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EMPIRICAL ARTICLE

Do people like financial nudges?

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Abstract

Do people like financial nudges? To answer that question we conducted a pre-registered survey presenting people with 36 hypothetical scenarios describing financial interventions. We varied levels of transparency (i.e., explaining how the interventions worked), framing (interventions framed in terms of spending, or saving), and 'System' (interventions could target either System 1 or System 2). Participants were a random sample of 2,100 people drawn from a representative Australian population. All financial interventions were tested across six dependent variables: approval, benefit, ethics, manipulation, the likelihood of use, as well as the likelihood of use if the intervention were to be proposed *by a bank*. Results indicate that people generally approve of financial interventions, rating them as neutral to positive across all dependent variables (except for manipulation, which was reverse coded). We find effects of framing and System. People have strong and significant preferences for System 2 interventions, and interventions framed in terms of savings. Transparency was not found to have a significant impact on how people rate financial interventions. Financial interventions continue to be rated positive, regardless of the messenger. Looking at demographics, we find that participants who were female, younger, living in metro areas and earning higher incomes were most likely to favor financial interventions, and this effect is especially strong for those aged under 45. We discuss the implications for these results as applied to the financial sector.

1. Introduction

Nudges, often described as freedom-preserving interventions that steer people in particular directions, attempt to change behavior without imposing mandates or significantly altering material incentives see, Osman et al., (2018) or Thaler and Sunstein (2021) for an overview. These behavioral interventions have been applied across a variety of domains, including conservation, recycling, weight loss, medicine adherence, and the general promotion of health and well-being (see Thaler and Sunstein (2021), and Mertens et al. (2022) for overviews), and have also been applied to the financial domain. Examples of behavioral interventions in finance include changing the default on pensions, so that a portion of an employee's salary is put into retirement saving unless they opt out (Thaler and Benartzi, 2004), or removing minimum repayment for credit card repayments, to stop people from anchoring on the minimum repayment (Sakaguchi et al., 2022), thereby increasing their credit card debt repayments.

1.1. Prior research

Despite the widespread use of behavioral interventions, both in and out of the financial domain, there have been debates about their acceptability, desirability and effectiveness, some of which we will address now. Prior work finds that most people do find behavioral interventions acceptable, at least if they are the kind of interventions that have been adopted or are under serious consideration by contemporary governments (Hagman et al., 2015; Jung and Mellers, 2016; Osman et al., 2018; Petrescu et al., 2016; Reisch and Sunstein, 2016; Reisch et al., 2016; Venema et al., 2018). At the same time, there are many qualifications to this general proposition. For example, people will not approve of behavioral interventions that they believe to be inconsistent with their values and interests (Reisch et al., 2016). Let us offer a few details.

1.1.1. Nudging oneself or nudging others

Some studies find that people's support for behavioral interventions is higher when they are given a justification of the policy in terms of its effects on *people in general* than when they are given a justification in terms of the effects on *themselves* (Cornwell and Krantz, 2014). There is also evidence that people also believe behavioral interventions to be more effective for others than for themselves, and that their judgments of the acceptability of behavioral interventions are predicted by how effective they anticipate the interventions will be on others' behavior (van Gestel et al., 2021). A systematic review of the acceptability of government intervention to change health-related behaviors found that support for the interventions was highest among those not engaging in the targeted behavior (Diepeveen et al., 2013). This means that those who do not smoke are much more accepting of interventions trying to reduce smoking—as we all know that smoking has adverse health consequences, including those who smoke.

1.1.2. Intervention characteristics

Prior work has explored the potential effects of transparency, messenger, and perceived manipulation and ethics.

Transparency

Some prior work has found that people evaluate behavioral interventions more favorably when they are transparent and when people are aware of the process that leads to behavioral change (Diepeveen et al., 2013; Felsen et al., 2013; Jung and Mellers, 2016; Osman et al., 2018; Petrescu et al., 2016; Reisch and Sunstein, 2016; Reisch et al., 2016, 2017; Sunstein, 2016c). One explanation of the preference for transparency is that it enables people to maintain a sense of agency over the behavior being targeted by the intervention (Osman, 2014). Free choice is underpinned by a sense of agency and so, relative to opaque interventions, if people know how behavior change is achieved, they think they can more easily choose to do otherwise, thus preserving their autonomy (Lin et al., 2017; Osman et al., 2017).

One concern of transparency, however, is that it may render the intervention less effective, if not completely ineffective (see Grüne-Yanoff (2012) for this line of argument). This concern appears to lack empirical support. Many interventions are transparent by their nature; consider a warning, a reminder, or a disclosure of information. Research by Loewenstein et al. (2015) does not find transparency to render interventions, particularly a weak default intervention, less effective or ineffective. Testing for end-of-life care preferences in a laboratory experiment, they find no evidence that informing participants that they were presented with a weak default, how this default works, and the other conditions present in the study, influences the default's effectiveness, as measured by the participants changing their decision at the end of the experiment. Similarly, Kroese et al. (2016), in a field experiment on healthy food choices, find no evidence that making subjects aware of the purpose behind a default intervention has any effect.

Research looking at consumer protection measures in several hypothetical and marginally incentivized consumer-related experiments similarly finds no evidence that stressing the potential behavioral influence of a pro-self as well as a pro-social default reduces their effectiveness (Steffel et al., 2016). Research by Bruns et al. (2018) tests for two different types of transparency and their combined effect (knowledge of the potential influence of the default and its purpose) and how they influence the effect of the default. They conduct a laboratory experiment where participants are nudged toward making contributions to carbon emission reduction by introducing a default value. Similar to the aforementioned studies, their findings demonstrate that the information on the potential influence combined with the purpose of the default, or just its purpose, do not significantly affect contributions, which were increased by the default value. Again, transparency with regard to the behavioral intervention implemented did not render it less effective. Similarly, research in diverse laboratory settings finds that a lack of transparency has little or no effect on people's experience of or evaluation of interventions (Michaelsen and Sunstein, 2023).

None of these studies rules out the possibility of scenarios under which transparency can backfire. Transparency might a) reduce the effectiveness of interventions (because it induces reflection or because people do not endorse the underlying goals), b) make interventions counterproductive (because people show reactance when they do not like being nudged), c) make interventions even more effective (because people would understand and support the underlying goals), or d) have no real impact on effectiveness at all (Sunstein, 2016b).

Hypothesis 1. *People have more positive attitudes toward transparent financial interventions.*

Perceived Manipulation and Concerns around Ethics

Are nudges manipulative? To answer that question, we need a definition of manipulation (Sunstein, 2016c). Some behavioral interventions are not plausibly characterized as manipulative; consider information that is relevant to consumer choices or a truthful warning that the risks associated with certain products. On the other hand, some people have expressed concern that certain interventions, including perhaps default rules, might turn out to be manipulative (Bovens, 2009; Hausman and Welch, 2010; Rebonato, 2014; Waldron, 2014), as they might 'operate in the dark', prohibit real structural change and infantilize adults, reducing their autonomy (Bubb and Pildes, 2013; Burgess, 2012; Conly, 2014; Halpern, 2016; Schmidt and Engelen, 2020).

Human reasoning has sometimes been said to consist of two families of cognitive operations: System 1 (automatic, fast, potentially biased) and System 2 (reflective, slow, deliberative) (Kahneman, 2011). System 1 interventions are those that target automatic processes, whereas System 2 interventions tend to be more informational and appeal to deliberative processes. Research by Hagman et al. (2015) found that support for interventions making active use of inertia and inattention (System 1) received significantly less support. Work by Felsen et al. (2013) found similar results, showing that participants were more likely to accept job offers from a company applying a System 2 intervention compared to a System 1 intervention, although the latter was still viewed favorably. There is some evidence that whether people prefer System 1 or System 2 interventions depends on the frame (Davidai and Shafir, 2020) and on the potential effectiveness (Davidai and Shafir, 2020; Sunstein, 2016c), with System 1 nudges having been found to be, on average, more effective (Hummel and Maedche, 2019). Effectiveness here can be framed in terms of objective measures (Cadario and Chandon, 2019; Davidai and Shafir, 2020; Hummel and Maedche, 2019), but potentially also in the individuals judging themselves as having made better decisions (Clavien, 2018; Jung and Mellers, 2016; Michaelsen et al., 2024). Interestingly, interventions turning out to be highly effective, or even the most effective, have been found to be inversely correlated with acceptance, where approval levels only increased with the *perceived* effectiveness of the intervention (Cadario and Chandon, 2019). This finding highlights a need to correct misconceptions about which interventions work best, in addition to highlighting effectiveness in general, to increase overall approval. This finding is also in line with guidelines proposed in the FORGOOD framework (Lades and Delaney, 2022), which proposes that ethical acceptability of behavioral interventions is partially determined by the public judging the intervention ('the means') based on its goal and its effectiveness ('the end').

Although the end may sometimes be judged to justify the means, research by Turetski et al. (2023) shows that large variation remains. The authors study how the ethics of an intervention varies across specific intervention types (i.e., defaults, incentives), the domains in which they are delivered (i.e., organ donation, retirement savings), and how the rationale for their use is presented (i.e., loss framing, resistibility). They observe significant effects of domain and the type of intervention, as well as a significant interaction between domain and the type of intervention, suggesting that certain types of interventions may differ in perceived ethics depending on their domain, or that nudges in certain domains may be deemed more ethical, depending on what type of intervention is used. These effects also persist for perceptions of threat to autonomy and expected success. In terms of intervention types, Turetski et al. (2023) find that defaults were, on average, rated as significantly less acceptable and more autonomy-threatening than all the other interventions, regardless of domain. These findings are similar to research by Jung and Mellers (2016) which also showed opposition to opt-out defaults for organ donations, as well as less favorable views for System 1 nudges (e.g., defaults and sequential orderings) as compared to System 2 nudges (e.g., educational opportunities or reminders). System 1 nudges were perceived as more autonomy threatening, but more interestingly, System 2 nudges were perceived as more effective for better decision making and more necessary for changing behavior, though there is evidence to the contrary (Davidai and Shafir, 2020; Hummel and Maedche, 2019). In addition to lower acceptance of defaults, Turetski et al. (2023) also found lower acceptability for social proof-based interventions. Notably, the authors do find that participants in their study tended to find most of the interventions acceptable and not-threatening to autonomy.

Research by Bruns and Perino (2023) shows that the maintenance of autonomy is a core determinant of intervention acceptability; when comparing recommendations, defaults, and mandates as three possible interventions to improve climate protection, they were rated increasingly as 'freedom threatening' (prohibiting autonomy) and correlated positively with levels of reactance, with mandates receiving the highest negative reactance. However, there is also work to indicate that behavioral interventions are not perceived as curtailing autonomy at all (Wachner et al., 2021), and that the implementation of behavioral interventions, whether the behavioral intervention was transparent or opaque, did not change choice satisfaction. Similarly, Michaelsen et al. (2024) find that despite participants who received a prosocial opt-out default nudge making more prosocial choices, they did not report lower autonomy or choice satisfaction than participants in opt-in default or active-choice conditions. This finding persisted even when the presence of the behavioral intervention was disclosed (transparency), and when monetary choice stakes were introduced. Adding in more nuance to the ethical concerns around autonomy, specifically with regards to behavioral interventions using defaults, Arvanitis et al. (2022) find that experiences of autonomy and choice satisfaction, in addition to the intervention type (defaults), are also dependent on the overall choice architecture in which the intervention type operates. In their study, participants faced a hypothetical choice of health insurance plans. The results showed that when there were three health plans to choose from, participants default-nudged by having one plan pre-selected (vs. no default plan) gave significantly lower ratings in one of three autonomy sub-scales. However, this negative effect vanished when participants faced nine options to choose from.

The difficulty of the debate around the manipulativeness and ethics of behavioral change interventions, as raised by Turetski et al. (2023), is partly a product of the possible incomparability of domains: 'We should avoid making generalized statements about the ethics of choice architecture interventions, and instead focus on exploring specific implementations of choice architecture interventions to better understand their acceptability in the public eye' (p. 7). However, the trend in findings seems to indicate a preference for System 2 nudges (Davidai and Shafir, 2020; Felsen et al., 2013; Hagman et al., 2015; Jung and Mellers, 2016), regardless of domain, on which we base our hypothesis.

Hypothesis 2. *People have more positive attitudes toward System 2 financial interventions.*

Messenger

Those who impose the intervention—the messenger—have been found to affect attitudes toward interventions as well. Some research finds that people trust interventions that are developed and proposed by researchers more than those that are developed and proposed by government (Osman et al., 2018). Research has also found that trust in government affects the acceptability of government interventions (Branson et al., 2012) and it has been suggested that when negative attitudes to interventions are found, they may stem from mistrust of government (Jung and Mellers, 2016). In support of this, Bang et al.

(2020) found that the acceptability of interventions depends on who designs and implements them and that these differences in acceptability were explained by perceived differences in the intention of the designer. Consistent with this, Tannenbaum et al. (2017) found that people's support for a intervention depended on whether they were told that it had been chosen by a policy-maker they supported or one they opposed (Bush vs Obama administration).

If we apply these messenger effects to the financial sector, we can identify several key parties who can propose and implement financial interventions: regulators and policy makers, independent researchers, and commercial organisations such as credit card unions and banks. It is possible that the former two would find widespread support for their interventions, if they are perceived as acting in the interest of the relevant people. By contrast, credit unions, banks and other for-profits might be assumed to have incentives that directly oppose those of the people. Prior research has shown that since the financial crisis, attitudes toward the financial services industry have become more negative (Bennett and Kottasz, 2012), and some authors have concluded that there is now a crisis of trust in that sector (Bachmann et al., 2011; Sapienza and Zingales, 2012).

This lack of trust may spill over into a mistrust of the interventions proposed by for-profit entities in the financial services. A review of 'creepy' interventions by de Jonge et al. (2022) showcases the example of ING, a Dutch bank, that decided to leverage large amounts of personal and transaction data to determine which customers had recently become parents. After having determined this the bank chose to tailor their product advertisements and 'nudge' these young parents to invest in financial products for their newborns. This led to widespread public and media outrage. The messenger, practice, and the goal were widely condemned. The argument can be made that this intervention could be classified only as 'sludge' (Thaler, 2018), and that it fails to comply with any of the tenets of the FORGOOD framework (Lades and Delaney, 2022). Although financial regulations have tightened—the Dutch regulator (Autoriteit Financiele Markten) warned other financial institutions about this practice it remains to be seen whether there is a messenger effect in the presence of financial interventions.

Hypothesis 3. *People have more positive attitudes toward financial interventions proposed 'in general' than those specifically proposed by a bank.*

With the foregoing research in mind, and aligned with our three hypotheses, we hypothesize that people most approve of transparent, system 2 financial interventions. To ensure accounting for differences in intervention characteristics we also split interventions into two frames: spending and saving.

We strongly suspected that in addition to a preference for transparent and system 2 interventions, people also prefer interventions that are savings-framed rather than spending-framed. Despite those frames being the inverse of each other (e.g., to spend less is to save more), there has been work to suggest positive framing (focusing on increasing the desirable behavior) as compared to negative framing (focusing on decreasing the undesirable behavior) can lead to increased intervention acceptability of a intervention (Nelson et al., 2021; Ouvrard et al., 2020; Rafaï et al., 2022). However, we do have to emphasize that the evidence is mixed, and derived exclusively from interventions in the *sustainability* domain.

