INCREASING ENGAGEMENT WITH RETIREMENT THROUGH PERSONALISED COMMUNICATION?

Technical Report

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Abstract

People are not doing enough to prepare for their retirement. A particular challenge for various stakeholders (governments, retirement providers, employers) is how to increase engagement with retirement? One solution is to rely on personalised communication. Personalisation implies tailoring communication to accommodate individual users. The idea is that personalising retirement communication ought to appeal to individuals more directly and increase engagement. Personalisation can be applied in various forms. On a very basic level, one can personalise by, for example, addressing people by name. For this investigation, however, we focus on a more advanced form where we personalise based on people's personality characteristics. For example, personalising communication for optimists, as opposed to pessimists by framing textual or visual prompts so that it appeals to optimists. We report the results of five studies. While we find encouraging evidence that people prefer personalized (as opposed to non-personalised) content about retirement, we did not observe changes in retirement engagement. We surmise that bridging the lack of engagement in the retirement domain may require more direct and concrete interventions. Furthermore, we cast doubt on whether personalisation is the right tool to use to correct entrenched behaviours such as retirement planning avoidance.

Keywords: Retirement; Pension; Savings; Personalization; Financial Decision-Making

1. Introduction

A large literature on financial decision-making notes that people do not adequately engage with their retirement. This can have disastrous consequences on later financial wellbeing. Many factors contribute to this problem. For instance, it has been found that people misunderstand savings growth (Mckenzie & Liersch, 2011), tend to defer retirement decisions (Krijnen et al., 2015), find retirement planning difficult (Krijnen et al., 2019), and lack appropriate financial understanding (Lusardi & Mitchelli, 2007; see also, Kerry, 2018; Topa et al., 2009 for systematic reviews).

And yet, most people seem to agree that engaging with one's retirement and adequately planning for it is an important financial step. For instance, in the U.S., the annual Gallup poll has identified not having enough money secured for retirement as among the top of participants' financial worries every year since polling on the issue began (Gallup, 2016-2019). Irrespectively, engagement with retirement remains grossly insufficient.

For example, survey data shows that a large percentage of people only begin to think about their retirement six to twelve months before making the decision to retire (Helman et al., 2008). In a recent survey in the Netherlands, 40% said they had never taken the time to think about their post-retirement income, 59% had not looked at their online pension overview, and 63% had not looked at their annual retirement statement (Pensioenmonitor, 2016). Combined with a lack of knowledge about retirement systems (in the Netherlands only 30% of respondents said they know how pensions are arranged; Pensioenmonitor, 2018), these numbers are worrisome.

As a result, many stakeholders (e.g., governments, retirement funds, employers) are interested in how to mitigate these issues. Behavioural researchers have focused on the individual and developed interventions aimed at reducing the severity of the issue. A lot of important work has been done to increase retirement savings (and planning) through nudges or changes in design. For example, one method shown to encourage worker participation in retirement plans is to change the default options so that people are, by default, enrolled in a plan rather than having to apply themselves (Madrian & Shea, 2001). Related, one company found that switching from an opt-in rule to an active decision increased enrolment rates about 25 percentage points (Choi et al., 2005). Others have found that changing the texts of messages, e.g., framing the future time point in relation to a "fresh start" increased people's contribution to a savings plan (Beshears et al., 2021). Another example is the use of goal framing where messages adjusted to promote goals also show promise in increasing engagement with retirement content (Eberhardt, et al., 2021). Various other small-scale intervention programs (e.g., meetings, educational seminars) have also been found to lead to an increase in knowledge, positive attitudes about retirement, as well as retirement planning (Leandro-França et al., 2016).

However, interventions like these, specifically those that target wide swaths of the population, aren't a panacea. For one thing there are indications that some of these have little to no effect on how much people save. For example, financially incentivizing people had almost no effect in Denmark (Chetty et al., 2014) while employer matching in the US was not successful at raising contributions to 401(k)'s (Choi et al., 2010). Interventions like automatic enrolment, which are designed to help everyone had similarly underwhelming results (Beshears et al., 2010). For another, not all retirement systems lend themselves to these strategies and retirement engagement cannot purely be boiled down to increasing contributions. In the Netherlands, for instance, individuals can rarely, if at all, increase their contribution to retirement as these are set by labour agreements. This is compounded by the fact that the population of interest is usually highly diverse. People differ in all sorts of dimensions such as age, income level, education, or socioeconomic status. These differences oftentimes result in varied preferences when it comes to how to approach retirement planning (Eberhardt, et al., 2018) or how people want certain information to be presented (Limpens & Vonken, 2018).

Lack of retirement engagement seems to be an entrenched negative behavioural tendency, one afflicting a diverse population. In this project, we set out to test whether a tailored intervention could help lead to increases in retirement engagement. Unlike the previously mentioned interventions where a single intervention tactic (e.g., framing of messages) is applied to the whole population of interest, we take a more stratified approach – focused on individuals' characteristics. Specifically, we focus on personalisation and take a closer look at whether personalized communication can lead to perceptible changes in retirement engagement intentions and behaviour. As we discuss in more detail below, research in other domains has shown that personalised content can be an effective way to reach participants and increase engagement in a variety of domains. Focusing on communication efforts to increase retirement engagement – by personalising the content and form of messages to meet recipients' characteristics and preferences – we aim to test the suitability and effect of this intervention strategy.

2. Theoretical Framework

2.1 Personalisation

Personalisation refers to the process of tailoring a certain means of communication to individual users. Simply put, to personalise means to adapt the means of communication for the person, using information that has been inferred from that person's behaviour or which has been supplied by the person themselves (Montgomery & Smith, 2009). Personalisation may thus be a useful strategy to employ to increase engagement with retirement. The main idea being that people will react more positively to personalised communication efforts, pushing them towards more engagement with retirement and retirement information. There are multiple points of focus one can zero in on when personalising. This can range from the very simple, e.g., referring to people by their name or some other personal information when communicating, to very advanced forms pf personalization, e.g., derive preferences from behaviour and then using these insights in future communication. It is important to note upfront that in the pension sector, "to personalise" may often refer to basic interventions such as addressing users by name in communication. We, however, will be focusing on what we consider to be a more advanced form of personalisation where we survey people and find out more about their personality traits and preferences, and then personalise pension communication content based on people's characteristics.

Most people may be familiar with personalisation that occurs in the online environment. The ranking of the posts in social media, the recommendations we get about what to buy, listen, or read is curated by algorithms that aim to personalise the experience for us (Zhou et al., 2012). Personalisation has been used in a variety of contexts, oftentimes with results that demonstrate a change in people's behaviour and intentions. There are many findings that show how personalisation can, in fact, increase satisfaction, trust, and lead to more positive behavioural change. For example, personalisation has been used to tailor diet styles to individuals with some success (Brindal & Golley, 2021). Personalisation has also been found to help with learning goals, increasing learning uptake in children (Baxter et al., 2017). In the consumer domain, personalizing electronic recommender agents or advertising campaigns has been shown to increase people's adoption of the recommendations and interaction rates with brands (Bright & Daugherty, 2012; Komiak & Benbasat, 2006). Similarly, adapting an online advice system on mobile phone contracts to match users' preferences has been shown to improve their purchase intention (Hauser et al., 2009). Personalisation has also been shown to decrease irritation with ads (Kim & Han, 2014). In the retirement context, Fuentes et al. (2016) demonstrated that personalised information led to increases in voluntary savings of about 10%-15%. Furthermore, Wang et al. (2020) conducted a field experiment in which they sent out personalized newsletters to 465,711 pension plan participants and found significantly higher clicking rates.

Before moving on there is a need to address the negative sides that may arise when talking about personalisation. To personalise, one often needs to obtain information about participants. People are often worried about their privacy, especially when organizations collect data unobtrusively (e.g., click behaviour, watch times, and similar). It has been found that personalisation decreases trust slightly and benefits marginally in the news and commerce settings, although there were no such trends in health settings (Bol et al., 2018). Others have found however, that providing technical details on personalisation does not lower the motivations of individuals to opt-out of personalised content (Strycharz et al., 2019). Overall, studies seem to converge that personalisation leads to mixed feelings for consumers. People tend to see multiple benefits along with some negatives (Lee & Cranage, 2011).

As hinted at in the previous paragraph, to personalize content for an individual, one needs data about this individual. One way is to collect data about people's previous interactions with information. This is especially relevant for website or advertising personalisation – data about how the user has previously interacted with the content can be used to personalise future interactions for the user. In the retirement context, this is also a possibility. This can, for instance, be done using online behaviour which has become more available in recent years through the proliferation of online retirement tools. Indeed, many people can now obtain information about their retirement in specified online retirement dashboards. Many countries now employ online retirement tools where people can be informed, interact, or change certain options about retirement. One such tool in the Dutch context is the "Mijnpensioenoverzicht" or "MijnABP" online tool from the ABP pension provider. Data mining techniques can then be used to extract usage patterns and find out more about what individuals prefer or gravitate towards (I-Hsien Ting et al., 2005; Mobasher et al., 2000, Wang et al. 2020).

However, these types of data collections may not always be useful. For instance, people may not engage with these tools. There is data suggesting that in the Netherlands specifically, 59% of pension savers had not looked at their online pension overview (Pensioenmonitor, 2016) meaning that they actually had not logged into some of these online tools.

Another way to collect data is to find out more about the individuals through interviews or surveys. In this case, one can focus on psychological differences between individuals to use as a personalisation guideline. In this project, we decided to focus on personality – i.e., a more psychological level of interest – as a cue to use for personalised tailoring of communication. Data on personality can be obtained not only through previous behaviour, but also more directly, e.g., through questionnaires, interviews, or observation (Ersner-Hershfield et al., 2009). Furthermore, personality differences tend to be quite stable between individuals and have been shown to be a predictor of a host of behaviours (Ozer & Benet-Martinez, 2006).

2.2 Personality and retirement

To identify personality characteristics relevant for retirement and retirement engagement, as a first step in this project we conducted an extensive literature review. We identified characteristics that are relevant for retirement engagement, but also crucially those that can be used to personalise communication. In a general sense, lack of engagement with retirement can be related to overall patterns of self-control and regulation failures, higher discounting of the future, financial decision-making skills, general outlooks on life, and propensities to plan. We briefly review the relevant personality characteristics below.

2.2.1 Discounting

Retirement events are by their nature related to the future and the unknown. Retirement engagement is thus an example of a time-dependent task where a trade-off needs to be made between costs and benefits at different points in time. Various authors agree that such time-dependent decision-making is inextricably connected to retirement planning (Griffin et al., 2012; Kerry, 2018). That said, people can differ in how much they value something now vs. how much they value it in the future. Said differently, people differ in how much they discount values given a certain delay – the classic finding being that people tend to discount the value of future rewards by preferring smaller sooner, rather than larger later rewards.

This *delay-discounting* effect has inspired influential theorizing in psychology and economics (Frederick et al., 2002) and it speaks to people's impulsivity (Stahl et al., 2014), which bears a host of individual and societal consequences.

The higher the level of discounting, the greater the tendency of a person to discount outcomes in the future (e.g., the benefits one would get from retirement savings). Levels of delay-discounting are seen as an important consideration in retirement planning models (Bidewell et al., 2006) and intertemporal preferences have been shown to be a stronger predictor of the importance of saving for retirement than a host of other variables such as age, race, parental income, or gender (Finke & Huston, 2013).

2.2.2 Numeracy

Various findings indicate that people's knowledge of financial matters has an impact on retirement readiness and planning. For instance, relying on the concept of financial literacy, it was shown that people who cannot perform calculations with interest rates are less likely to plan for retirement (Lusardi & Mitchell, 2011; Lusardi & Mitchelli, 2007). However, a recent meta-analysis found that financial literacy explains only very little variance in financial behaviours, and effects are not very long-lived (Fernandes et al., 2014). Even though a more recent meta-analysis by Kaiser et al. (2020) found significant effects of financial education on financial knowledge and downstream behaviour, one can conclude that financial literacy and the programs designed to improve it are not necessarily effective in changing financial behaviour. Numeracy, on the other hand, has much better construct validity than financial literacy and there is a wide range of validated tests developed to measure it (including an adaptive version, cf., Cokely et al., 2012).

Numeracy is defined as the ability to process basic probability and numerical concepts. Making good decisions in the real world requires some numerical ability (Peters et al., 2006). Previous research has shown strong correlations between an individual's level of numerical ability and their level of wealth, their level of financial knowledge, and the composition of their asset portfolios (Banks & Oldfield, 2007). Furthermore, Banks et al. (2011) found that in the years leading up to retirement, those who are more numerate accumulated financial assets at a faster rate than those who are less numerate and that they decumulate it at a faster pace after retirement.

2.2.3 Optimism

Retirement engagement can be thought of as a decision-making tendency that is constrained by general optimism levels. Optimism (along with its mirror characteristic, pessimism) is directly related to future planning proclivities (Carver & Scheier, 2014). There are several findings pointing out the benefits that are reaped by people who score higher on this characteristic. Levels of optimism have, for example, been shown to predict higher salaries later in life (Segerstrom, 2007). Optimists also increase goal engagement for high priority goals and tend to decrease engagement for low-priority goals (Geers et al., 2007). When optimists think toward the future, they generate more vivid mental images or positive events (Blackwell et al., 2013), and optimists have generally more favourable health outcomes.

