

# Debiasing investors with decision support systems: An experimental investigation

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## ABSTRACT

This research presents evidence that decision support systems can play an important role in debiasing behaviorally-challenged investors. An empirical study involving 119 participants provides strong evidence for the existence of cognitive biases in investment decision making and demonstrates the effectiveness of decision aids in lowering the negative impact of such biases on the ability of investors to make sound investment decisions. Additionally, such decision aids are shown to be more valuable in decision environments where the bias level is likely to be higher.

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## 1. Introduction

Due to recent innovations in the financial industry, the advent of the web and the proliferation of inexpensive personal computers, individuals are getting unparalleled opportunities for investment [6]. However, they face two critical problems: (i) a difficulty in finding the right investment instruments due to the enormous complexity of financial markets; and (ii) an increasing vulnerability to a vast amount of potentially biased and unsubstantiated information from the web. Individuals often make sub-optimal investment decisions due to these problems [5,6]. Statman [64] observes that today's investors are not faring any better than their predecessors a century ago in terms of the quality of decisions they make despite the increase in available information. He concedes that investor psychology, as a driving force in financial markets has not changed in the last 100 years despite technological and financial innovations.

The finding that financial markets are driven by human psychology is not new. The *Tulipmania*, which started with the speculative trading of tulip bulbs and ended with the spectacular market crash in Holland and England, occurred in the late 1630s. MacKay [53] presented a timeline of several panics and crashes in his book *Extraordinary Popular Delusions and the Madness of Crowds* first published in 1841. Slovic [62] discussed the implications of human psychology for investment decision making and Wright [76] outlined various information-processing biases from the perspective of financial decision making. More recently, the interest in psychology for understanding financial markets has resurfaced with the emergence

of a new field called *Behavioral Finance*. Behavioral finance through empirical studies demonstrates that individuals sometimes do not make rational choices and that these choices can have significant and persistent impact on financial markets.

The fact that psychological support is becoming increasingly critical to investors underscores the importance and urgency of incorporating such aid into investment decision support systems (DSS). DSS are defined as “computerized aids designed to enhance the outcomes of an individual's decision-making activities” [61]. In effect, DSS merge an individual's intellect with the capabilities of the computer to improve the quality of decisions [43]. The purpose of this study is to conduct an exploratory test of the efficacy of debiasing in the financial realm using a decision support system. In an experimental setting that relied on carefully designed investment scenarios and decision aids simulating a real-world investment context, participants were exposed to a number of investment scenarios, their initial investment decisions were observed, and then decision aids were provided in an effort to improve their decision making. We found that decision aids such as feedback and graphs could significantly mitigate the impact of cognitive biases and that the benefit of DSS appeared to be more pronounced the greater the initial bias. This study demonstrates the need and usefulness of a decision support system in lowering the impact of investors' psychological biases and as such, it attempts to bridge the existing gap between DSS and the psychology of investment decision making. To the best of our knowledge, no prior research has empirically validated the benefit of decision aids within an investment context involving cognitive biases.

In the following sections, we provide appropriate background by discussing major biases influencing investment decision making; the research framework and hypotheses to be tested; and the experimental design. We then present our findings, discussion and conclusions.

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## 2. Major cognitive biases influencing investment decision making

Biases are considered deviations from rational decision making versus the ideal where a decision-maker correctly assesses her current assets and all the consequences of making a choice [39]. Based on our literature review of investment psychology, we came to the conclusion that the majority of flawed investment decisions could be attributed to the three cognitive biases of: the framing and diversification heuristic leading to inconsistent asset allocation; the representativeness heuristic leading to trend following and insufficient diversification; and ambiguity aversion leading to inappropriate default choice. Thus, this study will focus on these three cognitive biases which we discuss below in more detail.

### 2.1. Framing and diversification heuristic leading to inconsistent asset allocation

Tversky and Kahneman [69] define a decision frame as “the decision-maker’s conception of the acts, outcomes, and contingencies associated with a particular choice.” A framing bias is said to occur when the manipulation of such a decision frame changes the decision-maker’s perspective about the problem. The impact of framing in investment decision making can be demonstrated by observing how individuals’ investment decisions change with the investment choices provided to them.

