giving feedback increased interest in annuities by 0.64 on the 7-point scale. This difference between the conditions was statistically significant ( $M_{\text{no feedback}} = 3.57$ ,  $SD = 1.94$  vs.  $M_{\text{feedback}} = 4.21$ ,  $SD = 1.87$ ,  $t(230) = 2.57$ ,  $p = .011$ ) and thus is in line with our prediction that giving feedback on annuity market rates increased interest in annuities.

When comparing the effect of giving feedback on annuity market rates between the two conditions, control and life expectancy information, we found an increase in interest in annuities both conditions (Table 6), with the larger increase in the life expectancy information condition (0.45 vs. 0.82), but the increase was statistically significant only in the life expectancy information condition (no information:  $M_{\text{no feedback}} = 3.67$ ,  $SD = 2.02$  vs.  $M_{\text{feedback}} = 4.13$ ,  $SD = 2.08$ ,  $t(111) = 1.18$ ,  $p = .241$ ; life expectancy information:  $M_{\text{no feedback}} = 3.47$ ,  $SD = 1.86$  vs.  $M_{\text{feedback}} = 4.29$ ,  $SD = 1.65$ ,  $t(117) = 2.54$ ,  $p = .012$ ). These results implied that there was only partial support for our

prediction that the effect on interest in annuities through giving feedback should be independent of having provided information on life expectancy or not. However, consistent with our prediction was that we found that giving feedback had a larger positive impact on interest in annuities when participants have been provided on a higher number than actual life expectancy.

Next, we tested if providing life expectancy information changed annuity valuations only for those who used reported attempts at using math as those were the participants where we expected they would use the number for life expectancy provided in their formula. First of all, confronting participants with numerical information about life expectancy could have triggered different processes for estimating an annuity value. Analyzing the percentage of participants that reported attempts at using math showed that this was not the case. There were no significant differences between the conditions ( $M_{\text{control}} = .42$ ,  $SD = .50$  vs.  $M_{\text{life expectancy information}} = .51$ ,  $SD = .50$ ,  $t(230) = -1.34$ ,  $p = .18$ ).

Then, we analyzed annuity rates between the control condition and the life expectancy information condition separately for those who reported attempts at using math versus not. For those who reported attempts at using math, we found that annuity rates did not decrease significantly at the mean ( $M_{\text{control}} = .60$ ,  $SD = 3.45$  vs.  $M_{\text{life expectancy information}} = .07$ ,  $SD = 0.09$ ,  $t(107) = 1.19$ ,  $p = .24$ ) but at the median ( $Mdn_{\text{control}} = .05$  vs.  $Mdn_{\text{life expectancy information}} = .04$ ,  $\chi^2 = 6.65$ ,  $p = .01$ ). For those who reported no attempts at using math, we found that annuity rates did not decrease significantly at the mean ( $M_{\text{control}} = .15$ ,  $SD = .74$  vs.  $M_{\text{life expectancy information}} = .25$ ,  $SD = 1.57$ ,  $t(121) = -.47$ ,  $p = .64$ ) but again as well at the median ( $Mdn_{\text{control}} = .05$  vs.  $Mdn_{\text{life expectancy information}} = .03$ ,  $\chi^2 = 3.95$ ,  $p = .05$ ).

As finding a significant decrease for those who did not report attempts at using math was an unexpected result, we further looked into how participants might have incorporated the life expectancy information eventually in their assessments of the financial value of annuities.