More relevant for retirement, optimists (as opposed to pessimists) tend to work harder, they expect to retire later, and they save more (Puri & Robinson, 2007). Furthermore, various life events may have an impact on people's retirement. For example, positive events such as getting married or getting promoted have an impact on the level of income. Conversely, negative events such as getting divorced or losing one's job can dampen retirement funds. People may differ in the extent to which they expect or wish to be reminded about such events, dependent on their particular outlook, i.e., whether it is optimistic or pessimistic. Differences in optimism/pessimism could thus have a strong effect on how people perceive their retirement benefits, but also how they perceive their retirement option in comparison to others meaning that this trait may be highly relevant to engagement.

2.2.4 Future-self continuity

The concept of future-self continuity heavily relies on theorizing proposing that a person at two different points in time (e.g., present vs. future) is not really the same person (Parfit, 1971). Research in psychology seems to confirm this assumption with findings indicating that people often do think about their future selves as though they are other people (Ersner-Hershfield, Wimmer, et al., 2009; Pronin et al., 2008). Most directly relevant, a simple measure of an individual's endorsement of similarity between present and future selves has been developed and shown to be highly related to retirement planning outcomes (Ersner-Hershfield, Wimmer, et al., 2009). Higher future self-continuity has been shown to predict reduced discounting of future rewards and greater accumulation of wealth (even after taking into consideration age and education). Importantly, an intervention that highlighted the social responsibility one has with their future self has been shown to lead to increases in savings, but only for people who were more connected to their future selves (Bryan & Hershfield, 2013). As the benefits of retirement are, by their nature, often thought of as being enjoyed by a future version of ourselves, future-self continuity relates strongly to planning this important life outcome that pertain to the future and may thus be highly relevant to retirement engagement.

2.2.5 Propensity to worry

People tend to differ to what extent they worry about their future. Propensity to worry has been tied, in the literature, with retirement anxiety that has been found to be a significant predictor of information search intentions (Eberhardt et al., 2019). Fletcher and Hansson (1991) determined that people for whom social transitions are more difficult have elevated scores in retirement anxiety. As such, general tendencies to worry can be related to retirement engagement. Studies have shown that propensity to worry predicts negative outcomes to uncertain future events while Constans (2001) and Lorcher (2003) found that those who worry often have less cognitive flexibility, less diversity of thought, reduced decision-making speed, attain less sleep, and tend to be perfectionists.

2.2.6 Propensity to plan

Propensity to plan can be thought of as the frequency with which people like to develop planning objectives (Lynch et al., 2010). Conceptually, this characteristic is rooted in the Theory of Planned Behaviour stating that behavioural intentions can be predicted from attitudes, subjective norms, and perceived behavioural control (Ajzen, 1991). People's tendency to plan can be related to retirement engagement. People with high propensity to plan tendencies have been found to be more rational, patient, and good at handling their money (Xiao & O'Neill, 2018). Higher propensity to plan has also been associated with greater financial preparedness and higher later life satisfaction. Retirement savings, another factor of long-term relevance, also increase with propensity to plan. For instance, those households who scored higher on propensity to plan had the highest average household income, as well as the largest retirement income (Lee & Kim, 2016).

2.3 Why would personality personalising work?

To conclude this section, we feel it is necessary to present arguments for why we should expect personalized communication efforts to increase engagement? Psychologically, a personalized message may be a particularly effective nudge in the right direction (Thaler & Sunstein, 2008). For one, previous research has shown that people are highly receptive to personalized content and find it useful as a decision aid. Tam and Ho (2006), for example, found that personalised content attracted more attention and enabled users to create preferences faster. On a more basic level, we know that people selectively expose themselves to messages that are in line with their pre-existing attitudes (Hart et al., 2009). While such a pervasive confirmation bias can lead to negative consequences, this cognitive tendency may be harnessed to increase information utility, i.e., the degree to which information can aid individuals in making future decisions. In a personalized system, communication framed to be in line with pre-existing psychological characteristics could increase information utility thereby leading higher engagement with personalised content.

Other findings suggest that personalized services can reduce information overload which in turn increases user satisfaction (Liang et al., 2006). One way in which personalisation can achieve this is that people aim to reduce effort with principles-of-least-effort predicting that information seekers will attempt to minimize the effort required to obtain information (Allen, 1977). More personalized communication content could thus, through the reduction of effort, reduce information overload and be more preferred. Moreover, findings from the literature on learning show, for example, that different learners do not benefit to the same degree from uniform types of instruction (Cronbach & Snow, 1977), with there being a consensus that instructional material should be adapted to the knowledge and needs of learners. Analogously, different individuals may not benefit to the same degree from uniform retirement communication. Finally, there is a literature precedent as well: several studies have shown benefits of personalised content on transfer and retention, as well as motivation (interest and intrinsic motivation) and perceived cognitive load (difficulty and invested mental effort) (Morena & Mayer, 2000; 2004).

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3. Methodology

In this section, we describe the methodological details of the five studies conducted during this project. In the review reported above, we highlighted several possible psychological characteristics one can focus on in the design of personalised retirement communication. We focus on these characteristics in the studies reported here. For each study we report the sample as well as the sample composition, and we describe the study procedure in as much detail as possible. For each of the studies, we pre-determined the sample size in line with available budget prior to running it.

3.1. Study 1

The idea that personalised (as opposed to non-personalised) communication will have a stronger impact on an individual and subsequently lead to more engagement and more positive behavioural intentions rests on a basic assumption. Specifically, people ought to *prefer* personalised content more than non-personalised. We are interested whether this is the case for retirement content. Preferred content ought to capture people's attention more and be chosen more often than chance. Indeed, there is some evidence to support this. Zander et al. (2015), using eye-tracking, found that personalised learning material presentations were selected more often, and people's eyes fixated more on them.

In Study 1, we set out to verify whether people would prefer retirement communication content (e.g., messages about one's retirement), which have been tailored to correspond to a specific level of a psychological characteristic, i.e., which have been personalised for them. Plainly said, we were interested in whether a person who scores highly on, for example, optimism, will prefer a retirement message tailored for high optimists (as opposed to a message tailored for low optimists)?

Of note, in Study 1, we did not examine whether this personalized content impacted engagement. We first wanted to verify and demonstrate whether there is actual preference for personalized retirement content when the personalisation is prepared with personality characteristics in mind. We thus predicted that people would prefer retirement messages presented in a manner that is consistent with their score on a psychological characteristic more, compared to that same information presented in a manner that is inconsistent with their score on a psychological characteristic. For example, a person who scores low on numeracy will be more likely to prefer the message tailored for the low numerate (i.e., information that is consistent with their score on this psychological characteristic).

3.1.1. Participants

Participants were recruited on the online platform Prolific (https://www.prolific.co/). We decided beforehand to collect at least 200 participants as this was the budget set aside for this study. For this, like for all the studies reported in the report, participants were compensated for their time corresponding to an hourly wage of 8.5 euros which is in accordance with Prolific guidelines of fair compensation (for a study of this length, i.e., an average of 10 minutes).

No participants were excluded from the analysis. Towards the end of the study, participants were asked to respond to several demographic questions and questions pertaining to retirement. The basic descriptive statistics (along with the description of the questions) of these responses are summarized in Table 1 below. We decided to focus on Dutch participants so only participants from the Netherlands whose first language was Dutch were eligible to participate. The survey was presented in Dutch.

Table 1. Basic descriptive statistics and description of questions participants were asked to respond to at the end of the survey in Study 1. The questions include basic demographic information about our sample and information on retirement.

Variable	Values	Frequencies
Sex	1. Male 2. Female	145 (58.0%) 105 (42.0%)
Age	Mean (SD): 30.1 (9.6) min < med < max: 18 < 27 < 64	-
Education (1 = no education to 7 = university education)	Mean (SD): 6.1 (1.1) min < med < max: 3 < 6 < 7	-
Working situation	Full Time Part Time Unemployed Self Employed Student 6. Retired	93 (50.8%) 41 (22.4%) 27 (14.8%) 21 (11.5%) 1 (0.5%) 0 (0.0%)
Income (1 = less than 8000 to 11 = more than 75.000)	Mean (SD): 7.2 (3.3) min < med < max: 1 < 8 < 12	-
Relationship status	1. Never married 2. Married 3. Divorced 4. Separated 5. Widowed	194 (77.3%) 51 (20.3%) 5 (2.0%) 1 (0.4%) 0 (0.0%)
Retirement worry	1. I do not worry 2. It is important to me 3. I keep well informed	86 (34.3%) 104 (41.4%) 61 (24.3%)
Are you currently in a retirement fund?	1. Yes 2. No	165 (65.7%) 86 (34.3%)
Do you think retirement funds are trustworthy? (1 = not at all to 7 = completely)	Mean (SD) : 4.4 (1.3) min < med < max: 1 < 5 < 7	-
How is your health? (1 = very bad to 5 = very good)	Mean (SD): 4.1 (0.7) min < med < max: 2 < 4 < 5	-

3.1.2. Procedure

After participants provided consent, they were presented with the instructions. Participants were told that an app is being developed that will provide information about retirement and as app developers, we wanted to make sure people engage with the retirement information. As a result, they were told, they will be presented with versions of the same information, but in different formats. Their task was to choose which version/format of information "you personally, not people in general, but you personally would prefer to see presented in the app?"

As an additional guide for making their choices, participants were told to choose the version/format that, if presented in such a way, would lead you to find out more about that aspect of retirement. For each preference, participants were asked: "*Which version/format of this retirement message would lead you to find out more about this aspect of your retirement?"* This was our main dependent variable. No other variables were used. We decided to focus on four psychological characteristics previously mentioned in the theoretical section of this report. Specifically, discounting, numeracy, optimism, and future-self continuity. We used validated questionnaires (see section 3.1.3.) to measure how people scored on each of these four psychological characteristics. It was randomly determined whether we presented these questionnaires either before participants made their preferences for the retirement messages or after. Finally, after participants provided their preferences, they were asked to respond to several demographic questions and questions pertaining to their retirement (see Table 1).

3.1.3. Measures

To measure *numeracy*, we used a four-question measure where people had to provide a correct response (Cokely et al., 2012). As an example of a question, participants were asked "Image we are throwing a five-sided die 50 times. On average, out of these 50 throws, how many times would this five-sided die shown and odd number (1, 3, or 5)?". Participants had to choose the correct answer out of four possible options. A person's score is then calculated by summing up how many correct answers they had.

To measure *delay discounting*, we used two questions (Reimers et al., 2009). First, participants were asked "Imagine you have to pay a ticket. Which would you rather pay? 45 euros in three days or 70 euros in three months?"[1] We also employed a continuous measure of delay discounting (Falk et al., 2016). Specifically, people were asked "In comparison to others, 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?" on a scale from 0 (completely unwilling to give up something today) to 10 (very willing to give up something today).

To measure trait *optimism*, we used a 10-question life orientation test (Scheier et al., 1994). Example items include "in uncertain times, I usually expect the best" and "I don't get upset too easily". Participants responded on a scale from 1 (strongly disagree) to 5 (strongly agree). The scale had a Cronbach's alpha of .77.

Finally, to measure *future-self continuity*, we used a visual interactive scale using concentric circles. One circle represented the future self while the other circle represented the present self (Ersner-Hershfield et al., 2009; Kamphorst et al., 2017). The participants were asked two questions "how similar do you feel to your future self" and "how connected do you feel to your future self" which were averaged to get a sense of future-self continuity. Participants could drag the circles and the more they overlapped, the more it indicated that they felt connected to their future-selves.

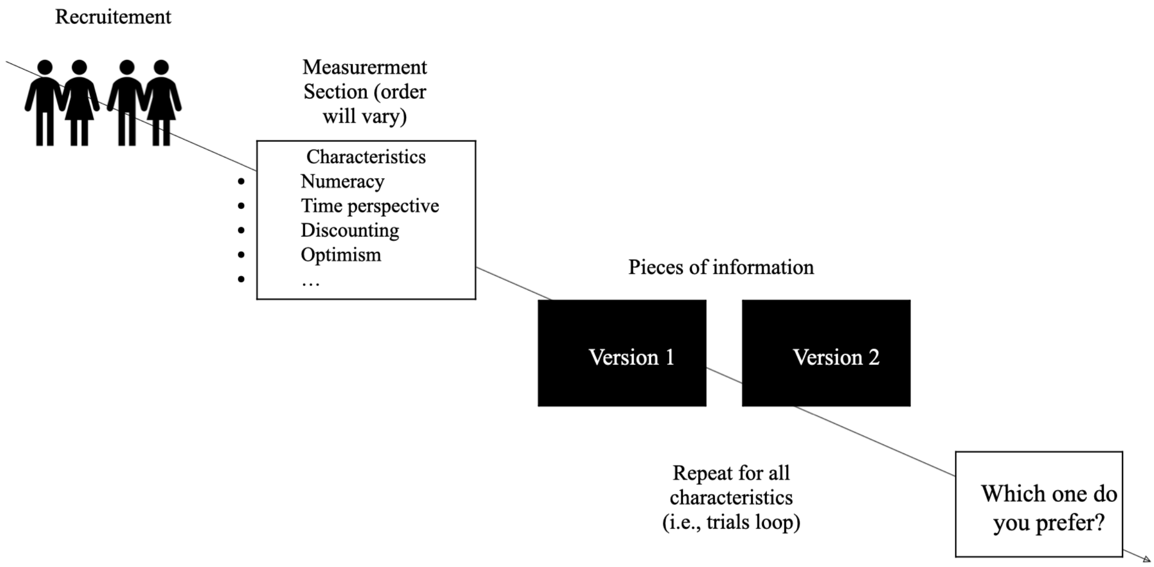
3.1.4. Retirement communication messages

Because we focused on four psychological characteristics, participants were asked to provide their preferences on four retirement messages. Crucially, the messages were designed to appeal either to a low end of the spectrum on a psychological characteristic (e.g., low numerates, low discounters, etc.) or to a higher end of the spectrum on a psychological characteristic (e.g., high numerates, high discounters, etc.). People thus had to choose their preferences four times. Each time, we provided participants with two versions (three version in the case of

[1] In hindsight, we decided not to rely on this measure because the validity of the question may depend on the amount chosen. Throughout the results, we will rely on the continuous measure when we discuss delay discounting.

numeracy) of the same retirement message that correspond either to a low score or a high score on a psychological characteristic. For example, a person can score either low or high in numeracy. For one version of a retirement message, we presented answers in percentages (tailored for high numerate individuals), while for the other version, we presented answers in frequencies (tailored for low numerate individuals). See Figure 1. for a representation of the procedure and the appendix for the message tailoring used in the study.