An investment menu, which refers to the number and types of assets (such as managed funds in a 401(k)) made available for investment, is an “opaque” frame which many investors cannot see through, and thereby do not understand the underlying risk characteristic of their investments [54]. Such a framing effect may lead to inconsistent asset allocation. This is unfortunate because it is often observed that the asset allocation decision is the most important one for an investor’s portfolio performance (e.g. [13]). Yet there is abundant evidence that many investors do not really understand the nature of the decision [7].

When individuals are unsure they tend to rely on heuristics or rules-of-thumb that allow them to make what to them seems a reasonable choice. Read and Loewenstein [56] have documented a “diversification heuristic” (or  $1/n$  heuristic), whereby people spread their allocation equally among all available options. Benartzi and Thaler [7] have provided evidence that this heuristic also appears to come into play for decisions as important as asset allocation. In a survey of the University of California employees, when, in the first treatment, they were told to allocate their money among five funds, of which four were fixed income and one equity, they did so in a manner suggesting a 43% equity share. While there is nothing wrong with this, in a second treatment employees were told to allocate their money among five other funds, of which, this time, four out of five were equity. In this case the asset allocation suggested a much higher 68% equity share. In fact, what was happening was that many respondents were putting exactly  $1/n$ th of their money into each of the  $n$  fund choices, hence the term  $1/n$  heuristic. The problem clearly was that the frame led people in the wrong direction.

### 2.2. Representativeness heuristic leading to trend following and insufficient diversification

Representativeness refers to an individual’s tendency to classify objects into different categories by observing only their representative or salient characteristics. The bias occurs because people judge probability in such cases “by the degree to which A is representative of B, that is, by the degree to which A resembles B” [70]. The representativeness bias motivates people to ignore sample size and mean reversion, and become overconfident about the significance of the information received [36]. For example, if a stock in the software industry is doing well, people may erroneously

believe that all stocks in that industry are also doing well (sample size neglect), and, if the price of a stock has been rising for some time, people may believe it will continue to trend upwards (neglect of mean reversion).

Indeed mean reversion in markets is a powerful and often underestimated force. De Bondt and Thaler [24] compared the performance of two groups of companies: winners (companies with higher than average returns over the last five years) and losers (companies with lower than average returns over the last five years). They found that looking forward the winners became losers and the losers became winners, thus stressing the existence of mean reversion in stock markets. Despite such evidence, past performance retains its allure. For example, De Bondt [23] finds in a survey of a group of investors from the *American Association of Individual Investors* that more people become bullish if the market has recently turned up. One manifestation of representativeness is the tendency for fund flows to be heavily weighted towards top performers [21]. The result of representativeness bias is trend following and insufficient diversification.

The reader might wonder if trend following is an unadulterated evil. It turns out not to be quite so simple. There is, in fact, evidence that risk-adjusted returns are positively serially correlated for 6–12 month return intervals (e.g. [57]). Nevertheless, as De Bondt and Thaler [24] showed, for periods of around five years the evidence favors reversals or negative serial correlation. Still, a case can be made for *slightly* leaning towards recent good performers if performance is viewed over the short term. Nevertheless, if applied naively, such an approach can lead to poor results, because one by-product of trend following can be insufficient diversification. If one, for example, only buys hot stocks, the result will probably be a poorly diversified portfolio.

### 2.3. Ambiguity aversion leading to inappropriate default choice

When individuals receive conflicting, incomplete, uncertain or excessive information, they experience ambiguity and make contradictory decisions [29]. The role of information overload causing ambiguity in investment decision making has been well documented. Studies from defined contribution pension plan demonstrate that participants tend to make their choices based on the “path of least resistance” [17]. When the complexity of decision making increases, people tend to expend less effort to actually make their decision, and select default options if available [18]. For example, over 80% of new plan participants in the Swedish national pension plan have decided to invest in the default option [72]. Iyengar et al. [41] observe that increasing the number of fund choices for retirement investment decreases plan participation because people become mentally paralyzed when offered excessive choices. Further, Agnew and Szykman [1] find that pension plan participants often choose the default option due to information overload.

