WORKING PAPER

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A megastudy on occupational pension uptake decisions

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Abstract

In an online vignette study involving 15,593 participants, we investigated the effectiveness of various nudging interventions, including defaults, pre-commitment strategies, evaluative labels, social norms, and their combinations, on annuity uptake decisions within the occupational pension scheme. Participants decided how to allocate their pension funds between a lump sum and an annuity using a continuous decision slider, offering a more flexible alternative to traditional binary choices. Our findings revealed a small but statistically significant effect of pre-commitment strategies on annuitization. However, contrary to expectations, all other interventions (defaults, social norms, evaluative labels, and their combinations) showed no significant effect on annuity uptake. Notably, we observed a consistent decision pattern across all conditions. On average, across all conditions, 51.2% of participants opted for less than 5% annuity uptake, 34.5% chose a mix, with a significant peak of 13% at exactly 50% annuity uptake, and 14.3% selected more than 95% annuity. This clustering around round numbers suggests a "round number bias" influenced by the 0–100% continuous scale used, where participants gravitated towards cognitively straightforward, salient options. These findings align with recent debates questioning the general effectiveness of nudging interventions, particularly in complex financial decisions, often involving deeply rooted preferences. The present study highlights the limitations of nudges in shifting behavior as our study also underscores the need for a better understanding of the driving forces behind annuity uptake rationales to effectively influence annuity uptake decisions.

Statement of relevance

Understanding how individuals make decisions about annuitizing their occupational retirement savings is crucial for policymakers and financial institutions aiming to promote long-term financial security. The present study provides valuable insights into the limited effectiveness of behavioral nudges (defaults, pre-commitment strategies, evaluative labels, and their combinations) in influencing annuitization decisions. Despite the growing use of these interventions in various financial domains, our findings suggest that individuals may resist external nudges when faced with complex, high-stakes decisions like retirement planning. Moreover, the identification of a substantial portion of the population who seems open towards partial or full annuitization highlights an important market for tailored annuity retirement products. These insights can shape the design of more effective policy interventions and financial tools that consider personal preferences, financial literacy, and risk tolerance. The present study not only advances academic understanding of behavioral decision-making in retirement planning but also provides actionable recommendations for improving the design of retirement systems and financial advice platforms.

1. Introduction

Global life expectancy has doubled over the last two centuries, with the average reaching over 70 years in 2021, compared to just 29.3 years in 1850 (Dattani et al., 2023). The OECD (2023) projects that by 2050, the proportion of individuals aged 65 and over will further increase from 18% in 2022 to 27%, outnumbering those aged 15-24. Combined with dropping birth rates (Eurostat, 2024), the demographic shift towards an aging population has placed immense pressure on the public pension systems globally. Adverse budgetary conditions (Bayar, 2018) and persistently low interest rates (Bielecki et al., 2020), have contributed to a declining ratio between retirement income (i.e., the sum of pillar I, II, and III pensions[1]) and the employment income at retirement (OECD, 2019). This trend has introduced concerns about the sustainability of pension systems across Europe. Several studies suggest that a part of the solution lies in stimulating choice for annuity products to mitigate shortages in old age (Benartzi et al., 2011; Inkmann et al., 2008).

Annuities are financial products that offer a solution for households and individuals to guard against longevity risk by converting a portion of their wealth into a guaranteed income stream until death. Rational choice theory predicts that individuals facing uncertainty about their lifespan, should always opt for annuities when nearing retirement to ensure financial stability (Davidoff et al., 2005; Yaari, 1965). However, empirical evidence consistently shows that few retirees actively choose to ever annuitize a significant part of their wealth, a phenomenon better known as the "annuity puzzle" (Modigliani, 1986). This behavior remains poorly explained by traditional economic models, which assume rational decision-making.

In the current study, we aim to address the universally acknowledged annuity puzzle through a large online vignette study, using data from a European country (Belgium). In contrast to real-life settings where pension choices are typically limited to a binary decision

[1] European pension systems often include three pillars: state pensions (Pillar I), employer-sponsored pensions (Pillar II), and voluntary personal savings (Pillar III), with terminology varying by country.

between a lump sum and an annuity, this study reframes the work-related Pillar II pension take-up decision as a continuous choice, in order to tap into more gradual decision preferences. To this extent, we asked participants what percentage of their work-related pension they want to annuitize. Utilizing a megastudy design, we examine the effects of defaults, social norms, evaluative labels, pre-commitments, and their combined interventions in an online choice environment that is presented to thousands of people. Additionally, for the purpose of describing our study sample, we collect data on general demographics, financial literacy, Big Five personality traits, self-efficacy, and self-control.

Despite the clear advantages of annuities for securing lifetime income and hedging against longevity risk, many people are reluctant to purchase them (Modigliani, 1986). Economic theories propose several rational explanations for this annuity puzzle, such as bequest motives (Lockwood, 2012), uncertainty about life expectancy (Edwards, 2008; Hurd & McGarry, 1995; Wu et al., 2015), low financial self-efficacy (Baláž, 2023), financial (annuity) literacy (Brown, 2007; Goedde-Menke et al., 2014; Lusardi & Mitchell, 2011), the irreversible character of annuities (Sinclair & Smetters, 2004), pre-existing state pension annuitization through social security (Dushi & Webb, 2004), adverse selection (Finkelstein & Poterba, 2004), market incompleteness (Davidoff et al., 2005), pricing considerations (Mitchell et al., 1999; Wettstein et al., 2021), and the option value of delaying annuitization (Milevsky & Young, 2007). However, none of these accounts can fully explain the observed non-purchase behavior of annuities in real-world markets through rational utility based models (Benartzi et al., 2011; Dushi & Webb, 2004).

Financial decisions, including those about annuities, are seldom made in a vacuum. While traditional economic models offer valuable insights, they often overlook the substantial influence of psychological factors (that may be economically irrational or suboptimal), cognitive biases, emotional responses, and contextual forces that shape individual choices

(Benartzi et al., 2011). Over the last decades, behavioral economics has emerged as a crucial lens to examine and explain the annuity puzzle, offering novel insights into its psychological underpinnings.

Central to the field of behavioral economics, lies the dual system theory, which distinguishes between two modes of thinking: the intuitive and automatic "System 1," and the deliberative and effortful "System 2" (Kahneman, 2011). System 1 operates rapidly and emotionally, using heuristics, while System 2 is thought to be slower, logical, and capable of complex reasoning. Although System 2 is often ideal for complex decisions, it demands significant cognitive resources and depletes easily (Baumeister et al., 1998).

To address these cognitive tendencies, behavioral economists employ "nudges". These nudges are subtle changes in choice architecture that can guide individuals towards better decisions without restricting freedom of choice (Thaler & Sunstein, 2008). Nudging interventions have shown considerable promise in influencing financial decision-making. For instance, Madrian & Shea (2001) found that changing the default option in 401(k) plans from non-enrollment to automatic enrollment, dramatically increased participation rates from 37% to 86%, showcasing the power of default effects. Thaler & Benartzi 's (2004) further expanded on this seminal work with the Save More Tomorrow™ program. This occupational pension savings program employed a pre-commitment strategy where employees pledged future salary increases to retirement savings, resulting in nearly quadrupled average savings rates from 3.5% to 13.6% over 40 months. In the realm of investment decisions, Beshears et al. (2015) revealed that social reference information can have nuanced effects. Indeed, when low-saving employees were informed about the high savings rates of their peers, instead of motivating them to save more, their savings rates decreased by 0.11 percentage points. However, when peer information was thoughtfully framed to emphasize positive behaviors and achievable goals, it led to an increase in savings rates of up to 1.1 percentage points.

Sunstein (2014) provides a comprehensive catalog of ten key distinct nudges, including defaults, social norms, pre-commitment strategies, implementation intentions, and simplification. Building on the work of Sunstein (2014), Mertens et al. (2022) categorized these nudges into three broad categories (see Table 1): decision structure (DS), decision assistance (DA), and decision information (DI). This categorization allows for a more nuanced understanding of how different types of nudges operate and their relative effectiveness across various domains.