Hypothesis 4. *People approve more of financial interventions that are savings rather than spending framed.*

1.1.3. Demographic characteristics

Prior research has found a possible effect of demographic characteristics on attitudes toward, and usage of, interventions. Work by Beshears et al. (2016) showed that low-income and younger people were most likely to stick with automatic enrollment into 401(k) plans, as well as sticking with the contribution rate default. Work by Shah et al. (2023) also looked at retirement savings, but did so in a Mexican context. They tested an intervention in which they send out text messages with different framing. The most effective framing was found to focusing on 'family security', where the intervention emphasized that retirement savings can aid toward securing a financially stable future for one's family. The researchers found a strong effect of age. Those over the age of 28 saw an increase in contribution rates by 89%. For those under the age of 28, however, this specific framing of the intervention backfired, decreasing contributions by 53%. This finding was explained by the average age of starting a family being 28 years in Mexico, which meant that the intervention is relevant to those around and over 28 years of age, but not to those who are younger. This is both a feature of the demographic and the intervention itself, raising questions about how to frame interventions to the extent that they are specific, yet not exclusive. A further review of individualised or 'smart' nudging can be found in Hallsworth (2023).

This work is a collaborative effort with a large Australian financial institution, and hence its exclusive focus on financial interventions. We also think that limiting ourselves to a single domain of interventions is positive, given the differences between intervention acceptability between domains (Turetski et al., 2023), allowing us to compare intervention types (e.g., defaults, social norms) more directly.

2. Method

We designed an online survey to test whether people like financial interventions. Resources for this survey, including the pre-registration, survey design, exact scenarios used and analytics files, can be found on the Open Science Framework, https://osf.io/6sfpm/.

2.1. Design

We used a mixed factorial design, with 2 levels for framing (spending, savings), 2 levels for system (System 1, System 2) and 2 levels for transparency (transparent, opaque), to give a 2 x 2 x 2 design. We prepared 18 unique financial interventions (see Appendix O). Of these 18 interventions, 12 are System 1 interventions and 6 are System 2 interventions (System), derived from interventions having been conducted, or being considered to be conducted, with the Australian financial institution. Of those 18, evenly spread across the two Systems, 9 financial interventions are framed in terms of spending, and 9 are framed in terms of savings (Frame). For all of these 18 scenarios we created transparent versions, explaining how exactly the intervention works in terms of the behavioral aspects it targets. This is known as the Transparency condition. This leads to a total of 36 scenarios. Figure 1 below shows all 36 conditions for clarification. The numbers in Figure 1 refer to the unique numbers for each intervention (scenario) for which details can be found in Appendix O.

To take account of the risk of information overload and fatigue, we did not present participants with all 36 scenarios. We divided the 36 scenarios into 4 blocks; Transparent x Spending (with 6 being System 1 and 3 being System 2), Opaque x Spending, Transparent x Saving and Opaque x Saving. Each participant would only see 2 scenarios of each of these 4 blocks, at random. The order of the four blocks was also randomized to ensure there were no ordering effects. Figure 1 shows the blocks and how they can be drawn from for clarification.

We tested people's attitudes toward these financial interventions across six dependent variables: approval, benefit, ethics, manipulation, the likelihood of use, and the likelihood of use when proposed by a bank. To measure these six variables, participants were asked to state their agreement with a bipolar Likert Scale (1 = Strongly Disagree, 3 = Neither Disagree nor Agree, 5 = Strongly Agree), with each of the interventions, to the following statements:

- 'I approve of *this intervention*'
- 'I see clear benefits to *this intervention*'
- 'I find *this intervention* ethical'
- 'I find *this intervention* manipulative'
- 'I would make use of *this intervention*'
- 'I would make use of *this intervention* if my bank were to apply this'

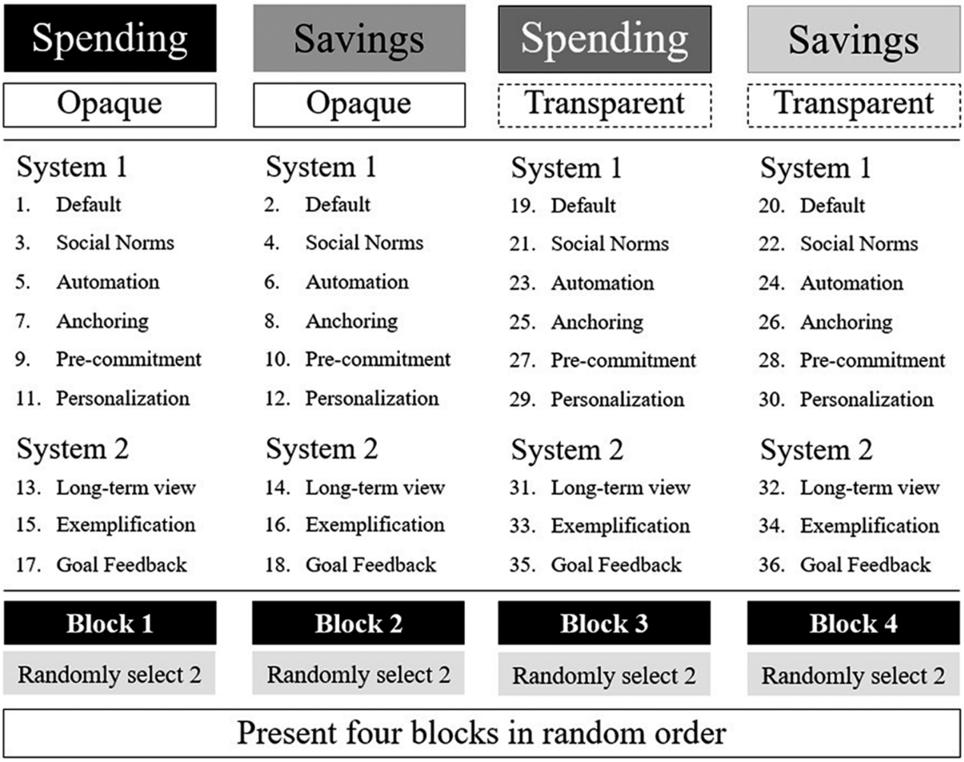

Figure 1. *The details of our survey's design. We created four blocks based on transparency and frame, with each block having interventions representing both systems of thinking. The numbers refer to the unique numbers for each intervention (scenario) for which details can be found in Appendix O. We drew two interventions from each block randomly, and the four blocks were always presented in random order.*

We have highlighted the phrase *this intervention* in our above statements as this was tailored to the intervention being proposed. For example, in scenarios 17, 18, 35, and 36, which all feature the Goal Feedback intervention, the statements to be rated would start with 'I approve of this feedback all the way to I would make use of this feedback if my bank were to apply it'.

2.2. Participants

We acquired a sample representative of the Australian population. In total, 2,100 participants were tested. The initial 100 were used to test for technical issues (there were none) followed by the remaining 2,000[1] .

Our pre-registration[2] outlines our five exclusion criteria. First, we excluded all participants who did not consent to the study. Second, we excluded all participants who had demographic criteria for which we had reached our quota. Third, we excluded all participants who did not complete the survey. These three exclusions left us with 1,891 participants. Our fourth and fifth exclusion criteria focused on the quality of the responses given. Criterion four removed all participants who completed the survey in under three minutes, and criterion five removed all participants for whom we could not spot variation in at least half of their answers, as we suspected these types of responses to be due to the participant

[1] This deviates from our initial pre-registration which did *not* include the inclusion of the pilot participants (n = 100)
[2] https://osf.io/6sfpm/

rushing through the survey. We did not find either of these quality issues within our results, so we did not have to discard data based on these exclusions, leaving us with a sample of 1,891 participants.

The initial number of participants (n = 2,100) was based on internal resource constraints. A power analysis reveals that for both the t-tests[3] as well as the linear models[4] conducted we reach a power of over .99, mostly due to the partial within-subjects design of our study.

2.3. Procedure

Upon entering the survey, participants were first presented with a quick introduction to the survey, and asked if they would consent to participating in the survey. If they consented, participants were asked for their demographic data to determine quota fit. When the quota had not yet been met, participants proceeded to seeing the first scenario describing a financial intervention. After reading the scenario describing a financial intervention, participants were asked to indicate their opinion of the financial intervention in terms of each of the six dependent variables by assigning a value on a 1–5 bipolar Likert scale (1 = 'strongly disagree', 5 = 'strongly agree'). This would continue for eight randomly allocated scenarios, drawn at random from the four pre-determined blocks of interventions. After having completed the rating of all eight scenarios, participants were also asked to complete the Cognitive Reflection Task (Frederick, 2005), Lusardi's Big Three as a measure of financial literacy (Lusardi, 2015) and to self-assess their understanding of financial management (1 = very low, 5 = very high) across eight different domains (e.g., mortgages, investing).

The experiment was presented via Qualtrics and launched with Dynata, a crowd sourcing system for participant recruitment to obtain a representative sample of Australian citizens. All participants were financially compensated for their time ($5.60 AUD), calculated according to Dynata's rates.

2.4. Analysis

We also pre-registered our analysis[5]. Initially, we aimed to run 3 models per dependent variable (approval, benefit, ethics, manipulation, likelihood of use and likelihood of use when proposed by a bank). The first model only regressing the dependent variable against our 3 main variables of interest (Transparency, System and Frame), with the second model also including demographic characteristics (age, gender, income, state, living conditions [metro, rural]) and the third model also incorporating the financial literacy score, cognitive reflection task scores and an accumulated rating of self-perceived efficacy across 8 domains in personal finance management[6]. All of these models were pre-registered to be simple linear models (OLS).

3. Results

We decided to deviate from our pre-registration in a number of meaningful ways: First, we will only present the models including all measured variables, as we no longer see the first and second models as adding any additional value. Second, we will apply a Linear Mixed Model rather than a simple OLS to allow us to account for the (fixed) effects of both the rounds of interventions and the participants. We have analyzed our results in simple OLS form as well and these results can be found in Table B1 in Appendix B. The appendix also houses the model-free means and standard deviations of all 36 scenarios across the six different dependent variables (Table A1, Appendix A) as this is an important fixed effect.

[3]when considering a small (0.2) effect size, a sample of 2,100, and a significance level of 0.05 for two sample and two-tailed samples, we find a power of ¿ 0.99, when considering an effect size of 0.1, this drops to 0.90.

[4]when considering a small (0.2) effect size, a sample of 2,100, and a significance level of 0.05 for models using 11 predictors, we find a power of 1, this level of power persists even when looking at smaller (0.1) effect sizes.

[5]https://osf.io/6sfpm/

[6]our original pre-registration did not include gender as a variable, but gender was always planned, and has been incorporated as a key demographic variable.

Table 1. *Results of mean difference t-testing between means of the ratings of the six dependent variables, and the neutrality point (3) of the bipolar 5-point Likert scale used to rate individual interventions for all six dependent variables, using a two-tailed test.*

						95% CI mean difference		
	t	df	*p*	Mean difference	SD	Lower	Upper	Cohen's *d*
Approval	54.267	14814	<0.001	0.498	1.129	0.480	0.516	0.442
Benefit	59.834	14814	<0.001	0.537	1.092	0.519	0.554	0.498
Ethics	57.199	14814	<0.001	0.512	1.091	0.495	0.530	0.469
Manipulation	−1.373	14814	0.170	−0.014	1.215	−0.033	0.006	0.012
Likelihood of use	24.985	14814	<0.001	0.261	1.274	0.241	0.282	0.205
Likelihood of use (bank)	18.933	14814	<0.001	0.197	1.266	0.177	0.217	0.156

Table 1 below shows the results for the mean difference testing between our six dependent variables and the point of neutrality. Because we used a bipolar 5-point Likert scale, our neutrality point is 3. We find that ratings for all variables, except for perceived manipulation, are statistically significantly different from neutrality. We will continue to discuss the results, per hypothesis, in turn.

3.1. Transparency

First, we hypothesized that people would have more positive attitudes toward transparent financial interventions, as compared to opaque financial interventions, in line with prior research on the positive effect of transparency on attitudes toward interventions. Figures 2 and 3 show that our study fails to replicate this effect. Across all six dependent variables, we fail to discern any effect of transparency, across any of the 36 scenarios. This lack of effect is further shown in Table 2, where Transparency fails to reach a level of significance in influencing any of the six attitudes toward the financial interventions, even when controlling for both individual participants and interventions as fixed effects.

3.2. System

Second, we hypothesized that people would have more positive attitudes toward financial interventions that target System 2, as compared to financial interventions that target System 1, in line with prior research on the more negative attitudes held toward System 1 interventions (perhaps because they were deemed to be more manipulative). Figure 4 shows that System 2 interventions were rated significantly more positive than their System 1 counterparts, except for manipulation in which case they are rated significantly lower. Table 2 shows this further as coefficients for the System 2, as compared to System 1, financial interventions are significantly higher (lower for manipulation).

3.3. Messenger

Third, we hypothesized that people would have more positive attitudes toward financial interventions in general, rather than financial interventions proposed *by a bank*, with the latter having a very strong messenger effect. A repeated measures *t*-test reveals the presence of a messenger effect; people rate their likelihood of making use of the intervention when proposed by a bank as 0.065 95% [0.078, 0.052] lower compared to when the messenger of the intervention is not disclosed. We would like to emphasize, however, that this messenger effect does not render the attitudes toward the intervention as

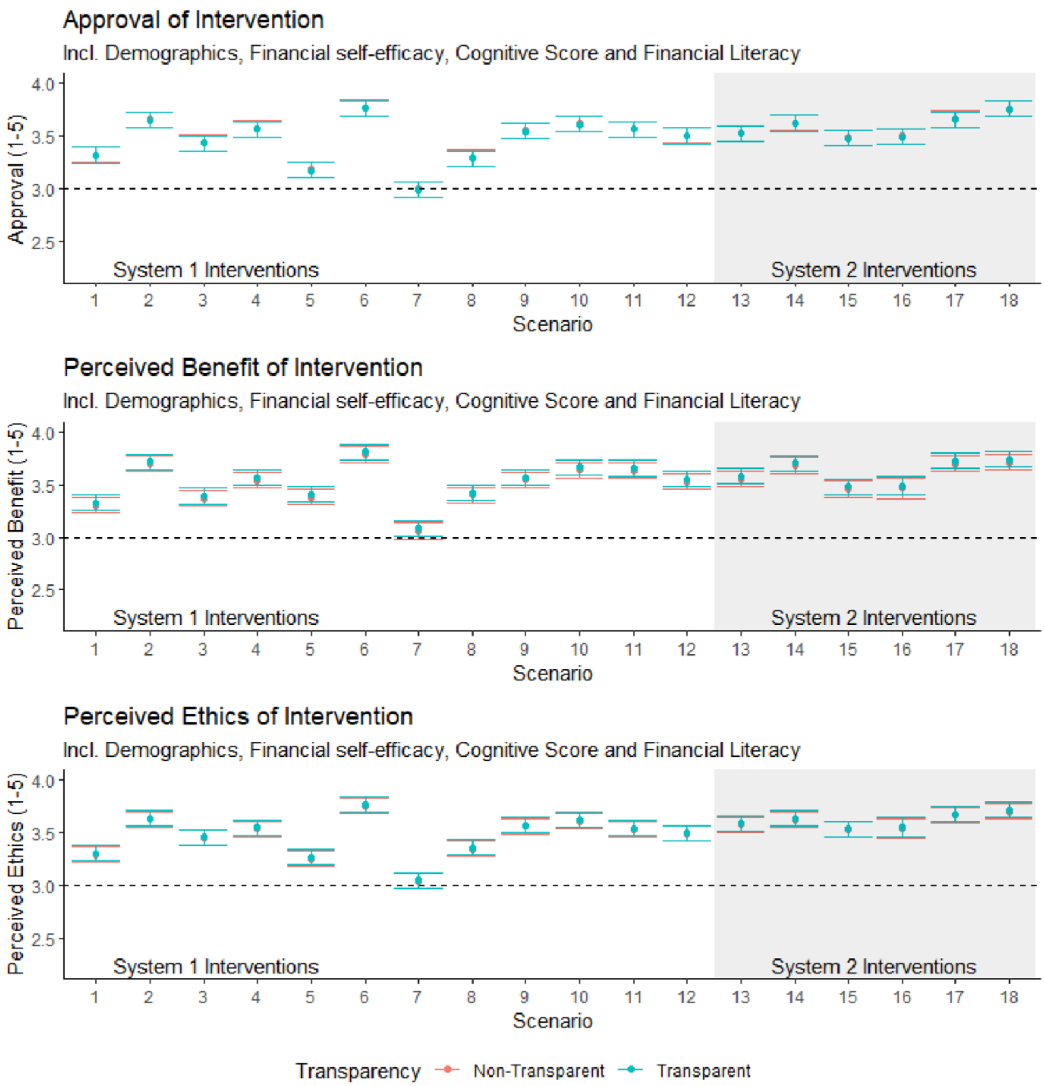

Figure 2. *The marginal mean effect of Transparency, Frame, and System, and its 95% confidence intervals, on the first three dependent variables. Estimations were averaged over the means of numerical variables and the levels for factor variables, weighting levels by their frequency in the data. Transparency is displayed on the initial 18 scenarios (opaque, red), with the transparent scenarios (19–36) plotted on top in teal. The dashed line at y intercept 3 indicates the attitudinal neutrality point, as interventions are rated across a bipolar Likert Scale (1 = Strongly Disagree–5 = Strongly Agree).*

negative. Comparing the overall mean of financial interventions proposed by a bank to the neutrality point, we continue to find that the likelihood of using a intervention, even when proposed by a bank, with a mean of 3.197 (95% [0.177, 0.217]) is significantly higher than neutrality (Table 1).