## 3. Research model and hypotheses

Despite the growing recognition of the role of psychology in investment decision making, the emphasis of current DSS in the financial realm is still on providing quantitative support (e.g. computation of fundamentals, risks and trends), and not debiasing. For example, in a recent paper, Weber [73] defines financial DSS as a tool that “formalizes domain knowledge about financial management and portfolio selection problems so that it is amenable to modeling and analytic reasoning”. This definition limits prospective support in investment DSS to only quantitative support such as modeling and analytic capability and not qualitative support such as debiasing. In another paper that deals with the development of DSS for stock evaluation, Samaras et al. [58] propose a multi-criteria based fundamental analysis technique while not considering the need for qualitative and psychological support for investors.

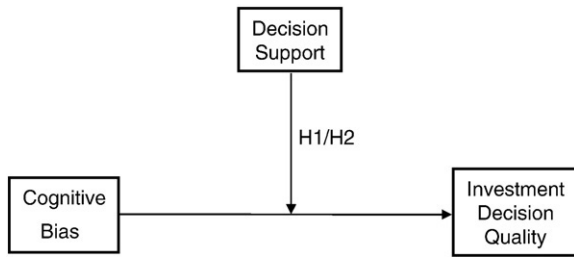


Fig. 1. Research model.

The lack of qualitative support such as debiasing in current DSS is critical because potential vulnerability to psychological biases is increasing due to the abundance and nature of information from the web [5]. Furthermore, Lusardi and Mitchell [52] find that Baby Boomers who are on the verge of retirement are likely to find financial insecurity in old age due to insufficient saving and planning. In this context, the need and usefulness of a DSS that can assist individuals in their retirement financial planning by guarding them against potential investment-related biases cannot be overemphasized.

The theoretical underpinning of our empirical work is based on the concept of debiasing, which refers to a procedure for reducing or eliminating biases of a decision-maker [3]. Biases are considered deviations from rational decision making vs. the ideal where a decision-maker correctly assesses her current assets and all the consequences of making a choice [39]. While there is still a debate regarding the underlying causes and nature of decision biases (e.g. [20]), decision theorists and psychologists have, nevertheless, made several attempts to identify and classify them. For example, Kahneman and Tversky [42] make a distinction between situations where decision makers lack competence (comprehension errors) and those where they are competent yet fail to make the right decisions (application errors). Fischhoff [33] focuses on the various sources of bias, which he identified as faulty decision makers, faulty tasks and mismatches between decision makers and tasks.

Researchers have proposed several debiasing strategies to improve the quality of decision making. Keren [44] suggested a general debiasing framework comprising the following three stages: (i) identification of the existence and nature of the potential bias; (ii) consideration of ways and techniques to lower the impact of the bias; and (iii) evaluation of the effectiveness of the selected technique. On the other hand, Fischhoff [33] recommended four levels of debiasing activity: (i) warnings; (ii) description of the problem; (iii) personalized feedback; and (iv) training. Evans [30] and Arnott et al. [4] advocate the development of DSS as a way to debias decision makers.

Researchers have also noticed that information presentation and displays have important cognitive implications [46] and influence decision making [40]. Several features of information systems tools

such as graphs, probability maps, feedback and multimedia could provide cognitive support and assist in the decision-making process (e.g. [8,49,71]).

Based on the forgoing discussion, the basic research model employed in this study is shown in Fig. 1. The model posits that cognitive bias has a detrimental impact on the quality of investment decisions and that decision aids can play a role in reducing such an impact.

Our research model as depicted in Fig. 1 attempts to assess the impact of cognitive biases on investment decision quality. While the model does not consider the potential impact of other variables such as overconfidence, age, gender, and investment experience on the quality of investment decisions, a post-hoc analysis was conducted to investigate any possible association between these variables and investors' decisions. This post-hoc analysis is reported in Section 5.

Several studies have observed the benefit of cognitive aids such as feedback and graphs in different contexts and experimental settings [8,25,66]. Benbasat et al. [8] showed the graphical presentation mode of information to have an impact on decision quality, decision-making time, use of information, and user perceptions. The influence of presentation mode and the perceived value of information were also linked to the degree of support the decision aids provide to decision makers [8]. A laboratory study assessing the effectiveness of different reporting formats for presenting accounting data found that graphical formats could improve the quality of decision-making tasks by improving the accuracy of forecast judgments [25]. Well-designed feedback, such as the one provided to decision makers at the right time was shown to enhance decision quality by providing cognitive control in the decision task [66]. Hence, our first hypothesis explores whether a DSS designed to ameliorate investment bias is effective in doing so. This hypothesis will be tested for each of the three cognitive biases discussed in Section 2.