First, DS interventions, which alter the arrangement of choice options (like changing choice defaults, altering range or composition of options, consequences or option-related effort) show the strongest effects on behavior change (d = 0.54). In the finance domain, these interventions demonstrate an average effect size of d = 0.33). Second, DA interventions (like providing reminders or facilitating commitment), which aid in follow-through with intentions, show a moderate effect (d = 0.28), with a finance-specific effect size of d = 0.21). Lastly, DI interventions (like providing social reference points, making information visible or adapting already available information attributes), which modify how information is presented, demonstrate an overall effect size of d = 0.34, with a finance-specific effect size of d = 0.23 (Mertens et al., 2022).

In the present study, our very large sample allows the simultaneous test of several nudge strategies to the context of work-related annuity take-up decisions, spanning every intervention category as proposed by Mertens et al. (2022). Table 1 provides an overview of the specific nudges employed, their category, their potential effects on financial decision-making, relevant references, and their implementation in this study.

Table 1
An overview of the nudges implemented in the current study

Category	Nudge	Description and Potential Effect on Financial Choice Behavior	Key references	Implementation in Current Study

DS	Defaults	Pre-selected options significantly influence choices due to inertia and status quo bias. Can dramatically affect retirement savings and annuitization rates.	Madrian & Shea (2001); 5/02/2026 21:39:00	Varying default annuitization rates (3 conditions: 0%, 50%, 100%)
DS	Reframing Binary Decisions	Altering the presentation of choices from binary to continuous can reduce ambiguity aversion and engage more deliberative thinking.	Brown et al. (2008); Agnew et al. (2008)	Reframing annuity choice from binary (annuity vs. lump sum) to continuous (percentage to annuitize); implemented uniformly across all conditions
DA	Pre-commitment reminders	Making decisions about future behavior addresses present bias and promotes long-term planning. Reminders on "if-then" plans bridge the gap between intentions and actions.	Thaler & Benartzi (2004); Beshears et al. (2015) Gollwitzer & Sheeran (2006); Soman & Zhao (2011)	Asking participants to state expected monthly needs in retirement and reminding them of their stated monthly needs during the annuity choice task (2 conditions: yes/no)
DI	Social Reference	Providing information about peers' behavior can influence decisions through social comparison and conformity.	Brown et al. (2008); Duflo & Saez (2003)	Informing participants about average Belgian pensioner's monthly expenses (2 conditions: yes/no)
DI	Evaluative Risk Labels	Simplified, visual risk assessments reduce cognitive load and leverage intuitive thinking.	Bateman et al. (2016); Vlaev et al. (2009)	Color-coded risk score indicating adequacy of chosen annuitization level ‘2 conditions: yes/no)

Note. DS= Decision Structure; DA= Decision Assistance; DI= Decision Information.

The interventions we selected for the current study are based on their proven effectiveness in other domains of human decision-making, their potential influence in financial contexts, and practical considerations. The reframing of the annuity choice task from binary to continuous format was applied to all participants as part of the outcome measure design, and was not experimentally varied. All other nudges were implemented through separate experimental conditions to examine their causal effects on annuitization decisions.

The current study investigates the effectiveness of various nudging interventions on annuity uptake decisions in work-related pension decisions. Employing a megastudy-inspired design, we conduct a large-scale online vignette study testing 24 conditions from a 3 x 2 x 2 x 2 full factorial design. We explore defaults, pre-commitment strategies, evaluative labels, social norms, and all their combinations, while also controlling for gender and age. Our aim is to address the annuity puzzle by enabling direct comparisons of intervention efficacy in influencing occupational pension take-up decisions. Rather than simulating the real-world

decision as a binary choice between a lump-sum payout and monthly annuitization, participants were given a more flexible, continuous option. This approach allowed for a more nuanced exploration of participants' preferences, giving them the freedom to choose any proportion of each option rather than being forced into a binary decision. By examining strategies across categories defined by Mertens et al. (2022), we provide a comprehensive comparison of behavioral interventions. Table S1 of the Supplementary information provides a complete study overview of the conditions. To our knowledge, this is the first study to apply a megastudy-inspired approach to explore the annuity puzzle, contributing significantly to behavioral science literature, pension decisionmaking and practical retirement policy.

When controlled for age, sex, and the other types of decision interventions, we aim to address the following research questions:

RQ1: How do DS interventions (defaults), DA interventions (pre-commitment strategy), and DI interventions ((1) social norms and (2) evaluative risk labels) independently influence annuitization decisions?

RQ2: How do multi-way interactions between DS, DA, and DI interventions affect annuitization?

RQ2.1: Do DA interventions moderate the DS–annuitization relationship?

RQ2.2: Do DI interventions ((1) social norms and (2) evaluative risk labels) moderate the DS–annuitization relationship?

RQ2.3: Do DA and DI interventions (1) social norms and (2) evaluative risk labels) interact to influence DS–annuitization?

RQ2.4: Do DI interventions (evaluative risk labels) interact with DI interventions (social norms) on annuitization?

RQ2.5: Do three-way interactions among DS, DA, and DI interventions affect annuitization?

RQ2.6: Do four-way interactions among DS, DA, and both DI type interventions affect annuitization?

2. Method

2.1 Participants

Calls for participation were distributed via social media, national newspapers, social secretaries, and university hospitals to ensure a representative sample of the Belgian adult population. Inclusion criteria required participants to be aged between 18 and 66 years old and not pensioned. The initial sample consisted of 32,067 entries. Incomplete data entries, entries with the pre-selected birth year of 1970 (a significant outlier), and non-binary gender entries[2] were also excluded, resulting in a final sample comprising 15,593 participants.

The mean age of participants was 54 years (SD = 12.85, 42.8% female). Participants reported a mean subjective life expectancy of 85.86 years (SD = 8.628), which is slightly optimistic compared to official estimates. In 2023, life expectancy at birth in Belgium was 82.3 years, 84.3 years for women and 80.2 years for men (Statbel, 2024). A comprehensive summary of the non-categorical descriptive statistics of the study population's individual characteristics can be found in Table S2 of the Supplementary Information.

As compensation, participants who completed the full questionnaire received an automated personalized 8-page research report. This report provided their personality profile, based on their answers on the mini-IPIP scales compared Belgian norm data from Donnellan et al. (2006), and their statistical probability of reaching 80 and 90 years, based on national longevity statistics from the IABE institute[3] (Antonio et al., 2020). This compensation strategy was designed to encourage truthful responses by offering personalized, valuable information to participants.

[2] Non-binary gender data were excluded due to insufficient sample size, preventing robust analysis.
[3] A membership organization for the actuarial profession in Belgium.

2.2 Design & Procedure

This study employed a randomized 3x2x2x2 between-subjects design (See Figure 1). Upon visiting the study website, participants were presented with a general introduction, and got informed about the voluntary and anonymous nature of the study, with a personalized research report serving as the sole participation incentive. After explicit agreement to the informed consent, participants interacted with a chatbot through a mobile interface designed to simulate a smartphone messaging experience (see Figure S1, for an example of the study interface). Subsequently, participants were asked to provide general demographic information (birth year, gender, and income).

