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Research Note

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Pausing, reading, and reflecting: decision points in high-risk investment consumer journeys

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Summary

We conducted an online experiment to better understand investors' user journeys, focusing on how comprehension of investment risks is affected by the introduction of so-called *microboundaries* or *decision points* (Soman, Xu, and Cheema, 2010). Decision points are small obstacles that slow down the user and encourage a brief moment of reflection and they have been shown in previous research to support better decisions.

In the current research we introduced decision points into a hypothetical investor journey on a mock crowdfunding website. These decision points took the form of salient and simple FAQ-style information and positive frictions – including checkboxes and manual-input fields. The additional information encouraged participants to pause, read, and reflect, with the result that their comprehension of key investment risks improved, they perceived high-risk investments as riskier, and they were less likely to recommend crowdfunding investments to friends.

Contrary to our hypotheses and other research, the introduction of positive frictions as decision points did not affect comprehension, risk perceptions, or recommendations beyond the summary information. Our findings also highlight the importance of making additional and more exhaustive risk information salient and accessible to further improve comprehension of investment risks. We further discuss implications for the design of information-based decision points and the need for further testing of positive frictions across policy areas.

Equality and diversity considerations

We have considered the equality and diversity issues that may arise in this Research Note.

Overall, we do not consider that the proposals in this Research Note adversely impact any of the groups with protected characteristics i.e. age, disability, sex, marriage or civil partnership, pregnancy and maternity, race, religion and belief, sexual orientation and gender reassignment.

1 Introduction and policy context

As noted in the Financial Conduct Authority's discussion paper DP21/1 (FCA, 2021), a well-functioning consumer investment market can not only help millions of consumers invest with confidence and save for planned and unexpected life events, but also provide essential funding to businesses in the real economy. However, social and economic developments, technological advances in the investment sector, and the Covid-19 pandemic have pushed more consumers towards high-risk investments, with many new investors in high-risk products predominantly researching and investing online. This raises consumer protection concerns, given evidence that some of these investors may not understand the risks involved or be able to absorb losses (FCA, 2021).

To help retail investors make more appropriate and effective investment decisions about high-risk investments[1], the FCA identified three areas where consumer harm can be addressed:

(i) the classification of high-risk investments that determines which (if any) marketing restrictions an investment is subject to

(ii) the consumer journey into high-risk investments which, if strengthened, would further distinguish the high-risk investment market from the mainstream one and help consumers understand the risks involved

(iii) the responsibilities of firms that approve financial promotions to ensure firms have the relevant expertise in the promotions they approve and the overall quality of financial promotions in the market is high.

Our research focuses on the second area identified, which deals with the process consumers must go through to access high-risk investments. By improving consumers' understanding of the risks of high-risk investments compared to the mainstream market, and facilitating more mindful investment decisions, consumers could be less likely to 'click through' and end up investing in inappropriate, high-risk products that do not meet their needs (FCA, 2021). We conducted three separate online experiments to test different tools that could further help consumers distinguish between high-risk and mainstream products:[2]

1. Improved risk warnings (Délias et al., 2022)
2. Decision points[3] in the consumer journey (this research note)
3. Updated investor categories in the self-certification process (Gilchrist et al., 2022)

[1] Any investment subject to marketing restrictions under FCA's rules can be considered high risk. This includes non-readily realisable securities (NRRSs), peer-to-peer (P2P) agreements, non-mainstream pooled investments (NMPIs) and speculative illiquid securities (SISs).

[2] The three online experiments were conducted by the same project team. Whenever we use the term "we" we refer to the authors of all three research notes.

[3] The FCA's consultation paper informed by these three online experiments (Financial Conduct Authority, 2022) uses the term "positive frictions" as a catch all for all decision points.

In Délias et al. (2022) we show that the framing, content and salience of risk warnings placed on high-risk investment products can improve consumers' comprehension of investment risks. However, risk warnings are merely the first line of defence against inappropriate investing. The usual user journey to investing in financial products includes other key steps and touch points which can be utilised to help consumers make better financial decisions. At the same time, we previously identified that investing in high-risk products that do not match investors' risk appetites or financial circumstances is too easy and frictionless (FCA, 2021).

We therefore want to understand how an improved user journey that makes use of these additional touch points can help retail investors understand the risks of high-risk investments.

This Research Note presents our findings from the second online experiment, testing the impact of decision points in high-risk investment user journeys. It focuses on decision points in the user journey for crowdfunding, an investment selected because of its growing popularity amongst newer, non-advised investors (FCA, 2021). Crowdfunding is also one of the main high-risk investments that can still be promoted to the mass market, but any resulting investment by retail consumers is subject to some restrictions.[4] However, the findings from this online experiment should not be limited to crowdfunding but seen as policy-relevant insights into the user journey of any high-risk investment product.

[4] Most shares or bonds bought through a crowdfunding platform are categorised by the FCA as Non-Readily Realisable Securities (NRRS). Their mass marketing is not banned, but for retail investors to be able to respond to the financial promotion, they must either fulfil the criteria of a high net worth or sophisticated investor, or only invest a maximum of 10% of their net assets in high-risk investments. They must also take an 'appropriateness test.'

2 Behavioural context and treatment design

Decision points – pausing, reading, and reflecting

As set out in the previous section, the FCA is concerned that some consumers are investing substantial amounts of money in high-risk investments, such as crowdfunding, by 'clicking through' the consumer journey and not understanding the risks involved. This can lead to decisions that do not meet their financial needs. Adding steps in the consumer journey that make investing just a bit more difficult, and disrupt automatic and mindless actions, could help address this potential harm.

These steps are referred to as *microboundaries* in the human-computer interaction research (Cox et al., 2016) or *decision points* in behavioural science (Soman, Xu, and Cheema, 2010).[5] Microboundaries act as small obstacles that slow down the user and encourage a brief moment of reflection, which can support better decisions.

The research on decision points further highlights the psychological mechanisms driving this behaviour change. Decision-making – also for financial products – can be conceptualised as two separate steps. First, people go through a pre-decision deliberation stage, where they think more carefully and form a decision, before entering a more automatic post-decision implementation stage. Decision points interrupt the automatic implementation stage and put people back into a more deliberative pre-decision stage, giving them time to pause, read and reflect.

Soman, Xu, and Cheema (2010) also suggest three ways in which decision points can be introduced:

1. **providing salient reminders or information**; these decision points not only inform, but also redirect people's attention to neglected considerations
2. **creating interruptions**; these decision points slow people down and allow them to pause and think
3. **inserting transaction costs**; these decision points create hassle associated with additional actions and thereby encourage deliberation

Their research suggests that while simplified and salient information provides the necessary basis for understanding risks by simply informing investors, it can also redirect their attention. Positive frictions on the other hand – in the form of design elements such as additional clicks or steps that complicate the investment journey – can create the interruptions and transaction costs that allow for additional reflection.

Together, we expect information and positive frictions to serve as the decision points that encourage investors to reflect more on the risks associated with high-risk investments and change their behaviour accordingly. The decision points we tested in our online experiment are summarised in Table 1; the remainder of the literature review highlights the behavioural insights that informed these interventions.

[5] We use the terms *microboundary* and decision point interchangeably throughout this research note.

Table 1: Overview of interventions and decision points

Intervention	Description	Behavioural rationale (set out below)
Summary Info Intervention	We add FAQ-style questions and short answers with icons as well as a salient link to further information with a note about a) the time required to read it and b) that it is the last chance to read it to the user journey.	Simplification and salience of information
Active Click Intervention	We build on the Summary Information Intervention and add two checkboxes to the user journey. They require users to confirm that they understand a) they can lose all their invested money and b) they are not protected in case their investment fails.	Positive frictions
Active Input Intervention	We build on the Summary Information Intervention and add two input fields instead of the checkboxes to the user journey. They require users to manually type in a) the amount of money they are prepared to lose and b) that they understand they are not protected in case their investment fails.	Positive frictions
Personalisation Intervention	We build on the Active Input Intervention and add an additional pop-up message to the last screen of the user journey, after the investment decision was made. It includes a) a personalised risk warning, b) a button requiring another click to continue the experiment, and c) a highly salient button leading to the additional risk information.	Personalisation and additional positive friction

Simplification and salience of information

One way to improve comprehension and foster deliberation in the high-risk investment journey, suggested by the literature examined above, is to introduce decision points that contain digestible risk information. Simplifying information is one of the most important policy tools derived from behavioural science (Madrian, 2014; Bhargava and Loewenstein, 2015). Through simplified information, individuals find it easier to navigate complex choice environments.

One example is the 'Pension Passport' developed for Pension Wise by the Behavioural Insights Team (BIT). BIT simplified the usual 50- to 100-page information pack issued to those approaching retirement into a single-page handout with a clear call to action to visit an advice website. This simple intervention led to a 10-fold increase in visits to the advice website (BIT, 2017).

Another important and widely used step in driving comprehension and engagement is making information more salient. The colour, size, and shape – among other attributes – of a user interface element can guide users' attention towards it (Wolfe and Horowitz, 2017). If investors' attention is directed towards new information, they are likely to engage with it rather than mindlessly clicking through the user journey.

Simplification makes comprehension easy, while salience of information through icons or colours makes interventions attractive to users. In a similar vein, BIT developed a practical guide for practitioners on how to make long and complex information – such as the terms and conditions of products – simple, salient, and engaging (BIT, 2019). Through a series of online experiments, they showed that presenting key information in the form of short answers to frequently asked questions – a form of simplification – significantly increases comprehension of the information. Similarly, using icons as visual elements that increase the salience of the presented information aided comprehension. The experiments also showed that opening additional information on a website can be encouraged by telling users how long it will take to read the information and that it is the last chance to read it.

Building on these findings, we designed our *Summary Info Intervention.* We hypothesise that decision points that provide salient information – in the form of FAQ-style questions and icons – redirect attention and increase deliberate engagement with the investment decision, leading to a better comprehension of key risks.

Positive frictions

A second way to change investors' journeys to high-risk investments is to introduce frictions in the user journey. Since frictions are a defining feature of 'sludge' – strategies that keep people from acting in a way they wanted to – they are often considered inherently harmful (see e.g. Sunstein and Gosset, 2020; Soman, 2020). They include waiting times, excessive paperwork, or online interfaces that make certain actions more difficult to take, for example by obscuring important information or requiring many additional clicks. A recent typology of frictions by Shahab and Lades (2021) focused on the distinction between the transaction costs they inflict on users. For example, choice overload creates search costs and long and complicated texts increase evaluation costs. Similarly, small frictions like checkboxes or manual text inputs lead to implementation costs, and induced stress causes psychological costs.

Recently, however, there has also been an increased interest in positive frictions, which act as what can be called 'sludges-for-good'. Soman (2020) develops a theoretical framework in which he recognises that decision points or cooling-off periods that impede decision-making and avoid "hot" emotional states may help consumers make better decisions. Importantly, these positive frictions create specific implementation costs that lead users to rethink their decision, but they avoid search, evaluation, and psychological costs.

A foundational paper in this area, Soman, Xu, and Cheema (2010) report multiple experiments where decision points were introduced to alter dietary choices. For example, they partitioned popcorn into multiple bags that reduced popcorn consumption at a cinema and used a queuing stand with ropes that reduced repeat visits at a buffet. Another decision point was recently tested by Twitter, who forced users to open links and articles before tweeting them (Kelly, 2020). The idea behind this intervention was to encourage users to pause and think about the quality of the link they were sharing, thereby reducing the spread of wrong or misleading news. These examples show that positive frictions are used to interrupt people and create implementation costs, thereby fostering deliberation about consumption decisions and other behaviours.