**H1.** Decision support will lower the impact of cognitive biases on the quality of investment decisions made by individuals.

Previous studies have found that as the decision-making environment becomes more complex, the behavior of the decision-maker and the benefits of DSS can also change [28,68]. For example, Todd and Benbasat [68] observed that the impact of decision aids is more pronounced in tasks involving a large number of alternative choices which may result in a more complex decision-making environment and cognitive bias. In other research, decision makers were found to either simplify environmental assumptions and use optimal models or rely on less accurate heuristic models retaining greater environmental realism of the decision context in order to cope with the increasing complexity of the decision environment [28]. Therefore, we hypothesize the following:

**H2.** The benefit of decision support increases as cognitive bias increases while individuals are engaged in investment decision making.

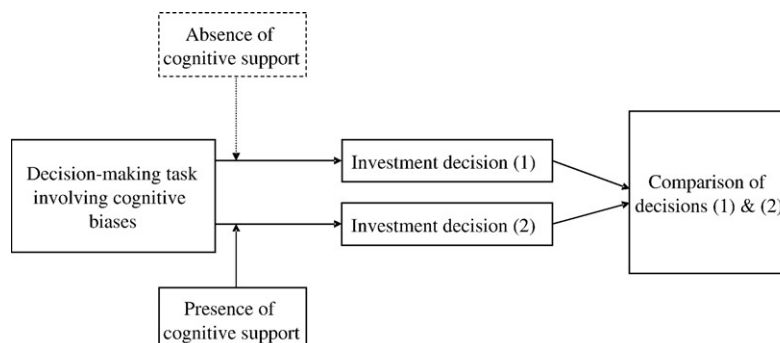


Fig. 2. Experimental setup.

#### 4. Experimental design

The experimental setup employed here is adapted from Lim and Benbasat [51]. In our setup (Fig. 2), the task entails decision making under the influence of potential cognitive biases. For each task, the outcome involves two asset allocation decisions: first, in the absence of decision aids and then with the support of decision aids (if necessary). Decisions 1 and 2 for each task are compared to assess the effectiveness of the decision aid provided for the decision task.

A simulated web-based DSS was used for this experiment. Participants were recruited by advertisement among staff and faculty members at a Canadian university. After logging into the system, participants were asked to provide some basic demographic data about themselves, namely their age, gender, marital status, education level, investment experience (both whether and for how long investments had been undertaken) and employment status. Subjective risk tolerance [15], which was employed to examine the framing bias, was assessed by asking participants to identify themselves as belonging to one of six investor types (ranging from very aggressive to very conservative). The definition and portfolio composition of each investor type was also provided to the participants. For example, a very aggressive investor is defined as “someone who is willing to assume substantial risk to earn high return and his/her portfolio is very heavily invested in stocks” whereas a very conservative investor is someone who is unwilling to assume any risk and the portfolio is very heavily invested in bonds.”

In this study, the overconfidence of individuals was assessed in two ways: miscalibration [50] and better-than-average tests [65]. In the former case, participants were asked five general investment knowledge questions and were subsequently asked how many of the five questions they thought they answered correctly. A comparison was then made between this estimate and the number of correct answers they actually provided. If individuals' estimates were higher than their actual correct answers, they were deemed overconfident using this metric. The five True/False questions used to assess the participants' investment knowledge were comparable to the ones used in previous studies (e.g. [1,74]) and were as follows: 1) It is conventional for a financial planner to argue that an individual's investment on stocks should decline as he/she approaches retirement. 2) If interest rates rise, the price of a bond will rise. 3) The price of a stock increases after the payment of a dividend. 4) Investing in bonds does not incur any risk. 5) All investment earnings are taxed at the same rate. In the latter case, participants answered the question “How do you rate your knowledge of retirement investments relative to other people?” using a scale from 1 (much less knowledgeable) to 10 (much more knowledgeable). If individuals rated themselves as higher than 5, they were deemed overconfident using this metric. For robustness, individuals were considered overconfident only when they exhibited this tendency according to both of these metrics. Empirical studies pertaining to investment decisions have followed similar approaches to assess individuals' investment knowledge and overconfidence [10,11].