The core of the experiment involved a vignette that described a retirement scenario. Participants were asked to imagine that they were 66 years old, about to retire, and eligible for a government-provided pension of €1,500 per month[4]. Additionally, they were informed that they had built up a €100,000 occupational pension fund through joint employer-employee contributions during their career. Subsequently, participants were asked to decide how they would like to take out this €100,000 pension fund using an interactive interface with two linked sliders (as illustrated in Panel D of Figure S1, and in Figure S3). The first slider indicated what percentage of the €100,000 they wanted to convert into monthly lifelong payments (annuitization), while the second slider automatically showed the remaining percentage they would receive as a one-time payment (lump sum). For example, moving the annuitization slider to 50% would result in €50,000 being converted to monthly payments of €246 for life, starting at the retirement age of 67, with the remaining €50,000 received as a lump sum. The sliders allowed for continuous adjustment between full annuitization (100% = €492 monthly for life, no lump sum) and full lump sum (0% = €100,000 one-time payment at

[4] A single, Belgian retiree reviving the minimum pension in January 2023 receives an average statutory pension income of €1,574 (Belgian Federal Pension Service, 2023).

retirement age, no monthly income). This allowed participants to choose any combination of monthly and one-time payments, with both percentages always totaling 100%.[5]

2.3. Implementation of Interventions

(1) Default Settings (DS).

Participants encountered one of three initial slider positions (see Figure S3): 0% annuitization (0-100), 100% annuitization (100-0), or equal distribution (50-50). These defaults served as participants' starting points, from which they could freely adjust their allocation.

(2) Pre-commitment (DA).

In conditions with pre-commitment (see Figure S4), before making their allocation decision, participants were asked to estimate the additional monthly income they believed they would need on top of their government pension during retirement. This estimate was later used as a visual reference point on the sliders during their decision-making process on annuitization allocation.

(3) Social Norms (DI).

In conditions with social norm information (see Figure S4), participants were shown that the average monthly expenses of a Belgian retiree amounted to €1,704. This reference point was indicated on the sliders to anchor participants' expectations regarding their retirement income needs.

[5] These monthly payment rates, while more generous than typical market rates, were deliberately calibrated to be actuarially advantageous beyond age 84 (17 years post-retirement). This design ensures annuitization is clearly economically advantageous for those with average life expectancy, making the persistent low annuitization rates (the "annuity puzzle") more striking and providing a conservative test of our behavioral interventions. Figure S2 illustrates these economic dynamics by simulating wealth trajectories under different distribution choices, demonstrating the annuity's increasing advantage beyond the break-even age.

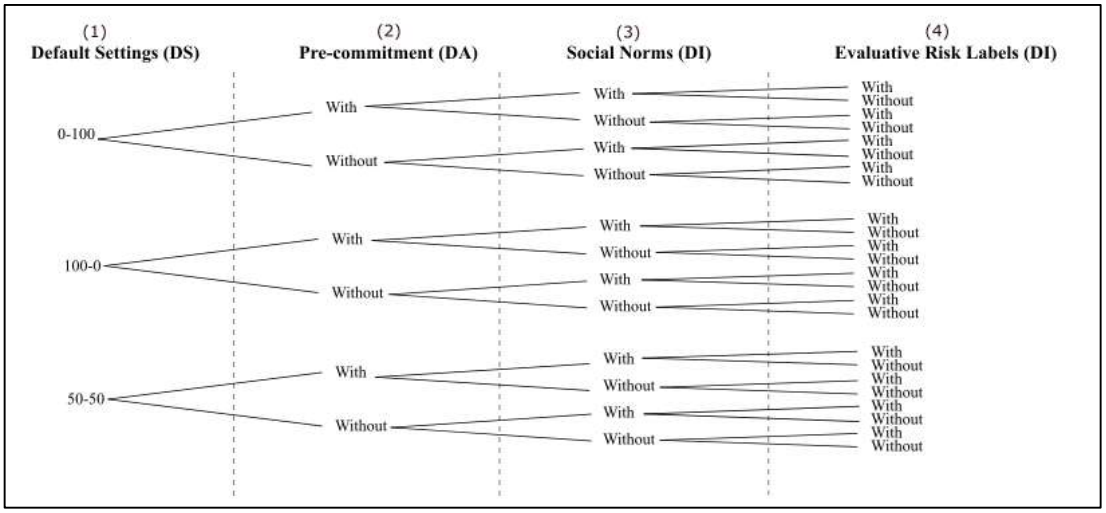
(4) Risk Labels (DI).

In conditions with evaluative risk labels (see Figure S5), participants received dynamic feedback on their choices through color-coded risk scores (A to D). These labels updated in real-time as participants adjusted their allocation, with greener scores (A) indicating better protection against longevity risk through higher annuitization levels, and redder scores (D) warning about increased risk from higher lump-sum percentages.

All the four interventions were crossed, leading to a 3 (Default Settings) *2 (Pre-Commitment) *2 (Social Norms) *2 (Evaluative Risk Labels) full factorial design with 24 conditions.

Figure 1

Study design (3x2x2x2)



Note. Our 3x2x2x2 design showing four manipulated variables: Default Settings (DS)(1), Pre-commitment (DA)(2), Social Norms (DI)(3), and Evaluative Risk Labels (DI)(4), resulting in 24 unique experimental conditions.

2.4. Study design (3x2x2x2) Analyses

Descriptive statistics (see Table S2 and S3) were calculated for non-categorical individual characteristics (e.g., age), while frequencies were reported for categorical variables (e.g., gender).

To address our research questions, we employed a univariate linear regression using the General Linear Model (GLM) procedure. The dependent variable was annuitization (the percentage allocated to the annuity option), with the four decision intervention variables, and age and sex as additional independent variables.

Significant main effects (RQ1) were further investigated using Pairwise Comparisons to evaluate the differences in estimated marginal means, controlling for other predictors in the model. When decision intervention variables consisted of more than two categories (e.g., information interventions), a Bonferroni correction was applied to control for multiple comparisons. Additionally, we calculated Hedges' g to report effect sizes, as it is particularly suitable for comparing groups of unequal sizes.

Significant interactions (RQ2 and its sub-RQ's) were explored through Bonferroni-adjusted Pairwise Comparisons of estimated marginal means, controlling for other predictors, and Hedges' g was again used to measure effect sizes across groups.

Given the large sample size and non-normal distribution of annuitization choices, we validated our findings using non-parametric Tobit regression model, which yielded consistent results.

2.5. Ethical considerations

The study received formal approval from the university ethics board (reference code 2021/138 FWO project number S006721N). All participants provided informed consent after being informed about the study's purpose, voluntary nature, and their right to withdraw at any time.

Data was collected anonymously, with no personally identifiable information linked to participants' responses. Email addresses for personalized reports were stored separately to ensure privacy. The study complied with GDPR regulations, ensuring secure and responsible data handling.