3.4. Frame

Last, we hypothesized that people would have more positive attitudes toward financial interventions that were savings rather than spending framed, as the savings frame is a more positive way of framing both the intervention as well as the desired behavior. Figure 4 shows support for this hypothesis, with savings

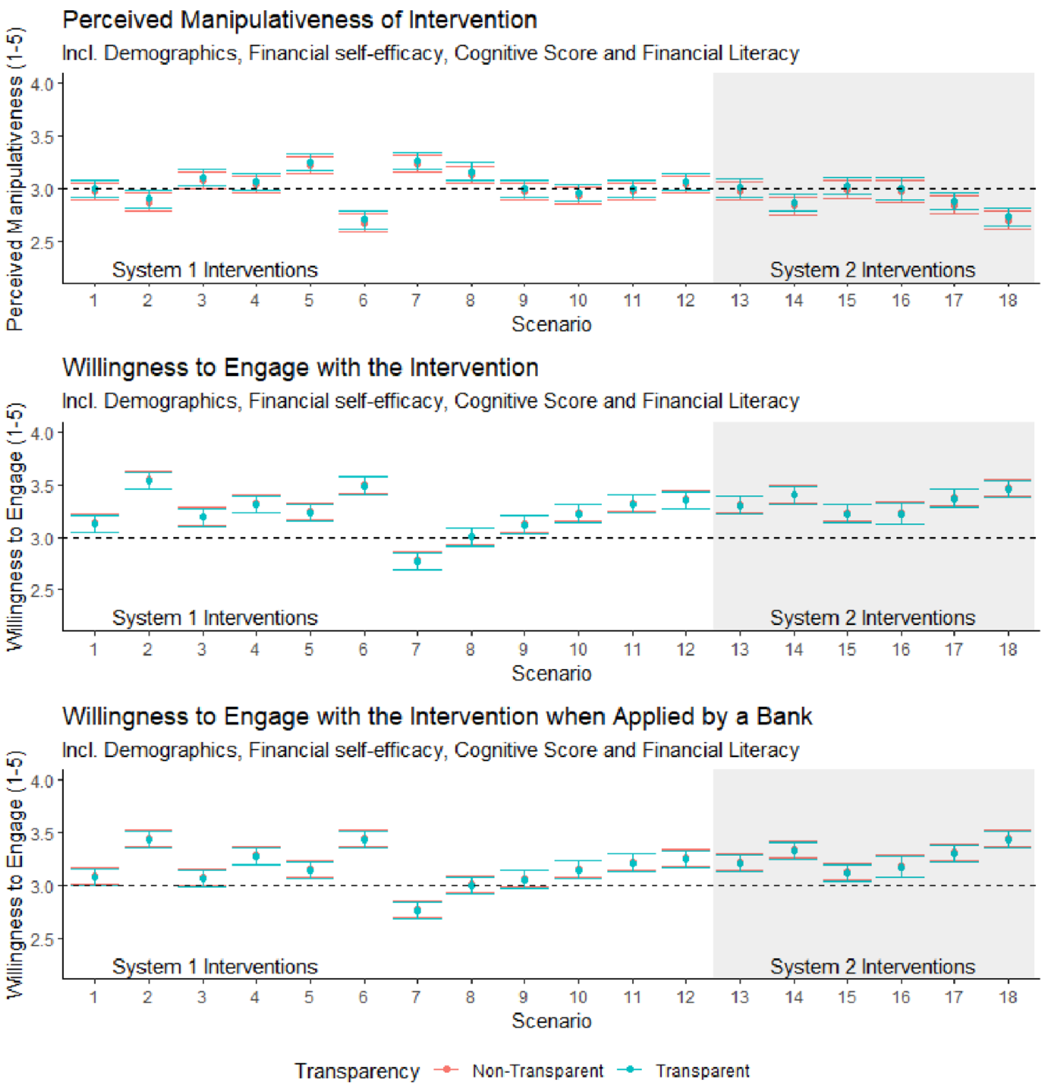

Figure 3. *The marginal mean effect of Transparency, Frame, and System, and its 95% confidence intervals, on the last three dependent variables. Estimations were averaged over the means of numerical variables and the levels for factor variables, weighting levels by their frequency in the data. Transparency is displayed on the initial 18 scenarios (opaque, red), with the transparent scenarios (19–36) plotted on top in teal. The dashed line at y intercept 3 indicates the attitudinal neutrality point, as interventions are rated across a bipolar Likert Scale (1 = Strongly Disagree–5 = Strongly Agree).*

framed interventions being rated significantly higher (lower for manipulation) across all dependent variables, without confidence intervals ever overlapping. Table 2 highlights this effect further with the coefficient for spending being significantly lower than that for savings.

3.5. Demographics

In addition to the effects of transparency, system, frame, and messenger, we would like to highlight several demographic and individual effects. Having controlled for individuals' views toward financial

Table 2. *Results from the linear mixed models accounting for individual scenario (Scenario) and participant (ID) as fixed effects for all six dependent variables.*

	Dependent variable					
	Approval (1)	Benefit (2)	Ethics (3)	Manipulation (4)	Use (5)	Use (bank) (6)
Transparency	−0.005	0.022	0.007	0.034	−0.015	−0.015
	(0.056)	(0.051)	(0.049)	(0.045)	(0.054)	(0.048)
System	0.153***	0.117**	0.162***	−0.134***	0.124**	0.115**
	(0.059)	(0.054)	(0.052)	(0.048)	(0.057)	(0.051)
Frame	−0.175***	−0.164***	−0.153***	0.124***	−0.155***	−0.174***
	(0.056)	(0.051)	(0.049)	(0.045)	(0.054)	(0.048)
Age	−0.117***	−0.093***	−0.097***	0.033***	−0.170***	−0.169***
	(0.012)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)
Gender	−0.131***	−0.160***	−0.091**	0.056	−0.080*	−0.076*
	(0.040)	(0.039)	(0.039)	(0.043)	(0.045)	(0.045)
Income	0.023***	0.020***	0.030***	0.016**	0.034***	0.033***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Area	−0.074*	−0.070*	−0.068	−0.088*	−0.095**	−0.111**
	(0.042)	(0.042)	(0.041)	(0.046)	(0.047)	(0.048)
CRT	−0.070**	−0.071**	−0.075**	−0.006	−0.172***	−0.170***
	(0.036)	(0.035)	(0.035)	(0.039)	(0.040)	(0.040)
Self-efficacy	0.018***	0.017***	0.021***	0.019***	0.016***	0.017***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Financial literacy	0.009	0.011	0.004	−0.213***	−0.100***	−0.112***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.023)	(0.023)
Constant	3.449***	3.390***	3.172***	2.735***	3.502***	3.406***
	(0.180)	(0.174)	(0.172)	(0.184)	(0.195)	(0.192)
Observations	14,807	14,807	14,807	14,807	14,807	14,807
Log likelihood	−19,644.190	−18,794.920	−18,611.110	−20,687.050	−20,456.730	−20,093.730
Akaike Inf. Crit.	39,330.380	37,631.840	37,264.220	41,416.100	40,955.450	40,229.460
Bayesian Inf. Crit.	39,490.480	37,791.500	37,423.880	41,575.760	41,115.110	40,389.120

Note: The reference levels for the instrumental variables are: Transparency (Opaque), System (1), Frame (Savings). Reference levels for the covariates are: Gender (Female), Area (Metropolitan). Age and Income are banded numerical variables, with age ranging from 18–24 to 85 and older, and Income ranging from under <$10,000 to over $150,000. The CRT (Cognitive Reflection Test), Self-efficacy and Financial Literacy variables are all numerical variables with ranges of 0–3, 8–40, and 0–3, respectively. The models include dummies for all Australian states.
**p*0.1; ***p*0.05; ****p*0.01.

interventions, we continue to find effects for all demographic variables measured. We consistently find an effect of age, with younger participants holding significantly more positive attitudes toward financial interventions. We also find a significant effect of gender, with women holding significantly more positive attitudes toward interventions than men. We also find an effect of income, with higher income earners holding significantly more positive views toward financial interventions, as well as area effects, with those living in more metropolitan areas holding significantly more positive views toward financial interventions than those who live more rural. Last, looking at our three measures of literacy and efficacy, we find that good performance on the Cognitive Reflection Task is significantly negatively associated with positive attitudes toward financial interventions; that those who rate themselves as having higher financial self-efficacy hold significantly more positive views toward financial interventions; and that

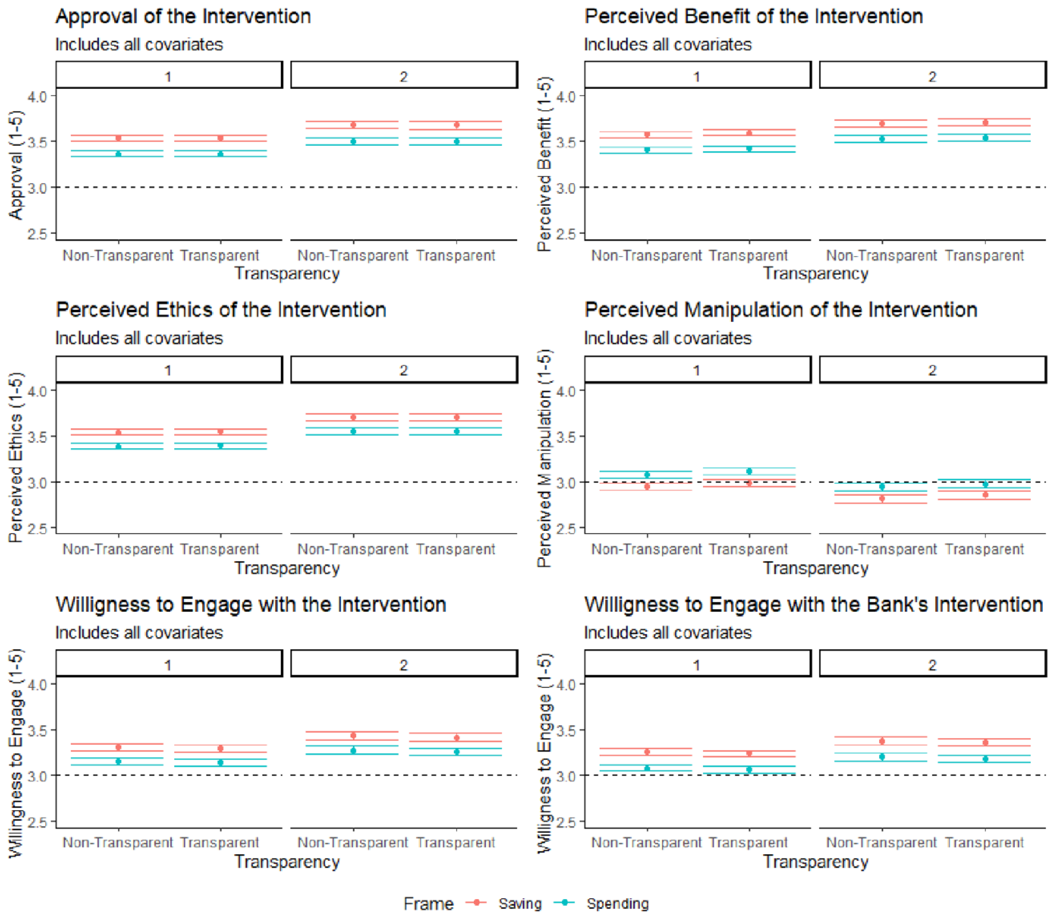

Figure 4. *The marginal mean effect of Transparency, Frame and System, and its 95% confidence intervals, on all six dependent variables. Estimations were averaged over the means of numerical variables and the levels for factor variables, weighting levels by their frequency in the data. The dashed line at y intercept 3 indicates the attitudinal neutrality point, as interventions are rated across a bipolar Likert Scale (1 = Strongly Disagree–5 = Strongly Agree).*

higher financial literacy significantly reduces the willingness to make use of a intervention, regardless of whether it is proposed by a bank or not, despite perceiving it as less manipulative.

To understand these effects further, we conducted an exploratory analysis[7] on the effect of the demographic variables on the effects of Transparency, System, and Frame of the interventions. We used model-based recursive partitioning creating decision trees[8], capped at a depth of 4 for legibility, for each of the six dependent variables, for which the decision trees and coefficient results can be found in Appendix C–N. We find that age, income, and gender are key decision nodes for our decision trees, for all six dependent variables, with the strongest partition centering around age. The first partition for all six dependent measures is based on age, with those below 45 being further partitioned into high and low income earners, and then further partitioned by gender for low income earners, and again on age for higher income earners. This partition shows that young, low income women approve of

[7] Although we did not pre-register this analysis on the OSF, we do share the exact code and models used for transparency and replication purposes.

[8] our analysis was conducted in R, using the *partykit* package, as can be identified in our code on the OSF.