For that, we analyzed the accuracy (i.e., dispersion) of estimated annuity rates. Like in Study 1, we used the log of the annuity rate as variable of interest. Then, we calculated group specific measures of dispersion. Groups were defined along the two dimensions: life expectancy information condition and having reported attempts at math or not. In particular, we first calculated the mean of the log of the annuity rate within each group. Then, we calculated for each participant the absolute distance to the group-specific mean of the log annuity rate. When we compared the means of the dispersion between those groups, we found that for those who did not report attempts at math, life expectancy information did not change the dispersion of estimated annuity rates ( $M_{\text{control}} = .88$ ,  $SD = .96$  vs.  $M_{\text{life expectancy information}} = .85$ ,  $SD = .91$ ,  $t(121) = .21$ ,  $p = .83$ ), but for those who reported attempts at math, the dispersion decreased significantly ( $M_{\text{control}} = 1.05$ ,  $SD = 1.70$  vs.  $M_{\text{life expectancy information}} = .50$ ,  $SD = .63$ ,  $t(107) = 2.34$ ,  $p = .02$ ). These results were consistent with our prediction that providing information on life expectancy was only effective for those who use math.

### 3.3.2 | Testing for alternative mechanisms

Presenting participants with a numerical information related to life expectancy at age 65 might have changed annuity valuations and/or interest in annuities not only through feeding into the valuation formula. To check for alternative mechanisms, first, we analyzed mortality salience as well as confidence in the value estimated. For both measures, we did not find significant differences between conditions (mortality salience:  $M_{\text{control}} = 3.35$ ,  $SD = 2.14$  vs.  $M_{\text{life expectancy information}} = 3.27$ ,  $SD = 2.09$ ,  $t(230) = .31$ ,  $p = .76$ ; confidence:  $M_{\text{control}} = 3.65$ ,  $SD = 1.91$  vs.  $M_{\text{life expectancy information}} = 3.61$ ,  $SD = 1.82$ ,  $t(230) = .17$ ,  $p = .87$ ).

## 3.4 | Discussion of Study 2

Study 1 provides evidence on the processes that individuals use to value annuities and shows that reporting attempts at using math is positively correlated with financial literacy and numeracy, annuity valuations that are closer to market rates, and that estimates of future life expectancy seem to be integrated into the math. In Study 2, we cross-validate if reports of attempts at math likely reflect the actual valuation process. In particular, we are interested if providing participants with numerical information on future life expectancy changes their assessments of the financial value of annuities and interest in annuities, and how the effect varies with reported attempts at math.

We designed an experiment where the manipulation is supposed to match a prominent valuation formula that participants reported in Study 1. There, we find that 42% of participants report to use a formula that includes a subjective estimate of life expectancy. Here, we provide 50% of participants information on future life expectancy so that they would use this number in their formula.

We find that providing information on life expectancy causally changed participants' annuity valuations and in turn increases their interest in annuities when combining it with feedback on market annuity rates. For participants who report attempts at math, the life expectancy information leads them to arrive at annuity valuations that are more accurate, that is, less dispersed around the mean, so the results of their valuations become more similar. For participants that report having guessed, providing the life expectancy information has no effect on the dispersion of annuity valuations. Interestingly, however, while this decrease in dispersion is consistent with participants using the formula, we also find that life expectancy information decreases estimated annuity rates at the median regardless of whether a participant reports attempts at using math or not. Additional evidence is however consistent with that providing information on life expectancy impacts valuations and interest in annuities through using it in the formula. Providing life expectancy information does not trigger higher mortality salience nor confidence on the annuity values estimated by participants.

So overall, we conclude from results in Study 2 that attempts as using math reported are likely a true reflection of the actual process individuals use to value annuities.

## 4 | GENERAL DISCUSSION

Annuities are financial products that should be attractive for individuals as they insure against running out of income in retirement. They are, however, rarely bought. The literature on annuities points toward that one reason for people to shy away from annuities is their perceived complexity which might require to do the math to understand them (Shu et al., 2016). Complexity in combination with low financial literacy and numeracy might make it for some individuals difficult to accurately assess the financial value an annuity can provide. With this contribution, we aim at identifying which processes people use to perform such valuations and link those to financial literacy, numeracy, estimates of future life expectancy, and valuation results.