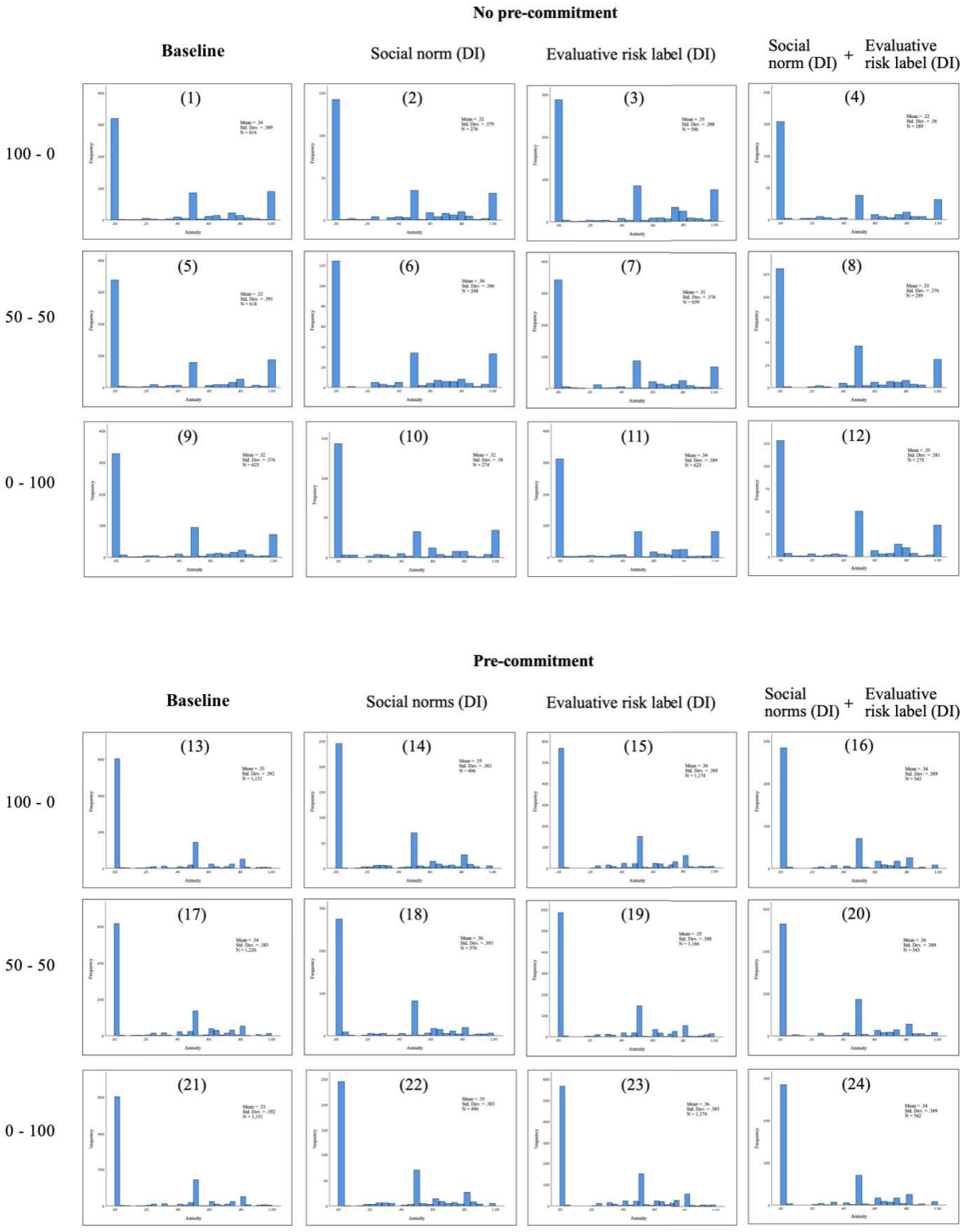
Minimal risks were involved, as participants only engaged with hypothetical retirement scenarios.

3. Results

Figure 2 presents frequency distributions of annuitization choices (0-100%) for conditions without and with pre-commitment. Histograms are organized by default settings (100-0, 50-50, 0-100) and decision information interventions (nothing, social norms, evaluative risk labels, combined). We refer to Table 2 for the detailed results regarding the degrees of freedom, and significance levels of the (interaction) effects of the different decision interventions on annuitization.

Figure 2

Distribution of Annuitization Choices Across Experimental Conditions



Note. Frequency distributions by default settings (rows: 100-0, 50-50, 0-100) and decision information (columns: nothing, social norm, evaluative risk label, combined) for conditions without pre-commitment

(top panel) and with pre-commitment (bottom panel). Numbers (1-24) correspond to conditions in Table S1. M = mean percentage, Std. Dev. = standard deviation, N = sample size.

For RQ1, we investigated how do DS interventions (defaults), DA interventions (pre-commitment strategy), and DI interventions (in terms of (1) social norms and (2) evaluative risk labels) independently influence annuitization. GLM analysis indicates a significant effect of DA interventions on annuitization ($g = 0.05$). Pairwise Comparisons reveal that individuals who were exposed to a pre-commitment strategy ($M = .36$, $SE = .004$, 95% CI [.35, .36]) opt to annuitize a slightly higher percentage of their work-related pension than individuals who were not exposed to a pre-commitment strategy ($M = .34$, $SE = .01$, 95% CI [.32, .35]). No significant effect is found for decision structure interventions in terms of (1) social norms and (2) evaluative risk labels. For an overview of the pairwise comparisons' results, see Table 3.

For RQ2, we examined how multi-way interactions between DS, DA, and DI interventions affect annuitization. For RQ2.1, no significant interaction effect was found between DS and DA interventions on annuitization. For RQ2.2, results showed non-significant interaction effects between DS interventions and both types of DI interventions (social norms and evaluative risk labels). For RQ2.3, we found no significant interaction effects between DA interventions and either type of DI interventions (social norms and evaluative risk labels). For RQ2.4, DI interventions in terms of evaluative risk labels did not significantly interact with DI interventions in terms of social norms on annuitization. For RQ2.5, none of the three-way interactions between DS interventions, DA interventions, and DI interventions (both social norms and evaluative risk labels) were significant. For RQ2.6, the four-way interaction between DS interventions, DA interventions, and both types of DI interventions were non-significant. We emphasize that all these null effects were obtained despite the very large statistical power resulting from the megastudy approach.

Table 2

Results Tests of Between-Subjects Effects

(Interaction) Effect Decision Interventions	df	*F*	Sig.	RQ
DS	2	0.48	.616	1
DA	1	8.56	.003**	1
Social Norms (DI)	1	0.22	.643	1
Evaluative Risk Labels (DI)	1	1.71	.191	1
DS * DA	2	0.62	.538	2
DS * Social Norms (DI)	2	1.40	.247	3
DS * Evaluative Risk Labels (DI)	2	0.54	.582	3
DA * Social Norms (DI)	1	0.18	.670	4
DA * Evaluative Risk Labels (DI)	1	0.17	.679	4
Social Norms (DI) * Evaluative Risk Labels (DI)	1	0.22	.636	5
DS * DA * Social Norms (DI)	2	1.18	.306	6
DS * DA * Evaluative Risk Labels (DI)	2	0.77	.462	6
DS * Social Norms (DI) * Evaluative Risk Labels (DI)	2	0.01	.991	6
DA * Social Norms (DI) * Evaluative Risk Labels (DI)	1	0.03	.865	6
DS * DA * Social Norms (DI) * Evaluative Risk Labels (DI)	4	0.49	.631	7

Note. **$p < .010$. df = degrees of freedom. RQ = research question. The dependent variable concerns annuitization. $df_{error} = 15{,}567$. Controlled for age and sex. DS= Decision Structure, DA= Decision Assistance, DI= Decision Information

Table 3

Estimates Pairwise Comparisons DS, DA and DI (in Terms of Social Norms and Evaluative Risk Labels) Interventions

Decision Interventions	*M*	*SE*	95% Confidence Interval	
			Lower Bound	Upper Bound
DS				
0-100	.34	.01	.33	.35
100-0	.35	.01	.34	.36
50-50	.34	.01	.33	.36
DA**				
No Pre-Commitment	.34	.01	.32	.35
Pre-Commitment	.36	<.01	.35	.36
DI – Social Norms				
No Social Norms	.34	.01	.34	.35
Social Norms	.35	.01	.34	.36
DI – Evaluative Risk Labels	.35	.01	.34	.36
No Evaluative Risk Labels	.34	.01	.33	.35
Evaluative Risk Labels	.35	.01	.34	.36

Note. The means represent the estimated marginal means (i.e., controlled for age and sex). **A significant effect on annuitization is found for decision assistance interventions (p <.010). Adjusted R Squared = .02

4. Discussion

Despite numerous economic theories addressing the 'annuity puzzle', a clear explanation for why retirees avoid annuitization remains elusive, with existing theories failing to fully account for observed behaviors across diverse contexts (Agnew et al., 2008; Beshears et al., 2014; Brown et al., 2008a; Dushi & Webb, 2004). This study explores the influence of Decision structure (DS) interventions (defaults), Decision Assistance (DA) interventions (pre-commitment strategies), Decision Information (DI) interventions (more specifically, (1) social

norms and (2) evaluative risk labels), and their combinations on the decision to allocate a portion of their occupational pension funds towards annuitization. We found that only DA interventions had a small but significant effect on annuitization ($g = 0.05$), with participants exposed to a pre-commitment strategy opting to annuitize a higher percentage of their pension (i.e. 36%) compared to those not exposed (34%). In contrast, DS and DI interventions did not yield significant effects on annuitization. Furthermore, no significant interaction effects were found between the different types of interventions and annuitization for RQ2 nor its sub-RQ's, suggesting that these interventions operated independently rather than interacting to influence decision-making.