Similar states of deliberation and vigilance can also be achieved through positive friction in financial decisions. Preliminary findings from a field experiment reported in Soman, Cheema, and Chan (2012) show the effects of decision points in spending decisions. Customers of a bank could select to receive warning messages on their phone after they had spent a certain amount with their credit cards, which they then had to click away if they wanted to keep spending. As a result, customers spent less money with more prudence. It is likely that such deliberation can also be achieved in investment decisions, through positive frictions that act as a decision point requiring additional thought and action.

Building on this discussion we designed our *Active Click* and *Active Input Interventions*. We hypothesise that decision points that create implementation costs – in the form of checkboxes or manual text inputs – will further increase deliberate engagement with the investment decision beyond the salient information, leading to a better comprehension of key risks.

Personalisation and additional positive friction

A further strategy to make information in the investor journey even more attractive and salient is personalisation. Our attention is drawn quickly to our own name and we find it easier to imagine the costs and benefits of our decisions when we are exposed to a message explicitly targeted at us (BIT, 2014). For example, a field trial for Her Majesty's Courts Service showed that personalised text messages were highly effective at increasing fine payment rates (Haynes et al., 2013). We combine this insight with an additional type of positive friction – the pop-up of an additional risk warning with an additional required click – to design our *Personalisation Intervention*. We hypothesise that the personalisation and additional screen and click serve as a decision point containing both highly salient information and strong positive friction, which lead to a further improvement in key risk comprehension.

3 Methodology and sample

Experimental design

We conducted an online experiment to test the four interventions involving decision points described above. We internally pre-registered the empirical methodology before analysing the data in a trial protocol. Participants were recruited through an online panel provider (Prolific). They were asked to go through a fictitious investment user journey, modelled on a typical experience of a crowdfunding retail investor. All participants were presented with a crowdfunding investment opportunity, consisting of three screens:

1. **Homepage:** this first screen was identical for all participants and introduced them to the investment product. It represents the homepage of a crowdfunding website a user who is interested in investing their money in crowdfunding would visit. Figure 1 below presents the homepage.

2. **Investment screen:** this second screen differed between the treatment groups. Participants were randomly allocated to a control group or one of four treatment conditions that correspond to the interventions described in Table 1. They were asked to imagine they were looking to invest £200 in the crowdfunding opportunity they saw – and enter that amount on the investment screen. All treatments outside the control condition included the salient and simple description of the key investment risks in the style of FAQs. They also provided a salient link to additional risk information that leveraged scarcity. Figures 2a – 2d show screenshots of the investment screens from all treatment conditions.

3. **Details screen:** this third screen prompted participants to enter their name and the date, and also included a mock-up of a card payment, mostly to add realism. In addition, it included the additional pop-up as part of the *Personalisation Intervention* – otherwise it was identical across treatments. Figures 3a and 3b show screenshots of the details screens.