After these preliminaries, all participants were exposed to three investment scenarios (each of which had two sub-scenarios) where financial decisions had to be made. In all scenarios, individuals were

asked to allocate \$100,000 of pension money among various investments. The scenarios were designed in such a way that the three types of biases which were described earlier were likely to be present. Additionally, a bias catalyst was applied at either a low or a high level. Thus there were six unique sub-scenarios (three scenarios with two bias catalyst treatment levels each). Note that each participant was randomly assigned three scenarios in such a way that no two scenarios were of the same bias type. The order in which these scenarios were presented to participants was completely random. Thus there were 48 different possible permutations of these six sub-scenarios. All possible permutations were used in the experiment and each participant completed 3 different scenarios involving the three biases examined in this experiment. For all scenarios, an initial decision was made by the participant (and recorded by the DSS). The DSS then issued decision support (if necessary in case of the framing bias) in the form of a decision aid only once. Participants were allowed (but not obligated) to change their initial decision based on the support received. The completely randomized design that we followed in this study should control for any potential biases resulting from the participants' previous experiences. For example, it is possible that someone might have invested in a bond fund in the past and was burned on it, and therefore, she was exhibiting a classic snake-bit effect by not willing to invest in a bond fund again regardless of what her risk level might be. However, it is reasonable to assume that the impact of such biases should not have a persistent impact on the outcome of a completely randomized experiment like ours.

Participants used their own computers for the experiment and were not monitored in any way. As an incentive to participate, at the conclusion of the experiment a lottery was conducted whereby four participants received cash awards. A similar incentive structure has been used in previous studies (e.g. [7]). A total of 143 university employees (faculty and staff) participated, 21 of whom did not complete the full experiment. Additionally, three participants spent such a short period of time performing the experiment that it was concluded that they might not have answered the questions with sufficient care and therefore, their data were not included in the analysis. We next turn to a detailed description of the three sets of scenarios and their associated bias catalysts, cognitive biases and decision aid.

Table 1 spells out the experimental design in greater detail. The first column on the left repeats the three bias-inducing behaviors and bias results. The second column from the left refers to factors which may serve as potential catalysts for bias. The second column from the right outlines the bias level manipulation scheme that we employed in our experiment. For example, the fund menu offering many equity funds constituted a high treatment level, whereas a menu consisting of only a bond fund and a stock fund made up a low treatment level. The column on the right outlines the corresponding decision support and their type provided to the participants. The decision aids were divided into two broad categories: *suggestive*, and *informative* using the framework proposed by Silver [60]. Suggestive guidance recommends how decision makers can respond to the current decision problem by incorporating the decision-makers' initial input, whereas

**Table 1**  
Bias catalysts, treatment levels and decision aid

Bias	Potential bias catalyst	Treatment levels	Decision aid
Framing and diversification heuristic leading to inconsistent asset allocation	Fund menu	High: many funds-skewed towards equity Low: bond fund and stock fund Low: bond fund and stock fund	Textual feedback ( <i>Suggestive</i> )
Representativeness heuristic leading to trend following and insufficient diversification	Return series depiction	High: salient trend Low: ambiguous trend	Graphical presentation ( <i>Informative</i> )
Ambiguity aversion leading to inappropriate default choice	Information load	High: more information Low: less information	Graphical presentation ( <i>Informative</i> )



Imagine you have \$100,000 in your pension. You have ten fund choices and you have to put all \$100,000 into these choices. How much of the \$100,000 would you put into each fund? You can put all of it, or none of it in any fund, but the total investments made must equal \$100,000. (You need not enter \$ or comma.)

Stock Funds (Nine choices)		Note: "Cap" is short for capitalization, which indicates the market size of a stock. Large cap, mid cap, and small cap refer to the size of the capital of companies issuing stocks. Value stocks are those stocks whose prices are low relative to their book value or earnings. Growth stocks are stocks whose prices are high relative to their book value or earnings. Core stocks fall between value and growth categories.
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Large Cap & Core	<input type="text"/>	
Large Cap & Growth	<input type="text"/>	
Mid Cap & Value	<input type="text"/>	
Mid Cap & Core	<input type="text"/>	
Mid Cap & Growth	<input type="text"/>	
Small Cap & Value	<input type="text"/>	
Small Cap & Core	<input type="text"/>	
Small Cap & Growth	<input type="text"/>	
Bond Fund	<input type="text"/>	
Total	<input type="text"/>	

Done

Fig. 3. High-bias treatment for framing bias.

informative guidance enlightens their judgment by furnishing relevant information regardless of their initial input or decision. In our study, we used textual feedback as a suggestive decision aid as the feedback level issued to the participants depended on their initial inputs. On the other hand, graphical presentations were used as informative aids as their goal was to assist decision makers by providing them structured and relevant information in an unambiguous manner.