4.1.Effectiveness of pre-commitment strategies

The significant effect of pre-commitment strategies on annuitization supports the existing literature, which highlights the power of commitment devices in promoting long-term behavioral outcomes, such as financial planning (Ashraf et al., 2006; Thaler & Benartzi, 2004). By encouraging individuals to commit to future goals, pre-commitment may help overcome present bias, often leading individuals to prioritize immediate needs over long-term security (O'Donoghue & Rabin, 2015). However, the (very) small effect size indicates that while pre-commitment nudges can be effective, their impact may be limited in the context of annuitization decisions. This suggests that additional or alternative interventions may be necessary to produce more substantial changes in behavior. Of course, it remains true that only a minor intervention without a meaningful cost is needed to trigger this effect and that even a small effect may correspond to considerable amounts of money in the volume of the entire population.

Recent theoretical developments in understanding commitment devices offer deeper insights into why pre-commitment showed modest effectiveness in our study. Rather than simply overriding present bias through external constraints, pre-commitment strategies may

work by triggering inferential processes about personal goals and their implementation (Van Dessel et al., 2022). When individuals are prompted to consider their future needs, this may activate both immediate intuitions about financial control and competing intuitions about long-term security (De Neys, 2023). This aligns with emerging evidence that financial decision-making involves multiple simultaneous intuitive processes rather than a simple conflict between intuitive and deliberative thinking (Voudouri et al., 2024). The small effect size we observed might therefore reflect that pre-commitment successfully activated long-term oriented intuitions about retirement security, but these had to compete with equally strong intuitions about maintaining financial flexibility and control. This interpretation is supported by research showing that commitment devices are most effective when they align with, rather than override, existing goals and preferences (Beshears et al., 2015; Rogers et al., 2014). In the context of pension decisions, where individuals face genuine uncertainty about future needs and circumstances, even activated long-term oriented intuitions may not be sufficient to overcome deeply held preferences for financial flexibility. This suggests that effective interventions might need to focus on reshaping how people think about the trade-off between security and control, rather than simply highlighting future needs.

4.2. Defaults

DS interventions (defaults) are well-known for their strong influence on behavior. According to a meta-analysis by Mertens et al. (2022), DS interventions typically show a notable effect size of d = 0.33 in the finance domain. Defaults, in particular, capitalize on status quo bias and inertia, guiding individuals toward pre-selected options with minimal cognitive effort (Samuelson & Zeckhauser, 1988). This behavioral intervention has been highly effective in retirement savings decisions (Madrian & Shea, 2001; Thaler & Benartzi, 2004). Here, we did not find a significant effect of defaults on annuitization decisions.

A critical consideration is whether our operationalization of "defaults" as starting positions on a continuous slider truly constitutes a default nudge in the traditional sense. Johnson & Goldstein's (2012) theoretical framework suggests that effective defaults operate through three key channels: endorsement (implicit recommendations from choice architects), ease (lower effort to maintain the default than to change it), and endowment (psychological ownership of the defaulted option). Our slider starting positions potentially failed to fully engage these mechanisms. Participants may not have perceived the starting position as an endorsement or recommendation, but rather as an arbitrary starting point, whereas traditional defaults derive much of their power from being perceived as implicit recommendations (McKenzie et al., 2006; C. Sunstein, 2013; Tannenbaum, 2012). Furthermore, the interactive slider design required minimal effort to deviate from the default position. This reduced, though did not fully eliminate, the effort asymmetry typically associated with default effects. The action cost was substantially lower than in classic default interventions, such as the opt-out organ donation framing described by Thaler & Sunstein (2008), which often require a deliberate, multi-step reversal.

Additionally, the immediate ability to adjust the slider may have prevented participants from developing any sense of endowment with the initial position, contrary to traditional defaults where status quo bias and loss aversion contribute to default adherence (Dinner et al., 2011; Kalkstein et al., 2022; Tversky & Kahneman, 1991). In fact, the interactive slider design may have encouraged active engagement and experimentation, the visual feedback of seeing how different allocations affected both monthly payments and lump sum amounts could have prompted participants to explore various options rather than accept the starting position. This dynamic interaction stands in stark contrast to traditional default implementations where the status quo option is more passive and static (Johnson & Goldstein, 2003). The engaging nature of sliders as an interface element has been shown to increase user

interaction and adjustment in other decision contexts (Chapman et al., 2019; Matejka et al., 2016). Meta-analyses of default effects support this interpretation, showing that defaults are most effective when they create genuine friction against change and maintain a truly passive status quo option (Jachimowicz et al., 2019; Venema et al., 2020). Our interactive implementation may have thus transformed what was intended as a default nudge into more of an exploratory decision tool, fundamentally changing how participants approached the choice task, and boosting rational decision-making processes rather than circumventing them.

Our interactive implementation may have thus transformed what was intended as a default nudge into more of an exploratory decision tool, fundamentally changing how participants approached the choice task. This transformation was likely amplified by the continuous nature of our dependent variable. While traditional binary defaults create clear decision boundaries that facilitate quick, intuitive choices (Thaler & Benartzi, 2004), continuous choice spaces require participants to consider multiple possible allocation points. This shift from a discrete to a continuous choice architecture may fundamentally alter how people process the decision task. Recent theoretical work on decision-making suggests that continuous choice spaces can trigger more elaborate information processing and comparison strategies compared to binary choices (De Neys, 2023; Voudouri et al., 2024).

Furthermore, by reframing the decision from a binary annuity vs. lump sum choice to a more flexible, adjustable option, our design may have altered how participants evaluated risk and uncertainty. Traditional binary annuitization decisions often trigger ambiguity aversion, pushing people toward the seemingly more concrete and immediate lump sum option (Brown et al., 2008b; Kahneman & Tversky, 1979). The continuous choice format, however, might have helped participants recognize that they weren't facing an all-or-nothing decision, potentially reducing the psychological barrier to considering partial annuitization. This interpretation aligns with research showing that breaking down complex financial

decisions into smaller, more manageable choices can lead to more optimal decision-making (Benartzi & Thaler, 2013; Thaler & Benartzi, 2004).

However, since we did not directly compare binary and continuous choice architectures, these interpretations remain speculative. Future research should systematically investigate how different choice architectures - binary versus continuous - affect both the decision process and outcomes in pension distribution decisions. Such research could help determine optimal ways to structure these important financial choices while maintaining decision-maker autonomy.

4.3. Social Norms and Evaluative Risk Labels

Despite the well-documented success of DI interventions, such as social norms and evaluative risk labels, in shaping behavior across a range of domains (Bateman et al., 2016; Festinger, 1954; Hummel & Maedche, 2019), our study found that these interventions had no significant impact on annuitization decisions. Social reference nudges, which have demonstrated a substantial impact on financial behaviors like retirement savings and stock market participation through peer influence and conformity bias (Banerjee & Das, 2023; Brown et al., 2008b; Duflo & Saez, 2003; Kubik et al., 2001), proved ineffective in the context of annuity choices. This observation may be attributed to the complex, individualized nature of retirement planning, where decisions are less susceptible to external social comparisons and more reliant on personal, intrinsic motivators (Brown, 2007).