Figure 1. Representation of the procedure used in Study 1. Participants had to provide their preference for the versions/formats of the messages four times. The order in which the message versions are presented was randomized.



3.2. Study 2

In Study 2, we used an online sample to investigate whether presenting textual information tailored to correspond to a particular level of either optimism or discounting will lead to higher engagement with an online retirement dashboard. We decided to focus on optimism and discounting as these two characteristics showed the most promise in Study 1 (see section 4.1.). Specifically, for these two psychological characteristics we found that people chose versions of tailored messages consistent with their score on the psychological characteristics – i.e., people scoring high/low on discounting/optimism choosing the version of a retirement message geared towards high/low discounters/optimists.

3.2.1. Participants

Participants were again recruited on the online Prolific platform (https://www.prolific.co/). We decided beforehand to collect at least 500 participants as this was the budget set aside for this study. No participants were excluded from the analysis. In total, 501 participants filled in the survey and completed the entire study. Towards the end of the study, participants were asked to respond to several demographic questions and questions pertaining to retirement. The basic descriptive statistics (along with the description of the questions) of these responses are summarized in Table 2 below. We decided to focus on Dutch participants so only participants from the Netherlands whose first language was Dutch were eligible to participate. The survey was presented in Dutch.

Table 2. Basic descriptive statistics and description of questions participants were asked to respond to at the end of the survey in Study 2. The questions include basic demographic information about our sample and information on retirement.

Variable	Values	Frequencies
Sex	1. Male 2. Female 3. Non-binary 4. Prefer not to say	166 (33.1%) 330 (65.9%) 4 (0.8%) 1 (0.2%)
Age	Mean (SD): 37 (13.2) min < med < max: 18 < 34 < 7	-
Education (1 = no education to 7 = university education)	Mean (SD): 6.5 (2.6) min < med < max: 2 < 17 < 19	-
Working situation	1. Full Time 2. Part Time 3. Unemployed 4. Self Employed 5. Student 6. Retired	214 (47.6%) 81 (18.0%) 72 (16.0%) 43 (9.6%) 40 (8.9%) 0 (0.0%)
Income (1 = less than 8000 to 11 = more than 75.000)	Mean (SD) : 8.4 (2.6) min < med < max: 1 < 9 < 12	-
Relationship status	1. Never married 2. Married 3. Divorced 4. Separated 5. Widowed	266 (53.3%) 183 (36.7%) 39 (7.8%) 6 (1.2%) 5 (1.0%)
Retirement worry	1. I do not worry 2. I worry somewhat 3. I am very worried	169 (33.7%) 284 (56.7%) 48 (9.6%)
Retirement informedness	1. I am not well informed 2. I am somewhat informed 3. I keep well informed	228 (45.5%) 208 (41.5%) 65 (13.0%)
Are you currently in a retirement fund	1. Yes 2. No	181 (36.1%) 320 (63.9%)
Retirement fund trust (from 1 = not at all to 7 = completely)	Mean (SD) : 4.6 (1.3) min < med < max: 1 < 5 < 7	-
How is your health (1 = very bad to 5 = very good)	Mean (SD) : 3.9 (0.9) min < med < max: 1 < 4 < 5	-

3.2.2. Procedure

After providing consent, participants were presented with instructions that varied dependent on the type of tailored textual prompt (i.e., the tailored retirement messages) that was presented. The prompts were tailored to correspond to what a person inclined towards a particular level of a personality characteristic (e.g., a low discounter) would gravitate towards.

We focused on discounting and optimism, with each being presented in two levels, i.e., high and low. As such, there were four possible combinations of the tailored prompts. This means that there were four between-subject groups in our design. Specifically: HOHD – High Optimism, High Discounting vs. HOLD – High Optimism, Low Discounting vs. LOHD – Low Optimism, High Discounting vs. LOLD – Low Optimism, Low Discounting.

For example, a person could randomly be assigned to the HOHD condition and receive a retirement message that used prompts tailored for a high optimist and a high discounter. To illustrate, an example of a HOHD text was:

> *You can find out more about retirement in our online dashboard. The dashboard has information on how retirement can provide opportunities for advancement and growth in a world that is constantly improving and how the financial benefits of retirement can be immediate impacting your current well-being.*
>
> *Would you be willing to visit this retirement dashboard?*

Another example for the HOLD instructions:

> *You can find out more about retirement in our online dashboard. The dashboard has information on how retirement can provide opportunities for advancement and growth in a world that is constantly improving and how the financial benefits of retirement come in the future impacting your future well-being.*
>
> *Would you be willing to visit this retirement dashboard?*

Another example for the LOHD instructions:

> *You can find out more about retirement in our online dashboard. The dashboard has information on how retirement can provide security and safety in an uncertain world and how the benefits of retirement can be immediate impacting your current well-being.*
>
> *Would you be willing to visit this retirement dashboard?*

Another example for the LOLD instructions:

> *You can find out more about retirement in our online dashboard. The dashboard has information on how retirement can provide security and safety in an uncertain world and how the benefits of retirement can come in the future impacting your future well-being.*
>
> *Would you be willing to visit this retirement dashboard?*

As seen from the examples, our main dependent variable was binary and participants were asked to indicate whether they would be willing to visit the retirement dashboard with a 1 = Yes, or 2 = Skip and do not visit the dashboard. It is important to note that the participants were not presented nor were they going to be presented with a real retirement dashboard. They did not know this at the outset of the study but all participants were debriefed at the end.

After participants provided their answer to the main dependent variable, they were presented with the personality measure questionnaires for optimism and discounting. The same measures were used as in Study 1. The optimism measure had a high internal consistence with a Cronbach's alpha of .87. The discounting measure was a single continuous scale question as in Study 1. In addition to the continuous measures, we used two questions where participants could self-select whether they identify themselves as being either, high/low optimisms vs. discounters. For the discounting self-selection question, participants were asked: "I generally consider myself to be 1 = someone who attached more value to short-term benefits; 2 = someone who attached more value to long-term benefits. For the optimism self-selection question, participants were asked: "I generally consider myself to be 1 = an optimistic person; 2 = a pessimistic person. While the continuous measures of optimism and discounting are valuable measures to use in our analyses, we decided to add these self-selection measures as an additional measure to help us categorize people into high or low levels of a particular personality characteristic. To do this we expected that the self-selection measure and the continuous measure ought to correlate – which we test in the results section of this study. Finally, participants responded to the demographic questions (see Table 2).

3.3. Study 3

In Study 3, we aimed to expand our investigation to other personality characteristics that were identified in the theoretical review, namely propensity to plan and propensity to worry. The idea was a combination of the approaches used in Studies 1 and 2. Specifically, we presented people with different versions of the same retirement message and looked at various outcomes such as engagement levels and attitudes. We expected that those individuals who score high on a particular level of a personality characteristic (e.g., propensity to plan or worry) will be more likely to engage with, pay attention to, and have more positive attitudes about retirement messages geared towards that level of personality characteristic. Specifically, we expected for instance that a person scoring high on propensity to worry will have more positive attitudes, engage more, and pay more attention to a retirement message that was designed for individuals who have a high propensity to worry.

Along with the two above-mentioned personality characteristics, we also looked at general trust in pension providers. While not a personality characteristic per se, people can differ in how much they trust pension providers. Anyone who saves for retirement is placing trust in a system to protect them over time. Furthermore, people who have low levels of trust tend to desire more freedom of choice with regards to their pension plans compared to those who trust their pension provider (van Dalen & Henkens, 2018). As such, we focused on this measure to examine to what extent a more general feature, rather than a personality characteristic, is amenable to personalisation and whether it will lead to changes in engagement, attitude, and attention.

3.3.1. Participants

Participants were recruited on the online platform Prolific. We decided beforehand to collect at least 500 participants as this was the budget set aside for this study. Expecting larger attrition rates as we didn't limit our sample to just one country (unlike the previous two studies) ultimately, we recruited 543 valid submissions. As mentioned, unlike the previous studies, we did not limit the participating country as we were looking to collect a larger, and perhaps more diverse sample. Participants came from 45 countries across all continents (Europe = 54.1%, North America = 24.7%, Africa = 9.6%, Australia = 2.2%, Asia = 2%, South America = 0.7%, Oceania = 0.6%, Unknown = 6.1%). With over 20% being US-American the United States contributed the most contributions by far, followed by the UK (9.6%), Poland (8.8%), Portugal (7.9%) and South Africa (7.9%). Most participants were under 30 (M = 26, SD = 8). Furthermore, over 60% were in a relationship. For other details on sample please see Table 3.

Table 3. Basic descriptive statistics and description of questions participants were asked to respond to at the end of the survey in Study 2. The questions include basic demographic information about our sample and information on retirement.

Variable	Values	Frequencies
Sex	1. Male 2. Female 3. Prefer not to say	177 (32.6%) 357 (65.7%) 9 (1.7%)
Age	Mean (SD) : 26 (8.1) min ≤ med ≤ max: 18 ≤ 23 ≤ 81 IQR (CV) : 8 (0.3)	-
Nationality	1. United States 2. UK 3. Poland 4. Portugal 5. South Africa 6. Unknown 7. Germany 8. Ireland 9. Italy 10. Canada [36 others]	109 (20.1%) 52 (9.6%) 48 (8.8%) 43 (7.9%) 43 (7.9%) 33 (6.1%) 26 (4.8%) 20 (3.7%) 20 (3.7%) 19 (3.5%) 130 (23.9%)
Household composition	1. Head of household age <60 2. Head of household age <60 3. Head of household age <60 4. Head of household age <60 5. Head of household age 60+ 6. Head of household age 60+	218 (40.1%) 112 (20.6%) 136 (25.0%) 44 (8.1%) 23 (4.2%) 10 (1.8%)
Household income	1. €15,000 - €30,0000 2. €30,0001 - €50,000 3. €50,001 - €75,000 4. €75,001 - €100,000 5. Greater than €100,000 6. Less than €15,000	137 (25.2%) 118 (21.7%) 85 (15.7%) 40 (7.4%) 36 (6.6%) 127 (23.4%)
Existing pension	1. No, I have not. 2. Yes, an employer one 3. Yes, I have both 4. Yes, privately	305 (56.2%) 139 (25.6%) 49 (9.0%) 50 (9.2%)

3.3.2. Procedure

After providing consent, participants were randomly presented with one of four retirement messages. The messages were tailored to be neutral, to appeal to people who score high on propensity to worry, to people who score high on propensity to plan, and people who have a high trust in pension providers. The fours messages were:

Neutral
Saving for retirement is critical for your financial wellbeing later in life. Take charge of your retirement today! This app will help you to manage your savings and help you achieve your optimal retirement income. Click here to get more information on how to be optimally prepared for retirement.

High Worry Proneness
Saving for retirement is critical for your financial wellbeing later in life. Take charge of your **carefree** retirement today! This app will help you to manage your savings **comfortably** and achieve your optimal retirement income **at ease**. Click here to get more information on how to prepare for retirement **while breathing easy**.

High Propensity to Plan
Saving for retirement is critical for your financial wellbeing later in life. **Start planning** your retirement today! This app will help you **set saving goals** and **provides you with a step-by-step plan** to help you achieve them. Click here to get more information on how to optimally **plan** your retirement.

High Trust in Pension Providers
Saving for retirement is critical for your financial wellbeing later in life. **Trust us to help you** take charge of your retirement today! **You can rely on this app** to help you to manage your savings and **assure** that you achieve your optimal retirement income. Click here to get more information on how your **trusted pension provider can help you** prepare for retirement.

After reading the message, participants were asked several questions pertaining to their engagement intentions, attitude, and attention i.e. the dependent variables – we detail those in section 3.3.3 below. At the end of the questionnaire, participants were asked to provide socio-demographic information.

3.3.3. Measures

Propensity to worry was measured using the Worry Domain Questionnaire (WDQ) from Tallis et al. (1992). Since this research endeavour is cantered around financial planning for retirement, participants were only presented with a partial WDQ, namely the five questions from the financial worry domain. Participants could respond on a scale of 1-5, with the responses being labelled "Not at all", "A little", "Moderately", "Quite a bit" and "Extremely", taken from the original WDQ.

Propensity to plan was measured using the questionnaire developed by Lynch et al. (2010). Responses were measured on a Likert scale from 1-7 ranging from "strongly disagree" to "strongly agree". The questions measuring trust in pension providers were taken from Hansen (2012) with responses ranging on the same seven-point Likert scale as presented above. As one of the dependent variables, time spent with the information, i.e., attention, was measured as the time (in seconds) participants spent reading the information before clicking through to the next page of the questionnaire.