#### 4.1. Scenarios involving framing and the diversification heuristic

As mentioned above, previous research has shown that the frame presented to decision makers has an impact on decisions. In the context of asset allocation and risk-taking, the frame is in terms of the number and type of investment funds offered to investors [54]. The bias catalyst, the fund menu, has two treatment levels. In the low bias catalyst case, there are simply a generic "stock fund" and "bond fund" to choose from. The bias catalyst is manipulated by increasing the number of fund choices available for investment. In the high-bias catalyst (Fig. 3), the nine equity choices correspond to the nine cells in a capital vs. growth potential matrix (e.g. Morningstar<sup>1</sup>). The DSS had a help file which provided sufficient information about the terms used in this experiment so that participants could make informed decisions. Participants were also provided with basic information alongside some investment scenarios on the same screen. For example, a brief note involving capital size and growth potential of stocks was provided in this scenario while more detailed information was available in the help file. In the low bias catalyst, only two funds (one stock fund and one bond fund) were available for investment.

Recall that subjective risk tolerance was obtained prior to the presentation of the scenarios. Objective risk tolerance was ascertained by asking participants to allocate \$100,000 among a certain number of stock and bond funds. Inappropriate asset allocation, which occurs when there is a mismatch between subjective and objective risk tolerance [15], is most likely to be observed in the high-bias case, because the frame is more opaque. Moreover, if an investor has a risk stance that is balanced, the high-bias scenario coupled with the diversification heuristic will push people into taking on too much equity risk.

Investor type was first mapped on to a subjective asset allocation (or equity share), according to Table 2, which is based on the general

investment guidelines (e.g. [12,67]). Then inconsistency was determined based on a comparison of subjective equity share and objective equity share. Several researchers contend that it is important for investors to stay within their risk tolerance level [32,35,38]. This is especially true for pension investment because older people cannot afford market shocks as that will increase their chance of low retirement income. Hanna and Chen [38] indicate that risk tolerance should be measured both subjectively and objectively. Subjective risk tolerance is measured by individuals' responses to a question involving the perception of their risk tolerance whereas objective risk tolerance is measured by the percentage of risky investments in their portfolios [15]. Researchers stress that it is important for investors to harmonize their objective and subjective risk tolerance [15]. Hence, it is critical that investment DSS help achieve that objective. If investors change their risk tolerance, this should be captured by reassessing the subjective risk tolerance from time to time and issuing decision aids accordingly. When bias is detected, individuals exhibiting inconsistency between their desired risk tolerance levels (subjective) and their actual asset allocation decisions (objective) were provided with a feedback. Individuals who did not exhibit the bias did not receive any feedback.

Depending on the degree of equity share inconsistency, participants received one of two types of feedback. To be concrete, take a growth-oriented investor who should allocate about 60% to equities (e.g. [67]). Because there is obviously some imprecision here, we assume that a 50–70% range is reasonable. The subject receives Level 1 feedback if her allocation is no more than 10% outside the permissible range (i.e., 40%–50% or 70%–80%), and Level 2 feedback if the stock allocation was more than 10% outside the permissible range (i.e., <40% or >80%). A similar approach was followed in a previous study in-

Table 2  
Investor types, recommended stock allocations and feedback levels

Investor types	Subjective stock allocation (% of portfolio)	Feedback Level 1 (stock as % of portfolio)	Feedback Level 2 (stock as % of portfolio)
Very aggressive	90–100	80–90	<80
Moderately aggressive	70–90	60–70; 90–100	<60
Growth-oriented	50–70	40–50; 70–80	<40; >80
Capital preservation-oriented	30–50	20–30; 50–60	<20; >60
Moderately conservative	10–30	0–10; 30–40	>40
Very conservative	0–10	10–20	>20

<sup>1</sup> <http://www.morningstar.com>.