Similarly, evaluative warning labels designed to simplify complex financial information and reduce cognitive load by engaging System 1 thinking (Bateman et al., 2016; Johnson et al., 2012; Thaler & Sunstein, 2008) did not influence annuity uptake in our study. Although such labels have been effective in other (financial) contexts by providing clear, accessible risk assessments (Bateman et al., 2016; Vlaev et al., 2009), they may not sufficiently address the cognitive biases and information-processing challenges inherent in

annuitization decisions (Kahneman & Tversky, 1979; Lusardi & Mitchell, 2011). Recent developments in dual-process theory suggest that even seemingly intuitive decisions involve multiple competing intuitions rather than a simple deliberative override of biased intuitive responses (De Neys, 2023; Voudouri et al., 2024). In the context of annuitization, simplified risk labels may fail to engage with deeply ingrained intuitions about financial security and control that influence pension decisions. This aligns with emerging evidence that, unlike more habitual consumer choices (e.g., energy efficiency or health), retirement planning decisions may be driven by sophisticated intuitive processes that integrate both immediate and long-term considerations, making them less susceptible to simple environmental cues (Van Dessel et al., 2022). Further research may be needed to refine how these interventions can be better contextualized for annuitization. Another potential explanation for our findings is that participants may have struggled to conceptualize the allocation of such a large sum of money (e.g., €100,000). Decision-making for large, abstract amounts may be more cognitively demanding than smaller, everyday financial decisions. This factor could have resulted in participants defaulting to familiar, simple choices (e.g., capital uptake or a round number split around 0 – 50 or 100% annuity) without fully engaging with the implications of annuitization. This cognitive challenge contrasts sharply with the approach in Thaler & Benartzi's (2004) *Save More Tomorrow* (SMarT) program, which targeted incremental increases in monthly payroll contributions rather than lump-sum allocations. Participants in the SMarT program only had to decide on small, periodic additions to their savings, typically from future pay raises. These manageable amounts, often tens of dollars rather than hundreds of thousands, allowed individuals to commit with minimal cognitive strain and without confronting the daunting concept of significant, one-time allocations. Future research could explore how framing the decision in terms of smaller, more relatable denominations affects annuity uptake, potentially mirroring the incremental design that proved successful in the SMarT program.

4.4. Nudge combinations

The absence of significant interaction effects between decision assistance and decision structure or decision information interventions (RQ2 to RQ5) suggests that these strategies did not mutually reinforce each other in the ways anticipated. One potential explanation is that the cognitive load imposed by managing several complex interventions simultaneously could have diluted their effectiveness. When faced with complex decisions, individuals may revert to simpler heuristics that override nuanced decision-making cues, as proposed by dual-system theory (Kahneman, 2011).

Recent theoretical developments offer a more nuanced explanation for this lack of interaction effects. Rather than simply overwhelming cognitive capacity, multiple simultaneous interventions may have created competing inferential processes that effectively neutralized each other (Van Dessel et al., 2022). Modern dual-process accounts suggest that decision-makers can simultaneously generate multiple sophisticated intuitions, even in complex scenarios (De Neys, 2021). In our case, different nudges may have activated distinct and potentially conflicting intuitions. For instance, social norms triggering conformity intuitions while evaluative labels activated risk-assessment intuitions. This interpretation aligns with emerging evidence that financial decisions involve parallel processing of multiple choice-relevant intuitions rather than a simple trade-off between heuristic and deliberative thinking (Voudouri et al., 2024). Under this framework, the absence of interaction effects may indicate that pension decisions require interventions that harmonize rather than layer different cognitive processes.

Overall, our findings suggest that while pre-commitment strategies show promise, other interventions, such as defaults, social norms, and evaluative labels, may need further refinement or may inherently lack effectiveness in influencing annuitization behavior within this specific context.

Importantly, the absence of significant effects for most interventions cannot be attributed to a lack of statistical power. With over 15,000 participants, this study qualifies as a large-scale behavioral experiment with more than sufficient sensitivity to detect even small effects. This strengthens the interpretation that the observed resistance to nudging may reflect the presence of strong, stable preferences or entrenched heuristics, rather than being the result of random variation or underpowered analysis. Especially in high-stakes financial contexts like annuitization, where decisions are shaped by deeply held beliefs and longstanding mental models, subtle behavioral interventions may not suffice to override dominant choice patterns.

4.5. Consistent decision patterns

We observed a consistent decision pattern across all conditions: on average, 51.2% of participants opted for more than 95% capital uptake, 34.5% chose a mix, with a notable peak of 13% at exactly 50% annuity uptake, and 14.3% opted for less than 5% annuity. An overview of the observed frequencies of annuity choice in every condition is provided in Figure 2. This uniformity suggests that participants possess strong preferences that are resistant to change through nudges alone. Research indicates that individuals often gravitate towards round numbers when making quantitative decisions, a phenomenon also known as "round number bias" (Pope & Simonsohn, 2011). The peaks at exactly 0%, 50%, and 100% annuity uptake suggest that participants favored these cognitively simpler, salient options, due to their cognitive accessibility (Gigerenzer & Gaissmaier, 2011; Hertwig & Grüne-Yanoff, 2017). These focal points may function as 'pre-existing defaults,' with 50% often perceived as a balanced allocation representing risk diversification (Muramatsu & Fonseca, 2012; Shah & Oppenheimer, 2008). By defaulting to these values, participants can avoid the cognitive effort of evaluating less prominent options. Moreover, this tendency may also stem from the participants' habitual exposure to binary decision-making frameworks commonly encountered in similar financial contexts. Traditional pension plans and retirement savings options often

present choices in binary terms, such as full withdrawal or full annuitization, conditioning individuals to think within these familiar boundaries even when presented with more nuanced options (Agnew et al., 2008). This interpretation is supported by research on choice bracketing showing how prior experience with decision formats can create persistent mental models that influence future choices (Koch & Nafziger, 2016; Read et al., 1999). People may automatically parse continuous choice spaces into discrete categories based on these learned mental models, effectively creating their own implicit defaults at psychologically meaningful points like 0%, 50%, and 100 (Wakita et al., 2012). Future research could explore how such implicit anchors influence financial decision-making, even without formal defaults, and whether alternative choice architectures could help overcome these ingrained decision patterns.

While our initial explanations offer some insights into the observed decision patterns, it's important to situate our findings within the broader context of recent debates on the effectiveness of nudging interventions. Several meta-analyses and systematic reviews have raised questions about the overall impact of nudges, suggesting that their effects may be smaller and less consistent than previously thought (Maier et al., 2022; Szaszi et al., 2022). In our study, many of the nudges we implemented did not produce the expected effects on annuity uptake decisions, despite being grounded in established behavioral theories and tested on a substantial sample size. This lack of significant outcomes highlights the potential limitations of nudging when applied to complex (financial) behaviors. Simultaneously, this observation suggests that while nudges can be effective in certain contexts, they may not suffice for influencing decisions that involve deeply rooted preferences or require a high level of deliberation.

4.6. Limitations

This study has several limitations that should be acknowledged. First, we employed a vignette-based design with hypothetical scenarios, which may not fully capture the complexities and emotional weight associated with real-world annuity decisions where actual financial stakes are involved. Implementing this type of experiment as a field study with real-life monetary consequences involves significant logistical and ethical complexities, making it challenging to replicate controlled conditions.

Second, while we used a continuous decision framework (sliders) to reflect the flexibility of annuitization options, this may have reduced the effectiveness of interventions like defaults, which are typically more impactful in binary decision contexts. Notably, we did not test the decision in a traditional binary format, limiting comparisons to real-world default effects.

Third, despite our efforts to create an ecologically valid testing environment with a large study sample (N = 15,593), the web-based nature of the study may have introduced sample biases, particularly in educational attainment. Our sample includes a relatively highly educated population. A majority held qualifications at ISCED level 6, corresponding to a Bachelor's degree, with 32.7% having completed an academic bachelor's programme and 29.8% a professionally oriented bachelor's degree. An additional 26.0% had completed upper secondary education (ISCED level 3 or 4), without pursuing tertiary education. This overrepresentation of highly educated individuals, who may be expecting a larger pension and thus less inclined to feel like they should buy an annuity, may limit the generalizability of our findings. Notably, Thaler & Benartzi's (2004) *SMarT* program primarily targeted blue-collar workers, who might respond differently to such interventions.