Figure 1: Homepage screenshot – identical across treatments

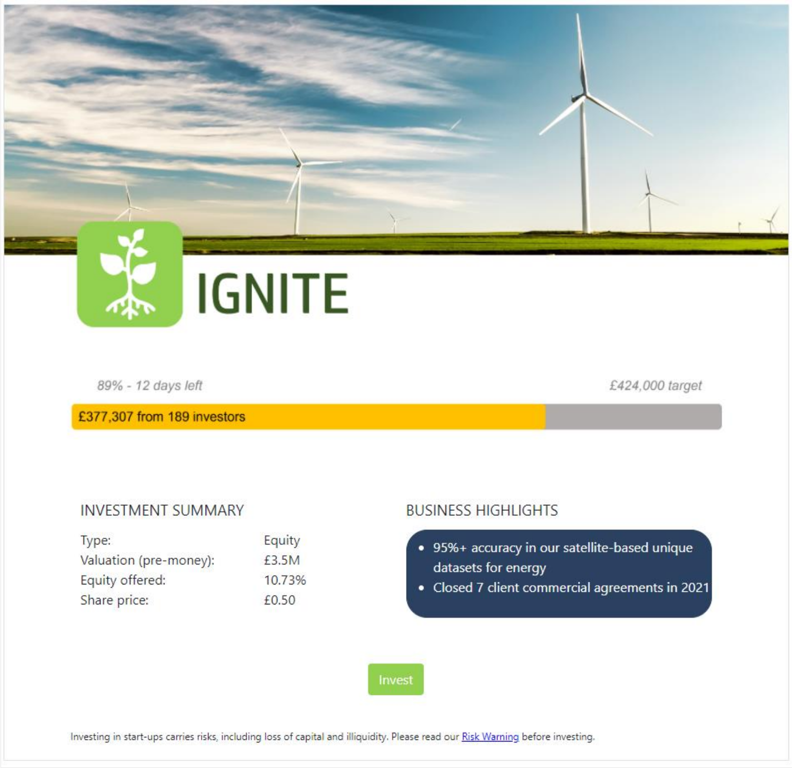


Figure 2a: Investment page screenshot – *Control*

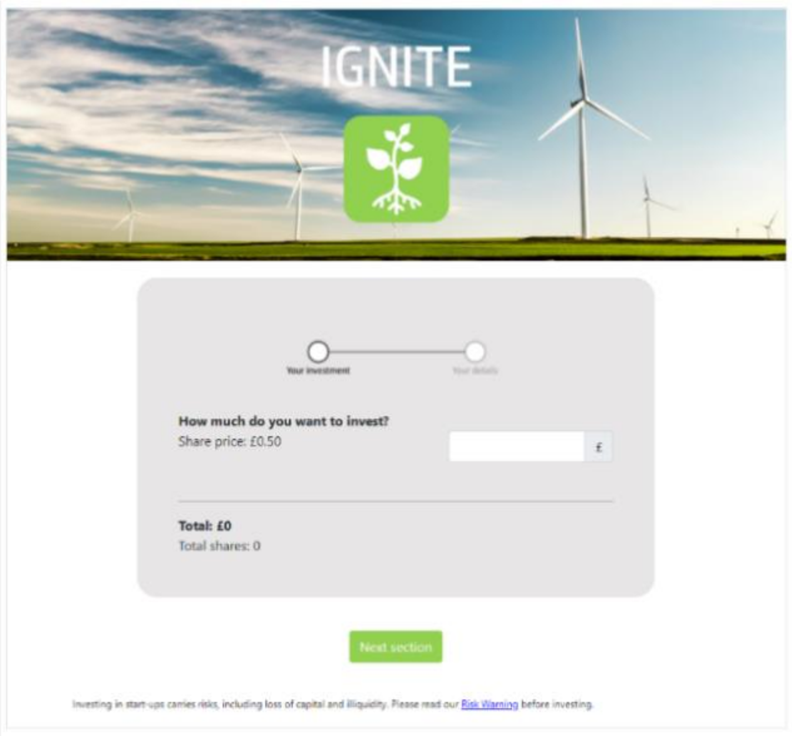


Figure 2b: Investment page screenshot – *Summary Info*

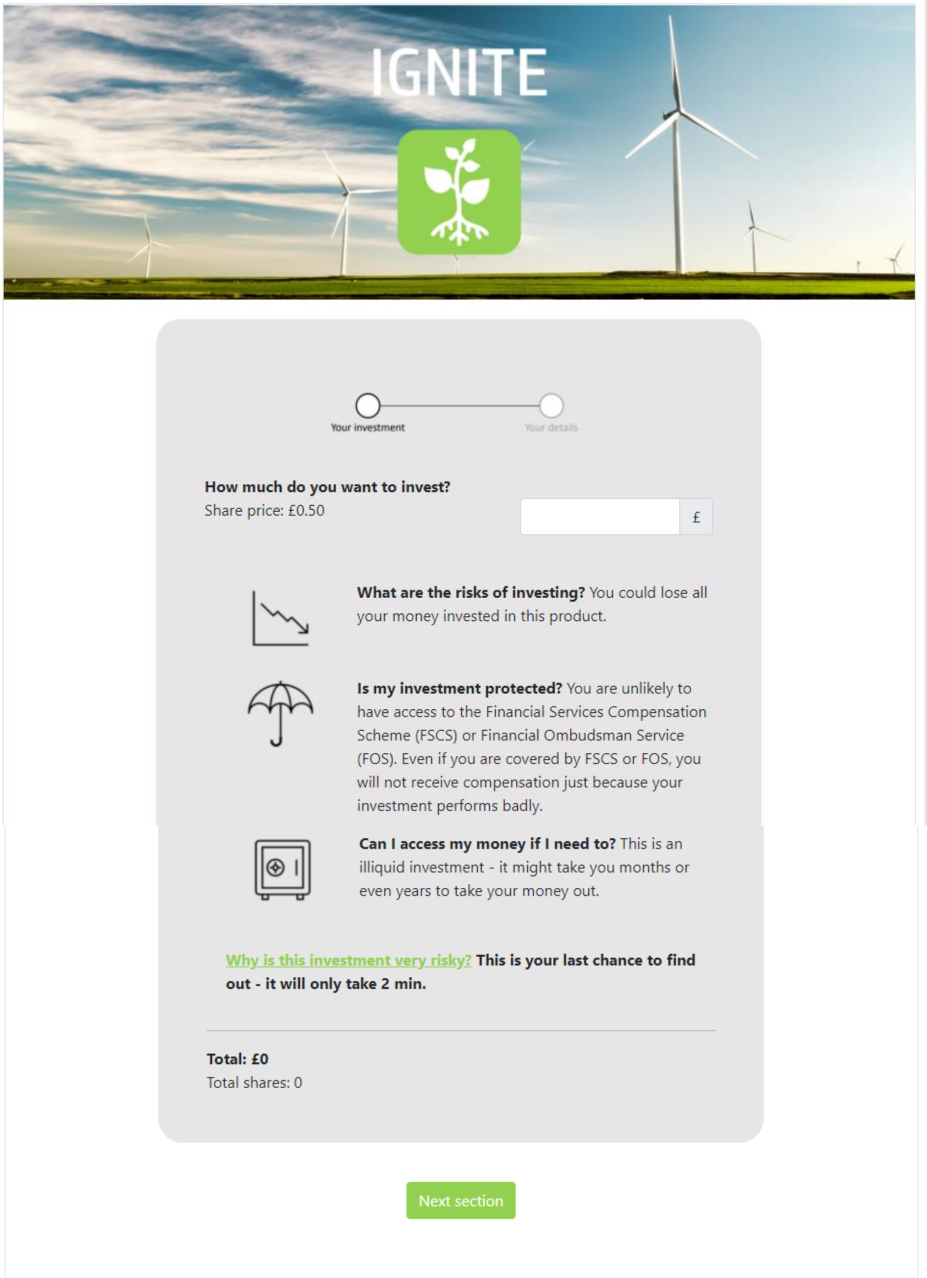


Figure 2c: Investment page screenshot – *Active Click*

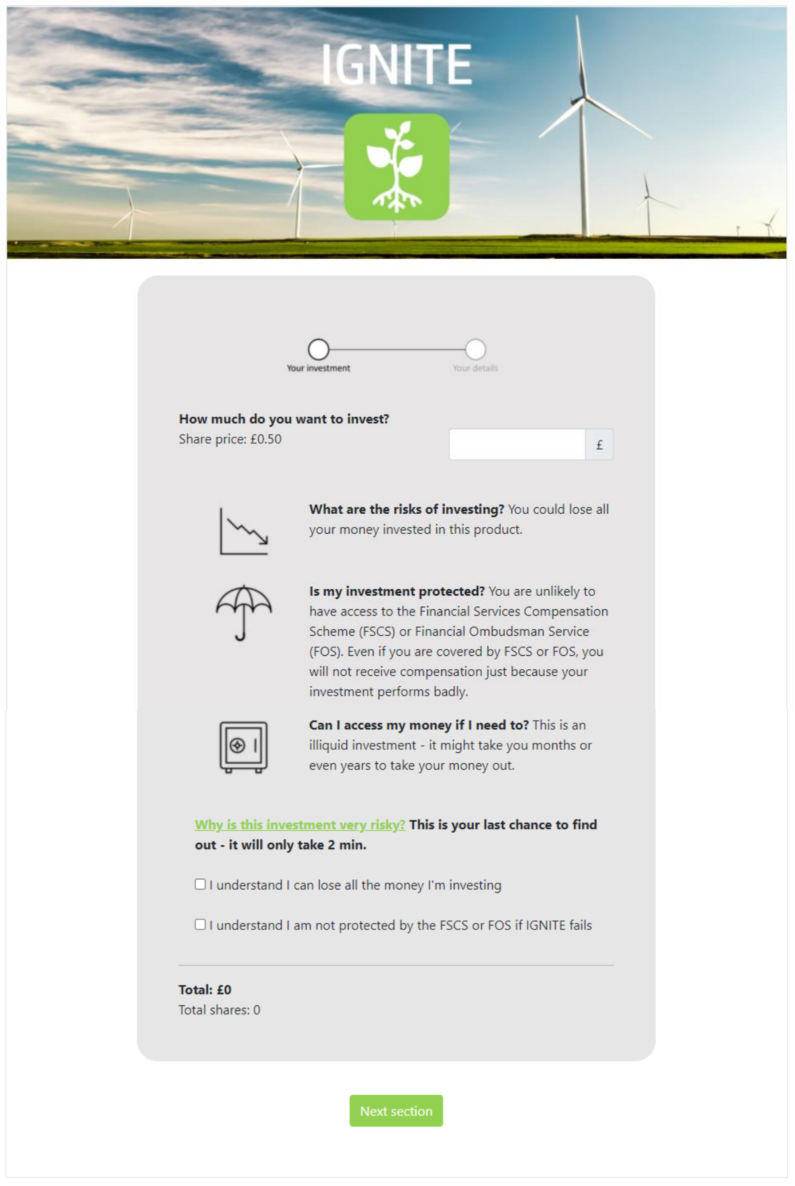


Figure 2d: Investment page screenshot – *Active Input* and *Personalisation*

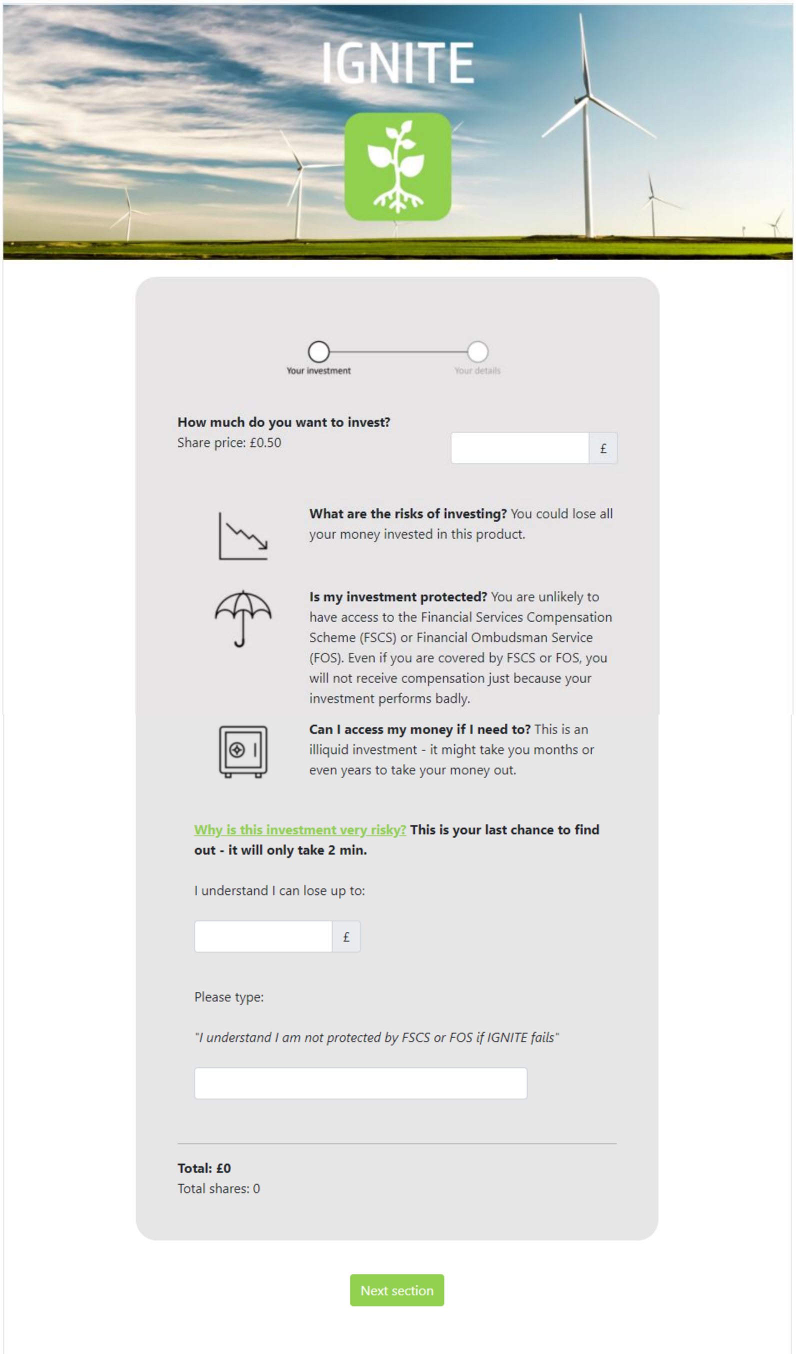


Figure 3a: Details page screenshot – identical across treatments

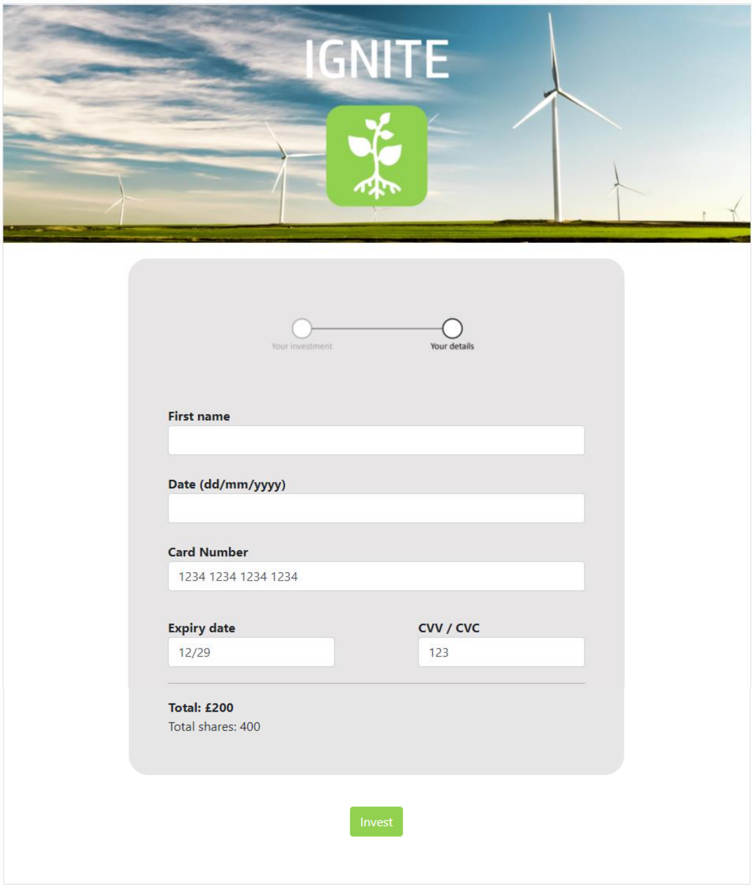
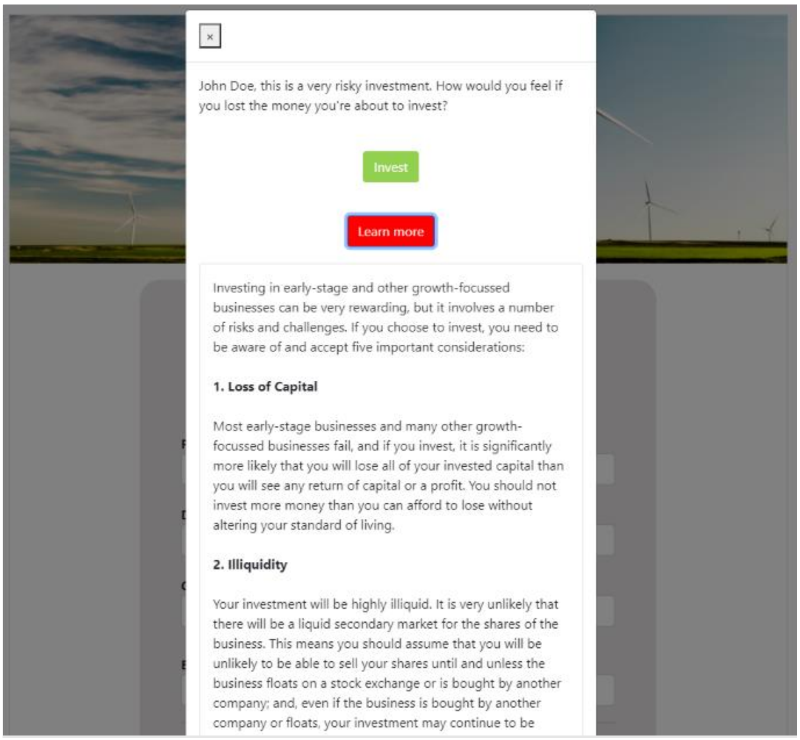


Figure 3b: Details page screenshot – additional pop-up in *Personalisation* treatment



After participants had entered their name and the date on the details screen, they continued to the survey element of our experiment, which included three of our four main outcome measures used for analysis.[6] First participants were presented with six multiple choice questions, covering comprehension of the most important risks associated with crowdfunding. Table 3 in Annex 1 gives an overview of these questions.

Next, participants were asked to rate the riskiness of the crowdfunding opportunity they had seen on a scale from 1-10. Then, participants decided whether they would recommend investing in start-ups through crowdfunding to their friends, and if they did, how much of a total of £16,000 they would recommend investing. We expect recommendations to friends to be good proxies for real-life behaviour as we tend to think more carefully about decisions that impact the impression others have of us – especially those who are close to us (Berger, 2014). Finally, participants completed questions on demographics and their investment experience before exiting the experiment. We also collected a fourth outcome measure – the number of clicks on the links to additional information – as a measure of engagement with the risk information.

Empirical strategy

Table 2 below presents the outcome measures used to assess the effectiveness of decision points, along with the associated research questions and regression models. To estimate the treatment effects of our interventions, we used standard binomial and logistic regression models with and without covariates. These covariates included the participant's age, gender, region, income, past investment experience, whether they hold above-mean savings and whether they receive an above-mean income. Unless stated otherwise, we report and visualise the results from the models excluding covariates. For logistic and binomial regressions, we report the average marginal effects in percentage points (pp).