Fig. 4. Level 2 feedback for framing bias.

volving anchoring and adjustment bias [34]. Level 1 feedback informs a participant that her allocation is *inconsistent* with her risk preference level, whereas Level 2 feedback alerts that her allocation is *very inconsistent* with her risk preference level.

With both feedback levels, participants are free to act on or ignore the feedback given to them. Feedback is issued only once in these scenarios. Hence, if participants, after revising (or not revising) their initial decision, remain inconsistent, they are not warned further. This aspect of the design was intended to avoid the potential convergence of participants' responses to their actual risk preferences due to successive feedbacks issued by the DSS. Another important attribute of the feedback is its non-directional nature. That is to say, the feedback only informed participants about their inconsistency, and did not tell them whether they should increase or decrease their stock allocation. The feedback was *suggestive* in nature, in the sense that it gave some indication about the magnitude of their inconsistency (i.e., inconsistent or very inconsistent). Such a neutral feedback has been used in previous studies (e.g. [34]) (Fig. 4).

#### 4.2. Scenarios involving representativeness heuristic

As mentioned earlier, because of representativeness, individuals often overrate the significance of salient information and trend-chasing without regard for proper diversification can result. Again, participants were asked to allocate \$100,000 among various investment choices, this time between just two stocks (X (winner) vs. Y

(loser), or A (winner) vs. B (loser)) in two scenarios. The potential bias catalyst here is return series depiction, and the treatments are manipulated by varying the salience of the presented return histories. In the low-bias treatment, it was clear that X outperformed Y over the last year, but it was also apparent that in certain months Y actually outperformed X. In the high level bias treatment, stock A consistently stayed above stock B over a six-month tracking period (Fig. 5). The return series for the stocks were generated in a spreadsheet using a random function with mean value of zero. In a randomly generated series, the shorter the time horizon, the more salient (due to the short-term trend) the series appears to be. As mentioned earlier, while a case can be made for leaning slightly towards the momentum stock, given that there are only two stocks available, diversification considerations are paramount. Thus a roughly even split (with perhaps a slight inclination towards the recent winner) makes the most sense [22].

The decision aid for the scenario depicted in Fig. 5 is shown in Fig. 6 where returns for a longer time horizon (three years) are presented in a chart form. Participants should be able to correctly infer that there is no significant difference in the historical performance of the two stocks over the 3-year period, because the cumulative returns for both of them over this time are roughly equal. A judicious move would be to allocate roughly equal amounts to these stocks after observing the graph in Fig. 6. The cognitive support in this case (i.e. the chart) is informative in nature as it is expected to enlighten the participants' judgment by furnishing relevant information to them regardless of their initial inputs [63]. This type of support was provided to all participants.

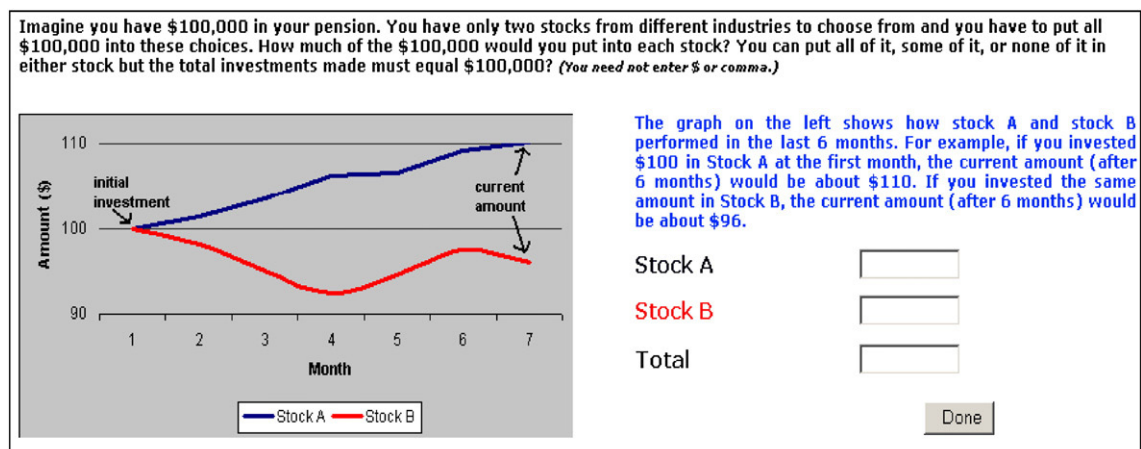


Fig. 5. High-bias treatment for representativeness.