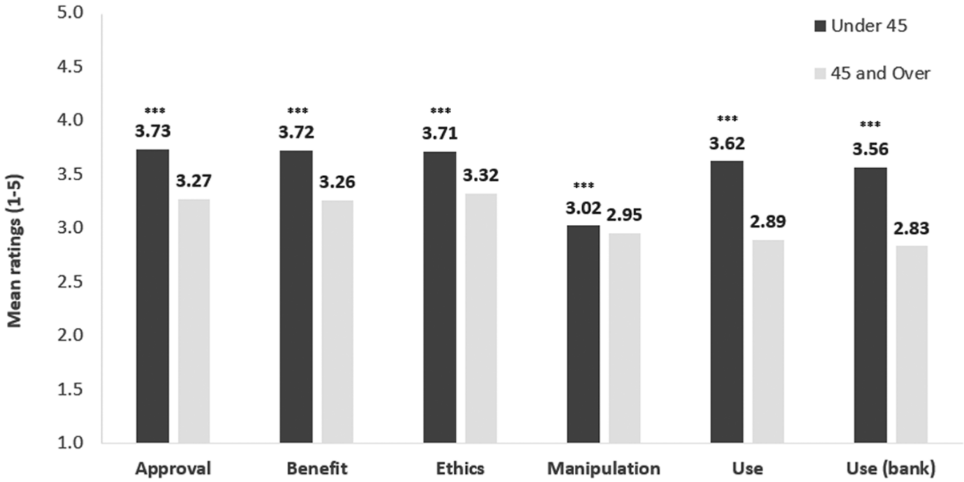

Figure 5. *The mean ratings across all six dependent variables, by the age cutoff point identified using model based recursive partitioning, which was found to be those under 45 and those 45 and over. Interventions are rated across a bipolar Likert Scale (1 = Strongly Disagree–5 = Strongly Agree), with neutrality being 3. Statistical significance is indicated by *, **, and *** for 10%, 5%, and 1% p-value, respectively, using a two-tailed test.*

financial interventions significantly more than their male counterparts (Appendix I), specifically having a significantly higher intercept (3.669, compared to 3.569) as well as a significantly higher coefficient for System 2 interventions (0.152, compared to −0.054). For the higher income earners under 45, this effect is further driven by age, with those under 35 having higher approval rates for financial interventions compared to those age 35–44. Looking at those over 45 years of age, we again see a partitioning based on income, although this split is less clear as it partitions those earning between $80,000 and $150,000 from all other income groups. This group is then again partitioned by age, where we again find that younger participants between 45 and 75 years of age have higher approvals for financial interventions than those 75 and older. This holds true for the other income groups as well. This pattern seemingly repeats for the other five variables, with the first partitioning being age-based, those under 45 being split from those over 45 of age. We explore this effect further in Figure 5 below, showing that those over 45 year have significantly lower ratings for financial interventions, across all six dependent variables. Across the second partitioning being income-based, with lower earners being partitioned away from higher incomes, although this partitioning is less clean. The third partitioning is often gender based, as seen with approval, benefit, manipulation, and likelihood of use when proposed by a bank, but further income and age partitioning is done here as well, making it more difficult to interpret the results. Appendix I–N show the coefficients associated with the impact of the partitions on the six dependent variables, through the changing coefficients for the three key predictor variables: transparency, system, and frame.

4. Discussion

4.1. Attitudes toward financial interventions

We find that, on average, people are highly supportive of financial interventions, showing that ratings are above neutrality for our five *positive* dependent variables, and not significantly different from neutrality for the negative dependent variable (rating the intervention in terms of it being perceived as *manipulative*), indicating that, on average, the financial interventions were not experienced as manipulative in nature. This finding of support is in line with most prior work reviewed, especially that of Sunstein (2015, 2016a).

In terms of our hypotheses, we find no support for our first hypothesis, showing that transparency has no significant impact on attitudes toward the financial interventions. This is line with previous experimental and field work showcasing that transparency need not change an intervention (Bruns et al., 2018; Kroese et al., 2016; Loewenstein et al., 2015; Michaelsen et al., 2024; Steffel et al., 2016). It is possible, however, that the lack of effect of transparency is mostly due to the interventions being quite clear in their purpose, with further explanation seeming to be unwarranted even when participants were assigned to see opaque interventions.

With respect to our second hypothesis; we do find support for the proposition that people prefer System 2 interventions. System 2 interventions were rated higher across all five positive dependent variables, as well as being rated as less manipulative. This is again in line with prior work (Arad and Rubinstein, 2018; Felsen et al., 2013; Gold et al., 2020; Hagman et al., 2015; Pechey et al., 2014; Petrescu et al., 2016; Sunstein, 2015). However, we do need to note that this comparison is not as clean as the comparison between transparent and opaque interventions. As both Figure 1 and Table O1 (Appendix O) shows, there is an imbalance between the System 1 and System 2 interventions proposed. First, we test six different System 1 interventions as compared to three different System 2 interventions. Although we do cross-validate them in terms of Frame as well as Transparency, it is difficult to compare a System 1 to a System 2 intervention directly. For example, when taking an opaque and spending-framed intervention as an example, one of the System 1 interventions for this focuses on social norms, making participants aware of how much other people are spending and how this can influence their own spending habits, whereas one of the System 2 interventions is grounded in taking a longer-term view, proposing a spending-tracker intervention to raise awareness of people's own spending habits. Although we report a significant difference between System 1 and System 2 across all six dependent variables, Figures 2 and 3 reveal that this may be largely driven by a strong attitudes toward specific interventions (e.g., scenario 5, 7, 17, 18). This is a limitation of this specific comparison that warrants highlighting. With regards to specific types of interventions, we did test two different default interventions for both spending (scenario 1, 19) and savings (scenario 2, 20), both when opaque (1, 2) and transparent (19, 20). Figures 2 and 3 have revealed there to be no effect of Transparency on this intervention type, but *t*-tests reveal there to be a significant difference between defaults and the other interventions. Looking at defaults for spending, we find a significant difference for defaults compared to other interventions, having been rated 0.097 95% [−0.014, −0.180] lower in terms of approval, 0.154 95% [−0.077, −0.232] lower in terms of benefit and 0.151 95% [−0.070, −0.233] lower in ethics, but we find no significant differences in manipulation or the likelihood of use, both general and when proposed by a bank. For defaults using the savings frame, we see find a significantly higher rating 0.095 95% [0.022, 0.168] for benefit, a 0.228 95% [0.144, 0.312] higher rating for likelihood of use, and a 0.179 95% [0.092, 0.265] for likelihood of use when proposed by a bank. As such, our findings are in line with prior work that argues that approval of interventions is not only type dependent (default), but also domain (spending, savings) dependent (Turetski et al., 2023), with no effect for transparency (Michaelsen et al., 2024; Wachner et al., 2021).

We find support for our third hypothesis as well, finding that people rate their likelihood of making use of a financial intervention slightly higher when the messenger for this intervention is not *explicitly* disclosed. As suggested by the literature, this could be due to the negative perceptions of the financial sector (Bachmann et al., 2011; Bennett and Kottasz, 2012; Sapienza and Zingales, 2012), or a perceived misalignment between the goals of the individual and the messenger (de Jonge et al., 2022). This effect however, is slight, and we do continue to find positive attitudes toward the financial interventions for both 'messenger types', with people indicating a positive likelihood of making use of the intervention.

We also included a framing variable, displaying interventions that were framed in terms of either spending or saving. There is some prior literature to suggest that people prefer a positive frame over a negative frame, but that evidence is mixed and largely derived from the sustainability domain (Nelson et al., 2021; Ouvrard et al., 2020; Rafaï et al., 2022). We do find a strong preference, which remains consistent across all six measures; people prefer interventions promoting their savings behaviors rather than prohibiting their spending behaviors. Further exploration of this result is needed to understand why exactly this is. We hypothesized that savings-frame is can be perceived as the positive inverse of the spending-frame, which is inherently negative (i.e., 'save more' vs. 'spend less'). However, this is merely a speculation and will warrant further exploration.

There is also the need to highlight that this results suffers a similar limitation to our result for comparing System 1 and System 2 interventions directly. Table O1 (Appendix O) reveals details of the exact interventions tested, and although we attempted to make the spending and saving-frames the inverse of each other, this was not always possible. For example, scenarios 3 and 4 are the exact inverse of each other, with the spending-frame focusing on social norms in spending, with the savings-frame focusing on social norms in savings behavior. But even here, the example mentioned displays slight differences, with spending focusing on grocery spending, and savings focusing on money saved when switching utility providers. Although we report a significant difference between spending and savings-framed interventions across all six dependent variables, these comparisons are again not as clean as comparing the transparent and the opaque interventions, and this is again a limitation of this specific comparison that warrants highlighting.

4.2. Demographic effects

Beyond the characteristics of the financial interventions themselves, we find consistent demographic effects. On average, younger people, women, those earning higher incomes and living in more metropolitan areas are more favorable toward financial interventions. Using model based recursive partitioning, we find that this effect is strongest for age, with those under 45 having significantly more positive attitudes toward behavioral interventions.

Prior work has confirmed that demographic characteristics can affect the effectiveness of interventions, but we are not aware of work having looked at demographic characteristics affecting *attitudes* toward financial interventions, or interventions in general.

We can speculate about the reasons for the effects that we observe. People may reject the need for interventions in their behavior if they (over)confident that they can manage themselves. Research by Menkhoff et al. (2013) finds that age is negatively correlated with overconfidence, whereas work by Prims and Moore (2017) finds that it is confidence and not overconfidence that increases with age (the difference being whether the confidence is proportionate to one's abilities). Work by Hansson et al. (2008) finds the opposite: age is positively correlated with overconfidence. From these conflicting findings, it is difficult to draw a strong conclusion. Another possible explanation is that with increases in age comes a decrease in support of guidance and automation. interventions are a form of guidance, and several interventions do rely on a form of automation, or at least delegation. Work by Lee et al., 2021 has shown that age is negatively correlated with acceptance of automation. Further testing reveals that there are significant differences between our age groups for financial literacy and financial self-efficacy. We find that financial literacy increases with age, reaching its peak at age group 65–74 (2.27), followed by ages 55–64 (2.10) and 75–84 (2.08), which are all statistically different from each other. The highest financial literacy score (ages 65–74) is 1.076 95% CI[1.021, 1.132] higher than the lowest score of (ages 18–24). We find a similar trend when looking at financial self-efficacy with the highest scores being associated with the higher age groups: ages 85 and older score themselves at 28.22, followed by those aged 65–74 (28.03) and 75–84 (27.70). However, these three scores are not significantly different from each other. Statistically significant lower self-efficacy scores are reached from age group 55–64, with scores that are 1.97 95% CI[0.778, 3.165] lower than the highest score. Further research could explore domains in which younger people are assumed, or rate themselves, to be more knowledgeable and confident than older people, and see whether this high approval of interventions persists in those domains as well.

Similarly, looking at gender effects, research has found that women are less confident in their financial knowledge and decision-making than men are (Barber and Odean, 2001; Beckmann and

Menkhoff, 2008). This (lack of) confidence does not map onto performance; overconfidence has been found to often be detrimental in financial decision-making, specifically investing. However, it is possible to speculate that those who deem themselves as less able (in this case, women) would be more willing to follow advice, guidelines and here, an intervention. Looking at our own data, we do find that women rate themselves 2.633 95%[2.425, 2.841] lower in terms of financial self-efficacy, and also hold significantly lower financial literacy scores, which are lower by 0.555 95% [0.523, 0.587] as compared to those of the men. Further research could explore domains in which women are assumed, or rate themselves, to be more knowledgeable and confident than men, and see whether this high approval of interventions persists.

We are unaware of prior work showing that attitudes toward interventions are dependent on income levels. However, the argument can be made that for those with lower incomes, more is at stake; if the intervention backfires they stand to forego a relatively larger portion of income (or overall wealth). This may make lower income individuals more hesitant to follow a intervention, out of a fear of losing control over their money. But this again remains speculative. Within our own data we do again find effects of income on financial literacy and self-efficacy. There was a significant difference in financial literacy scores for the twelve different income groups $F(11, 15118) = 25.04$, $p < 0.001$ as well as a significant difference in financial self-efficacy scores $F(11, 15118) = 94.82$, $p < 0.001$. Contrary to the age group differences, these results are not linear in nature. Although the lowest income group has a significantly lower literacy score as compared to the highest income level (0.518 95% CI[0.420, 0.615]), there are income groups that do not have statistically different scores (e.g., groups 2 and 9, or 3 and 11). The same holds true for financial self-efficacy. We find this effect difficult to interpret and urge further study.

4.3. Implications and applications

A key finding of this research is that there is a variability of attitudes toward interventions, depending on individual characteristics. We find that intervention attitudes are significantly more positive for women, higher income earners and those who are younger (under 45). These findings may have implications for market segmentation and personalization for both policy and feature/product design in the financial domain, particularly given increased use of artificial intelligence to deliver a broader range of customer experiences.

This finding is relevant to the increasing interest in individualised or personalised interventions (Dimitrova et al., 2017; Mills, 2022; Peer et al., 2020; Schöning et al., 2019), or *smart* nudging (Mele et al., 2021). For a recommendation on studying and applying personalised interventions, see Hallsworth (2023). With the availability of data in the financial services being extremely high, there is also the opportunity to apply data-driven interventions to customers, to help them reach their (financial) goals. The data-driven intervention is different from the personalized intervention by not being based on demographic characteristics (e.g., age, gender, income), but based on observed behavior (e.g., amount spent per spending category, savings held, the level of debt incurred and for what, types of investments held and their spread). For example, a customer who has an outstanding credit card debt at a magnitude of several months' wages, with strong tendencies to shop online at night, could benefit from a data-driven intervention that emphasises how much the customer has already spent on online shopping, and how that money could be used to pay down their credit card debt, saving them money on the interest incurred with holding the debt. However, we recognize that there are potential ethical concerns with respect to *who* applies the intervention, *how* it is applied, and *what* it is aiming to achieve. These concerns deserve further attention and research.

4.4. Future research

Our simplest and most important finding is that people have positive attitudes toward interventions in the financial domain. At the same time, these attitudes do depend on how the intervention is framed and which System it targets. Strong preferences were found for System 2 interventions that were framed in terms of savings. Additionally, we find demographic effects, showing that intervention attitudes are significantly more positive for those under 45, women, higher income earners and those living in metro areas. These findings may have implications for market segmentation and personalization for both policy and feature/product design in the financial domain. As we have mentioned, it is not yet known whether, and to what extent, people are comfortable with high levels of personalization when it comes to interventions, and what they deem acceptable data to use to personalise interventions. Research has found that the data deemed acceptable to use for personalization is limited in scope, pertaining mostly to age and gender (Piller and Müller, 2004), but acceptability was also found to depend on the goal of the personalization (de Jonge et al., 2022). Whether similar findings hold for interventions in the financial domain or beyond remains to be seen.

Data availability statement. Replication data and code can be found on the Open Science Framework at https://osf.io/6sfpm/.

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Ethical standards. The research meets all ethical guidelines, including adherence to the legal requirements of the study country.

References

Arad, A. & Rubinstein, A. (2018). The people's perspective on libertarian-paternalistic policies. *The Journal of Law and Economics*, *61*(2), 311–333.

Arvanitis, A., Kalliris, K., & Kaminiotis, K. (2022). Are defaults supportive of autonomy? An examination of nudges under the lens of self-determination theory. *The Social Science Journal*, *59*(3), 394–404.

Bachmann, R., Gillespie, N., & Kramer, R. (2011). Trust in crisis: Organizational and institutional trust, failures and repair. *Organization Studies*, *32*(9), 1311–1313.

Bang, H. M., Shu, S. B., & Weber, E. U. (2020). The role of perceived effectiveness on the acceptability of choice architecture. *Behavioural Public Policy*, *4*(1), 50–70.

Barber, B. M. & Odean, T. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The Quarterly Journal of Economics*, *116*(1), 261–292.