Table 2: Research questions, empirical strategy, and dependent variables

Research question	Empirical strategy and dependent variable
Primary analysis Do decision points improve participants' comprehension of key investment risks?	Binomial regression models - Successes defined as the total number of comprehension questions (out of 6) answered correctly - Failures defined as the total number of comprehension questions (out of 6) answered incorrectly

[6] Our survey block contained two additional items that were intended to be used as additional outcome variables. We asked participants whether they would consider investing in start-ups in the future and if they did, how much of their savings they would be willing to invest in start-ups. However, due to a programming error, only few participants answered these questions, so we were not able to use it for analysis. Instead we are relying on the items relating to recommendations to friends as measures of behavioural intent.

Research question (continued)	Empirical strategy and dependent variable (continued)
Secondary analysis I Do decision points increase risk perceptions?	Logistic regression models - 1 if participant gives a risk score of 8 or above[7] on a scale from 1-10, and - 0 otherwise
Secondary analysis II Do decision points reduce the likelihood of recommending investing to a friend?	Logistic regression models - 1 if the participant would recommend their friend to invest any positive amount of their savings in crowdfunding, and - 0 otherwise
Do decision points reduce the recommended investment amount?	OLS models - amount (£0 - £16,000) the participant stated they would recommend their friend to invest
Secondary analysis III Do decision points increase the likelihood of participants clicking through the risk warning and being exposed to full risk information?	Logistic regression models - 1 if the participant clicked at least once on the link to "take 2min to learn more", and - 0 otherwise
Exploratory analysis I Does the likelihood of clicking through to the full risk information mediate the main effect of decision points on key risk comprehension?	Causal mediation analysis using *mediation* package (Tingley et al. 2013) Same dependent variables as primary analysis and secondary analysis III
Exploratory analysis II Do decision points improve understanding of individual key investment risks?	Logistic regression models - 1 if the participant answered the comprehension question correctly, and - 0 otherwise

Sample description and attrition

We collected a total of 4,627 responses and after excluding incomplete responses, duplicate panel IDs, and responses that did not meet the targeted population, we worked with a total sample of 4,008 participants. A-priori power analyses for logistic models

[7] The cut-off point on the 1-10 risk scale was chosen to be consistent with the analysis in the other experiments the FCA conducted on high-risk investments (see Délias et al., 2022). Similar results were obtained when using a linear regression estimating the risk level on the 1-10 scale.

revealed that with 750 participants per condition we would be sufficiently powered to detect effects of 6.5pp, 7.2pp, and 6pp for a control group baseline of 25%, 50%, and 75%, respectively. The participants were randomly allocated to one of five treatment conditions – Table 4 in Annex 2 shows the number of observations in each group. The number of observations is marginally lower in the *Active Input* treatment, which is due to a higher attrition – participants dropping out before completing the experiment – which will be discussed further below. Overall, the observed frequencies are not significantly different across treatment conditions (X-squared (4) = 4.0983, p = 0.393).

To check whether our randomization was successful, we test for balance on demographic, financial and investment experience characteristics.[8] We find the sample is balanced on gender, age, savings, discretionary income, previous investment experience, and previous investments in start-ups. The observed imbalance in region and income does not appear to be systematic. For robustness we include specifications which include these covariates in all subsequent analyses. Table 4 in Annex 2 presents summary statistics of all characteristics across the treatment groups.

Finally, we examine attrition in the experiment. Although the majority of participants finished the experiment, a total of 612 participants, or 13.2% of the sample who started the experiment did not finish. A first inspection reveals that the majority of these dropouts can be accounted for by a few screens in the experiment. 23.9% of those who did not finish dropped out at the screen where they were asked to state their savings and discretionary income. It seems that participants were particularly uncomfortable answering these questions related to personal finances. Around 31.5% dropped out at the investment stage with another 22.6% dropping out at the screen where they were asked to enter their name and saw a mock-up of a typical credit card payment box.

Further analysis reported in Table 5 in Annex 2 reveal that participants exposed to the *Active Input* treatment were 6.2pp less likely to finish the experiment than the control group. Similarly, participants in the *Personalisation* condition were 4pp less likely to finish the experiment. These higher attrition rates can likely be explained by the increased friction on the investment screens of the *Active Input* and the *Personalisation* conditions. Participants had to enter three correct values as opposed to one in the remaining treatments in order to pass the validation check and advance in the experiment. This made errors significantly more likely with 10% and 7.53% of participants struggling to pass the validation check, respectively. Column 3 of Table 5 in Annex 2 shows that each error in the investment screen reduced the likelihood of completing the experiment by 3.1pp. We do not attempt to correct for the attrition but rely on complete cases in the subsequent analyses.[9]

[8] We use a series of linear probability models where treatment dummies serve as dependent variables and the individual characteristic as the predictor.

[9] The strategy is different from the experiment reported in Gilchrist et al. (2022). We do not have sufficient data to perform valid imputations of missing data, as the covariates were collected after most participants had dropped out. Furthermore, missingness in this experiment is likely due to treatment assignment, not risk comprehension, which means that the bias introduced by complete-case analysis is likely negligible (see White and Carlin, 2010). As a result, we use complete-case analysis with the as the more conservative approach given the levels of attrition and report our results alongside a sensitivity analysis in Annex 3.

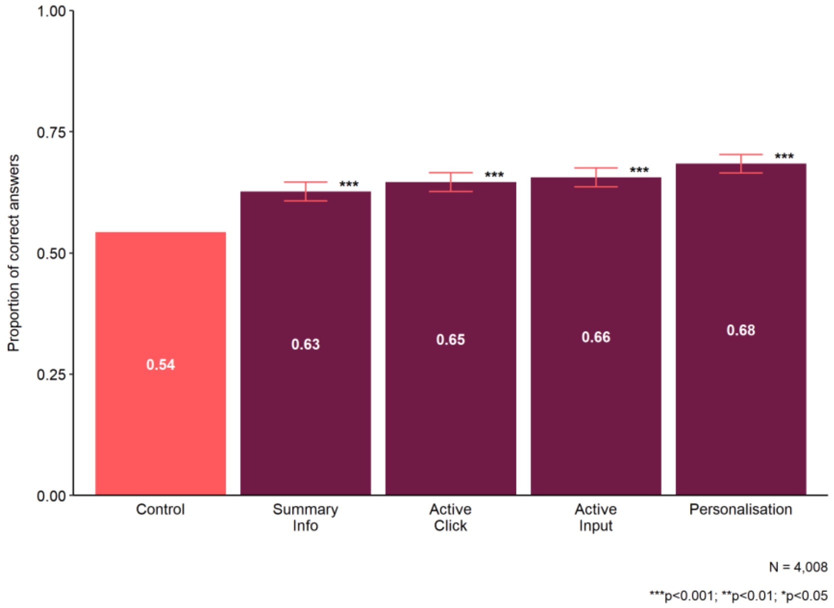
4 Results

Comprehension of key investment risks

Adding decision points to retail investors' user journeys significantly improves their understanding of key crowdfunding risks. The effect is mainly driven by the salient and simple FAQ-style information – positive frictions do not improve comprehension any further.

The results from the primary analysis presented in Table 6 in Annex 5 show that all treatments significantly increase the likelihood of answering any comprehension question correctly. The effect is strongest for the *Personalisation* treatment, which made participants 14.1pp (~26%) more likely to answer correctly, and weakest for the *Summary Info* treatment, which made them 8.3pp (~15%) more likely to answer correctly. Pairwise comparisons further reveal that the *Personalisation* condition outperforms all other treatments (p = 0.044 against *Active Input*). The other interventions do not significantly differ from each other. This suggests that the effect is mainly driven by the salient and simple information provided in all treatments and that the positive frictions – checkboxes and manual input boxes – do not further improve comprehension. Only the pop-up with a personalised risk warning and easily accessible additional information improved comprehension. The results are visualised in Figure 4.

Figure 4: Key risk comprehension



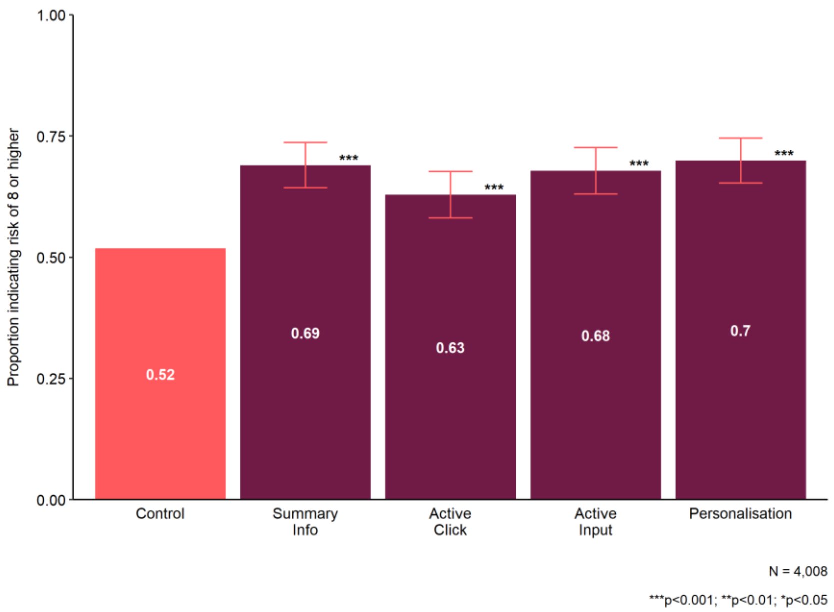
These results are robust to the inclusion of the covariates. In addition, the analysis shows that an increase in age of 10 years is associated with a significant 1pp increase in the likelihood of answering any question correctly. Male participants and participants with savings above the median were 3.5pp and 4.4pp more likely to answer any comprehension question correctly, respectively. We also conduct sensitivity checks, described in Annex 3 and are able to rule out that the results are driven by the higher attrition in the *Active Input* and *Personalisation* treatments.

Perceived riskiness

Adding decision points to retail investors' user journeys significantly increases their risk perceptions of crowdfunding. Again, the effects are driven by the highly salient and simple information.

The results of the first secondary analysis presented in Table 7 in Annex 5 show that all four treatment conditions significantly increased the perception of the riskiness of crowdfunding. Participants in the *Personalisation* treatment were 18.1pp (~35%) more likely to give crowdfunding a risk rating of "8" or higher. Pairwise comparisons further reveal that the *Summary Info*, *Active Input*, and *Personalisation* treatment had indistinguishable effects, while the *Active Click* treatment increased risk perceptions marginally less (p = 0.023, p = 0.247, p = 0.075, compared to the *Personalisation*, *Active Input*, and *Summary Info* conditions, respectively). Adding checkboxes to a user journey seems to have a marginally weaker effect on perceptions of riskiness. The results are visualised in Figure 5.

Figure 5: Perceived riskiness



These results are also robust to the inclusion of the covariates. The models show that an increase in age of 10 years is associated with a significant 3pp increase in risk perceptions, while male participants were 3.9pp more likely to give crowdfunding a higher risk score. Participants with savings above the median and with discretionary income above the median were 9.6pp and 3.7pp more likely to consider crowdfunding high-risk, respectively.

Recommending to a friend

Adding decision points to retail investors' user journeys significantly deters recommendations to friends (which act as a proxy for real-life behavioural intent). Participants in our experiment were less likely to recommend investing in crowdfunding, and if they did, recommended to invest a smaller amount.