When asking individuals how they value annuities, we find that 42% of participants in Study 1 report attempts at math. Most of them, use a simplified but correct version of the actuarial annuity valuation formula (i.e., the Division Rule)—except that no discounting is involved and not all participants include accurate parameter values (e.g., life expectancy) in the formula. The other 58% of participants say they guessed.

Based on a series of tests, it seems that what participants report they do corresponds to what they actually do. First, we show that reporting a more sophisticated process (math vs. guessing) is more likely among participants' that have higher objective and subjective numeracy as well as financial literacy. Second, we show that reports of having used math (and the corresponding formula) predicts the direction and accuracy of the valuation result: That is, for those who report attempts at math, higher estimated life expectancy is correlated with lower estimated annuity rates. For those who guess, this is not the case. Moreover, for those who report attempts at math and possess high financial literacy, the estimated annuity rates are more accurate. Their calculated values are closer to an objective benchmark (i.e., market annuity rates). Third, our test of causally changing annuity valuations and interest in annuities through an intervention that is only supposed to work if the process evidence of Study 1 reflects what participants actually did is successful. In Study 2, we use the insights from Study 1 to design an experiment where we provide information on future life expectancy. In Study 1, this was a parameter of the mathematical process found. In this out of sample test, we find that participants' annuity valuations become as predicted lower and interest in annuities changes as well in line with our predictions. That is, if we provide participants with feedback on market annuity rates, the lower valuations caused by the life expectancy information make annuities based on market rates look more attractive and interest in annuities increases.

### 4.1 | Theoretical implications

Shu et al. (2016) conjecture that as annuities are complex products and individuals need the ability to “do the math” to properly understand the value they can provide them. When analyzing annuity

valuation processes, we find that 42% of participants in our sample report to “do the math” when assessing the financial value of an annuity. Brown et al. (2017, 2021) find that valuations were closer to actuarial rates, the higher a participant's numeracy is. Our results show the process behind this finding: Higher numeracy is related to a higher likelihood to apply math, and using math is related to getting valuations that are on average closer to market rates. Likewise, Brown et al. (2017) conjecture that valuation results might derive from applying the heuristic: “How long will it take me to break even.” Our results uncover that a central element in the valuation formula that participants use is indeed the expected number of years an annuity is going to pay, that is, life expectancy. Our finding that participants ignore the interest rate in their reasoning, that is, neither compound or discount payments, could explain why the variation in interest rates does not relate to pension plan members' annuitization choices in Chalmers and Reuter (2012). The finding of Hurwitz, Mitchell, and Sade (2022) that an anchoring intervention increases interest in annuities in the presence of information on market annuity rates can be explained by our results derived in Study 2. There, we show that when one provides individuals with information on future life expectancy, they use this number in their valuation formula.

The difference in annuity valuations between our conditions in Study 1 (higher annuity rates in the payout than in the lump-sum condition) mimics the results of Binswanger and Carman (2010) in their analysis of backward versus forward valuations of consumption streams as well as Goldstein et al.'s (2016) analysis of annuity adequacy evaluations in lump-sum versus payout formats. Like Binswanger and Carman (2010), we have no clear evidence to explain this result. They find suggestive evidence that particular mistakes or loss aversion might partially explain the differences. For our data, however, these explanations are even less likely to hold. Binswanger and Carman (2010) document that a potential mistake participants could have made is to use the payout (in their case consumption) as an upper bound for the premium (in their case savings). In our data, less than 9% of respondents might have made such a mistake, while in their data, it is more prevalent (20%). Likewise, loss aversion is an unlikely candidate as our task referred to a third person, which makes it less likely to trigger strong feelings of gains and losses. Also, the difference cannot be explained by the ignorance in regard to discounting or compounding, as ignoring interest has the same effect in both conditions (mathematically) on annuity rates estimated. Potential other explanations, which we cannot test with our data, are, for example, the differences of the conditions in terms of dealing with small (payouts) versus large numbers (lump sum) (see also Goldstein et al., 2016), and multiplication (payouts) versus division (lump sum). There is evidence that small versus large numbers and multiplication versus division create a different level of difficulty and are processed differently in the brain (e.g., Campbell, 1995; Dehaene et al., 2008; Hyde & Spelke, 2009; LeFevre & Morris, 1999). Likewise, we cannot study whether this difference is caused by an endowment effect (i.e., in the lump-sum condition, one needs to give up an amount of money, while in the payout condition, one needs to pay for receiving something).