Attitude was measured by seven Likert-scale items (1 = "strongly disagree" to 7 = "strongly agree") based on the questionnaire used by Tsang et al. (2004). As the original set of questions was used to measure attitude towards mobile advertising they were adapted accordingly for this study. Specifically, participants were asked: I feel that receiving retirement information is pleasant; I feel that the provider of this message is a good source for retirement information; I feel that the provider of this message is a trustworthy source for retirement information; I feel that following up with this message would provide the information I need; I feel that following up with this message would help me better plan my retirement; I feel that following up with this message would make me feel more relaxed about retiring in the future; and Overall I like this message. The answers to these questions were averaged to produce a single score on the attitude measure.

Finally, a series of behavioural proxy questions was used to measure behavioural intention. Seven items were scored on the same Likert scale of 1-7 as attitude. Specifically, participants were asked: I am planning to look up information about my pension in the upcoming months; I will check the balance of my retirement account; I will consult financial or pension related literature or related content from the internet to gain more insights and knowledge about the topic; I will discuss my retirement finances with friends or family; I will speak with a professional financial advisor; I will investigate or take advantage of retirement savings education resources offered by my employer; and I will spend time working towards identifying or developing additional savings for my retirement (e.g. long-term investment opportunities outside of government and employer-sponsored plans)? The answers to these questions were averaged to produce a single score on the behavioural measure.

3.4. Study 4

Evidence so far hints that people prefer retirement messages that are in line with their score on a particular psychological trait (Study 1). However, we failed to observe that these messages were able to nudge people towards more engagement more with retirement content (Study 2). In Study 3, there was some slight indication that this is true for the propensity to plan characteristic, and a message tailored for people high in propensity to plan, but the statistical relationship is quite weak.

For Study 4, we therefore decided to switch our focus from textual messages towards actual pieces of retirement information, i.e., stimuli that provides some visual information about retirement rather than just signalling a connection to retirement in general as used in the textual messages in the previous three studies. Specifically, whether people with different personality characteristics will be more/less likely to prefer certain pieces of information about retirement. This includes information about e.g., current pension pots – how much money would a person obtain if they retired now, future projections of pension funds, whether it is possible to take out a lump sum of their retirement savings, etc. We switched focus towards pieces of information as it could be that textual messages simply were not powerful enough to nudge a change in engagement behaviour or that they simply did not have a direct and concrete link to one’s retirement. Specifically, it could be that the personalisation efforts would work better had we presented information that has more concrete content about retirement – the textual information presented in the previous studies could have been defocused from retirement content.

The goals of Study 4 were similar to Study 1. In effect, we wanted to investigate whether there are retirement pieces of information that different individuals (i.e., those that differ in some personality characteristic) will prefer as opposed to other retirement pieces of information. The results of this investigation have two main values: a) it is valuable to find out whether people who score differently on particular personality characteristics actually value different pieces of retirement information including whether some pieces of retirement information are just preferred more overall – this is relevant particularly to the Dutch retirement context as we used pieces of information that are normally presented by one of the largest retirement funds in the Netherlands (ABP) in their online tool available to their large base of users and b) finding out these differences will help us in later figuring out whether we can use some pieces of retirement information for personalisation, e.g., presenting people who score low on a personality characteristic a set of pieces of information while presented people who score high a personality characteristic with a set of *different* pieces of information.

3.4.1. Participants

The study investigated whether people who differ in their disposition on optimism and discounting may find different pieces of information about retirement more important, useful, understandable, or relevant. We ran the online on

Prolific. The sample was limited to Dutch residents as we used pieces of retirement information modelled on what is already available to Dutch residents who are members of a large retirement fund, from 18-50 years of age, those that were employed either full-time or part-time, and (since the survey was written in Dutch) those who were fluent in Dutch. In total, we recruited 200 participants as this was the budget set aside for this study. The study took around 10-12 minutes to complete and participants were paid a flat fee for their participation (see Table 4 for details about sample and additional questions asked).

Table 4. Basic descriptive statistics and description of questions participants were asked to respond to at the end of the survey in Study 4. The questions include basic demographic information about our sample and information on retirement.

Variable	Values	Frequencies
Sex	1. Male 2. Female 3. Prefer not to say	122 (61.0%) 76 (38.0%) 2 (1.0%)
Age	Mean (SD) : 29.4 (7.5) min ≤ med ≤ max: 18 ≤ 28 ≤ 51	-
Education	1. Geen Basisonderwijs 2. Basisschool 3. Middelbaar/geen opleiding 4. Middelbaar/met diploma 5. Hoger beroepsonderwijs of 6. BA 7. MA 8. PhD 9. Anders	0 (0.0%) 0 (0.0%) 2 (1.0%) 37 (18.6%) 67 (33.7%) 37 (18.6%) 46 (23.1%) 9 (4.5%) 1 (0.5%)
Are you currently in a retirement fund	1. Yes 2. No	32 (17.5%) 151 (82.5%)
Retirement fund trust (from 1 = not at all to 7 = completely	Mean (SD) : 4.4 (1.3) min ≤ med ≤ max: 1 ≤ 5 ≤ 7	-
How well informed do you think you are about retirement (from 1 = not well informed at all to 7 = completely informed)	Mean (SD) : 4 (1.5) min ≤ med ≤ max: 1 ≤ 4 ≤ 7	-

3.4.2. Procedure

After providing consent, participants were presented with the following instructions:

> In this survey, we will ask you to evaluate certain pieces of information about retirement.
>
> For example, a piece of information about retirement could be how much money you currently have saved.
>
> For each piece of information, we will ask you how **important / useful / understandable / relevant** this information is for you.
>
> We will present you with 7 pieces of information.
>
> Please note: these are examples of information that you could receive from your pension fund. When evaluating, imagine that the examples would contain your own personal pension information. Please focus on the type when

reviewing information that is depicted and whether it would be important / useful / understandable / relevant to you if it were on your personal situation would be coordinated.

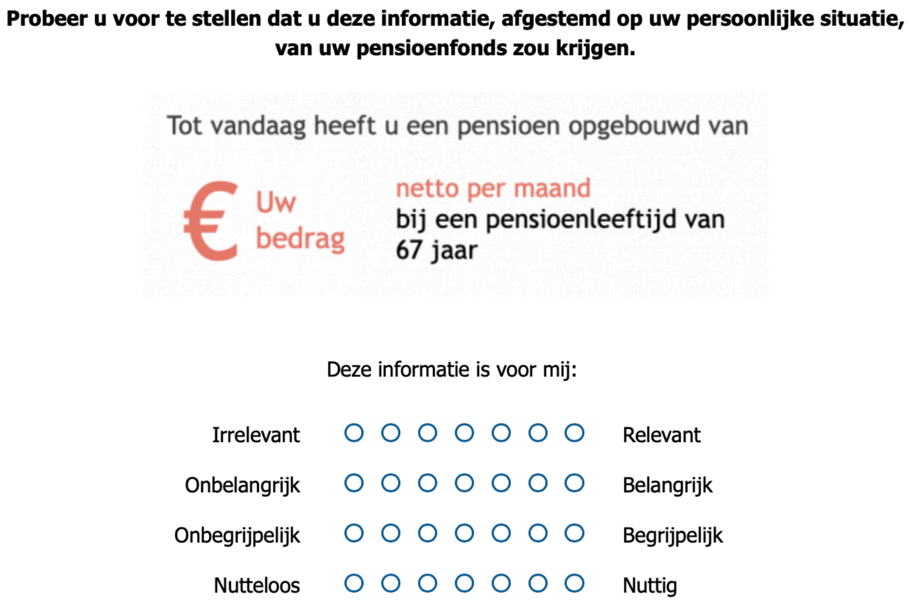
Participants were randomly presented with 7 pieces of information and for each piece of information, they were asked to provide their answer on bipolar scales that were adjusted to each of the four evaluation adjectives. For example, 1 (not important) to 7 (important) or 1 (Useless) to 7 (Useful).

The seven pieces of information are identified as (note that the shorthand is reported in parenthesis – we use this shorthand in the figures for ease of viewing):

1. **Pensioensopbouw (popbouw)** – this piece of information shares details on how much money one can incur during the retirement process
2. **Inkomsten Uitgeven (inuit)** – this piece of information shares details on how much later expenses and incomes will be (when retired)
3. **Pensioenpot (pot)** - piece of information shares details on how much money currently there is in the pension pot
4. **Scenario Vergelijken (vergelijken)** - piece of information shares details on how different life events and scenarios can impact pension
5. **Lump Sum (lumpsum)** - piece of information shares detail on how much money pension savers can withdraw, if they wish so, at once in a lump sum
6. **Belegginsresultaten (blgresult)** - piece of information shares details on investment returns by the pension fund
7. **Dekkinsgraad (dgraad)** - piece of information shares details on the current coverage ration of the pension fund

An example of how the experimental setup looked like with one of the pieces of information and the evaluation questions is below (see Figure 2). A text was presented above the pieces of information each time reading: "Try to imagine you would receive this information, tailored to your personal situation, from your pension fund". Screenshots of all 7 of the pieces of information is shown in the appendix.

Figure 2. An example of how the experimental setup looked like with one of the pieces of information and the evaluation questions as shown to participants in Study 3. Participants responded to the same evaluation question for all seven of the randomly presented pieces of information.



After participants provided their evaluations of the 7 pieces of retirement information, they were asked to provide their answers to the same continuous and dichotomous self-selection questions about optimism and discounting as in Study 2. The Cronbach's alpha score for the optimism scale was .84.

3.5. Study 5

Results from Study 4 showed that people who differ in their discounting level also preferred certain pieces of retirement information more than others. The goal of Study 5 was the investigate whether people with different levels of discounting will engage more with a dashboard that is personalized for them (i.e., a dashboard that contains pieces of information relevant for a particular level of discounting) and find the dashboard more important, useful, understandable, relevant, and engaging, as opposed to a dashboard that is non-personalised (i.e., a dashboard that contains pieces of information relevant for most people).

We therefore predicted an interaction between type of dashboard and level of discounting. Specifically, we predicted that the personalized dashboard will be more liked by the low discounters (as opposed to high discounters) which for the non-personalized dashboard there will be no difference dependent on discounting level. Note that data from a previous study show that the non-personalized dashboard ought to be generally more preferred, so we expect to see a main effect of dashboard.

3.5.1. Participants

We ran the study using the online platform Prolific. The sample was limited to Dutch residents, those that did not participate in our studies previously, and (since the survey was written in Dutch) those who were fluent in Dutch. We decided beforehand to recruit 400 individuals. The study took less than 5 minutes to complete, and participants were paid a flat fee for their participation (see, Table 5 for details about sample and additional questions asked).

Table 5. Basic descriptive statistics and description of questions participants were asked to respond to at the end of the survey in Study 5. The questions include basic demographic information about our sample and information on retirement.

Variable	Values	Frequencies
Sex	1. Male 2. Female 3. Prefer not to say	198 (49.4%) 199 (49.6%) 4 (1.0%)
Age	Mean (SD) : 29.2 (11) min < med < max: 18 < 25 < 75 IQR (CV) : 11 (0.4)	-
Education	1. Geen Basisonderwijs 2. Basisschool 3. Middelbaar/geen opleiding 4. Middelbaar/met diploma 5. Hoger beroepsonderwijs of 6. BA 7. MA 8. PhD 9. Anders	0 (0.0%) 1 (0.2%) 5 (1.2%) 87 (21.7%) 103 (25.7%) 97 (24.2%) 82 (20.4%) 19 (4.7%) 7 (1.8%)
Are you currently in a retirement fund?	1. Yes 2. No 3. I don't know	123 (30.7%) 232 (57.9%) 46 (11.5%)
Retirement fund trust (from 1 = not at all to 7 = completely)	Mean (SD) : 4.3 (1.1) min < med < max: 1 < 4 < 7 IQR (CV) : 1 (0.3)	1 : 6 (1.5%) 2 : 18 (4.5%) 3 : 57 (14.2%) 4 : 128 (31.9%) 5 : 142 (35.4%) 6 : 42 (10.5%) 7 : 8 (2.0%)
How well informed do you think you are about retirement (from 1 = not well informed at all to 7 = completely informed)	Mean (SD) : 3.2 (1.5) min < med < max: 1 < 3 < 7 IQR (CV) : 2 (0.5)	1 : 50 (12.5%) 2 : 106 (26.4%) 3 : 85 (21.2%) 4 : 63 (15.7%) 5 : 70 (17.5%) 6 : 17 (4.2%) 7 : 10 (2.5%)

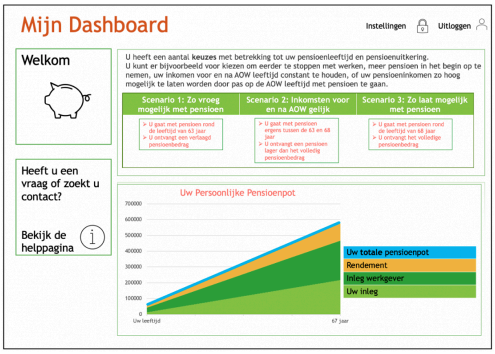
3.5.2. Procedure

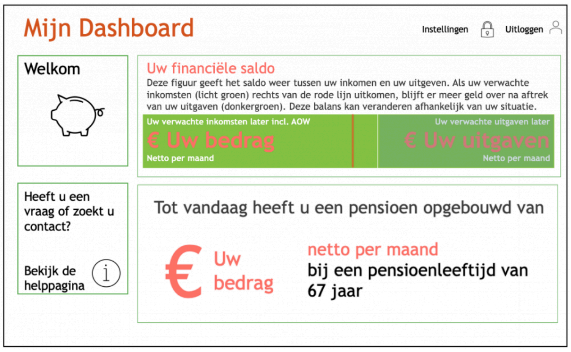
After providing consent, participants were presented with the following instructions:

> In this study, we ask you to evaluate a dashboard with information about your pension. For example, this dashboard can show how much money you currently have saved for retirement.
>
> Take as much time as you need to see and read what is presented on the dashboard. You will then be asked to rate how important / useful / understandable / relevant the dashboard is to you, on a scale from 1 (not at all) to 7 (completely).
>
> Please note: the dashboard contains examples of information that you can obtain from your pension fund. When evaluating, imagine that the dashboard would contain your own personal retirement information.