The results of the second secondary analysis are reported in Table 8 in Annex 5 and show that all treatment conditions reduced the likelihood of recommending investing in crowdfunding to a friend. In the *Personalisation* treatment participants were 8.9pp (~10%) less likely to recommend investing in start-ups through crowdfunding. A similar picture arises for the recommended investment amount. All four treatments reduced the recommended amount significantly, with participants in the *Personalisation* treatment on average recommending their friends to invest £597.13 (~26.5%) less than participants in the control group. The results are visualised in Figures 6 and 7.

Figure 6: Recommendations to a friend – Likelihood of recommendation

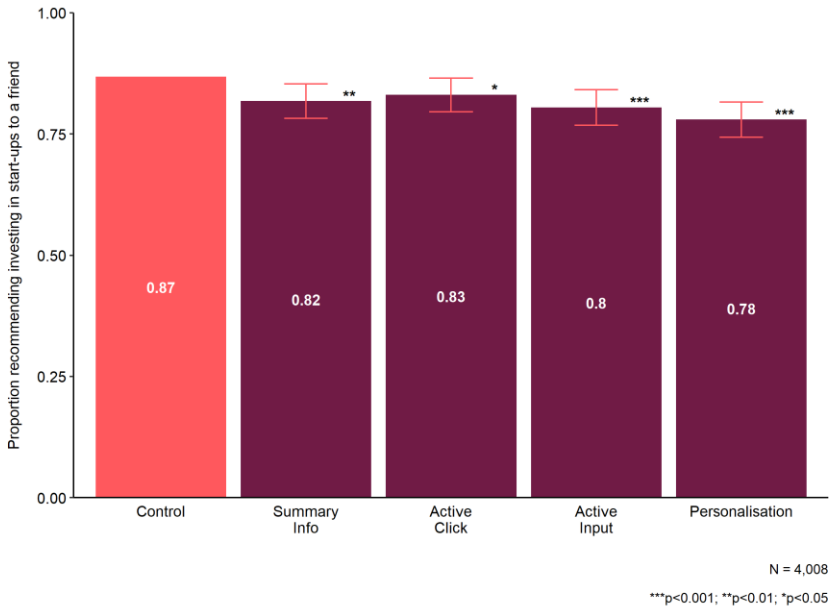
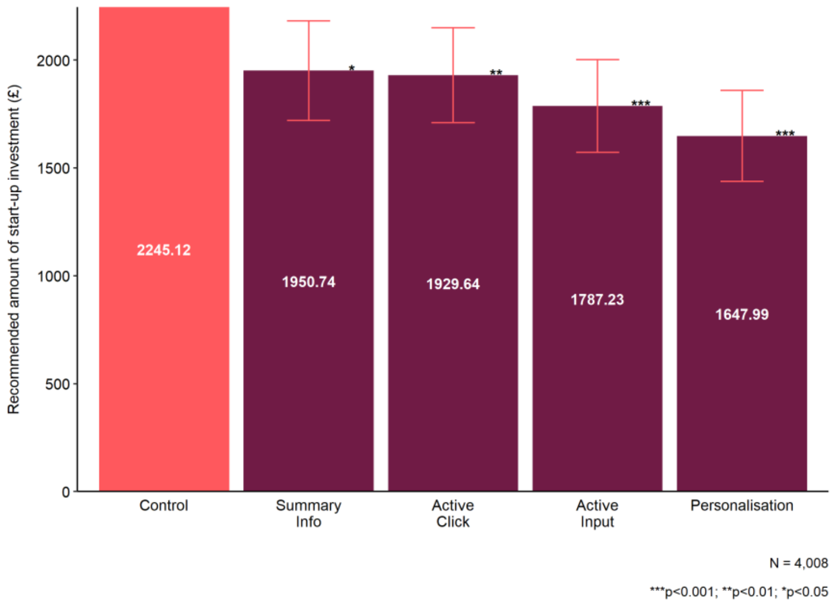


Figure 7: Recommendations to a friend – Recommended amount



The *Active Click* condition has the directionally smallest effect on the likelihood of recommendation with participants being 3.8pp (~4%) less likely to recommend investing through crowdfunding. The *Summary Info* condition has the directionally smallest effect on the amount recommended with participants recommending £294.38 (~13%) less on average than the control group. However, pairwise comparisons reveal that there are no significant differences both in the likelihood of recommending investing in crowdfunding and the recommended investment amount between the treatment conditions. This again suggests that the salient and simple information deters recommendations, rather than positive frictions.

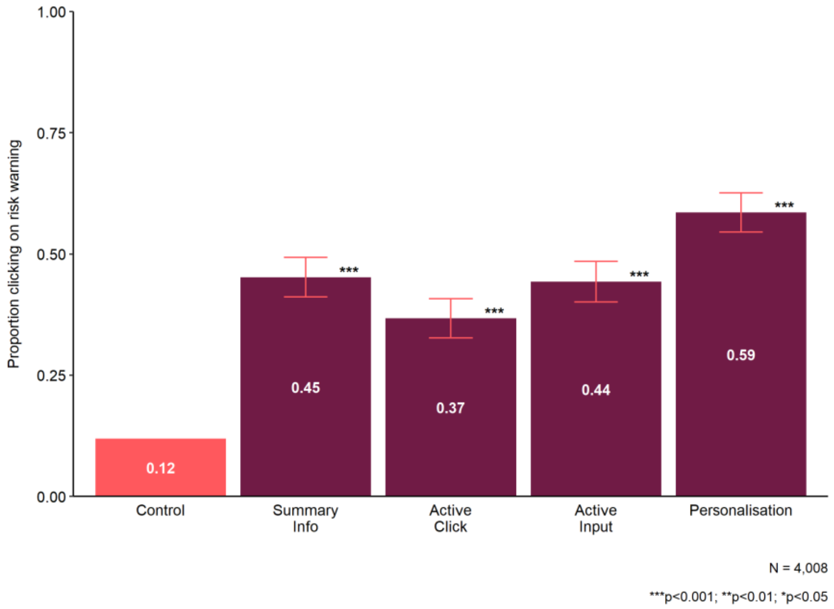
These results are robust to the inclusion of the covariates. An increase in age of 10 years is associated with a significant 4pp decrease in recommendation likelihood and a £117.18 decrease in the recommended amount. Male participants were 4.5pp less likely to recommend investing through crowdfunding. Participants with savings above the median were 6.5pp less likely to recommend investing in start-ups and on average recommended to invest £474.45 less.

Accessing additional risk information

Adding decision points to retail investors' user journeys significantly increases the likelihood of participants clicking on risk warnings to receive additional information. The more salient the risk warning and link, the more likely people will click on it.

The results of the third secondary analysis are presented in Table 9 in Annex 5 and show that all treatment conditions significantly increased the likelihood of clicking through the risk warning. Only 12% of participants clicked on the risk warning in the control group, where the link was presented in small text at the bottom of the page. In the *Personalisation* treatment, participants were 46.6pp (~388%) more likely to click the link to the additional information. The *Active Click* condition has the weakest effect on the likelihood of clicking through the risk warning with participants being 24.8pp (~207%) more likely to click and be exposed to the additional information. The differences between these treatment conditions are statistically significant.[10] Overall, the effect was strongest in the *Personalisation* treatment where the additional screen included a highly salient button leading to further information, and weakest in the *Active Click* condition where checkboxes provided positive friction. The results are visualised in Figure 8.

Figure 8: Click through risk warning to additional information



These results are robust to the inclusion of covariates. The models show that male participants were 3.1pp more likely to click on the risk warning and be exposed to additional information. Those with savings above the median were 5.1pp more likely to click through, while those with a discretionary income above the median were 4.7pp less likely to click through to the additional information.

[10] The *Active Click* treatment led to significantly less click throughs on the risk warning than the *Summary Info* (p = 0.005), the *Active Input* (p = 0.021), or the *Personalisation* treatment (p < 0.001). At the same time the *Personalisation* condition led to a significantly higher likelihood of clicking on the risk warnings than both the *Summary Info* (p < 0.001) and the *Active Input* treatments (p < 0.001). There was no significant difference between the *Summary Info* and *Active Input* treatments (p = 0.996).

5 Exploratory analyses

Direct and indirect effects on risk comprehension

Additional risk information – accessible through a single salient click on a risk warning – plays an important role in high-risk investors' user journeys. Exposure to this additional information partly drives the improved comprehension of key risks and can explain how the Personalisation Intervention outperformed the other treatments.

In the first exploratory analysis, which was not part of the trial protocol, we investigate whether the main effects of decision points on key risk comprehension are mediated by exposure to additional risk information. In other words, we analyse whether decision points affected comprehension directly, or indirectly by making participants more likely to click on the risk warnings and read the additional risk information. The results suggest that the interventions improve comprehension directly and indirectly – both by providing simple and salient information as a decision point and by increasing exposure to additional information. This means that salient and easily accessible additional information can improve comprehension beyond the effect of the decision points we tested.

Furthermore, the *Personalisation* treatment outperforms all the other interventions almost entirely because it made the additional information most salient and accessible. We cannot conclude from this analysis that the additional information directly caused participants to understand risks better, since participants who click on the additional information are likely to be different – in terms of attention or effort – from those who do not in the first place. However, it suggests that making risk warnings and additional information more accessible through a salient button is associated with higher levels of risk comprehension. A technical summary of the mediation analysis can be found in Annex 4.

Comprehension of single investment risks

Decision points significantly improve understanding for all questions other than understanding how a return can be made from crowdfunding. The sub-group of participants across treatments who didn't click through to extra information only saw improved comprehension for three of the six questions, underlining the importance of easily accessible additional information.

The results from the second exploratory analysis – which was not included in the trial protocol – are presented in Table 11 in Annex 5 and in Figure 9. We pool all interventions together and find that introducing decision points in the user journey significantly improves comprehension of all key risks other than Question 4 *"how you can make a return"*. Table 12 in Annex 5 further supports this result and presents a model where the treatments were not pooled, and no covariates were used. It shows that while participants in the *Personalisation* treatment had a significantly improved understanding of *"how they can make a return"*, participants exposed to weaker decision points in the other treatments did not. At the same time, it suggests that three of the key risk questions were harder to understand or more difficult, as the effects are smaller and only marginally significant (see Annex 1 for an overview of the six key risk questions).

Table 13 in Annex 5 and Figure 10 present the results of a sub-group analysis for those participants who did **not** click through the risk warning to see the additional information, with pooled treatments and including covariates. These results should be interpreted carefully and cannot be considered causal, because the participants who do click on the link are likely to be different to the ones who do not in ways that we do not observe in this experiment. The decision points in our interventions only significantly improve comprehension for three of the six key risk questions. This sub-group was still more likely to comprehend *"the key risks associated with crowdfunding"* (Question 1), know *"what happens if the start-up fails"* (Question 2), and be able to *"describe the risk associated with crowdfunding"* (Question 3), compared to the control group. However, they were not more likely to understand *"how you can make a return"* (Question 4), *"what happens if the company issues more shares" (Question 5)*, and *"the best method for investing in start-ups"* (Question 6). It seems that the latter questions require a deeper understanding derived from the additional information, while the former are more apparent from the decision points introduced in the investors' user journeys. This also underscores the importance of addressing all key risks in the decision points that provide salient and simple information.