Fourth, we did not consider reaction time when measuring participant decision-making. Reaction time can provide valuable insights into how confidently or automatically participants make their choices, particularly in complex financial decisions. Including this

measure in future studies could help differentiate between thoughtful deliberation and quick, heuristic-based decisions.

Finally, the simplified nature of our experiment did not account for the real-world complexities of annuity decisions, such as tax implications or financial advice, which could influence participant behavior in practice.

5. Conclusion

Our study highlights the challenges of influencing annuitization decisions through behavioral interventions. While pre-commitment strategies showed a small effect, other interventions did not yield the expected outcomes. Notably, the consistent decision patterns unaffected by nudging may not be attributed to statistical power issues, given the scale of this megastudy (N = 15,593). This observation suggests that individuals may rely on strong preferences and simple heuristics, which are to a large extent resistant to nudge interventions, when faced with complex financial decisions. Future efforts to address this resistance should focus on developing tailored approaches that more effectively address the cognitive and emotional factors influencing annuitization, thereby supporting individuals in making informed choices for their retirement security.

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Supplementary information

Table S1

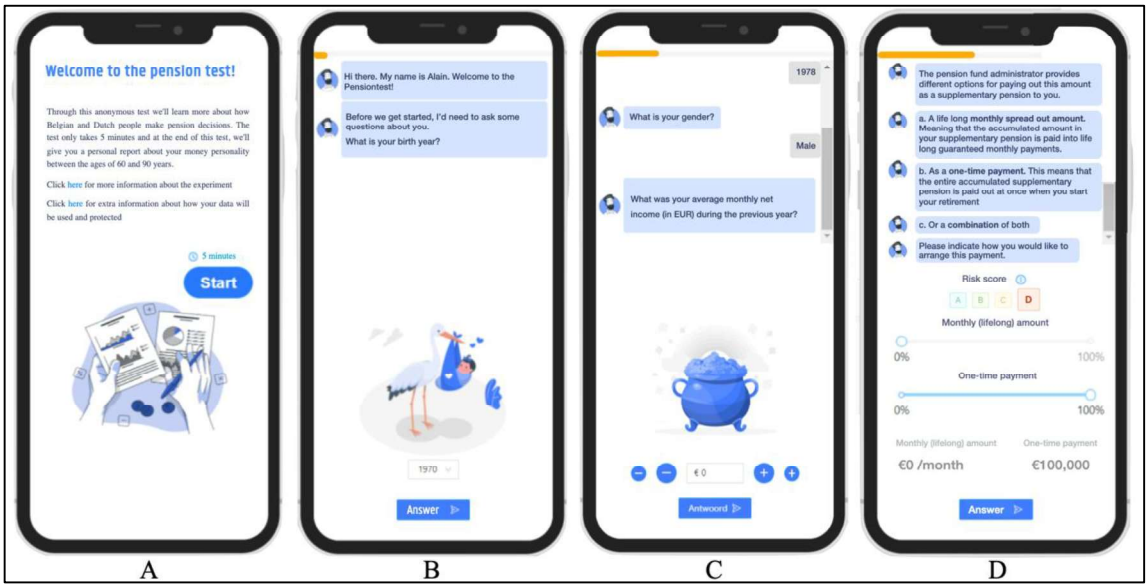
Study conditions overview

Condition	Default (DS)	Pre-commitment (DA)	Social norms (DI)	Evaluative risk labels (DI)	*n*
1	100-0	No	No	No	614
2	100-0	No	Yes	No	274
3	100-0	No	No	Yes	586
4	100-0	No	Yes	Yes	289
5	50-50	No	No	No	618
6	50-50	No	Yes	No	248
7	50-50	No	No	Yes	639
8	50-50	No	Yes	Yes	259
9	0-100	No	No	No	625
10	0-100	No	Yes	No	274
11	0-100	No	No	Yes	623
12	0-100	No	Yes	Yes	275
13	100-0	Yes	No	No	1,153
14	100-0	Yes	Yes	No	557
15	100-0	Yes	No	Yes	1,134
16	100-0	Yes	Yes	Yes	551
17	50-50	Yes	No	No	1,226
18	50-50	Yes	Yes	No	576
19	50-50	Yes	No	Yes	1,166
20	50-50	Yes	Yes	Yes	543
21	0-100	Yes	No	No	1,151
22	0-100	Yes	Yes	No	496
23	0-100	Yes	No	Yes	1,174
24	0-100	Yes	Yes	Yes	542

Note: The table represents our 3x2x2x2 experimental design where participants were assigned to one of 24 combinations of default settings, pre-commitment, social norms and evaluative risk labels. The sample size for each condition is provided.

Figure S1

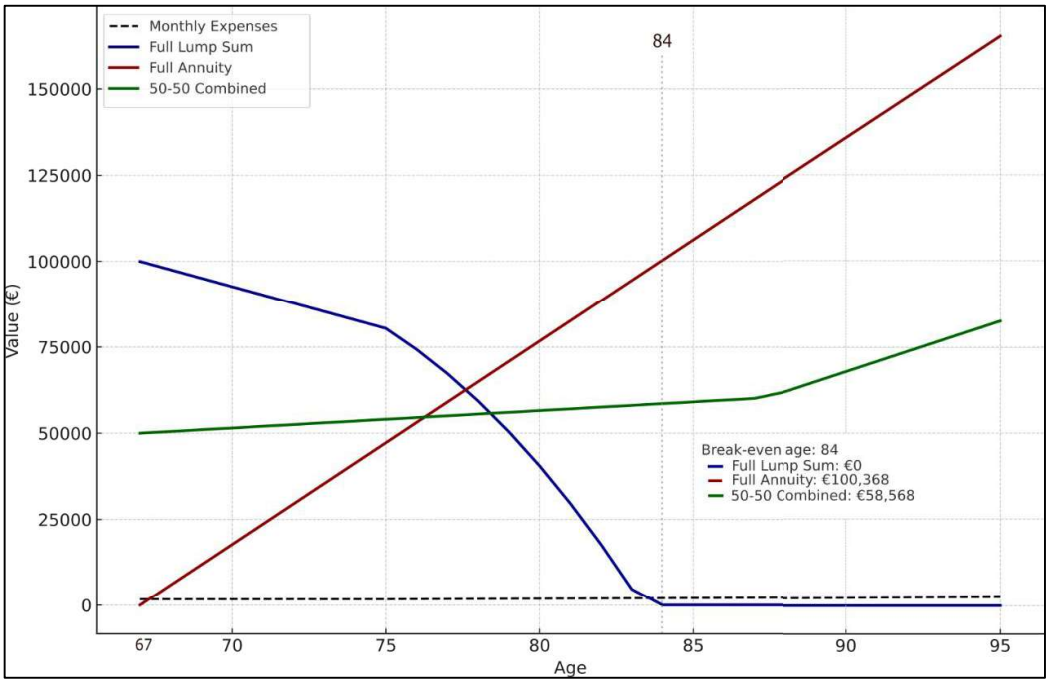
Study conditions overview



Note: The chatbot interface design (Dutch original translated to English for clarity) showing: (A) Welcome screen with study information, (B) Initial demographic questions with chatbot introduction, (C) Income assessment screen, and (D) Example pension distribution decision interface with evaluative risk score visualization and dual slider system.

Figure S2

Simulated Wealth Trajectories Under Different Pension Distribution Choices



Note: The graph compares three simulated pension distribution strategies starting at age 67, with monthly expenses increasing by 2% annually after age 75 to reflect higher healthcare and assistance needs. Initial conditions: €1,500 state pension, €1,704 monthly expenses during retirement. At the break-even age of 84, the full annuity (€492/month) has accumulated €100K, while the 50-50 split strategy (€50,000 + €246/month) shows a total value of €59K, and the remaining lump sum has decreased to €0K.