Afterwards, participants were randomly presented either with a dashboard that has been personalised for low discounters (with pieces of retirement information shown in Study 4 to be preferred by low discounters) or with a non-personalised dashboard (with pieces of information shown in Study 4 to be preferred in general) (see Figure 3 for an example).

Figure 4. Examples of the two dashboards used in Study 5. The dashboard on the left is personalised to appeal to low discounters (based on the results from study 4). The dashboard on the right is non-personalised. Under each of the dashboards, participants were presented with the 4 evaluation questions as detailed in the instructions.





After having a look at the dashboard, participants evaluated it on how important, useful, relevant, and understandable the dashboard is (on scales from 1 to 7) similar to Study 4. Additionally, we also measured the time participants spent with the dashboard in front of them. Afterwards, they were asked two questions designed to gauge their level of engagement. Specifically, they were asked: “Would you be willing to share additional financial information with a pension fund in order to personalise this dashboard for you” and “Would you be willing to leave your contact details so that we can contact you about developing such a dashboard?” Both questions could be answered with either a yes or a no. Subsequently, participants were asked a question measuring their level of discounting using the same continuous measure as in Studies 2 and 4. Finally, participants were asked to respond to demographic questions on sex, age, education, whether they have been (or currently) are a member of a retirement fund, and how trustworthy they think retirement funds are.

4. Results

4.1. Results Study 1

We first looked at whether people, in general, preferred certain textual message versions (i.e., independent of their psychological characteristics). For example, information related to numeracy was presented in three formats: one tailored for low numerate individuals, one for mid numerate, and one for high numerate. In Table 5, we report the choice frequencies and the binomial test results. We used binomial tests to compare the observed choice frequency to a hypothetical frequency that would have been observed had participants not have a preference. For instance, if people had no preference between two messages, we would observe a 50/50 split. If the binomial test result is significant, that means that there are significant deviations from the hypothetical frequency. The results are reported in Table 6.

Table 6. Frequencies on how participants in Study 1 chose the retirement message versions/formats, compared to a hypothetical frequency of no preference. The p value is related to a binomial test comparing the actual frequency to a hypothetical frequency which would have resulted had the choices been made randomly.

Personality Characteristic	Message versions/formats	Choice frequency	Hypothetical frequency	Test result
Numeracy	1. Low 2. Mid 3. High	69 (27.5%) 62 (24.7%) 120 (47.8%)	30/30/30	p = .003
Discounting	1. Low 2. High	187 (74.5%) 64 (25.5%)	50/50	p < .001
Optimism	1. Low 2. High	99 (39.4%) 152 (60.6%)	50/50	p = .04
Future-self	1. Low 2. High	117 (46.6%) 134 (53.4%)	50/50	p = .62

The results seem to suggest that our participants, in general, preferred retirement messages tailored for the high numerate, high optimist, and the low discounters. Results for the future-self did not differ significantly. Next, we verified whether the order in which the psychological characteristics were measured had an impact on message version/format preferences. Using chi-square tests we found that order did not impact how people chose the message format versions (all *p*s > 0.05).

Do people prefer retirement messages tailored to their level of a psychological characteristic? To perform the analyses, we looked at whether people's scores on a psychological characteristic can predict people's choice preferences for the retirement message. We first looked at numeracy. Because there were three message formats and people's score on numeracy could vary between 0 and 4, we used an ordinal logistic regression to perform the analysis. Predicting message choice based on numeracy score, we did not find significant results for any of the three versions of the numeracy messages (all *p*s > .21).

We then looked at delay discounting using the continuous measure as a predictor for retirement message choice. Using a logistic regression and found that, indeed, people who said they were willing to give up something today to benefit from it in the future (low discounters) were more likely to choose the low discounting version of the retirement message, $b = -0.17$, $z = -2.22$, $SE = 0.08$, $p = .02$.

There was no effect for the future-self measure using the same method as for discounting, $b = -0.00$, $z = -1.47$, $SE = 0.001$, $p = .14$. The effect for the optimism measure was also not significant, $b = 0.14$, $z = -0.72$, $SE = 0.20$, $p = .47$ although it was in the predicted direction with people who scored higher in optimism, choosing to prefer the retirement message tailored for high optimists.

Another way of looking at the results could be to focus on the participant, rather than the sample level as the regressions do above. Specifically, to look at the percentage of people that did choose the retirement message consistent with their score on a psychological characteristic. This, however, requires us to artificially split people into categories according to their score on the psychological measures. Artificially dichotomizing continuous or rank measures is unrecommended (Dawson & Weiss, 2012) so this approach is purely exploratory, and we use it only to help in future hypothesis generation. The simplest way to dichotomize scores is to take the mid-point of the scale. For example, for the optimism scale that goes from 1 to 5, binning those people who scored 2.5 or less into low while those that score more than 2.5 as high optimists. Looking at the results this way, we can see, in Table 7, that at least for discounting and optimism, the majority (> 50%) of individuals chose the retirement message that was tailored to their score on a psychological characteristic. The results again here show that there does not appear to be any correspondence for future-self continuity and the numeracy measures.

Table 7. Percentage of choices that were consistent (i.e., choosing a retirement message format consistent with a score on psychological characteristic) as opposed to inconsistent (i.e., choosing a retirement message format inconsistent with a score on a psychological characteristic).

	Discounting	**Optimism**	**Future-self**	**Numeracy**
Consistent choice	69.72%	59.36%	45.24%	31.08%
Inconsistent choice	30.28%	40.64%	54.76%	68.92%

4.2. Results Study 2

We first wanted the verify whether the dichotomous self-selection questions (e.g., I consider myself an optimist/pessimist) correlate with the continuous measures. If so, this would allow us to use the self-selection questions to *categorize* people into the personality groups. For the dichotomous self-selection questions, overall, 79.04% of the people said that they are someone who attached more value to long-term benefits (a low discounter). Further, 66.47% of the people said that they consider themselves to be a generally optimistic person. The results of the logistic regressions showed that indeed, the higher the optimism score on the questionnaire (continuous measure), the more likely that someone has self-selected as optimistic, $b = 2.73$, SE = .24, $z = 11.38$, $p < .001$. Similarly, the more someone said that they were willing to sacrifice something today (continuous measure), the more likely they were to self-select as attaching more value to long-term benefits, $b = 0.49$, SE = .06, $z = 7.80$, $p < .001$. These results suggest that it is valid to use the binary self-selection variables to categorize people into low vs. high optimistic and low vs. high discounting.

4.2.1. Matching and dashboard selection

Overall, *66.07%* of people said they'd be interested in visiting the retirement dashboard. One thing worth noting here is that this may be a high number leading to a ceiling effect and lack of variation in responding. An interesting thing to note here is that this number is quite a lot higher than what we see in the real world where people do not check or verify their online dashboards. This could be an indication of a large demand effect occurring – we come back to this in the discussion. Another reason could be that people simply were interested in seeing what the dashboard is like. It may therefore be difficult to nudge people with a tailored prompt to visit a retirement dashboard, if such a high number are already willing to do so. It could also be a simple demand effect.

We first created a *matching* variable. Basically, whether the message shown *matched* the personality characteristics of the participant viewing it. There are three distinct levels of matching possible given the four textual prompts and the two personality characteristic levels. First, there could be a full match where there are matches on both personality traits to the message, second, there could be a partial match where only one of the personality traits matches the message, or third, there would be no match, where neither of the personality traits matches the message.

To test matching, we used a logistic regression. There was no effect of matching on willingness to visit the retirement dashboard (all *p*s > .45 for the three levels of matching). Essentially, whether there was a full, or partial match with personality and the textual prompt, this did not lead to a higher likelihood to select to view the retirement dashboard.

Adding the demographic variables, does not change the results. There was still no effect of matching. We do see that those with higher education and higher retirement worry were more likely to say that they would visit the dashboard. Similarly, looking only at people who are currently a member of fund and not a member separately, does not change the results.

4.3. Results Study 3

Before we move on with the main analysis, we first noticed that there were several extreme values associated with the time measure (as is not unusual in online environments as sometimes people may leave the screen or there may be a technical error that occurs during the presentation of the study material). To ensure the quality of the data, all outliers above the third quartile plus the interquartile range (IQR) multiplied by 1.5 the third quartile and 1.5 IQR below the first quartile were excluded from the data (Carling, 2000). This decreased the sample size to 495. The results below are reported with this sample size.

To gain an overview over independent and dependent variables, in Table 8 we report the means for each personality trait as well as the outcome variables attitude, behavioural intention, and attention by message used in the Study. It should be mentioned again that propensity to worry was measured on a five-point Likert scale. Attention was measured in seconds. All other variables were measured on a Likert scale of one through seven.

Table 8. Means and SDs (in parenthesis) of Predictor Variables (Personality characteristics -first three rows) and Outcome Variables (rows 4 -6) by Message version for Study 3.

	Neutral Message	Worry Message	P2P Message	Trust Message
Propensity to Worry (Trait)	2.91 (0.94)	2.83 (0.94)	2.96 (0.9)	2.83 (0.9)
Propensity to Plan (Trait)	4.75 (1.11)	4.84 (1.15)	4.85 (1.05)	4.69 (1.06)
Trust in Pension Provider (Trait)	4.48 (1.01)	4.54 (1.17)	4.57 (1.2)	4.59 (1.00)
Attitude	4.66 (1.13)	4.69 (1.3)	4.97 (1.06)	4.38 (1.27)
Behavioural Intention	4.03 (1.37)	4.14 (1.36)	4.23 (1.36)	4.15 (1.27)
Attention (excl. Outliers)	13.85 (6.44)	15.42 (7.66)	13.88 (6.78)	17.27 (7.12)

For all the analyses reported, we relied on linear regressions with attitude, behaviour, or attention as the dependent variable, the type of message (neutral, worry, P2P and trust) as a categorical predictor, the psychological characteristic score (propensity to worry, propensity to plan and trust in pension providers) and their interaction effect. The effect of interest is an interaction between the personality characteristic measure and the message variable. In other words, if we find an interaction between message and relevant personality characteristic that would indicate that a personalised message for a particular personality characteristic leads to observable changes in one of the outcome variables.

First, we looked at the interaction effect of the Worry Message and the personality trait propensity to worry. There was no interaction for either of the three dependent variables of attitude, behaviour, or attention (all *p*s > .65). Similar findings were obtained for the trust message and the general trust measure (all *p*s > .18).

There was also no interaction effect between the propensity to plan message and the propensity to plan measure on attitude and attention (*p*s > .57). However, there was some indication of an interaction effect between the propensity to plan message and the personality trait propensity to plan, $b = .28$, SE = .14, $p = .05$. However, it worth noting that the p value is quite high and on the border of a pre-determined alpha of .05 meaning that these results may not be that reliable. The interaction however does indicate that people who scored higher on propensity to plan, when receiving the propensity to plan message, showed an increase of around 0.539 points in the behavioural intention outcome. The results overall again point to a lack of success in personalised messages leading to higher engagement, more positive attitudes, or attention with retirement information.