Figure 9: Comprehension by question

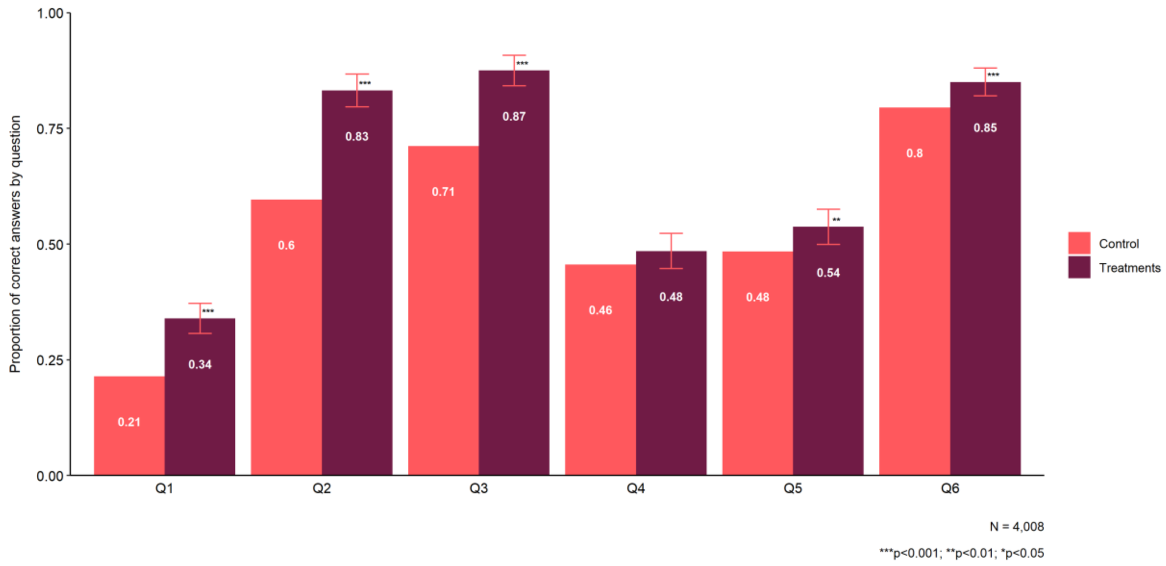
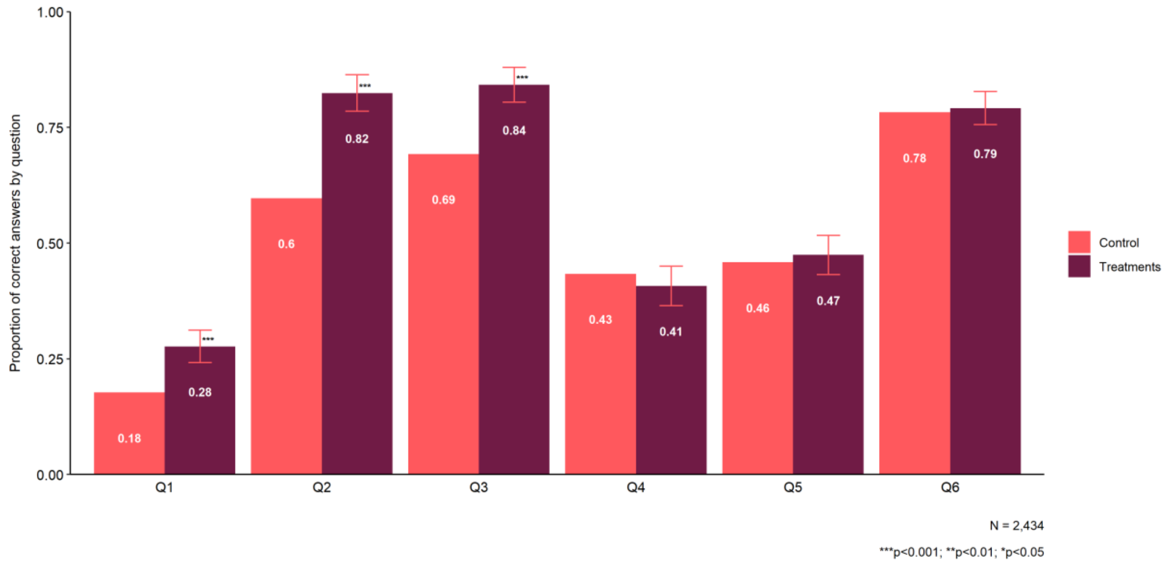


Figure 10: Comprehension by question – subgroup analysis



6 Discussion

Decision points allow people to pause, read, and reflect

The results from our online experiment suggest that information decision points are an effective tool that improves retail investors' understanding of key investment risks and can change their behaviours. They encourage investors to pause, read, and reflect before making decisions on purchasing high-risk investment products. Overall, we found that the salient and simple information disclosure was the most effective element of our interventions. Positive frictions did not improve comprehension, risk perceptions, or recommendation intentions any further – we discuss this further in the next section.

Disclosure interventions are not always effective – they might be based on incorrect interpretations of the behavioural drivers of people's actions, be too complex and confusing, lack comparability, or be ignored due to people's limited attention (see Loewenstein, Sunstein, and Golman, 2014). Importantly, the information we provided as a decision point is simple and salient. We built on existing work by ensuring our salient and simple information is both *easy* – short and focusing on the important takeaways in a simple and plain language – and *attractive* – using icons that made it more salient (BIT, 2014 and 2019). Our experiment confirms that simple and salient FAQ-style information with icons as eyecatchers significantly improves understanding of key risks of high-risk investment products.

What have we learnt about positive frictions?

While interventions that feature salient and simple FAQ-style information improve risk comprehension in our experiment, positive frictions do not seem to further aid understanding. Even in the *Personalisation* intervention, which included a pop-up with a personalised risk warning requiring an additional click to continue, the additional effect is mostly driven by the fact that additional information was more salient and accessible on the pop-up, not the positive frictions themselves. We hypothesise that positive frictions were relatively ineffective – over and above providing salient and simple information – because they might be more suited to changing behaviours rather than improving understanding and because they might be difficult to test in online lab experiments.

Previous studies that successfully employed positive frictions to change consumer behaviours (see Soman, Cheema, and Chan, 2012; Soman, Xu, and Cheema, 2010) differed from our study in two important ways. Firstly, they investigated the impact of positive frictions on behaviours and actions, rather than comprehension. It is likely that decision points that provide information – such as our salient and simple FAQ-style summaries – encourage reflection about the key risks more explicitly, while decision points that merely interrupt – such as positive frictions – might alter behaviours through multiple channels, not just reflection and comprehension. This could explain why positive frictions are relatively less effective at improving understanding than at driving behaviour change. In fact, the experiment reported in Gilchrist et al. (2022) shows that positive frictions can lead to behaviour changes in the high-risk investment space. Checkboxes and manual input fields to provide evidence of sufficient wealth or experience significantly reduced the proportion of participants who self-certified as eligible to invest in high-risk investment products.

Secondly, the studies by Soman, Cheema, and Chan (2012) and Soman, Xu, and Cheema (2010) tested positive frictions in the field where consumers make real decisions, rather than in an inconsequential and hypothetical online environment. Online experiments are valuable policy tools (Nieboer, 2020), but they might be less suited to tests of positive frictions because their nature is to interrupt thought processes that might only occur in real life. One piece of evidence from our experiment that illustrates the difficulty of testing frictions online is the significantly higher attrition in the treatments that featured strong positive frictions – similar to the attrition in Gilchrist et al. (2022). In other words, more participants dropped out when they had to type statements in the manual text-entry boxes. A possible explanation for this attrition is that participants who faced the friction did not want to or were not able to continue their investment journey, so the positive friction might have succeeded in changing their behaviour. However, we cannot say for certain whether these participants would also stop their investment journey if their own money was at stake. Field trials, i.e. testing these positive frictions with real firms and consumers, could shed more light on when positive frictions are effective.

Interestingly, we also observed that the checkboxes added in the *Active Click* treatment had directionally somewhat weaker effects – and they even had a significantly smaller effect on the likelihood of accessing additional risk information. We hypothesise people have developed a habit of mindlessly ticking checkboxes when present rather than reading or clicking any additional information (Wood and Rünger, 2016), or a form of clicking fatigue. As a result, we expect some individuals to tick a checkbox as soon as they see it – knowing they need to take this action to proceed – and ignore any other relevant information on the screen. Even though checkboxes did not undermine the principal goal of the interventions, this undesirable side-effect should caution their use.

The positive frictions tested in this experiment did not have a negative impact on consumers' comprehension of risks – they merely did not improve comprehension over and above providing simple and salient information. The literature (e.g., Soman, Xu, and Cheema, 2010; Hayes, Lee, and Thakrar, 2018) – suggest that frictions can serve as effective decision points that encourage reflection and lead to better decisions, so they should not be disregarded based on their limited impact on risk comprehension in our online experiment. Further research is needed to continue to test positive frictions as decision points and policy tools, where possible in field settings and targeting behavioural outcomes rather than comprehension.

Annex 1: Comprehension questions

Table 3: Risk comprehension questions

Question	**Answer options** (correct answer underlined)
What are the key risks associated with investing in start-ups like IGNITE?	A. <u>Loss of capital and illiquidity</u> B. Loss of capital and volatility of share prices C. Loss of capital, illiquidity, and volatility of share prices D. Investing in start-ups is relatively low risk
What will happen to your investment if IGNITE fails?	A. I might be able to apply for compensation from the Financial Services Compensation Scheme (FSCS) if the platform through which I invested is regulated by the Financial Conduct Authority B. IGNITE will return my investment as part of the liquidation process C. <u>I am unlikely to get my money back</u> D. I will be able to sell my shares and minimise my losses
Which of these best describes the risk associated with investing in start-ups like IGNITE?	A. You are unlikely to lose any money you invested B. You may lose some of the money you invested C. <u>You may lose all of the money you invested</u> D. You may lose all of the money you invested, and then still owe more on top of that
How can you make a return on your investment?	A. I will receive dividends periodically B. I will be able to trade my shares with other investors C. <u>I will be able to sell my shares if IGNITE is bought by another company or floats on a stock exchange</u> D. I will be able to sell my shares back to IGNITE founders
What will happen to the level of your shareholding if IGNITE issues more shares after you invested?	A. <u>The percentage of the business that I own will decline</u> B. The percentage of the business that I own will increase C. The percentage of the business that I own will not change D. IGNITE cannot issue new shares unless it floats on a stock exchange
Which of these is the best method to use when investing in start-ups?	A. Invest a large proportion of your investable capital into multiple start-ups to spread your risk B. Invest a large proportion of you investable capital into a single start-up to maximise potential gains C. Only invest if you are new to investing, there are more stable and profitable investments out there for experiences investors D. <u>Invest a relatively small portion of your investable capital in start-ups, the majority of your investable capital should be invested in safer, more liquid assets</u>

Annex 2: Sample description and attrition

Table 4: Sample description

	Control	Summary Info	Active Click	Active Input	Personalisation
Observations	820	812	803	752	821
Average age	32.443	32.337	32.523	32.592	32.855
Female (%)	50.122	48.153	50.560	51.197	50.061
Region					
South East England (%)	14.390	15.517	14.072	14.761	15.104
Greater London (%)	14.390	14.655	15.691	12.101	14.982
Northern Ireland (%)	2.073	2.586	1.743	2.128	2.314
Income					
Less than £12,000 (%)	25.366	21.675	22.167	21.676	23.264
£24,000 - £36,000 (%)	23.902	25.246	23.412	24.069	23.995
Greater than £72,000 (%)	2.073	1.724	2.740	3.457	2.801
Average savings (£)*	7,957.353	6,800.252	7,403.368	7,758.724	8,672.404
Average discretionary income (£)*	512.158	475.482	535.296	527.545	549.451
Non-investor (%)	48.049	50	50.809	47.606	51.279
Invested in start-ups (%)	3.415	4.433	4.234	5.053	4.750

* The displayed values represent the trimmed means (excluding the top and bottom 1% outliers).