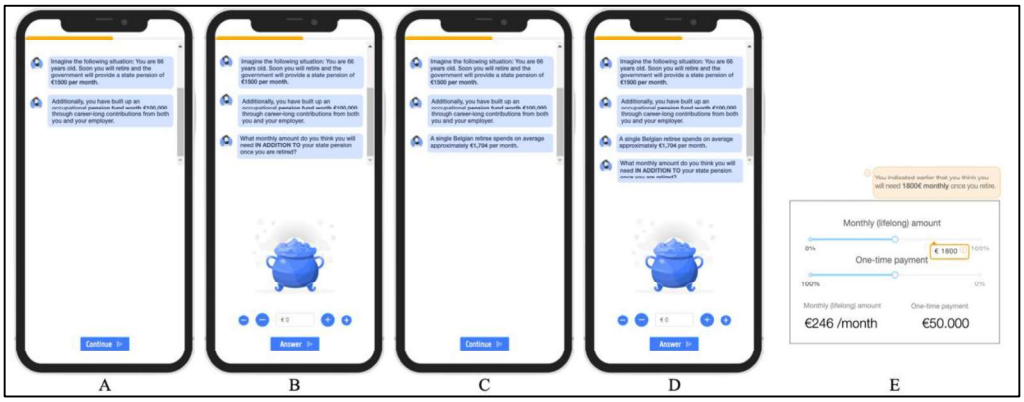
Figure S3

Default Settings (DS) Implementation Showing Three Initial Slider Positions

Note: Implementation of the three default settings showing initial slider positions and corresponding monetary outcomes: balanced (50-50), full annuitization (100-0), and full lump sum (0-100). First number in each pair represents percentage allocated to lifelong monthly payments (annuity).

Figure S4

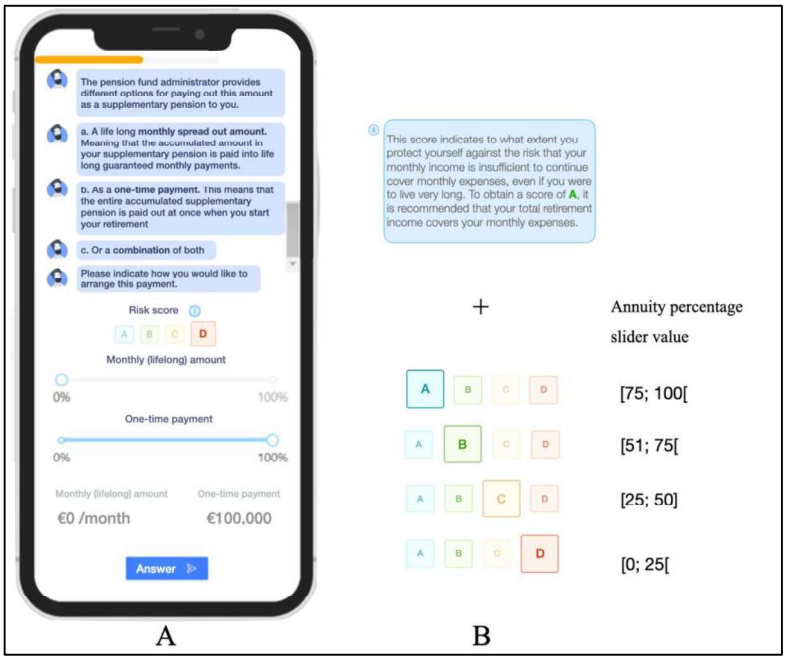
Implementation of Pre-commitment (DA) and Social Norms (DI) Manipulations



Note: Sequential interface showing all possible manipulation combinations: **(A)** Basic control condition showing only the retirement scenario (€1,500 state pension and €100,000 occupational pension fund), seen by participants who received neither pre-commitment nor social norm interventions; **(B)** Pre-commitment only condition, where participants indicate their desired additional monthly retirement income using a numeric input field with +/- adjustments; **(C)** Social norm only condition, informing participants that an average single Belgian retiree spends €1,704 monthly; **(D)** Combined condition showing both the social norm information and pre-commitment prompt; and **(E)** Example of the decision interface showing the 50-50 default position (€246/month and €50,000 lump sum). Regardless of the default setting (0-100, 50-50, or 100-0), participants who received a pre-commitment intervention saw their indicated monthly need displayed in an orange tooltip with a visual pointer (shown example: €1,800). For amounts exceeding the maximum possible displayable monthly income of €1,992 (€1,500 state pension + €492 maximum annuity), the reminder was adjusted to acknowledge this excess (e.g., "You indicated earlier that you think you will need more than 1992€ monthly once you retire").

Figure S5

Implementation of the Evaluative Risk Labels (DI) in the Decision Interface



Note: Panel A shows the decision interface with evaluative risk labels, featuring (1) a color-coded risk score system ranging from A (green) to D (red), (2) an information icon that, when clicked, explains how the score indicates protection against longevity risk, and (3) the dual-slider system for allocation decisions. Panel B illustrates how the risk scores dynamically updated based on annuitization percentages: scores of A (green) for 75-100% annuitization, B (light green) for 51-75%, C (orange) for 25-50%, and D (red) for 0-25%. The risk labels provided real-time feedback as participants adjusted their allocation between monthly payments and lump sum, with higher annuitization levels resulting in better risk scores reflecting greater protection against longevity risk.

Table S2

Descriptives Non-Categorical Individual Characteristics

	M	*SD*	Min.	Max.	Cronbach's α	n_{items}
Age	50	11	18	66		
Life Expectancy	5.4	1.1	1.0	7.0		
Neuroticism	4.8	1.2	1.5	7.0	.61	2
Extraversion	4.0	1.2	0.7	6.7	.73	3
Openness	4.1	1.1	0.3	6.3	.70	4
Agreeableness	5.1	1.0	1.0	7.0	.71	4
Conscientiousness	4.5	1.1	0.5	6.5	.71	4
Self-Control	3.5	0.8	1.0	7.0	.67	5
Financial Self-Efficacy	2.8	1.1	1.0	7.0	.78	6
Financial Literacy	2.6	0.7	0.0	3.0	.44	3

Note. **Life expectancy**: 7-point likelihood scale of reaching age 85 (Hurd & McGarry, 1995). **Personality traits** measured via Dutch Mini-IPIP (Donnellan et al., 2006), 7-point scale, with items like "I sympathize with others' feelings" (Agreeableness), "I get chores done right away" (Conscientiousness), "I don't talk much" (Extraversion), and "I'm not interested in abstract ideas" (Openness). **Self-Control** (Tangney et al., 2004): "I find it difficult to break bad habits"; **Financial Self-Efficacy** (Lown, 2011): "I lack confidence in my ability to manage my finances"; both 7-point scales. **Financial Literacy** used Lusardi's (2011) BIG 3 with multiple choice items like "If you have €100 in a savings account with 2% annual interest, how much would you have after five years?

Table S3

Categorical Individual Characteristics

	n	%
Sex		
Female	6,680	42.8
Male	8,913	57.2
Marital Status		
Single/Not Married	2,646	17.0
Cohabiting	1,468	9.4
Legal Cohabiting	1,799	11.5
Married	8,360	53.6
Divorced	1,141	7.3
Widow(er)	179	1.1
Salary		
< 2000	6,279	40.3
2000	3,577	22.9
> 2000	5,737	36.8
Highest Educational Degree		
Secondary Education	4,059	26.0
Professional Bachelor	4,653	29.8
Academic Bachelor	779	5.0
Academic Master	5,097	32.7
PhD	592	3.8
None	413	2.6
Employment Status		
Unemployed	457	2.9
Governmental Official	2,622	16.8
Laborer	909	5.8
Employee	6,706	43.0
Self-Employed	4,562	29.3
Self-Employed in Secondary Occupation	337	2.2

Note. Salary is expressed in net income (in euros) per month.