4.4. Results Study 4

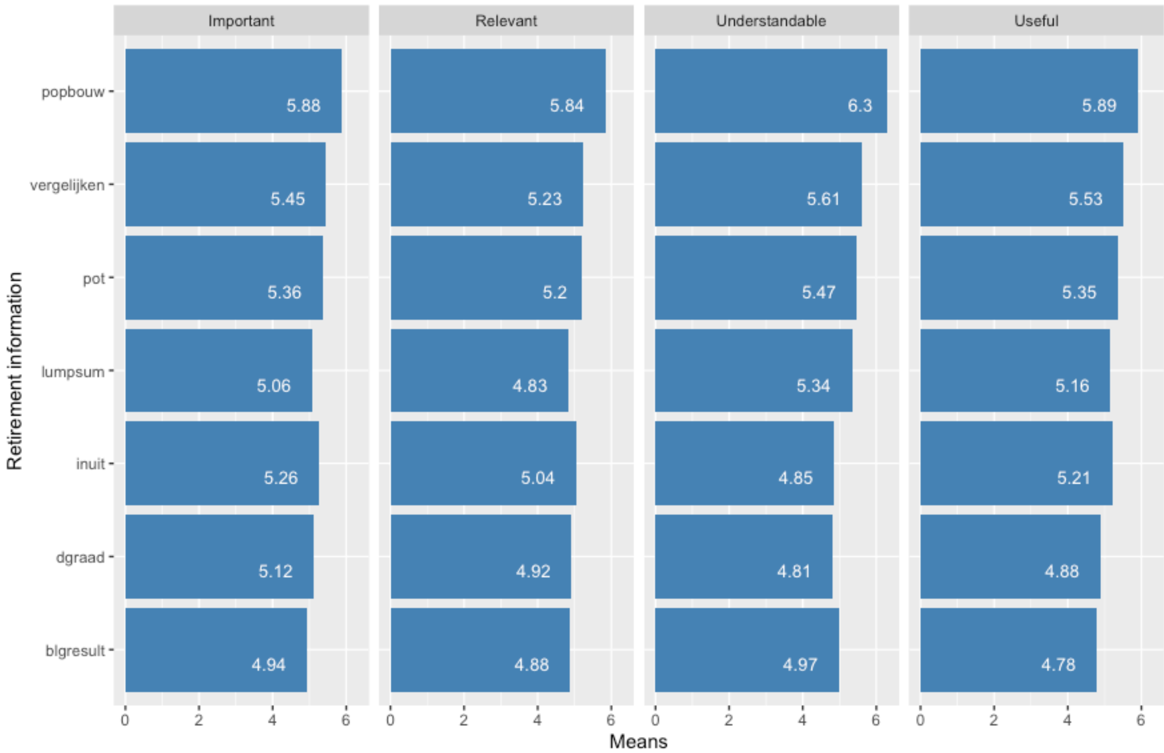
Do people who differ in their scores on discounting and optimism find different pieces of retirement information more important, useful, understandable, or relevant? For each of the seven pieces of information (see Appendix for the visual examples of the pieces of information), participants were asked to provide their evaluation on a scale from 1 to 7.

Once more, for ease of understanding, the seven pieces of information are identified as (note that the shorthand is reported in parenthesis – we use this shorthand in the figures for ease of viewing):

8. **Pensioensopbouw (popbouw)** – this piece of information shares details on how much money one can incur during the retirement process
9. **Inkomsten Uitgeven (inuit)** – this piece of information shares details on how much later expenses and incomes will be (when retired)
10. **Pensioenpot (pot)** - piece of information shares details on how much money currently there is in the pension pot
11. **Scenario Vergelijken (vergelijken)** - piece of information shares details on how different life events and scenarios can impact pension
12. **Lump Sum (lumpsum)** - piece of information shares detail on how much money pension savers can withdraw, if they wish so, at once in a lump sum
13. **Belegginsresultaten (blgresult)** - piece of information shares details on investment returns by the pension fund
14. **Dekkinsgraad (dgraad)** - piece of information shares details on the current coverage ration of the pension fund

First, we looked at the basic mean statistics of the seven pieces of retirement information, as a function of each of the four evaluation questions. We present the results in Figure 3 below. Clearly, the highest preferences in terms of importance, usefulness, understandability, and relevance is associated with the pensioensopbouw piece of information. One can speculate on reasons for this as it could be that most individuals in our sample think of this as a basic and necessary piece of information about retirement.

Figure 3. Means in Study 4 on how understandable, important, useful, and relevant, each of the seven pieces of retirement information were evaluated as by participants.



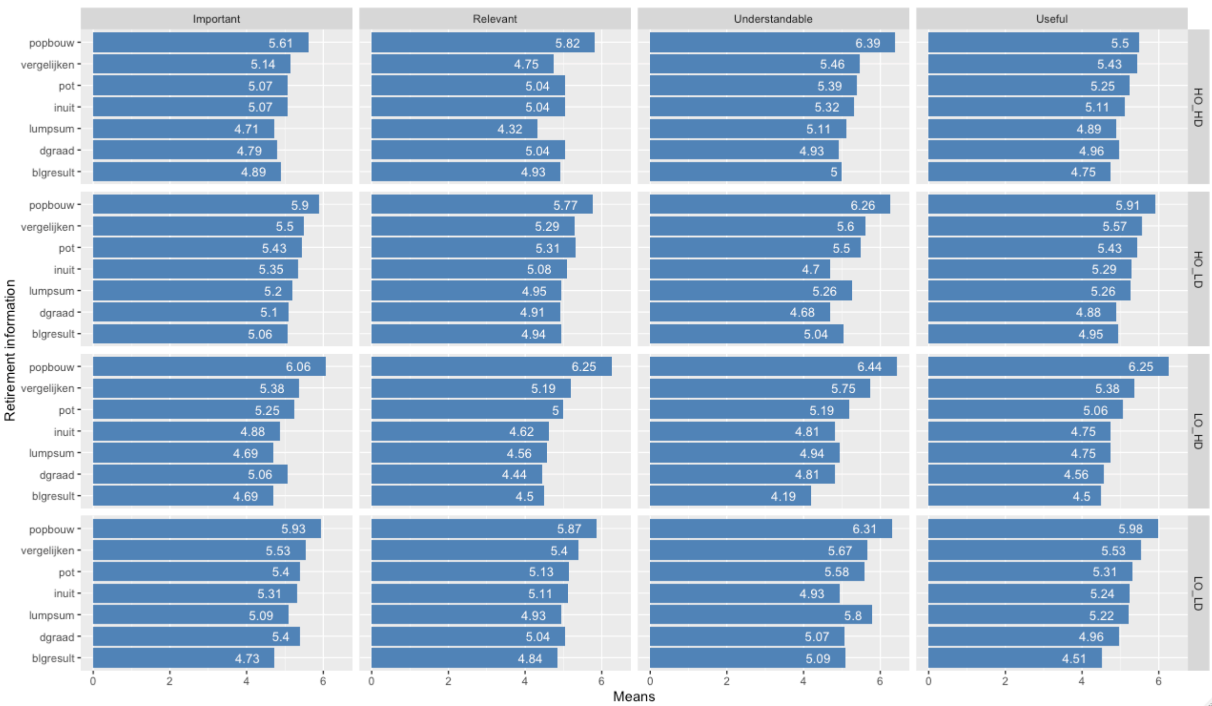
Moving on, we are interested in whether the evaluations of the pieces of information differ dependent on how people score on the two measured personality characteristics, namely optimism and discounting. There were again 4 possible combinations of the personality characteristics:

- HO_HD - High optimism, High Discounting
- HO_LD - High optimism, Low Discounting
- LO_HD - Low optimism, High Discounting
- LO_LD - Low optimism, Low Discounting

To group people into these combinations, we relied on the self-selection questions (similar to Study 2). The results of the logistic regressions showed that indeed, the higher the optimism score on the questionnaire (continuous measure), the more likely that someone has self-selected as optimistic, $b = 0.94$, SE = .574, $z = 11.38$, $p < .001$. Similarly, the more someone said that they were willing to sacrifice something today (continuous measure), the more likely they were to self-select as attaching more value to long-term benefits, $b = 2.35$, SE = 1.63, $z = 7.80$, $p < .001$. These results suggest that it is valid to use the binary self-selection variables to sort people into low vs. high optimistic and low vs. high discounting.

How people evaluated the seven pieces of information, dependent on the 4 potential personality combinations is presented in Figure 4. The figure shows that there is clearly variation in how people grouped into one of the 4 personality combinations evaluate the seven pieces of retirement information. Although it is important to note that most still seem to prefer the pensioensopbouw piece of information overall.

Figure 4. Means in Study 4 on how understandable, important, useful, and relevant, each of the seven pieces of retirement information was evaluated, as a function of the four different personality characteristic combination.



Using regression analyses, we then proceed to investigate whether there are relationships in preference between how people score on optimisms and discounting and how they evaluated the seven different pieces of information. Note, the seven pieces of information were used as the dependent variable so there are seven columns in the tables below. Since we asked four questions on preference, we split the regressions into four separate tables (see Table 9.1 to Table 9.4), e.g., one for each of the four evaluation questions. The pieces of information are shown as numbers from 1 to 7 and correspond to the order presented on page 27 of this document.

Table 9.1 Predicting importance with optimism and discounting for different pieces of information.

	Dependent variable: importance evaluation of the seven pieces of information						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Optimism	0.013	0.168	-0.026	0.206	0.109	-0.073	0.204
	(0.192)	(0.185)	(0.205)	(0.180)	(0.198)	(0.204)	(0.220)
Discounting	0.035	-0.068	0.502*	0.650***	0.345	0.632**	0.497*
	(0.192)	(0.185)	(0.205)	(0.180)	(0.198)	(0.204)	(0.220)
Constant	5.880***	5.265***	5.360***	5.450***	5.065***	5.120***	4.935***
	(0.094)	(0.091)	(0.101)	(0.088)	(0.097)	(0.100)	(0.108)
Observations	200	200	200	200	200	200	200
R^2	0.0002	0.004	0.030	0.076	0.019	0.046	0.034
Adjusted R^2	-0.010	-0.006	0.020	0.067	0.009	0.037	0.024
Residual Std. Error (df = 197)	1.335	1.289	1.424	1.251	1.376	1.421	1.528
F Statistic (df = 2; 197)	0.022	0.432	3.049*	8.115***	1.888	4.799**	3.443*
Note: rows show regression coefficients and standard errors							*p<0.05;* ***p<0.01;*** p<0.001

Table 9.2 Predicting usefulness with optimism and discounting for different pieces of information. Coefficients presented with standard errors in parentheses.

	Dependent variable: usefulness evaluation of the seven pieces of information						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Optimism	0.037	0.124	0.325	0.114	0.125	0.282	0.382
	(0.194)	(0.203)	(0.194)	(0.176)	(0.210)	(0.205)	(0.198)
Discounting	0.128	-0.030	0.383*	0.326	0.350	0.260	0.442*
	(0.194)	(0.203)	(0.194)	(0.176)	(0.210)	(0.205)	(0.198)
Constant	5.895***	5.210***	5.350***	5.525***	5.160***	4.885***	4.785***
	(0.096)	(0.100)	(0.095)	(0.086)	(0.103)	(0.101)	(0.097)
Observations	200	200	200	200	200	200	200
R^2	0.003	0.002	0.039	0.022	0.018	0.021	0.050
Adjusted R^2	-0.007	-0.008	0.030	0.012	0.008	0.011	0.041
Residual Std. Error (df = 197)	1.351	1.408	1.350	1.220	1.459	1.428	1.378
F Statistic (df = 2; 197)	0.264	0.187	4.029*	2.199	1.787	2.101	5.219**
Note: rows show regression coefficients and standard errors							*p<0.05;* ***p<0.01;*** p<0.001

Table 9.3 Predicting understandability with optimism and discounting for different pieces of information. Coefficients presented with standard errors in parentheses.

	Dependent variable: understandability evaluation of the seven pieces of information						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Optimism	0.178	0.386	0.411	-0.085	-0.024	-0.124	0.353
	(0.155)	(0.238)	(0.213)	(0.195)	(0.205)	(0.244)	(0.238)
Discounting	-0.053	-0.499*	0.269	0.440*	0.298	0.463	0.763**
	(0.155)	(0.238)	(0.213)	(0.195)	(0.205)	(0.244)	(0.238)
Constant	6.305***	4.850***	5.475***	5.610***	5.335***	4.815***	4.975***
	(0.076)	(0.117)	(0.104)	(0.096)	(0.101)	(0.120)	(0.117)
Observations	200	200	200	200	200	200	200
R^2	0.007	0.030	0.031	0.025	0.011	0.018	0.069
Adjusted R^2	-0.003	0.020	0.021	0.015	0.001	0.008	0.059
Residual Std. Error (df = 197)	1.078	1.657	1.477	1.352	1.422	1.695	1.651
F Statistic (df = 2; 197)	0.668	3.012	3.178*	2.555	1.066	1.820	7.289***
Note: rows show regression coefficients and standard errors							*p<0.05;* ***p<0.01;*** p<0.001

Table 9.4 Predicting relevance with optimism and discounting for different pieces of information

	Dependent variable: relevance evaluation of the seven pieces of informaiton						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Optimism	-0.0001	0.162	0.049	-0.007	0.110	0.132	0.163
	(0.201)	(0.206)	(0.207)	(0.199)	(0.214)	(0.216)	(0.215)
Discounting	-0.038	-0.117	0.581^{**}	0.678^{***}	0.611^{**}	0.386	0.651^{**}
	(0.201)	(0.206)	(0.207)	(0.199)	(0.214)	(0.216)	(0.215)
Constant	5.835^{***}	5.045^{***}	5.205^{***}	5.230^{***}	4.830^{***}	4.920^{***}	4.880^{***}
	(0.099)	(0.101)	(0.102)	(0.098)	(0.105)	(0.106)	(0.106)
Observations	200	200	200	200	200	200	200
R^2	0.0002	0.004	0.041	0.057	0.045	0.020	0.052
Adjusted R^2	-0.010	-0.006	0.031	0.048	0.035	0.010	0.042
Residual Std. Error (df = 197)	1.395	1.430	1.441	1.383	1.484	1.504	1.496
F Statistic (df = 2; 197)	0.018	0.408	4.180^{*}	5.963^{**}	4.605^{*}	2.016	5.400^{**}

Note: rows show regression coefficients and standard errors *p<0.05;* ***p<0.01;*** p<0.001

As a robustness check, the four evaluation questions could be tapping into the same construct of a general preference. It may thus be possible to combine the questions into a single measure of overall retirement information preference. To do this, we first looked at the correlation between the four evaluation measures. For all seven pieces of information, we see that understandability does not correlate well with the other measures scoring a correlation of r < .50 consistently. However, the other three measures consistently have a high correlation of r > .70 meaning that they could be averaged and combined. The Cronbach's alpha value of the three combined variables is .82.