Beckmann, D. & Menkhoff, L. (2008). Will women be women? analyzing the gender difference among financial experts. *Kyklos*, *61*(3), 364–384.

Bennett, R. & Kottasz, R. (2012). Public attitudes towards the UK banking industry following the global financial crisis. *International Journal of Bank Marketing*, *30*(2), 128–147.

Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C., & Skimmyhorn, W. L. (2016). *Does borrowing undo automatic enrollment's effect on savings?* RRC Paper No. NB16-03. Cambridge, MA: National Bureau of Economic Research.

Bovens, L. (2009). The ethics of nudge. *Preference change: Approaches from philosophy, economics and psychology*, 207–219. Dordrecht: Springer Netherlands.

Branson, C., Duffy, B., Perry, C., & Wellings, D. (2012). *Acceptable behaviour: Public opinion on behaviour change policy*. London: Ipsos MORI.

Bruns, H., Kantorowicz-Reznichenko, E., Klement, K., Jonsson, M. L., & Rahali, B. (2018). Can nudges be transparent and yet effective? *Journal of Economic Psychology*, *65*, 41–59.

Bruns, H. & Perino, G. (2023). The role of autonomy and reactance for nudging—experimentally comparing defaults to recommendations and mandates. *Journal of Behavioral and Experimental Economics*, *106*, 102047.

Bubb, R. & Pildes, R. H. (2013). How behavioral economics trims its sails and why. *Harvard Law Review*, *127*, 1593.

Burgess, A. (2012). 'Nudging' healthy lifestyles: The UK experiments with the behavioural alternative to regulation and the market. *European Journal of Risk Regulation*, *3*(1), 3–16.

Cadario, R. & Chandon, P. (2019). Effectiveness or consumer acceptance? tradeoffs in selecting healthy eating nudges. *Food Policy*, *85*, 1–6.

Clavien, C. (2018). Ethics of nudges: A general framework with a focus on shared preference justifications. *Journal of Moral Education*, *47*(3), 366–382.

Conly, S. (2014). Against autonomy: Justifying coercive paternalism. *Journal of Medical Ethics*, *40*(5), 349–349.

Cornwell, J. F. & Krantz, D. H. (2014). Public policy for thee, but not for me: Varying the grammatical person of public policy justifications influences their support. *Judgment and Decision Making*, *9*(5), 433.

Davidai, S. & Shafir, E. (2020). Are 'nudges' getting a fair shot? joint versus separate evaluation. *Behavioural Public Policy*, *4*(3), 273–291.

de Jonge, P., Verlegh, P. W., & Zeelenberg, M. (2022). If you want people to accept your intervention, don't be creepy. *Lab to field: How to successfully translate and scale behavioural insights*. In Behavioral science in the wild (pp. 284–291). Toronto, Canada: University of Toronto Press.

Diepeveen, S., Ling, T., Suhrcke, M., Roland, M., & Marteau, T. M. (2013). Public acceptability of government intervention to change health-related behaviours: A systematic review and narrative synthesis. *BMC Public Health*, *13*(1), 1–11.

Dimitrova, V., Mitrovic, A., Piotrkowicz, A., Lau, L., & Weerasinghe, A. (2017). Using learning analytics to devise interactive personalised nudges for active video watching. *Proceedings of the 25th conference on user modeling, adaptation and personalization*, 22–31.

Felsen, G., Castelo, N., & Reiner, P. B. (2013). Decisional enhancement and autonomy: Public attitudes towards overt and covert nudges. *Judgment & Decision Making*, *8*(3), 202–213.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, *19*(4), 25–42.

Gold, N., Lin, Y., Ashcroft, R., & Osman, M. (2020). 'Better off, as judged by themselves': Do people support nudges as a method to change their own behavior? *Behavioural Public Policy*, 1–30.

Grüne-Yanoff, T. (2012). Old wine in new casks: Libertarian paternalism still violates liberal principles. *Social Choice and Welfare*, *38*(4), 635–645.

Hagman, W., Andersson, D., Västfjäll, D., & Tinghög, G. (2015). Public views on policies involving nudges. *Review of Philosophy and Psychology*, *6*(3), 439–453.

Hallsworth, M. (2023). A manifesto for applying behavioural science. *Nature Human Behaviour*, 1–13.

Halpern, D. (2016). *Inside the nudge unit: How small changes can make a big difference*. London, UK: Random House.

Hansson, P., Rönnlund, M., Juslin, P., & Nilsson, L.-G. (2008). Adult age differences in the realism of confidence judgments: Overconfidence, format dependence, and cognitive predictors. *Psychology and Aging*, *23*(3), 531.

Hausman, D. M. & Welch, B. (2010). Debate: To nudge or not to nudge. *Journal of Political Philosophy*, *18*(1), 123–136.

Hummel, D. & Maedche, A. (2019). How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics*, *80*, 47–58.

Jung, J. Y. & Mellers, B. A. M. (2016). American attitudes toward nudges. *Judgment and Decision Making*, *11*(1), 62–74.

Kahneman, D. (2011). *Thinking, fast and slow*. London, UK: Macmillan.

Kroese, F. M., Marchiori, D. R., & De Ridder, D. T. (2016). Nudging healthy food choices: A field experiment at the train station. *Journal of Public Health*, *38*(2), e133–e137.

Lades, L. K. & Delaney, L. (2022). Nudge for good. *Behavioural Public Policy*, *6*(1), 75–94.

Lee, C., Gershon, P., Reimer, B., Mehler, B., & Coughlin, J. F. (2021). Consumer knowledge and acceptance of driving automation: Changes over time and across age groups. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *65*(1), 1395–1399.

Lin, Y., Osman, M., & Ashcroft, R. (2017). Nudge: Concept, effectiveness, and ethics. *Basic and Applied Social Psychology*, *39*(6), 293–306.

Loewenstein, G., Bryce, C., Hagmann, D., & Rajpal, S. (2015). Warning: You are about to be nudged. *Behavioral Science & Policy*, *1*(1), 35–42.

Lusardi, A. (2015). Financial literacy: Do people know the ABCS of finance? *Public Understanding of Science*, *24*(3), 260–271.

Mele, C., Spena, T. R., Kaartemo, V., & Marzullo, M. L. (2021). Smart nudging: How cognitive technologies enable choice architectures for value co-creation. *Journal of Business Research*, *129*, 949–960.

Menkhoff, L., Schmeling, M., & Schmidt, U. (2013). Overconfidence, experience, and professionalism: An experimental study. *Journal of Economic Behavior & Organization*, *86*, 92–101.

Mertens, S., Herberz, M., Hahnel, U. J., & Brosch, T. (2022). The effectiveness of nudging: A meta-analysis of choice architecture interventions across behavioral domains. *Proceedings of the National Academy of Sciences*, *119*(1), e2107346118.

Michaelsen, P., Johansson, L.-O., & Hedesström, M. (2024). Experiencing default nudges: Autonomy, manipulation, and choice-satisfaction as judged by people themselves. *Behavioural Public Policy*, *8*(1), 85–106.

Michaelsen, P. & Sunstein, C. R. (2023). How do people evaluate default nudges? *Default nudges: From people's experiences to policymaking implications.* London, UK: Springer. 31–57.

Mills, S. (2022). Personalized nudging. *Behavioural Public Policy*, *6*(1), 150–159.

Nelson, K. M., Bauer, M. K., & Partelow, S. (2021). Informational nudges to encourage pro-environmental behavior: Examining differences in message framing and human interaction. *Frontiers in Communication*, *5*, 610186.
Osman, M. (2014). *Future-minded: The psychology of agency and control*. London, UK: Bloomsbury Publishing.
Osman, M., Fenton, N., Pilditch, T., Lagnado, D., & Neil, M. (2018). Whom do we trust on social policy interventions? *Basic and Applied Social Psychology*, *40*(5), 249–268.
Osman, M., Lin, Y., & Ashcroft, R. (2017). Nudging: A lesson in the theatrics of choice. *Basic and Applied Social Psychology*, *39*(6), 311–316.
Ouvrard, B., Abildtrup, J., & Stenger, A. (2020). Nudging acceptability for wood ash recycling in forests: A choice experiment. *Ecological Economics*, *177*, 106748.
Pechey, R., Burge, P., Mentzakis, E., Suhrcke, M., & Marteau, T. M. (2014). Public acceptability of population-level interventions to reduce alcohol consumption: A discrete choice experiment. *Social Science & Medicine*, *113*, 104–109.
Peer, E., Egelman, S., Harbach, M., Malkin, N., Mathur, A., & Frik, A. (2020). Nudge me right: Personalizing online security nudges to people's decision-making styles. *Computers in Human Behavior*, *109*, 106347.
Petrescu, D. C., Hollands, G. J., Couturier, D.-L., Ng, Y.-L., & Marteau, T. M. (2016). Public acceptability in the UK and USA of nudging to reduce obesity: The example of reducing sugar-sweetened beverages consumption. *PLoS One*, *11*(6), e0155995.
Piller, F. T. & Müller, M. (2004). A new marketing approach to mass customisation. *International Journal of Computer Integrated Manufacturing*, *17*(7), 583–593.
Prims, J. P. & Moore, D. A. (2017). Overconfidence over the lifespan. *Judgment and decision making*, *12*(1), 29.
Rafaï, I., Ribaillier, A., & Jullien, D. (2022). The impact on nudge acceptability judgements of framing and consultation of the targeted population. *Behavioural Public Policy*, 1–16.
Rebonato, R. (2014). A critical assessment of libertarian paternalism. *Journal of Consumer Policy*, *37*, 357–396.
Reisch, L. A. & Sunstein, C. R. (2016). Do Europeans like nudges? *Judgment and Decision Making*, *11*(4), 310–325.
Reisch, L. A. Sunstein, C. R., & Gwozdz, W. (2016). Better than a whip?: European attitudes toward health nudges. SSRN: Social Science Research Network. [https://doi.org/10.2139/ssrn.2836325].
Reisch, L. A., Sunstein, C. R., & Gwozdz, W. (2017). Beyond carrots and sticks: Europeans support health nudges. *Food Policy*, *69*, 1–10.
Sakaguchi, H., Stewart, N., Gathergood, J., Adams, P., Guttman-Kenney, B., Hayes, L., & Hunt, S. (2022). Default effects of credit card minimum payments. *Journal of Marketing Research*, *59*(4), 775–796.
Sapienza, P. & Zingales, L. (2012). A trust crisis. *International Review of Finance*, *12*(2), 123–131.
Schmidt, A. T. & Engelen, B. (2020). The ethics of nudging: An overview. *Philosophy Compass*, *15*(4), e12658.
Schöning, C., Matt, C., & Hess, T. (2019). Personalised nudging for more data disclosure? On the adaption of data usage policies format to cognitive styles.
Shah, A. M., Osborne, M., Lefkowitz Kalter, J., Fertig, A., Fishbane, A., & Soman, D. (2023). *Identifying heterogeneity using recursive partitioning: evidence from SMS nudges encouraging voluntary retirement savings in Mexico. PNAS nexus*, *2*(5), pgad058.
Steffel, M., Williams, E. F., & Pogacar, R. (2016). Ethically deployed defaults: Transparency and consumer protection through disclosure and preference articulation. *Journal of Marketing Research*, *53*(5), 865–880.
Sunstein, C. R. (2015). *Which nudges do people like? A national survey.* (June 22, 2015). Available at: https://ssrn.com/abstract=2619899
Sunstein, C. R. (2016a). Do people like nudges. *Harvard DASH*, *68*, 177.
Sunstein, C. R. (2016b). *The ethics of influence: Government in the age of behavioral science*. London, UK: Cambridge University Press.
Sunstein, C. R. (2016c). People prefer system 2 nudges (kind of). *Duke LJ*, *66*, 121.
Tannenbaum, D., Fox, C. R., & Rogers, T. (2017). On the misplaced politics of behavioural policy interventions. *Nature Human Behaviour*, *1*(7), 1–7.
Thaler, R. H. (2018). Nudge, not sludge. *Science*, *361*(6401), 431–431.
Thaler, R. H. & Benartzi, S. (2004). Save more tomorrow™: Using behavioral economics to increase employee saving. *Journal of Political Economy*, *112*(S1), S164–S187.
Thaler, R. H. & Sunstein, C. R. (2021). *Nudge: The final edition*. London, UK: Yale University Press.
Turetski, D., Rondina, R., Hutchings, J., Feng, B., & Soman, D. (2023). An experimental investigation into whether choice architecture interventions are considered ethical. *Scientific Reports*, *13*(1), 18334.
van Gestel, L. C., Adriaanse, M. A., & de Ridder, D. T. (2021). Who accepts nudges? nudge acceptability from a self-regulation perspective. *PLoS One*, *16*(12), e0260531.
Venema, T. A., Kroese, F. M., & De Ridder, D. T. (2018). I'm still standing: A longitudinal study on the effect of a default nudge. *Psychology & Health*, *33*(5), 669–681.
Wachner, J., Adriaanse, M., & De Ridder, D. (2021). The influence of nudge transparency on the experience of autonomy. *Comprehensive Results in Social Psychology*, *5*(1–3), 49–63.
Waldron, J. (2014). It's all for your own good. *The New York Review of Books*, *9*.