Table 5: Attrition

	Completion Dummy			
	By Treatment	By Mobile Usage	By number of errors	
Treatment – Ref: Control				
Summary Info	-0.015 (0.012)			
Active Click	-0.012 (0.012)			
Active Input	-0.062*** (0.014)			
Personalisation	-0.040** (0.013)			
Mobile usage		-0.033*** (0.009)		
Errors investment screen			-0.031*** (0.008)	
Errors details screen				-0.105** (0.040)
Observations	4,403	4,465	4,403	4,210
Log Likelihood	-1,316.402	-1,468.003	-1,322.398	-808.079
Akaike Inf. Crit.	2,642.804	2,940.006	2,648.796	1,620.159

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed for logistic regressions as there are no AMEs associated with them.

Annex 3: Sensitivity check descriptions

To rule out that the higher attrition in the *Active Input* and *Personalisation* treatments drives the results from our primary analysis, we conduct three additional sensitivity checks, following the best- and worst-case scenario methodology. We add the dropouts back into the dataset and test how the results change assuming different patterns of attrition. The results remain virtually unchanged when assuming that drop-outs would have answered all questions correctly. When assuming drop-outs would have answered all comprehension questions incorrectly, the effect sizes are strongly reduced. The effects remain statistically significant, however, the difference between the *Active Input* and *Personalisation* treatment becomes insignificant ($p = 0.159$). Finally, if we assume that drop-outs would have answered 4 question correctly – the median number of correct responses across all treatments – the effects are almost identical to the results reported here and the *Personalisation* treatment significantly outperforms all other treatments.

Annex 4: Mediation analysis

As described in the results section, we conduct a mediation analysis to investigate whether exposure to additional information after clicking on the risk warning mediates the main effects of our interventions on risk comprehension. The model in column 2 of Table 10 in Annex 5 reveals that information exposure through a click on risk warnings increases the likelihood of answering any comprehension question correctly by 11.7pp. At the same time the effects of the different decision points are much smaller than in the model in column 1, taken from the primary analysis. Once clicks on the risk warnings are included as a covariate, the effect of the *Personalisation* condition decreases from 13.9pp to 8.4pp, while the effect of the *Summary Info* condition decreases from 8.4pp to 4.3pp. The model in column 3 establishes that treatment assignment significantly impacts the likelihood of clicking through the risk warning.

These results and the causal mediation analysis visualised in Figures 11 and 12 show that risk warning exposure significantly mediates the main effects. 48.2% of the effect between the control group and the *Summary Info* condition is mediated with a mediation effect of 4pp. The main effect remains significant, which means that both adding the decision point and exposure to additional information improve key risk comprehension. Interestingly, also the effect between the *Active Input* and *Personalisation* conditions was 58.1% mediated by clicks on the additional information, with a mediation effect of 1.6pp. Here the main effect becomes insignificant, suggesting that the Personalisation intervention outperformed all other treatments almost entirely because it made the additional information more salient and accessible.

Figure 11: Mediation analysis between *Control* and *Summary Info* conditions

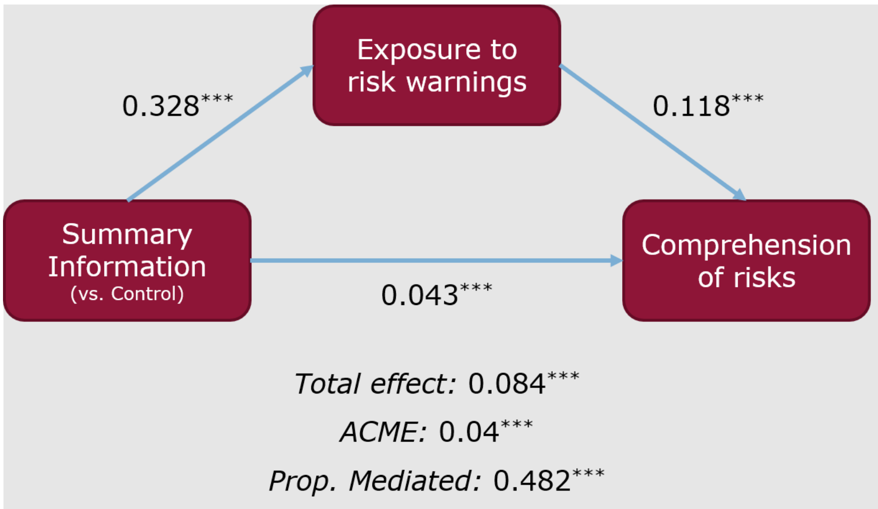
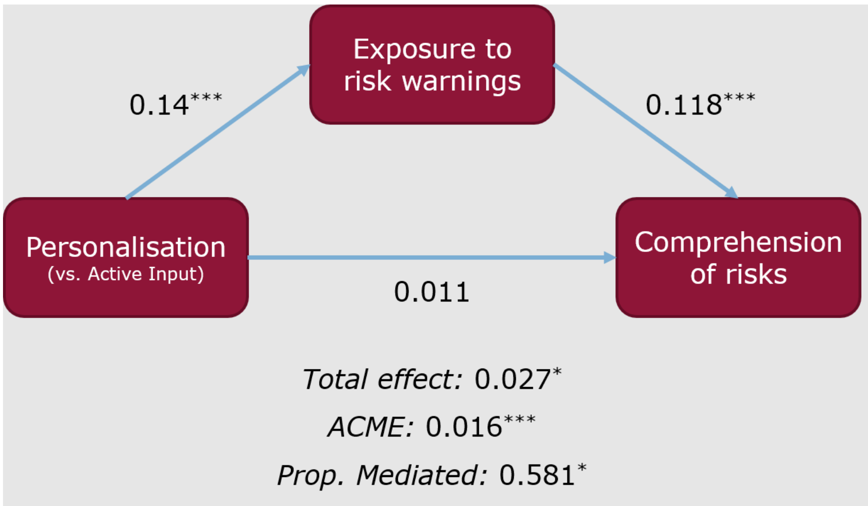


Figure 12: Mediation analysis between *Active Input* and *Personalisation* conditions



Annex 5: Regression tables

Table 6: Key risk comprehension

	Comprehension: Average likelihood of answering a question correctly	
	(1)	(2)
Treatment – Ref: Control		
Summary Info	0.083*** (0.010)	0.084*** (0.010)
Active Click	0.103*** (0.010)	0.103*** (0.010)
Active Input	0.113*** (0.010)	0.113*** (0.010)
Personalisation	0.141*** (0.010)	0.139*** (0.010)
Age		0.001*** (0.0003)
Gender – Ref: Female		
Male		0.035*** (0.006)
Non-binary		0.071 (0.037)
Prefer not to say		0.120** (0.041)
Savings above median (£2,000)		0.044*** (0.007)
Discretionary income above median (£400)		-0.002 (0.007)
Non-investor		-0.003 (0.007)
Region	No	Yes
Income	No	Yes
Observations	4,008	4,008
Log Likelihood	-6,608.911	-6,510.864
Akaike Inf. Crit.	13,227.820	13,083.730

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 7: Risk perceptions

	Risk perception	
	Logistic: Risk score equal or greater than 8	
	(1)	(2)
Treatment – Ref: Control		
Summary Info	0.171*** (0.024)	0.169*** (0.023)
Active Click	0.111*** (0.024)	0.111*** (0.024)
Active Input	0.160*** (0.024)	0.156*** (0.024)
Personalisation	0.181*** (0.024)	0.175*** (0.023)
Age		0.003*** (0.001)
Gender – Ref: Female		
Male		0.039* (0.015)
Non-binary		0.084 (0.085)
Prefer not to say		0.047 (0.104)
Savings above median (£2,000)		0.096*** (0.016)
Discretionary income above median (£400)		0.037* (0.017)
Non-investor		-0.004 (0.016)
Region	No	Yes
Income	No	Yes
Observations	4,008	4,008
Log Likelihood	-2,574.915	-2,498.232
Akaike Inf. Crit.	5,159.830	5,058.465

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 8: Recommendations to a friend

	Recommend to a friend			
	Logistic: Binary indicator of recommendation		OLS: Amount recommended	
	(1)	(2)	(3)	(4)
Treatment – Ref: Control				
Summary Info	-0.051** (0.018)	-0.050** (0.018)	-294.383* (117.751)	-295.586* (117.660)
Active Click	-0.038* (0.018)	-0.036* (0.017)	-315.483** (112.453)	-319.616** (112.073)
Active Input	-0.064*** (0.019)	-0.063*** (0.018)	-457.888*** (109.476)	-456.710*** (108.536)
Personalisation	-0.089*** (0.019)	-0.084*** (0.018)	-597.132*** (107.554)	-583.824*** (107.189)
Age		-0.004*** (0.001)		-11.718*** (3.327)
Gender – Ref: Female				
Male		-0.045*** (0.012)		-2.406 (72.833)
Non-binary		-0.106 (0.093)		-362.172 (421.150)
Prefer not to say		-0.214 (0.113)		767.967 (846.736)
Savings above median (£2,000)		-0.065*** (0.013)		-474.450*** (74.499)
Discretionary income above median (£400)		-0.015 (0.014)		-135.988 (83.543)
Non-investor		0.008 (0.013)		-127.210 (77.476)
Constant			2,245.122*** (79.839)	2,998.556*** (193.847)
Region	No	Yes	No	Yes
Income	No	Yes	No	Yes
Observations	4,008	4,008	4,008	4,008
R^2			0.008	0.033
Adjusted R^2			0.007	0.026
Log Likelihood	-1,874.915	-1,781.024		
Akaike Inf. Crit.	3,759.830	3,624.047		
Residual Std. Error			2,230.630 (df = 4003)	2,209.416 (df = 3977)
F Statistic			8.108*** (df = 4; 4003)	4.543*** (df = 30; 3977)

Note: * p<0.05; ** p<0.01; *** p<0.001;
OLS: Robust standard errors in parentheses
Logistic: Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Logistic: Constants are not displayed as there are no AMEs associated with them.