However, the difference in valuations between the conditions helps to understand widely documented low annuity demand: Participants who approach retirement planning in terms of a desired payout envision too high annuity rates than the market does deliver. Thus, they might initially view annuities positively (cheap) when thinking about them but will be negatively surprised (e.g., when checking rates on a website) when confronted with market lump sums needed to reach the desired payout. Thus, they shy away from annuities. Participants who approach retirement planning in terms of how much an accumulated nest egg (savings) will deliver might regard annuities from the beginning as poor products that deliver low payouts. For that reason, they might not even check out markets rates and as well shy away from annuities.

## 4.2 | Practical implications

Our experiment where we provided information on future life expectancy and feedback on market annuity rates reveals why studying individual decision-making processes is important beyond scientific curiosity and theory building but also for policy-makers. There is an ongoing discussion about which techniques are effective for improving households' financial decision-making. Initiatives to improve financial literacy often have limited success (Fernandes et al., 2014). The effectiveness of de-biasing and providing decision support seem to crucially depend on decision-makers' capabilities and (potentially biased) awareness of their skills (Cordes et al., 2019; Foltice & Langer, 2018). And while there are many examples of successful nudging interventions, numerous interventions have proven to be ineffective or even resulting in worse outcomes (see, e.g., O'Keefe & Hoeken, 2021; Sunstein, 2017). Our results demonstrate that investigating judgment and decision-making at a very basic process level helps to improve and deepen our understanding of how individuals approach such decisions and, therefore, provides a basis to design effective interventions or, depending on the results, to opt for other strategies.

## 4.3 | Limitations and directions for future research

For 42% of our participants, we improve our understanding of their valuation process, that is, for those who report attempts at math. For the other 58%, more work and methodological progress seems needed to understand what guessing really means. In addition, based on existing evidence on the processing of numbers (e.g., Campbell, 1995; Hyde & Spelke, 2009; LeFevre et al., 1993), more tests are needed to understand how the numbers presented in a decision-making scenario per se (e.g., small or large ones and round or nonround) are related to triggering certain decision-making processes (Hurwitz & Sade, 2021). Likewise, differences in culture or mathematical education at school might result in different processes used by individuals (e.g., Foltice & Langer, 2017, 2018) and, in consequence, require different interventions. Also, we did not ask about bequest

motives or participants' number of children, which are important for financial decisions about annuities (e.g., Inkmann et al., 2011; Lockwood, 2012; Ponds et al., 2022). However, bequest motives likely do not affect our main findings in Study 1 as we used vignettes in which all participants were presented with the same information. The findings of Study 2 are likely unaffected by bequest motives because participants were randomly assigned to conditions in a between-subjects design. Yet, future research should examine whether bequest motives might moderate how people assess the value of annuities. In addition, using the more granular P-Fin Index (Yakoboski et al., 2020) to assess financial literacy along eight different dimensions might uncover additional insights on who uses which valuation process and how that relates to valuation outcomes. Our sample is not representative and was predominantly female. However, we find that accounting for gender does not affect our main conclusions in both studies.

Finally, our studies examine participant's evaluations of hypothetical annuities, and thus, external validity may be limited. When making actual judgments and decisions about annuities, it is possible that people would be more (or less) likely to use math. That is, our estimates at the mean (e.g., the fraction reporting attempts at math and annuity rates) should not be taken at face value.

## DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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