Appendix A

Table A1. *Model-free means and standard deviations across all 36 scenarios, for all 6 dependent variables.*

	Approval		Benefit		Ethics		Manipulation		Use (general)		Use (bank)	
Scenario	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	3.26	1.18	3.27	1.07	3.23	1.16	2.76	1.17	3.09	1.25	3.04	1.21
2	3.69	1.06	3.70	1.01	3.66	1.09	2.87	1.21	3.57	1.14	3.44	1.21
3	3.51	1.16	3.43	1.17	3.48	1.13	3.11	1.24	3.27	1.28	3.13	1.29
4	3.65	1.01	3.62	1.07	3.58	1.02	3.03	1.24	3.38	1.19	3.33	1.21
5	3.17	1.24	3.37	1.13	3.26	1.17	3.26	1.20	3.19	1.31	3.17	1.24
6	3.75	1.06	3.79	1.05	3.76	1.03	2.76	1.27	3.48	1.24	3.45	1.22
7	2.90	1.30	2.98	1.23	2.98	1.21	3.27	1.22	2.73	1.38	2.73	1.33
8	3.21	1.22	3.32	1.19	3.27	1.17	3.11	1.21	2.92	1.35	2.94	1.37
9	3.56	1.06	3.58	1.06	3.60	1.01	2.92	1.18	3.12	1.28	3.12	1.29
10	3.68	1.03	3.71	0.99	3.66	1.00	2.89	1.22	3.30	1.30	3.25	1.26
11	3.61	1.10	3.71	1.02	3.57	1.10	2.99	1.24	3.35	1.25	3.25	1.24
12	3.49	1.14	3.50	1.12	3.48	1.10	3.07	1.20	3.31	1.23	3.22	1.26
13	3.51	1.10	3.52	1.08	3.54	1.08	3.05	1.21	3.33	1.25	3.22	1.27
14	3.59	1.06	3.64	1.08	3.62	1.08	2.94	1.21	3.43	1.23	3.34	1.24
15	3.48	1.11	3.42	1.11	3.52	1.06	2.97	1.21	3.24	1.28	3.12	1.26
16	3.54	1.08	3.49	1.07	3.58	1.07	2.98	1.22	3.24	1.29	3.15	1.27
17	3.66	1.08	3.71	1.02	3.66	1.00	2.85	1.22	3.39	1.29	3.33	1.24
18	3.75	1.06	3.70	1.05	3.73	1.08	2.67	1.26	3.43	1.26	3.36	1.28
19	3.39	1.12	3.37	1.08	3.38	1.12	3.23	1.12	3.17	1.29	3.13	1.26
20	3.62	1.07	3.71	1.00	3.60	1.05	2.91	1.21	3.52	1.17	3.44	1.17
21	3.36	1.07	3.33	1.12	3.43	1.04	3.06	1.19	3.11	1.23	3.01	1.26
22	3.48	1.11	3.48	1.11	3.51	1.12	3.07	1.20	3.25	1.21	3.23	1.22
23	3.18	1.24	3.40	1.16	3.26	1.18	3.19	1.23	3.27	1.29	3.11	1.26
24	3.78	1.05	3.80	1.04	3.78	1.04	2.66	1.23	3.51	1.24	3.44	1.27
25	3.06	1.17	3.14	1.14	3.08	1.11	3.24	1.12	2.78	1.30	2.77	1.32
26	3.36	1.14	3.49	1.12	3.42	1.08	3.15	1.18	3.07	1.33	3.06	1.30
27	3.56	1.11	3.56	1.09	3.56	1.07	3.10	1.24	3.19	1.35	3.07	1.33
28	3.55	1.14	3.60	1.03	3.58	1.05	3.00	1.18	3.17	1.30	3.07	1.29
29	3.53	1.15	3.58	1.09	3.51	1.11	2.97	1.24	3.30	1.29	3.20	1.26
30	3.49	1.10	3.55	1.04	3.48	1.06	3.02	1.17	3.33	1.18	3.23	1.21
31	3.55	1.08	3.62	1.00	3.63	0.94	2.95	1.17	3.30	1.24	3.23	1.24
32	3.67	1.08	3.77	1.01	3.66	1.09	2.81	1.25	3.41	1.23	3.36	1.22
33	3.47	1.09	3.49	1.08	3.53	1.01	3.05	1.15	3.19	1.24	3.11	1.23
34	3.50	1.09	3.51	1.11	3.57	1.07	3.01	1.22	3.25	1.22	3.22	1.25
35	3.65	1.05	3.71	1.00	3.67	1.04	2.85	1.21	3.34	1.29	3.27	1.28
36	3.76	1.01	3.74	0.93	3.68	0.98	2.73	1.19	3.46	1.22	3.49	1.12

Appendix B

Table B1. *Results from the linear models (OLS) for all six dependent variables.*

	Dependent variable					
	Approval (1)	Benefit (2)	Ethical (3)	Manipulative (4)	Use (5)	Bank_Use (6)
Transparency	−0.002	0.016	0.005	0.036*	−0.017	−0.018
	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)
System	0.138***	0.120***	0.158***	−0.132***	0.121***	0.121***
	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)
Frame	−0.173***	−0.170***	−0.154***	0.126***	−0.157***	−0.178***
	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)	(0.020)
Age	−0.118***	−0.094***	−0.098***	0.034***	−0.171***	−0.169***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Gender	−0.129***	−0.157***	−0.088***	0.055***	−0.076***	−0.073***
	(0.019)	(0.019)	(0.019)	(0.021)	(0.021)	(0.021)
Income	0.024***	0.020***	0.030***	0.016***	0.034***	0.033***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Area	−0.071***	−0.065***	−0.063***	−0.088***	−0.092***	−0.109***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.023)	(0.022)
CRT	−0.072***	−0.075***	−0.079***	−0.004	−0.174***	−0.174***
	(0.017)	(0.017)	(0.017)	(0.019)	(0.019)	(0.019)
Self-efficacy	0.018***	0.017***	0.021***	0.019***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Literacy	0.008	0.011	0.003	−0.213***	−0.100***	−0.112***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Constant	3.479***	3.408***	3.183***	2.717***	3.510***	3.410***
	(0.079)	(0.078)	(0.077)	(0.087)	(0.088)	(0.087)
Observations	14,807	14,807	14,807	14,807	14,807	14,807
R^2	0.073	0.060	0.072	0.047	0.119	0.125
Adjusted R^2	0.072	0.059	0.071	0.046	0.118	0.124
Residual Std. Error	1.089 (df = 14787)	1.061 (df = 14787)	1.055 (df = 14787)	1.188 (df = 14787)	1.200 (df = 14787)	1.188 (df = 14787)
F Statistic	60.079*** (df = 17; 14789)	47.601*** (df = 17; 14789)	55.919*** (df = 17; 14789)	37.354*** (df = 17; 14789)	99.660*** (df = 17; 14789)	106.877*** (df = 17; 14789)

Note: The reference levels for the instrumental variables are: Transparency (Opaque), System (1), Frame (Savings). Reference levels for the covariates are: Age (18–24), Gender (Female), Income (<$10,000), Area (Metropolitan). The CRT (Cognitive Reflection Test), Self-efficacy and Financial Literacy variables are all numerical variables with ranges of 0–3, 8–40, and 0–3, respectively. The models include dummies for all Australian States. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix C

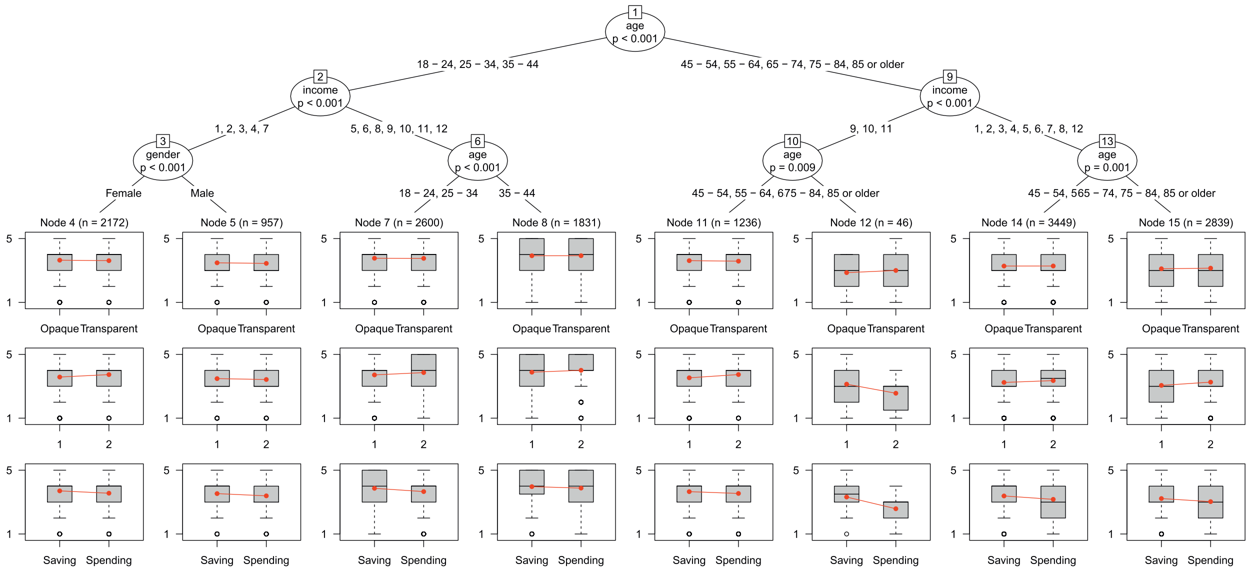

Figure C1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix D

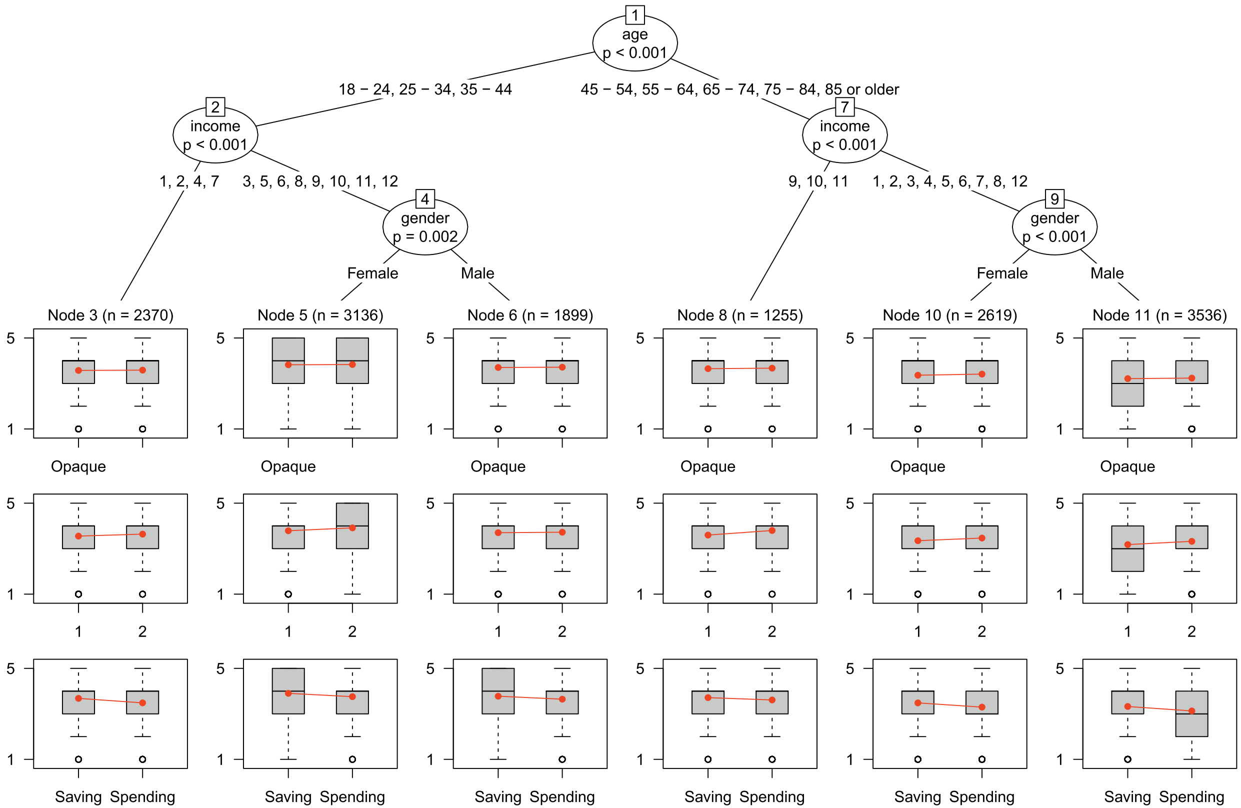

Figure D1. *Results of the model-based recursive partitioning when predicting the perceived benefit of the intervention, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix E

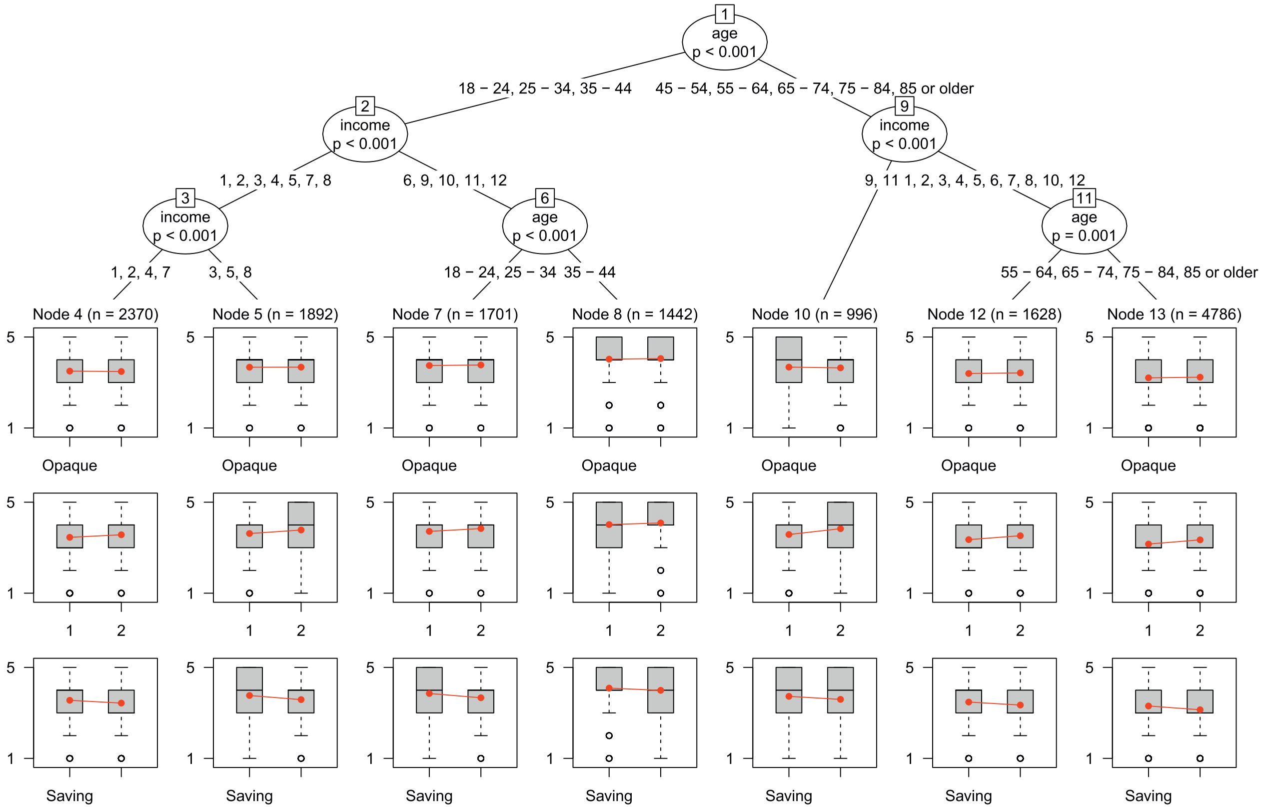

Figure E1. *Results of the model-based recursive partitioning when predicting the perceived ethics of the intervention, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix F