Table 9: Click through risk warning

	Engagement	
	Likelihood of clicking through to the full risk warning	
	(1)	(2)
Treatment – Ref: Control		
Summary Info	0.332*** (0.021)	0.328*** (0.021)
Active Click	0.248*** (0.020)	0.249*** (0.020)
Active Input	0.323*** (0.021)	0.324*** (0.021)
Personalisation	0.466*** (0.021)	0.464*** (0.021)
Age		-0.0001 (0.001)
Gender – Ref: Female		
Male		0.031* (0.015)
Non-binary		0.327*** (0.087)
Prefer not to say		0.228* (0.106)
Savings above median (£2,000)		0.051** (0.016)
Discretionary income above median (£400)		-0.047** (0.017)
Non-investor		0.025 (0.016)
Region	No	Yes
Income	No	Yes
Observations	4,008	4,008
Log Likelihood	-2,460.395	-2,435.196
Akaike Inf. Crit.	4,930.789	4,932.392

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 10: Mediation analysis

	Mediation analysis - Modelling outcome and mediator		
	Average likelihood of answering a question correctly		Likelihood of clicking through to the full risk warning
	(1)	(2)	(3)
Treatment – Ref: Control			
Summary Info	0.084*** (0.010)	0.043*** (0.010)	0.328*** (0.021)
Active Click	0.103*** (0.010)	0.072*** (0.010)	0.249*** (0.020)
Active Input	0.113*** (0.010)	0.073*** (0.010)	0.324*** (0.021)
Personalisation	0.139*** (0.010)	0.084*** (0.010)	0.464*** (0.021)
Age	0.001*** (0.0003)	0.001*** (0.0003)	-0.0001 (0.001)
Gender – Ref: Female			
Male	0.035*** (0.006)	0.032*** (0.006)	0.031* (0.015)
Non-binary	0.071 (0.037)	0.034 (0.039)	0.327*** (0.087)
Prefer not to say	0.120** (0.041)	0.096* (0.043)	0.228* (0.106)
Savings above median (£2,000)	0.044*** (0.007)	0.038*** (0.007)	0.051** (0.016)
Discretionary income above median (£400)	-0.002 (0.007)	0.004 (0.007)	-0.047** (0.017)
Non-investor	-0.003 (0.007)	-0.006 (0.007)	0.025 (0.016)
Risk warning exposure		0.118*** (0.007)	
Region	Yes	Yes	Yes
Income	Yes	Yes	Yes
Observations	4,008	4,008	4,008
Log Likelihood	-6,510.864	-6,356.725	-2,435.196
Akaike Inf. Crit.	13,083.730	12,777.450	4,932.392

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 11: Comprehension by question

	Comprehension questions					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatments	0.125***	0.236***	0.163***	0.029	0.053**	0.055***
	(0.017)	(0.018)	(0.017)	(0.019)	(0.019)	(0.015)
Age	0.003***	0.004***	0.002**	-0.0004	0.0005	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender – Ref: Female						
Male	0.027	0.023	0.029*	0.016	0.097***	0.017
	(0.015)	(0.013)	(0.012)	(0.016)	(0.016)	(0.012)
Non-binary	0.021	0.023	0.004	0.110	0.163	0.096
	(0.093)	(0.073)	(0.068)	(0.097)	(0.093)	(0.052)
Prefer not to say	0.040	0.085	0.077	0.244*	0.194	0.115*
	(0.112)	(0.078)	(0.066)	(0.102)	(0.107)	(0.055)
Savings above median (£2,000)	-0.002	0.029*	0.062***	0.050**	0.055***	0.071***
	(0.016)	(0.013)	(0.012)	(0.017)	(0.017)	(0.013)
Discretionary income above median (£400)	-0.003	-0.022	-0.012	0.044*	-0.005	-0.010
	(0.017)	(0.014)	(0.013)	(0.018)	(0.018)	(0.013)
Non-investor	0.041**	0.012	-0.008	-0.035*	-0.045**	0.019
	(0.016)	(0.013)	(0.012)	(0.017)	(0.017)	(0.012)
Region	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Control group average	0.21	0.6	0.71	0.46	0.48	0.8
Observations	4,008	4,008	4,008	4,008	4,008	4,008
Log Likelihood	-2,445.537	-1,936.614	-1,647.685	-2,741.305	-2,698.592	-1,735.707
Akaike Inf. Crit.	4,947.074	3,929.228	3,351.370	5,538.611	5,453.184	3,527.413

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 12: Comprehension by question – treatments not pooled

	Comprehension questions					
	(1)	(2)	(3)	(4)	(5)	(6)
Summary Info	0.128***	0.145***	0.115***	0.019	0.050*	0.042*
	(0.022)	(0.023)	(0.021)	(0.025)	(0.025)	(0.019)
Active Click	0.148***	0.233***	0.169***	0.003	0.024	0.040*
	(0.022)	(0.022)	(0.019)	(0.025)	(0.025)	(0.019)
Active Input	0.083***	0.287***	0.183***	0.015	0.052*	0.057**
	(0.022)	(0.021)	(0.019)	(0.025)	(0.025)	(0.019)
Personalisation	0.147***	0.286***	0.178***	0.079**	0.079**	0.078***
	(0.022)	(0.021)	(0.019)	(0.025)	(0.025)	(0.018)
Control group average	0.21	0.6	0.71	0.46	0.48	0.8
Observations	4,008	4,008	4,008	4,008	4,008	4,008
Log Likelihood	-2,469.286	-1,953.699	-1,693.881	-2,768.081	-2,767.265	-1,761.822
Akaike Inf. Crit.	4,948.571	3,917.397	3,397.762	5,546.163	5,544.531	3,533.644

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Table 13: Comprehension by question – subgroup analysis

	Comprehension questions					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatments	0.099***	0.227***	0.150***	-0.026	0.016	0.009
	(0.018)	(0.020)	(0.019)	(0.022)	(0.022)	(0.018)
Age	0.003**	0.005***	0.002*	-0.001	0.0001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender – Ref: Female						
Male	-0.002	0.031	0.027	0.020	0.111***	0.033
	(0.018)	(0.017)	(0.017)	(0.021)	(0.021)	(0.017)
Non-binary	0.108	0.056	-0.002	0.008	0.177	0.091
	(0.191)	(0.134)	(0.140)	(0.184)	(0.186)	(0.129)
Prefer not to say	-0.077	0.010	0.220***	-0.124	-0.118	0.061
	(0.154)	(0.156)	(0.012)	(0.170)	(0.177)	(0.152)
Savings above median (£2,000)	-0.024	0.044*	0.065***	0.055**	0.025	0.094***
	(0.019)	(0.018)	(0.017)	(0.021)	(0.022)	(0.018)
Discretionary income above median (£400)	0.008	-0.025	-0.017	0.031	0.011	-0.007
	(0.020)	(0.019)	(0.018)	(0.023)	(0.023)	(0.019)
Non-investor	0.014	0.017	-0.008	-0.040	-0.064**	0.030
	(0.019)	(0.018)	(0.017)	(0.021)	(0.021)	(0.018)
Region	Yes	Yes	Yes	Yes	Yes	Yes
Income	Yes	Yes	Yes	Yes	Yes	Yes
Control group average	0.18	0.6	0.69	0.43	0.46	0.78
Observations	2,434	2,434	2,434	2,434	2,434	2,434
Log Likelihood	-1,331.211	-1,244.483	-1,163.204	-1,627.949	-1,630.570	-1,237.491
Akaike Inf. Crit.	2,718.421	2,544.967	2,382.407	3,311.898	3,317.141	2,530.982

Note: * p<0.05; ** p<0.01; *** p<0.001;
Log odds were transformed into average marginal effects (AMEs) for ease of interpretation.
Constants are not displayed as there are no AMEs associated with them.

Annex 6: Bibliography

Behavioural Insights Team (2014). *EAST. Four simple ways to apply behavioural insights*, available online at: https://www.bi.team/wp-content/uploads/2015/07/BIT-Publication-EAST_FA_WEB.pdf

Behavioural Insights Team (2017). *Improving engagement with pension decisions: The results from three randomised controlled trials*, available online at: https://www.bi.team/wp-content/uploads/2017/10/Pension-wise-trials.pdf

Behavioural Insights Team (2019). *Best practice guide. Improving consumer understanding of contractual terms and privacy policies: evidence-based actions for businesses*, available online at: https://www.bi.team/wp-content/uploads/2019/07/Final-TCs-Best-Practice-Guide-July-2019-compressed.pdf

Berger, Jonah (2014). Word of mouth and interpersonal communication: A review and directions for future research. *Journal of Consumer Psychology* 24 (4), pp. 586-607.

Bhargava, Saurabh, and George Loewenstein (2015). Behavioral Economics and Public Policy 102: Beyond Nudging. *American Economic Review* 105(5), pp. 396-401.

BritainThinks (2021). Understanding self-directed investors: A summary report of research conducted for The Financial Conduct Authority. Available online at: https://www.fca.org.uk/publication/research/understanding-self-directed-investors.pdf

Cox, Anna L., et al. (2016). Design Frictions for Mindful Interactions: The Case for Microboundaries. *Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems*, pp. 1389-1397.

Délias, Dunvel, Flo Farghly, Lucy Hayes, Cherryl Ng, and Max Spohn (2022). Going beyond “capital at risk”: behaviourally informed risk warnings for high-risk investment products. *FCA Research Note*. Available online at: https://www.fca.org.uk/publication/research/behaviourally-informed-risk-warnings.pdf

Financial Conduct Authority (2021). DP 21/1: Strengthening our financial promotion rules for high-risk investments and firms approving financial promotions. *Discussion Paper.* Available online at: https://www.fca.org.uk/publication/discussion/dp21-1.pdf

Financial Conduct Authority (2022). CP 22/2: Strengthening our financial promotion rules for high-risk investments (including cryptoassets). *Consultation Paper.* Available online at: https://www.fca.org.uk/publication/consultation/cp22-2.pdf

Gilchrist, Cameron, Lucy Hayes, Cherryl Ng, Patrick Sholl, and Max Spohn (2022). To certify or not to certify: decision points in the certification process. *FCA Research Note*. Available online at: https://www.fca.org.uk/publication/research/decision-points-self-certification.pdf

Hayes, Lucy, William Lee, and Anish Thakrar (2018). Now you see it: drawing attention to charges in the asset management industry. *FCA Occasional Paper* 32. Available online at: https://www.fca.org.uk/publication/occasional-papers/occasional-paper-32.pdf

Haynes, Laura C. et al. (2013). Collection of Delinquent Fines: An Adaptive Randomized Trial to Assess the Effectiveness of Alternative Text Messages. *Journal of Policy Analysis and Management* 32 (4), pp. 718-730.

Kelly, Makena (2020). *Twitter would like you to actually read stories before you retweet them*. The Verge. Available online at: https://www.theverge.com/21286855/twitter-articles-prompt-unread-feature-conversations

Loewenstein, George, Cass R. Sunstein, and Russell Golman (2014). Disclosure: Psychology Changes Everything. *Annual Review of Economics* 6 (1), pp. 391-419.

Madrian, Brigitte C. (2014). Applying insights from behavioral economics to policy design. *Annual Review of Economics* 6 (1), pp. 663-688.

Nieboer, Jeroen (2020). Using online experiments for behaviourally informed consumer policy. *FCA Occasional Paper 51*. Available online at: https://www.fca.org.uk/publication/occasional-papers/occasional-paper-51.pdf

Shahab, Sina, and Leonhard K. Lades (2021). Sludge and transaction costs. *Behavioral Public Policy*, pp. 1-21.

Soman, Dilip, Jing Xu, and Amar Cheema (2010). Decision Points: A Theory Emerges. *Rotman Magazine,* Winter 2010, pp. 64-68.

Soman, Dilip, Amar Cheema, and Eugene Y. Chan (2012). Understanding consumer psychology to avoid abuse of credit cards. In: *Transformative consumer research for personal and collective well-being*. Abingdon: Routledge. Chapter 20.

Soman, Dilip (2020). Sludge: A Very Short Introduction. *BEAR.* Available online at: https://www.rotman.utoronto.ca/-/media/Files/Programs-and-Areas/BEAR/White-Papers/BEARx BIOrg-Sludge-Introduction.pdf?la=en&hash=DCB98795CB485977A04DDB27EFD800C3DA 40220E

Sunstein, Cass R., and Julien L. Gosset (2020). Optimal Sludge? The Price of Program Integrity. *Duke Law Journal Online* 70, pp. 74-90.

Tingley, Dustin, et al. (2013). *Mediation: R Package for Causal Mediation Analysis.* Available online at: https://cran.r-project.org/web/packages/mediation/vignettes/mediation.pdf

White, Ian R. and John B. Carlin (2010). Bias and efficiency of multiple imputation compared with complete-case analysis for missing covariate values. *Statistics in Medicine* 29 (28), pp. 2920-2931.

Wolfe, Jeremy M., and Todd S. Horowitz (2017). Five factors that guide attention in visual search. *Nature Human Behaviour* 1, Article 0058.

Wood, Wendy, and Dennis Rünger (2016). Psychology of Habit. *Annual Review of Psychology* 67, pp. 289-314.

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