Using the combined measure of preference (averaging the score on important, relevant, and useful, we again looked at the same type of analysis as above. We report the findings in Table 10, which is similar to those above.

Table 10. Predicting preference (combined DV) with optimism and discounting for different pieces of information

	Dependent variable: preference (combined importance, usefulness and relevance evaluation) of the seven pieces of information						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Optimism	0.017	0.151	0.116	0.104	0.115	0.114	0.250
	(0.183)	(0.181)	(0.186)	(0.165)	(0.186)	(0.186)	(0.195)
Discounting	0.042	-0.072	0.489^{**}	0.551^{**}	0.435^{*}	0.426^{*}	0.530^{**}
	(0.183)	(0.181)	(0.186)	(0.165)	(0.186)	(0.186)	(0.195)
Constant	5.870^{***}	5.173^{***}	5.305^{***}	5.402^{***}	5.018^{***}	4.975^{***}	4.867^{***}
	(0.090)	(0.089)	(0.092)	(0.081)	(0.091)	(0.092)	(0.096)
Observations	200	200	200	200	200	200	200
R^2	0.0004	0.004	0.039	0.060	0.032	0.031	0.051
Adjusted R^2	-0.010	-0.006	0.029	0.050	0.022	0.021	0.041
Residual Std. Error (df = 197)	1.271	1.256	1.296	1.150	1.292	1.296	1.354
F Statistic (df = 2; 197)	0.035	0.383	4.023^{*}	6.287^{**}	3.270^{*}	3.122^{*}	5.268^{**}

Note: rows show regression coefficients and standard errors *p<0.05;* ***p<0.01;*** p<0.001

Overall, as presented in Tables 9.1 to 9.4, as well as Table 10, for none of the four evaluation questions, optimism scores didn't seem to correlate with any of the pension pieces of information. However, the results for discounting are a bit more interesting. For importance, the lower a discounter someone was, the more important they thought the pensioenpot, scenario vergelijken, dekkingsgraad, and beleggingsresultaten was. For usefulness, the lower a discounter someone was, the more useful they thought the pensioenpot and beleggingsresultaten was. For understandability, the lower a discounter someone was, the more understandable they thought the Inkom Uitgeven, Scenario Vergelijken, and beleggingsresultaten was. Finally, for relevance, the lower a discounter someone was, the more relevant they thought the pensioenpot, scenario vergelijken, lump sum, and beleggingsresultaten was. We see therefore that people do prefer certain pieces of information more dependent on how they score on the measure of discounting. Discounting as such seems to be quite stable in consistently revealing itself as quite a stable predictor of preference for retirement information.

4.4. Results Study 5

To simplify the presentation of the results we created a single preference measure (similar to Study 4) by combining the three separate measures used as the DV's. To create the preference variable, again similar to Study 4, we looked at the correlation between the four evaluation questions and found that, beside understandability, the three other measures correlated highly with each other ($r > .70$). We averaged them and created a single measure of preference. The three variables have a Cronbach's alpha value of .84.

For our main analysis, as discussed in the methods section, we predicted an interaction between discounting score, and type of dashboard. This interaction ought to show that those scoring as being lower in discounting would prefer the personalised dashboard (as it was personalised for low discounters) more than the general non-personalised dashboard. We also expected to see a main effect of dashboard as well as the non-personalised dashboard was found in Study 4 to score quite high in terms of preference. In Table 11 we show the results of the regression analyses on the preference variable, as well as the four measures separately, and the time spent on dashboard page as DV's.

Table 11. Predicting preferences, importance, usefulness, understandability, relevance, and time spend with a discounting, dashboard, and their interaction in Study 5.

	Dependent variable:					
	Preference	Important	Useful	Understandable	Relevant	Time on page
	(1)	(2)	(3)	(4)	(5)	(6)
Discounting	0.089^{**}	0.089^{*}	0.091^{*}	0.013	0.086^{*}	1.259
	(0.032)	(0.035)	(0.035)	(0.037)	(0.039)	(0.890)
Dashboard	-0.265^{*}	-0.142	-0.351^{*}	0.001	-0.302	6.998
	(0.133)	(0.147)	(0.147)	(0.153)	(0.163)	(3.723)
Interaction	0.035	0.045	0.071	-0.061	-0.012	-2.771
	(0.064)	(0.070)	(0.070)	(0.073)	(0.078)	(1.780)
Constant	4.909^{***}	4.945^{***}	5.087^{***}	5.452^{***}	4.693^{***}	44.127^{***}
	(0.067)	(0.074)	(0.074)	(0.076)	(0.082)	(1.862)
Observations	401	401	401	401	401	401
R^2	0.027	0.018	0.029	0.002	0.019	0.022
Adjusted R^2	0.020	0.010	0.022	-0.005	0.012	0.014
Residual Std. Error (df = 397)	1.328	1.471	1.471	1.525	1.626	37.150
F Statistic (df = 3; 397)	3.666^{*}	2.376	4.009^{**}	0.295	2.601	2.928^{*}

Note: rows show regression coefficients and standard errors *p<0.05;* ***p<0.01;*** p<0.001

We see no interaction appearing for any of the evaluation measures nor for the measure of time spent on dashboard. Two main affects appear for some variables. Overall, the lower of a discounter someone, is the more they prefer, find the dashboard important, useful, and relevant. There is also a main effect of dashboard with the non-personalized dashboard being preferred more and judged as more useful – this is in line with expectations as this dashboard had pieces of information generally evaluated more positively (in Study 4).

We then focused on the two engagement questions. For both questions, 270 people clicked yes, while 131 clicked no. This again hints at generally high levels of engagement (similar to Study 2) which is opposite to what we see in the real world perhaps again indicating a high demand effect. There was no difference in clicking behaviour between the two questions. To test whether there were any differences dependent on discounting and dashboard type, we ran logistic regressions where 0 was coded as yes, while 1 was coded as no. Results are shown in Table 12 below. The results again only show a main effect of discounting. The lower discounter someone is, the more likely they are to say yes to these questions. There was again no interaction.

Table 12. Predicting engagement with a discounting, dashboard, and their interaction for the two engagement question in Study 5.

	Dependent variable:	
	Share information	Share contact
	(1)	(2)
Discounting	-0.206***	-0.206***
	(0.052)	(0.052)
Dashboard	-0.148	-0.200
	(0.220)	(0.220)
Interaction	0.082	0.062
	(0.105)	(0.105)
Constant	-0.761***	-0.761***
	(0.110)	(0.110)
Observations	401	401
Log Likelihood	-244.077	-244.014
Akaike Inf. Crit.	496.153	496.029
Note: rows show regression coefficients and standard errors		*p<0.05;* ***p<0.01;*** p<0.001

5. Conclusion and discussion

Across five studies and around 1800 participants, we investigated whether we could increase engagement with retirement through personalised communication. Overall, our results do not provide strong support for this possibility. In short, while we did find that textual messages, as well as specific pieces of information about retirement are judged differently dependent on a person's personality characteristic, employing these directly did not lead to statistically significant changes in engagement behaviour. Specifically, presenting participants with retirement messages and pieces of retirement information personalised to their personality characteristics, did not lead them to display higher engagement with retirement content, did not capture their attention more, nor did it lead to overall more positive attitudes about the process of communication. The results, although initially disappointing, still provide additional insights into the role of personalisation in impacting low retirement engagement levels and how future research can begin to tackle lack of engagement with retirement content. In the discussion below we cast a serios look on whether personalisation using psychological characteristics is the best intervention to apply at this point for increasing engagement with retirement planning.

We have established early on in this report that people are not engaging enough with their retirement. In some sense, this seems to be an empirical truism at this point. Even naively surveying ourselves, family, friends, or co-workers, we would see that people either pay little attention to their retirement, or have not made any concrete steps to find out more about the situation their retirement plans are in. This has been attributed to many factors. Most notably, people's genuine tendency to discount the values and utilities associated with the future. Retirement, by its very nature, is an outcome for which our future selves should be worried about. Indeed, for most people, the erroneous belief is that retirement is something that they simply cannot worry about *right now*. There are more pressing issues that plague us presently (current financial situation for example), worries about future uncertainty (am I even going to reach retirement age) general anxiety about the state of affairs in the future (what will the world look like 20, 30, or 40 years in the future?), whether resources are really better spent now (why not invest money now and make better use of it rather than stash it for the future) or simple biases that people succumb to like the present bias where people psychologically have a need to resolve events immediately rather than later (Goda et al., 2019; Maden & Johson, 2010; Zhang, 2013). Many other behaviours have been identified as well that contribute to people's general lack of engagement with retirement such as misunderstand savings growth (Mckenzie & Liersch, 2011), our tendency to defer retirement decisions (Krijnen et al., 2015), the fact that most people find retirement planning difficult (Krijnen et al., 2019), and our overall lack of financial understanding (Lusardi & Mitchelli, 2007).

This is all to say that retirement engagement, or lack thereof, seems to be quite an entrenched and stubborn behaviour. This is not to say though that we should not be working on ways and interventions that could help people overcome it and lead to more positive outcomes. As detailed in the introduction, several interventions, nudges, and procedures have shown promise in this regard. However, most of these skip over a crucial step. Namely, in most of the cases, people are not even aware of, nor have they ever gotten information about their retirement. As we've seen from the many survey results reported in the introduction, a vast majority of individuals does not consult literature on retirement, does not engage with nor use increasingly available online dashboards to get acquainted with their retirement situation, nor do they know how to even approach finding out more about these things.

For this reason, we focused on the very initial step – getting engaged with retirement information, i.e., finding out more information or being willing to receive further information. This, to us, seems like the crucial step to take when it comes to a lack of retirement engagement. One promising way identified in the literature to increase engagement, in particular through common means of communication, such as textual messages, visuals, or reminders, has been the concept of personalisation.

Personalisation has been shown, in various domains, to be quite a potent tool that can impact behavioural change. Importantly, we have not focused on what we have referred to as simple personalisation forms. Specifically, interventions where communication is personalised through, for example, using given names. Here, we focused on a more advanced or deeper form, one where the focus is on a person's personality. In other literature, personalisation has been shown to increase customer intention to adopt changes and increase emotional and cognitive trust (Komiak & Benbasat, 2006). Personalised content is more easily accepted and evaluated more highly in contexts of online banner ads (Tam & Ho, 2006). Personalising websites so that they are tailored to participants' cognitive style has been shown to increase purchase intention (Hauser et al., 2009).

Previous findings suggest that personalisation can be an effective tool at instigating behavioural change. But how well would it do with such an entrenched problem as retirement planning avoidance? To personalise communication, we decided to focus on personality characteristics. Indeed, lack of engagement with retirement is often painted as a deep rooted and often purely behavioural problem. It stands to reason those interventions focused on behavioural components may be successful. We set about to identify potential personality characteristics that could be related to retirement and retirement behaviour. Guided by the literature, we settled on numeracy, discounting, optimism, future-self continuity, propensity to plan, and propensity to worry.

As hinted at in the opening lines of this section, our results effectively point to the fact that personalisation may be a far cry from a successful intervention if one's goals is to get people to engage more with retirement. In three studies that directly tested whether personalised content will get people to be more likely to visit an online retirement dashboard (Study 2), engage more, pay attention, and judge more positively (Study 3) or find a retirement dashboard more important, useful, relevant, and understandable (Study 5), we failed to observe predicted effects. The personalised messages and dashboards did not lead to statistically significant changes in engagement outcomes above and beyond non-personalised or neutral messages and dashboards.

We did however observe that people, depending on their personality, did prefer content that was personalised for them. For instance, in Study 1, we found that people scoring lower on discounting were more likely to prefer messages geared towards lower discounters. Similarly, optimists were more likely to prefer messages geared towards optimists. In Study 2, we also found that there are particular pieces of information about retirement that people who differ in discounting prefer more or less. These findings do hint that there is a possibility to personalise content for people, dependent on their personality. However, whether this will be effective in changing engagement behaviour remains questionable.

5.1 Failures of personalisation

Are there previous attempts of personalisation that did not work out? Within the social sciences literature it is always difficult to judge to what extent the literature is presented genuinely. This is because studies that work, i.e., studies that show significant results of an intervention, have a greater chance of being published (Franco et al., 2014). Nevertheless, there are some indications that personalisation has not worked consistently in the many domains it has been tried. Ginns et al. (2013) did a meta-analysis of very simple personalisation attempts in the education domain focusing on using first-person, rather than third person addressing or directly addressing the user. They found that not all studies demonstrated an effect of such a basic personalisation on motivation, cognitive load, and learning outcomes. Zander et al. (2013) also found that personalising multimedia content did not lead to perceptible changes in learning outcomes. In the financial domain there is a proliferation of personal budget apps and approaches to help people navigate their finances. In a meta-analysis ran by Netten et al. (2012), while there was some benefit of personalisation in this domain, the authors caution that looking at the effects more deeply, the impact tends to still depend on the user group and since sub-samples are smaller some effects may not even reach statistical significance. Spicker (2013) goes on to argue that personalisation is not and cannot always be effective as it is time consuming, difficult, and dependent on so many conditions that mismatches are inevitable.