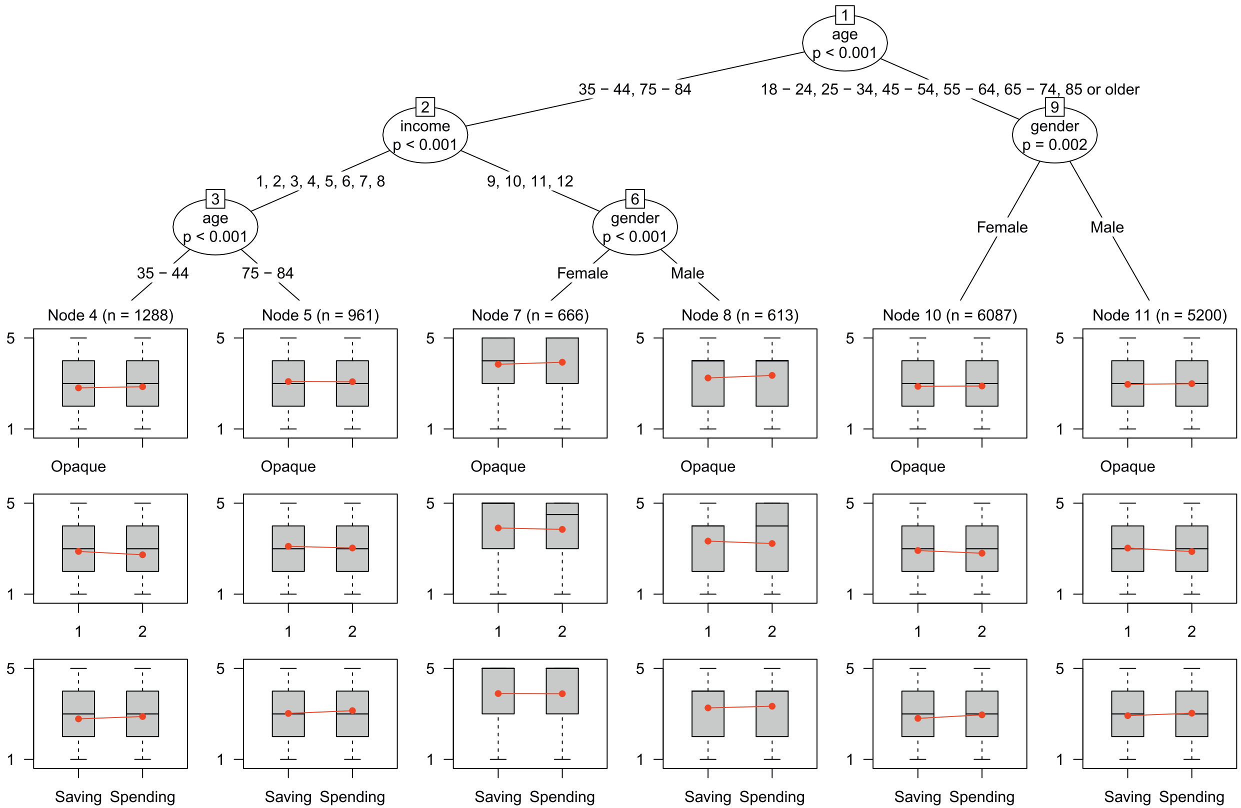

Figure F1. *Results of the model-based recursive partitioning when predicting perceived manipulation of the intervention, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix G

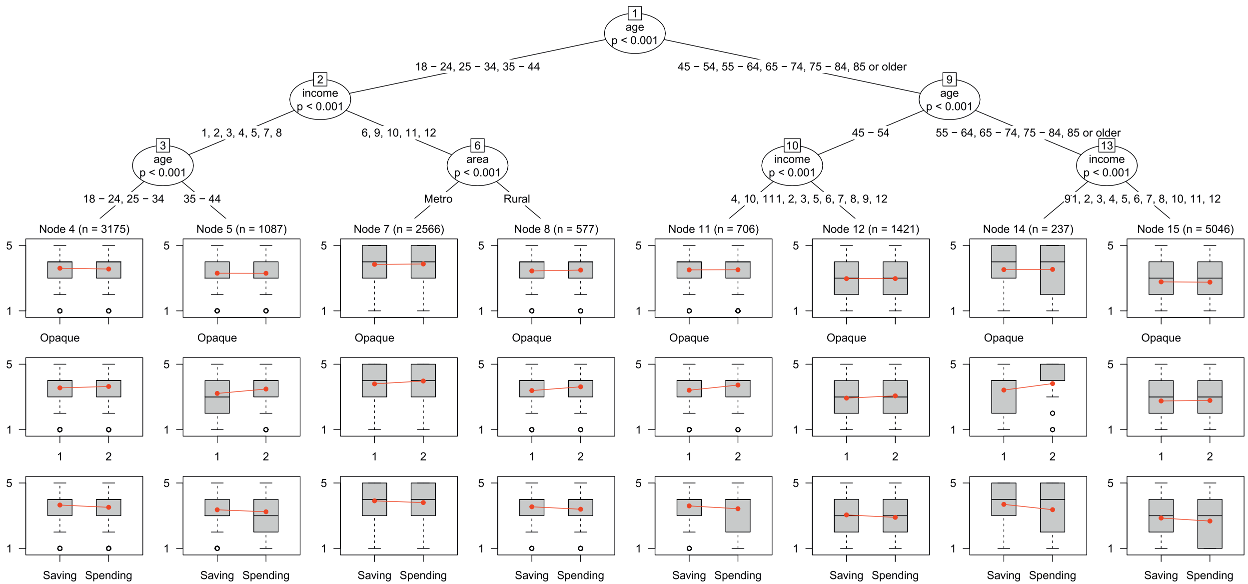

Figure G1. *Results of the model-based recursive partitioning when predicting the likelihood of use of the intervention, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix H

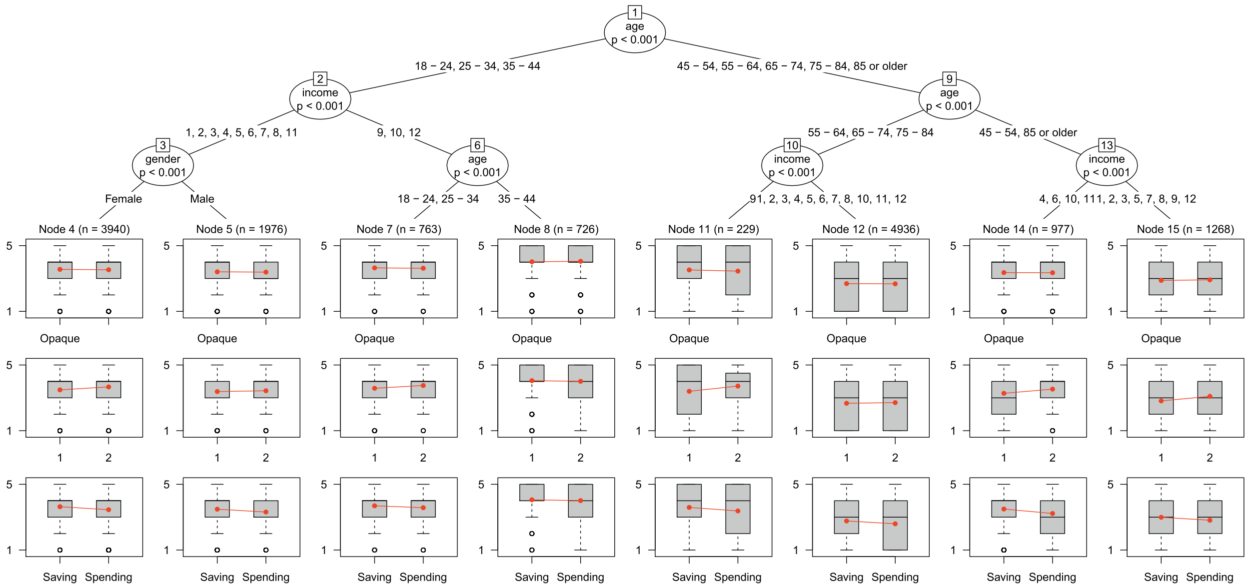

Figure H1. *Results of the model-based recursive partitioning when predicting the likelihood of use of the intervention when proposed by a bank, based on its Transparency, System and Frame. Results show a significant impact of Age, Income and Gender. Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, 12 are based on $90,000–$100,000, $100,000–$150,000 and over %150,000. Depth is capped at 4 for legibility.*

Appendix I

Table I1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System and Frame.*

	Approval					
	Group	n	Intercept	Transparency	System	Frame
Node 4	Age: 18—44, Income: 1–4, 7, Gender: Female,	2172	3.669	−0.031	0.152	−0.146
Node 5	Age: 18–44, Income: 1–4, 7, Gender: Male,	957	3.569	−0.039	−0.054	−0.140
Node 7	Age: 18–44, Income: 5, 6, 8–12, Age: 18–34	2600	3.818	−0.005	0.142	−0.204
Node 8	Age: 18–44, Income: 5, 6, 8–12, Age: 35–44	1831	3.926	0.005	0.120	−0.092
Node 11	Age: 45 + Income: 9 -11, Age: 45–74	1236	3.605	−0.040	0.203	−0.108
Node 12	Age: 45 + Income: 9–11, Age: 75 +	46	3.375	0.133	−0.474	−0.660
Node 14	Age: 45 + Income: 1–8, 12, Age: 45–64	3449	3.346	0.002	−0.115	−0.212
Node 15	Age: 45 + Income: 1–8, 12, Age: 65 +	2839	3.134	0.037	0.208	−0.197
Inner nodes:						7
Terminal nodes:						8
Parameters per node:						4
Objective function (residual sum of squares):						17933.22

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (n) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix J

Table J1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System, and Frame.*

	Perceived benefit					
	Group	*n*	Intercept	Transparency	System	Frame
Node 3	Age: 18–44, Income: 1, 2, 4, 7,	2370	3.649	0.008	0.094	−0.201
Node 5	Age: 18–44, Income: 3, 5, 6, 8–12, Gender: Female	3136	3.860	0.005	0.131	−0.150
Node 6	Age: 18–44, Income: 3, 5, 6, 8–12, Gender: Male	1899	3.763	0.009	0.026	−0.131
Node 8	Age: 45 + , Income: 9–11	1255	3.649	0.042	0.202	−0.105
Node 10	Age: 45 + , Income: 1–8, 12 Gender: Female	2619	3.424	0.040	0.120	−0.189
Node 11	Age: 45 + , Income: 1–8, 12 Gender: Male	3536	3.271	0.016	0.151	−0.200
Inner nodes:						5
Terminal nodes:						6
Parameters per node:						4
Objective function (residual sum of squares):						16753.41

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (*n*) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix K

Table K1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System, and Frame.*

	Perceived ethics					
	Group	*n*	Intercept	Transparency	System	Frame
Node 4	Age: 18–44, Income: 1–8, Income: 1, 2, 4, 7	2370	3.530	−0.021	0.118	−0.126
Node 5	Age: 18–44, Income: 1–8, Income: 3, 5, 8	1892	3.716	−0.002	0.162	−0.186
Node 7	Age: 18–44, Income: 6, 9–12, Age: 18–34,	1701	3.805	0.016	0.124	−0.187
Node 8	Age: 18–44, Income: 6, 9–12, Age: 35–44,	1442	4.055	0.021	0.076	−0.099
Node 10	Age: 45 + , Income: 9, 11,	3.676	−0.053	0.263	−0.139	
Node 11	Age: 45 + , Income: 1–8, 10, 12,	3.676	−0.053	0.263	−0.139	
Node 12	Age: 45–85+, Age: 45–54, Income: 2, 4, 6	1628	3.415	0.017	0.176	−0.137
Node 13	Age: 45–85+, Age: 55–85+,	4786	3.237	0.016	0.189	−0.170
Inner nodes:						6
Terminal nodes:						7
Parameters per node:						4
Objective function (residual sum of squares):						16461.17

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (*n*) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix L

Table L1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System, and Frame.*

	Perceived manipulation					
	Group	*n*	Intercept	Transparency	System	Frame
Node 4	Age: 35–44 & 75–84, Income: 1–8, Age: 35–44	1288	2.799	0.052	−0.152	0.107
Node 5	Age: 35–44 & 75–84, Income: 1–8, Age: 75–84	961	3.044	−0.003	−0.077	0.122
Node 7	Age: 35–44 & 75–84, Income: 9–12, Gender: Female	666	3.866	0.091	−0.066	−0.003
Node 8	Age: 35–44 & 75–84, Income: 9–12, Gender: Male	613	3.231	0.119	−0.118	0.084
Node 10	Age: 18–34 & 45–74, 85 +, Gender: Female	6087	2.829	0.022	−0.124	0.158
Node 11	Age: 18–34 & 45–74, 85 +, Gender: Male	5200	2.950	0.037	−0.161	0.116
Inner nodes:						5
Terminal nodes:						6
Parameters per node:						4
Objective function (residual sum of squares):						21031.35

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (*n*) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix M

Table M1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System, and Frame.*

	Likelihood of use					
	Group	*n*	Intercept	Transparency	System	Frame
Node 4	Age: 18–44 Income: 1–5, 7, 8, Age: 18–34,	3175	3.651	−0.052	0.090	−0.142
Node 5	Age: 18–44 Income: 1–5, 7, 8, Age: 35–44,	1087	3.282	−0.009	0.273	−0.129
Node 7	Age: 18–44 Income: 6, 9–12 Area: Metro	2566	3.844	0.020	0.175	−0.110
Node 8	Age: 18–44 Income: 6, 9–12 Area: Rural	577	3.447	0.037	0.2294	−0.151
Node 11	Age: 45–85+ Income: 4, 10, 11,	706	3.504	−0.006	0.323	−0.182
Node 12	Age: 45–85+ Income: 1–3, 5–12,	1421	3.007	−0.005	0.142	−0.153
Node 14	Age: 55–85+ Income: 9,	237	3.621	−0.068	0.442	−0.357
Node 15	Age: 55–85+ Income: 1–8, 10–12,	5046	2.858	−0.025	0.037	−0.185
Inner nodes:						7
Terminal nodes:						8
Parameters per node:						4
Objective function (residual sum of squares):						21180.15

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (*n*) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix N

Table N1. *Results of the model-based recursive partitioning when predicting approval of the intervention, based on its Transparency, System, and Frame.*

	Likelihood of use when proposed by a bank					
	Group	*n*	Intercept	Transparency	System	Frame
Node 4	Age: 18–44 Income: 1–8, 11, Gender: Female	3940	3.595	−0.028	0.185	−0.189
Node 5	Age: 18–44 Income: 1–3, Gender: Male,	1976	3.479	−0.021	0.061	−0.177
Node 7	Age: 18–44 Income: 9, 10, 12, Age: 18–34	763	3.657	−0.034	0.171	−0.115
Node 8	Age: 18–44 Income: 9, 10, 12, Age: 35–44	726	4.054	0.030	−0.041	−0.047
Node 11	Age: 45–85+ Age: 55–84 Income: 9	229	3.575	−0.141	0.364	−0.235
Node 12	Age: 45–85+ Age: 55–84 Income: 1–8, 10–12	4936	2.766	−0.019	0.047	−0.175
Node 14	Age: 45–85+ Age: 45–54, 85+ Income: 4, 6, 10, 11	977	3.427	−0.022	0.261	−0.277
Node 15	Age: 45–85+ Age: 45–54, 85+ Income: 1–3, 5, 7–9, 12	1268	2.895	0.022	0.280	−0.186
Inner nodes:						7
Terminal nodes:						8
Parameters per node:						4
Objective function (residual sum of squares):						20883.65

Note: Income levels have been condensed for legibility, with level 1 being <$10,000, level 2 being $10,000–$19,999 up to levels 10, 11, and 12 which are based on $90,000–$100,000, $100,000–$150,000, and over $150,000. Depth is capped at 4 for legibility. The count (*n*) is measured in ratings, not participants, with each participant rating 8 interventions each.

Appendix O

Table O1. *The exact scenarios tested.*

Scenario	System	Transparency	Mechanism	Frame	Intervention
1	1	0	Default	Spending	Many people use a credit card for their spending. When repaying a credit card there tends to be 3 options of repayment: 1. repayment in full, 2. minimum repayment or 3. repayment of any other amount between the two. Research has found that when one of these options is 'pre-selected' or highlighted, e.g., repayment in full, this option is more likely to be selected by the customer themselves. The credit card provider chooses the option that is pre-selected.
2	1	0	Default	Saving	Many people do not save enough, and some do not save at all. To make sure people save most financial institutions sign new customers up to both a transaction account and a savings account, with an easy money transfer between both. This default set up is used to indicate to people that not only should they be spending, they should also be saving money. People can opt out of having a savings account, but by default, it is included when signing up for a transaction account.
3	1	0	Social Norms	Spending	Many people do not know what they "ought" to be doing financially, and simply want to align themselves with what the majority are doing. To help guide them, it can be communicated what the majority of people are doing with their money. One example could be that "78% of Australians are spending between $500 and $600 on food, per month".