This is not to say that personalisation is not a worthwhile and interesting intervention and technique to pursue. However, this does indicate that in other domains, there have been cases where personalisation has failed to produce significant changes in behaviour. Perhaps this technique is more suited for contexts where vast troves of concrete behavioural data can be obtained to then slowly, but surely, adapt the environment for the users. This of course perfectly corresponds to many online environments. Indeed, ostensibly your music, news, shopping list, and friend suggestions are perfectly curated and personalised in the online environment. Given the success of these services, it is safe to say that these techniques there work or at least provide a significant edge over competition. Although it is worth noting that people are increasingly less likely to accept such levels of algorithmic personalisation (Kozyreva et al., 2021).

Furthermore, it may be that our personalisation focus is debatable. Perhaps personalisation based on personality characteristics is not the most fruitful approach. One could argue that personalising on other aspects could potentially be more useful. In the financial domain in particular, perhaps one can focus on personalising retirement content for those who are closer vs. further away from retirement, or those that have started saving vs. those that have not saved anything for retirement are better approaches. Rather than focusing on the more psychological characteristics to personalise, one ought perhaps better focus on the more situational aspects and thus find more stable results. To what extent would we then be talking about personalisation rather than applying interventions for particular groups remains to be discussed, but perhaps this may lead to practically effective interventions.

5.2 Limitations

There are several components of our design and experimental approach that deserve unpacking and some critical reflection. Indeed, the most obvious explanation for why we failed to observe an effect of personalisation is that we simply failed to concretely produce personalised content. It could well be that the messages and dashboards we used simply were not personalised enough. However, this begs the question to what extent on ought to dichotomize between simple personalisation vs. non-personalisation or degrees of personalisation. One argument against this is that we tried to rely on what our data was telling us. Indeed, we tried to rely on those personality characteristics and stimuli that have been shown to lead to perceptible personalised changes. Nevertheless, there still remains the possibility that we had not tapped into the “right” form of personalisation.

Another limitation, one that plagues most research on retirement, is the fact that our samples simply may not have been diverse enough. To get adequately sized samples, research in psychology and marketing has to turn to online services where larger samples can be recruited more easily. These samples tend to skew younger and perhaps even towards those that are no saving for retirement. Indeed, in our samples (even those focused only on participants from the Netherlands) we saw that almost half consistently kept saying that they were not part of retirement funds. To what extent retirement messages at all are relevant to these samples is a necessary question to ask. Perhaps we failed to see observable effects of personalisation simply because our sample skewed towards general interest or general disinterest on retirement. Indeed, in both studies 2 and 5, we found that the majority of people were willing to engage with an ostensible retirement dashboard when we asked them. This goes against what we see in the real world where surveys show that people do not engage or check their retirement information. What is more likely to have occurred perhaps in these experiments is a simple case of demand effect – most participants, wanting to be good subjects in an experiment or simply being interested in what we were offering decided that they are interested, even though outside this context they would not have been. In these circumstances, we fail to see enough diversity in the answers to be able to reach adequate statistical conclusions.

Another relevant point could be that we relied on self-reports to obtain personality information. While these are standard approaches in the social sciences, it could be that people misrepresent their answers, whether consciously or unconsciously. Obtaining erroneous findings on personality necessarily leads to erroneous implications of personalised messages and information if the personalisation is based on personality. Other ways of obtaining information about a person's personality could be more effective. For example, research shows that others (such as our family and friends) tend to provide quite accurate estimates of people's personality (Funder & Colvin, 1988).

From a more methodological standpoint, the choice to use binary measures as dependent variables (i.e., in Study 1 and 2) could have, without intention, reduced our ability to discern significant effects. Binary variables, as opposed to more interval or continuous measures (e.g., Likert scales) tend to decrease the chance of obtaining significant differences as they obscure a lot of dispersion in the data. On another note, related to sample, there still remains the possibility that these effects would be significant in larger samples, e.g., national samples. There however, we would still caution researchers and practitioners to be vary of practical (e.g., effect size), as well as statistical (e.g., p value less than .05) significance as with larger sample, increasingly minute differences can become statistically significant.

Finally, an important caveat to mention is this type of research is what we have come to notice as the "general principle" effect. In a lot of cases, we observed that a particular message, or dashboard which has ostensibly been personalised for a particular personality characteristic was preferred by a majority of participants. It is not hard to see why. Perhaps, simply, framing things in a particular way, or showing information that is preferred by for example low discounters and optimists, is something that once they are confronted with it, is simple appealing to most people. It is just that they had not had the chance to be exposed to it. This may be a general issue with personalisation research. Perhaps some forms of presentation may just be appealing to most people, irrespective of their personality because it makes intuitive sense, or because it is relevant for everyone. This may be especially the case in retirement contexts where most people do not seem to have prior experience with retirement content. It is worth to keep this in mind when designing and launching personalised interventions.

5.3 Implications

Personalisation, while intuitively appealing, may not be as amenable to direct implementation, in particular when it comes to domains pertaining to finances and retirement. This, at the outset, is the conclusion we would send out to industry and policy makers given the results of our findings. While it is difficult to argue definitively based off a couple of data points, we fail to observe any effect of personalised content on retirement engagement indicators with our large samples and careful methodological approach.

Industry should take note that not all approaches to personalisation may be fruitful. In our case, while personalisation in the online, consumer, or advertisement domains, that relies heavily on extremely large datasets of previous user behaviour (e.g., clicks, log-ins) may show promise in these industries, the same principles may not translate and transfer directly when relying on surveys to find information on which to personalise and on behaviours that are deeply entrenched. Financial institutions may do well in first weighing the pros and cons of obtaining information about users on their personality and what type of intervention they plan to use.

Lack of retirement engagement is a difficult and pernicious behaviour, one that has many consequences for individuals and their financial wellbeing. We would caution against the urge to apply, what may be termed as small-scale, personalisation interventions as they may simply not be powerful enough to lead to effective changes in behaviour. We would instead advise to invest more research in accurately understanding the root causes of such behaviour and perhaps investigating more overt, group-centred interventions such as targeting people who differ in their savings, previous interactions with retirement, their age, or even their levels of income.

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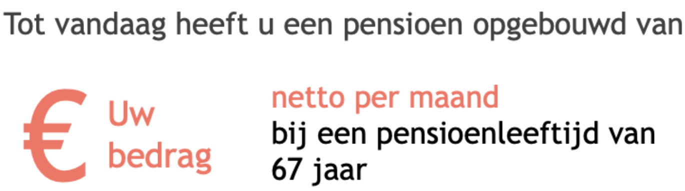
7. Appendices

Tailored messages for each of the four personality characteristics and the three levels used in Study 1

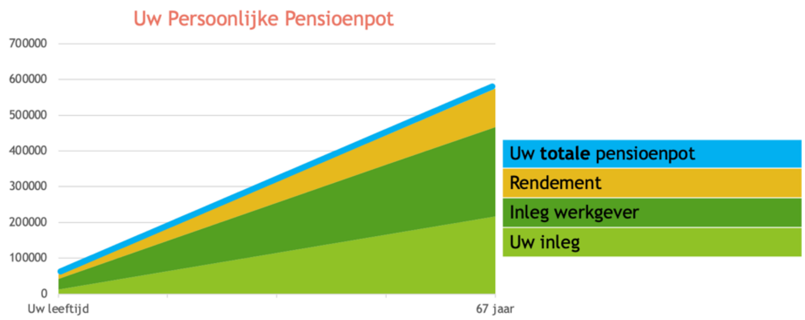
Psychological Characteristic	Message tailoring Low	 Mid	 High
Numeracy	What is your pension accrual? According to available data, if nothing changes your retirement savings are similar to 2 out of 5 other Dutch people. Based on current projections, we estimate that of those 2 people, only one will have a retirement income that is higher than their expenses. Click here to find out how your pension income will relate to your expenses.	What is your pension accrual? According to available data, if nothing changes your retirement savings are similar to 40 out of 100 other Dutch people. Based on current projections, we estimate that of those 40 people, only 20 will have a retirement income that is higher than their expenses. Click here to find out how your pension income will relate to your expenses.	What is your pension accrual? According to available data, if nothing changes, your retirement savings are similar to 40% of the Dutch population. Based on current projections, we estimate that of that 40%, only 50% will have a retirement income that is higher than their expenses. Click here to find out how your pension income will relate to your expenses.
Delay discounting	Your personal pension pot consists of how much you save, your employers' contribution and the returns from your retirement fund. You can always increase your savings, but this comes with some costs. For example, it means losing some expendable income. Given your current financial situation, we have cataloged several recommendations on how you can get the costs over with as soon as possible. Click here to find out how.		Your personal pension pot consists of how much you save, your employers' contribution and the returns from your retirement fund. You can always increase your savings, but this comes with some costs. For example, it means losing some expendable income. Given your current financial situation, we have cataloged several recommendations on how you can delay these costs so that they come at some later time in the future. Click here to find out how.
Optimism	Is your situation changing, relationship, living, working? Events such as having to work fewer hours which decreases salary, getting divorced, or increases in mortgage payments can impact your retirement income. Click here and, in our interactive tool, you can see how each change will impact your retirement income.		Is your situation changing, relationship, living, working? Events such as an increase in salary, getting married, or paying off your mortgage can impact your retirement income. Click here and, in our interactive tool, you can see how each change will impact your retirement income.
Future-self	Your retirement directly benefits you and it is yourself who will face the consequences of the choices you make. Find out which actions you can take right now to benefit your retirement.		Your retirement doesn't benefit just you, but also your future self. This future version of yourself is completely dependent on you and will face the consequences of your choices. Find out which actions you can take right now to benefit the retirement of your future self.

Pieces of retirement information presented to participants in Study 4

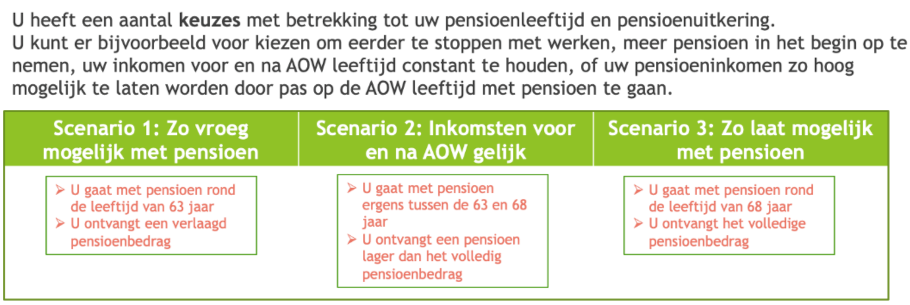
Info 1:



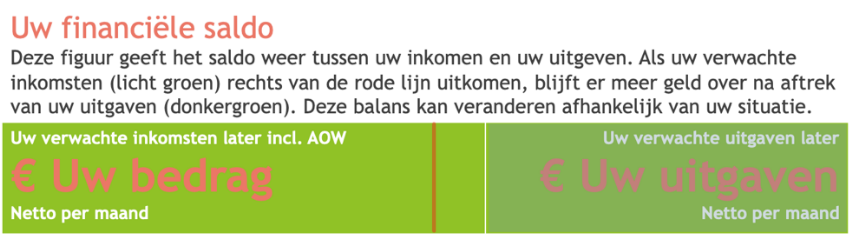
Info 2:



Info 3:



Info 4:



Info 5:

Eenmalig bedrag opnemen op pensioendatum

In het nieuwe pensioenstelsel mogen deelnemers **eenmalig een bedrag opnemen**. De resterende levenslange pensioenuitkering is daarna wel lager. Daarom gelden de volgende voorwaarden:

- de hoogte van het bedrag is maximaal 10% van het ouderdomspensioen;
- het bedrag kan alleen op de pensioendatum worden opgenomen;
- Klik hier om te zien wat dit voor u betekent/hoeveel u op zou kunnen nemen

Info 6:

Beleggingsresultaten

Over de afgelopen 20 jaar behaalde dit pensioenfonds een gemiddeld rendement van ongeveer **7% op jaarbasis**.

De financiële wereld verwacht voor de komende jaren een **lager rendement** van gemiddeld rond de 4%. Dit komt vooral doordat we denken dat de rente laag zal blijven. Dit drukt het verwachte rendement op obligaties.

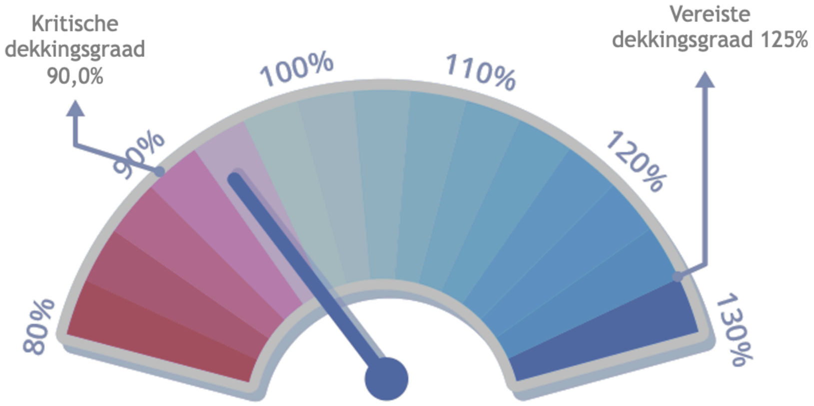
We streven ernaar om dit rendement op een duurzame en verantwoorde wijze te behalen.

Info 7:

Actuele dekkingsgraad

De dekkingsgraad is de verhouding tussen het geld dat het fonds in kas heeft en het geld dat het fonds nodig heeft om alle pensioenen nu en in de toekomst te kunnen uitbetalen.

- De actuele dekkingsgraad is 93,2%. Een verlaging van de pensioenen is daarmee dit jaar van de baan.



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