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
4	1	0	Social Norms	Saving	Many people do not know what they 'ought' to be doing financially, and simply want to align themselves with what the majority are doing. To help guide them, it can be communicated what the majority of people are doing with their money. One example could be that "78% of Australians are saving between $100 and $160 per year by switching utility providers".
5	1	0	Automation	Spending	Most people can't accurately keep track of when their bills need to be paid, and as a result they might pay them late, if at all. Most companies, such as utility companies, know this and set a default option for recurring automated payments (direct debits) so the bill gets sent to the customer's bank account and gets automatically paid, without the customer having to consciously accept the bill and pay it, or move money around to do so. This happens regardless of the amount needed to be paid. Customers can opt-out of this system, but the only alternative is to pay each bill manually.
6	1	0	Automation	Saving	Many people do not save enough, leading them to not have enough money for emergency expenses or to do the things they want to do. To help increase savings, it is possible to set up a direct debit from the account your income is paid into, to your savings account. Where every single time you get paid, part of your income gets automatically directed to your savings account. This is also known as paying yourself first.
7	1	0	Anchoring	Spending	Many people overspend, meaning they spend everything in their bank account. Unfortunately, most people underestimate their spending, and spend more than expected. Therefore, this leads to people spending more than their account balance (which is the anchor). To make sure people don't spend more than they hae, several financial institutions have allowed people to 'hide' their account balances or show people a range of how much money they have left (e.g., 'your balance is between $330 and $380').

(Continued)

Table O1. (Continued).

Scenario	System	Transparency	Mechanism	Frame	Intervention
8	1	0	Anchoring	Saving	Many people do not save enough, and some do not save at all. To make sure people do save, some apps allow people to 'hide' their savings account. It means their savings balance doesn't show up on the home screen, nor the initial balance screen. This is done so people don't spend their savings.
9	1	0	Pre-commitment	Spending	Many people spend more than they would like to. Every year, many Australians get a tax return. Lots of people spend their tax return in full, without saving any of it. To prevent overspending customers can be asked how much (%) of their tax return they would like to spend, weeks before the tax return comes in. When the tax return does come in, customers are reminded of the amount (%) they committed to spending (rather than spending all of it).
10	1	0	Pre-commitment	Saving	Many people do not save enough. Every year, many Australians get a tax return. To prevent customers from saving less than they would like to, customers can be asked how much of their tax return they would like to save, weeks before the tax return comes in. When the tax return does come in, customers are reminded of their initial pre-commitment to save a certain amount of their tax return.
11	1	0	Personalization	Spending	Many people do not know what they 'ought' to be doing financially. To help guide people, their data (age, gender, income, recurring expenses, living arrangements, family situation, lifestyle etc.) can be used to give personalized feedback. This feedback can take many forms, such as: 'you spent $200 per month on take away coffee on the days you go into the office, you can save this money by making your own coffee at home'.

(Continued)

Table O1. (Continued).

Scenario	System	Transparency	Mechanism	Frame	Intervention
12	1	0	Personalization	Saving	Many people do not know what they 'ought' to be doing financially. To help guide people, their data (age, gender, income, recurring expenses, living arrangements, family situation, lifestyle etc.) can be used to give personalized feedback. This feedback can take many forms, such as: 'you are with energy provider X, people living together with 3 other people [like you] tend to be able to save \$50–\$70 per quarter switching to energy provider Y'.
13	2	0	Long-term view	Spending	Many people spend more than they'd like to, as they underestimate the longer-term value of their spending. Apps can track spending and show customers an 'end of the year report', showing how much they spent in total, as well as per spending category. In addition to a yearly report, these apps can also project future costs, indicating that 'if you keep spending at this rate, in ten years you will have spent \$200,000'.
14	2	0	Long-term view	Saving	Many people save less than they'd like to, as they underestimate the longer-term value of their savings. Apps can keep track of savings and show customers an 'end of the year report', showing how much they saved in total, as well as per pay cycle, per month and ultimately, per year. In addition to a yearly report, these apps can also project future savings, indicating that 'if you keep saving at this rate, in ten years you will have saved \$200,000'.
15	2	0	Exemplification	Spending	Many people spend more than they'd like to. Financial apps keep track of spending and show customers an 'end of the year report', showing how much they spent in total, as well as per spending category. However, to most people, the dollar amount of money (e.g., \$20,000) means very little. However, saying that 'you spent \$20,000 this year, which is the equivalent of a second-hand Hyundai i30', means a lot.

(Continued)

Table O1. (Continued).

Scenario	System	Transparency	Mechanism	Frame	Intervention
16	2	0	Exemplification	Saving	Many people save less than they'd like to. Financial apps can keep track of saving and show customers an 'end of the year report', showing how much they saved in total, as well as per pay cycle. However, to most people, the dollar amount of money in savings (e.g., $20,000) means very little. However, saying that 'you've saved $20,000, which is the equivalent of a second hand Hyundai i30', means a lot.
17	2	0	Goal Feedback	Spending	Many people spend more than they would like to and as such would like to reduce their spending. One strategy for reducing spending is to set a budget, either for all spending or per category. Most financial apps allow customers to set a spending limit. Apps then also give feedback on the spending goal: 'you have spent $200 on eating out so far, this is 75% of your monthly category budget and there's 10 more days left in the month'.
18	2	0	Goal Feedback	Saving	Many people struggle with saving as it means giving up spending now to have money to spend later. One strategy for saving more is to set yourself an ambitious saving goal. Customers can set themselves a savings goal. Once the goal is set in a financial app, the app can then give feedback on progress toward the savings goal: 'you have saved $3,000 so far, this is 75% of your savings goal for 2022 and there's three more months left in the year'.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
19	1	1	Default	Spending	A lot of people use a credit card for their spending. When repaying a credit card there tend to be 3 options of repayment: 1. repayment in full 2. minimum repayment or 3. repayment of any other amount between the two. Research has found that when pre-selecting one of those options, e.g., repayment in full, this option is more likely to be selected by the customer themselves. This pre-selection works as a default. Even though the customer can select any other option, they are more likely to stick with the option pre-selected for them. Which option gets pre-selected depends on the credit card provider.
20	1	1	Default	Saving	Many people do not save enough, and some do not save at all. To make sure people save most financial institutions sign new customers up to both a transaction account and a savings account, with an easy money transfer between both. This default set up is used to indicate to people that not only should they be spending, they should also be saving money. People can opt out of having a savings account, but by default, it is included when signing up for a transaction account. This default set-up works as it enrols more people into holding savings accounts than if the savings account would have to be requested separately, thereby increasing the likelihood of people using the savings account and saving in general.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
21	1	1	Social Norms	Spending	Many people do not know what they 'ought' to be doing financially, and simply want to align themselves with what the majority are doing. To help guide them, it can be communicated what the majority of people are doing with their money. One example could be that '78% of Australians are spending between $500 and $600 on food, per month'. This information allows people to tailor their own spending to fit what the majority of people are doing, if they so wish.
22	1	1	Social Norms	Saving	Many people do not know what they 'ought' to be doing financially, and simply want to align themselves with what the majority are doing. To help guide them, it can be communicated what the majority of people are doing with their money. One example could be that '78% of Australians are saving between $100 and $160 per year by switching utility providers'. This information allows people to tailor their own saving to fit what the majority of people are doing, if they so wish.
23	1	1	Automation	Spending	Many people can't accurately keep track of when their bills need to be paid, and as a result they might pay them late, if at all. Most companies, such as utility companies, know this and set a default option for recurring automated payments (direct debits) so the bill gets sent to the customer's bank account and gets automatically paid, without the customer having to consciously accept the bill and pay it, or move money around to do so. This happens regardless of the amount needed to be paid. Customers can opt-out of this system, but the only alternative is to pay each bill manually. This default allows customers to 'set and forget' their direct debits so bills get paid on time, the company gets the money owed, the customer does not get charged late fees and can continue to use the company's services.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
24	1	1	Automation	Saving	Many people do not save enough, leading them to not have enough money for emergency expenses or to do the things they want to do. To help increase savings, it is possible to set up a direct debit from the account your wage is paid into, to your savings account. Where every single time you get paid, part of your income gets automatically directed to your savings account. This is also known as paying yourself first. This set up works in that it allows people to treat themselves as a bill, saving first, and then ‘make do’ with the money remaining. As the initial pay to themselves is already in the savings account, people are less likely to move the money back into their transaction account and spend it. Research has shown that this helps people save more money.
25	1	1	Anchoring	Spending	Many people overspend, meaning that they spend everything they have in their bank account, if not more. To make sure people do not spend more than they have, several financial institutions have allowed people to ‘hide’ their account balances or show people a range of how much money they have left (e.g., ‘your balance is between 330*and*380’). This leads people to spend less money and reduces the chances of obtaining an overdraft fee. The reason this works is that people tend to anchor on their account balance, almost setting it as a ‘goal’ to spend until the balance hits zero. Unfortunately, most people underestimate their spending, and therefore spend more than expected, now spending more than the anchor, their account balance. Without the anchor, in this case the account balance, people don’t have this ‘goal’ in mind and tend to spend less.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
26	1	1	Anchoring	Saving	Many people do not save enough, and some do not save at all. To make sure people do save, some apps allow people to ‘hide’ their savings account. It means their savings balance doesn’t show up on the home screen, nor the initial balance screen. This is done so people don’t spend their savings. The way this works is that when people tend to anchor on the total of all their account balances, even the ones they want to save and not spend, and almost setting it as a ‘goal’ to spend until the balance hits zero. In their mind they don’t have \$2,000 to spend with \$8,000 in savings, but they have \$10,000 available to them to spend. Without this anchor, in this case the total account balance of \$10,000, people don’t have this ‘goal’ in mind and tend to spend less, as their new focus is ‘only’ \$2,000.
27	1	1	Pre-commitment	Spending	Many people spend more than they would like to. Every year, many Australians get a tax return. Lots of people spend their tax return in full, without saving any of it. To prevent people from spending their entire tax return, customers can be asked how much (%) of their tax return they would like to spend, weeks before the tax return comes in. When the tax return does come in, customers are reminded of the amount (%) they committed to spending (rather than spending all of it). This works as people get reminded of their initial commitment (spending only a % of their return, and not the whole tax return) when they weren’t tempted by all the money they have just received.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
28	1	1	Pre-commitment	Saving	Many people do not save enough, if they save at all. Every year, many Australians get a tax return. To prevent people from saving less than they would like to, customers can be asked how much of their tax return they would like to save, weeks before the tax return comes in. When the tax return does come in, customers are reminded of their initial pre-commitment to save a certain amount of their tax return. This works as people get reminded of their initial commitment (saving) when they weren't tempted by all the money they have just received.
29	1	1	personalization	Spending	Many people do not know what they 'ought' to be doing financially. To help guide people, their data (age, gender, income, recurring expenses, living arrangements, family situation, lifestyle etc.) can be used to give personalized feedback. This feedback can take many forms, such as 'you spent $200 per month on take away coffee on the days you go into the office, you can save this money by making your own coffee at home'. This feedback works as it gives people a detailed insight into their own behavior and spending, and at the same time gives them a very clear and actionable way of reducing their spending, if they desire to do so.
30	1	1	personalization	Saving	Many people do not know what they 'ought' to be doing financially. To help guide people, their data (age, gender, income, recurring expenses, living arrangements, family situation, lifestyle etc.) can be used to give personalized feedback. This feedback can take many forms, such as 'you are with energy provider X, people living together with 3 other people [like you] tend to be able to save $50–$70 per quarter switching to energy provider Y'. This feedback works as it gives people a detailed insight into their own behavior and spending, and at the same time gives them a very clear and actionable way of increasing their savings, if they desire to do so.

(Continued)

Table O1. (Continued).

Scenario	System	Transparency	Mechanism	Frame	Intervention
31	2	1	Long-term view	Spending	Many people spend more than they'd like to, as they underestimate the longer-term value of their spending. It's entirely possible for apps to track spending and show customers an 'end of the year report', showing how much they spent in total, as well as per spending category. In addition to a yearly report, these apps can also project future costs, indicating that 'if you keep spending at this rate, in ten years you will have spent $200,000'. This projection works in showing people that all those smaller amounts per pay cycle, per month and ultimately per year do add up and can lead to a much larger sum of money that got spent than many people think they have spent. This shows people the impact of continuing to spend as they are, or the possible impact of changing their spending behavior.
32	2	1	Long-term view	Saving	Many people save less than they'd like to, as they under-estimate longer-term value of their savings. Apps can keep track of savings and show customers an 'end of the year report', showing how much they saved in total, as well as per pay cycle, per month and ultimately, per year. In addition to a yearly report, these apps can also project future savings, indicating that 'if you keep saving at this rate, in ten years you will have saved $200,000'. This projection works in showing people that all those smaller amounts per pay cycle, per month and ultimately per year do add up and can lead to a much larger sum of money that saved than many people think they could possibly save. This shows people the impact of continuing to save as they are, or the possible impact of changing their saving behavior if they are so inclined.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
33	2	1	Exemplification	Spending	Many people spend more than they'd like to, as they underestimate how much the longer-term value of their spending is and what they could have done with that money had they not spent it. Financial apps keep track of spending and show customers an "end of the year report", showing how much they spent in total, as well as per spending category. However, to most people, the dollar amount of money (e.g., $20,000) means very little. However, saying that "you spent $20,000 this year, which is the equivalent of a second-hand Hyundai i30", means a lot. This example shows people what they could have done with such a large sum of money. As people can picture the true value of that money, rather than just the money, it becomes much more salient and is more likely to change behavior. In this case, reduce spending.
34	2	1	Exemplification	Saving	Many people save less than they'd like to, as they underestimate how much the longer-term value of their saving is. Financial apps can keep track of savings and show customers an 'end of the year report', showing how much they saved in total, as well as per pay cycle. However, to most people, the dollar amount of money in savings (e.g., $20,000) means very little. However, saying that 'you've saved $20,000, which is the equivalent of a second-hand Hyundai i30', means a lot. The providing of this example works in showing people what they could have done with such a large sum of money. As people can picture the true value of that money, rather than just the money, it becomes much more salient and is more likely to change behavior. In this case, increase savings.

(Continued)

Table O1. *(Continued).*

Scenario	System	Transparency	Mechanism	Frame	Intervention
35	2	1	Goal Feedback	Spending	Many people struggle with spending more than they would like and actively try to reduce their spending as a result. One way to reduce spending is to set a budget, either for all spending or per category. Most financial apps allow customers to set a spending limit. Apps then also give feedback on the spending goal: "you have spent $200 on eating out so far, this is 75% of your monthly category budget and there's 10 more days left in the month". This feedback works as it reminds people of their longer-term goal, shows them how well they are doing toward this goal and if any changes are required in their short-term spending to make sure the goal is met.
36	2	1	Goal Feedback	Saving	Many people struggle with saving as it means giving up on spending now to have money to spend later. One way to increase savings is to set yourself an ambitious saving goal. Customers can themselves a savings goal. Once the goal is set in app, the app can then also give feedback on progress toward the savings goal: "you have saved $3,000 so far, this is 75% of your savings goal for 2022 and there's three more months left in the year". This feedback works as it reminds people of their longer-term goal, shows them how well they are doing toward this goal and if any changes are required in their short-term spending to make sure the goal is met.

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