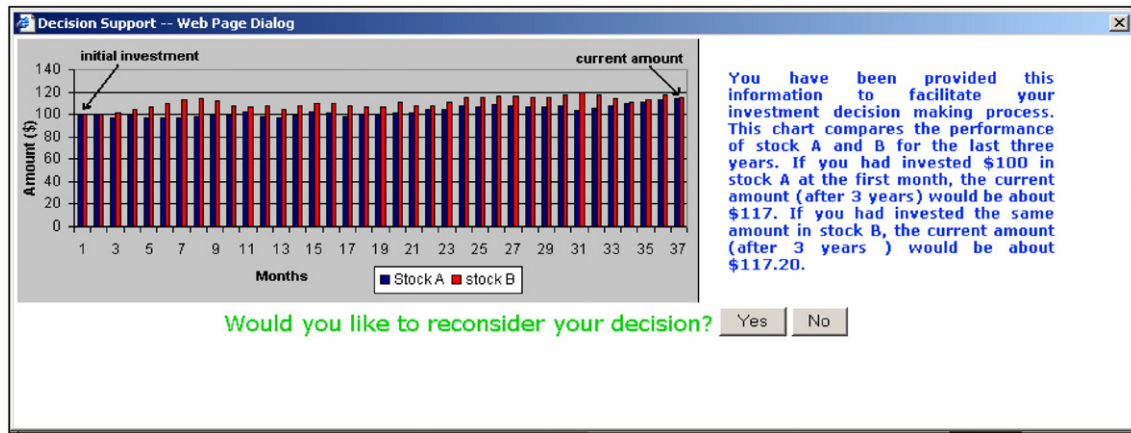


Fig. 6. Decision aid for high-bias treatment (representativeness).

#### 4.3. Scenarios involving ambiguity aversion

Due to ambiguity, individuals may become unable to process the information provided to them. As a result they may accept default choices (if available) which are sometimes demonstrably sub-optimal. Again, in our experiment we asked participants to allocate \$100,000 among available funds. In this case, all funds are bond funds. In the low-bias catalyst scenario, there are only three bond funds, while in the high-bias catalyst scenario (Fig. 7), there are six bond funds to choose from. In both cases the information is somewhat opaque. Individuals must sort through fund descriptions to obtain information on historical gross returns and management expense ratios (MER), and then net out the latter from the former to arrive at net returns (e.g. [16]). It is expected that participants affected by information overload will accept the default investment option. This option entails putting half of their money into a sub-optimal bond fund (default choice) and the remainder (split evenly) among the other available funds. A careful comparison of the bond histories shows that this particular default fund has underperformed at all horizons, and has the highest fees. Because there is no other information about these funds, and, as

participants are told that performance is comparable among funds, a decision to accept the default investment option could only be due to information overload.

The decision aid for the scenario depicted in Fig. 7 is shown in Fig. 8 where an unambiguous chart showing average compounded net returns for all funds for all holding periods is presented. As in the case of representativeness, this cognitive support (i.e., a graph) is informative in nature, as it is expected to assist the participants' decision making by presenting the information in a more understandable format [63]. As such this type of support was provided to all participants regardless of their initial decision.

#### 5. Results

Initially, a pre-determined alpha of 5% was selected to test our research hypotheses. However, because each hypothesis involves testing of three separate biases (framing, representativeness, and ambiguity) with each participant, we adjusted the selected alpha level to control for the overall Type I error by following the Bonferroni inequality approach [37]. Thus, an individual level of significance was computed for each

**Smart Bond Fund:** The primary objective of this fund is *total return with interest rate anticipation* as its management style. The fund has the following asset allocation: Corporate bonds-70.7%, Provincial bonds-3.6%, Canada bonds-15.3%, and others (including cash) -10.4%. The net historical compound returns (before management fees) for 1 year, 5 year, and 10 year periods are respectively 4.3%, 8.1% and 8.5%. The management fee for this fund is 1.68%.

Suppose you have been investing \$100,000 in the following manner since the last 2 years.

National Bond Fund	<input type="text" value="50000"/>
XYZ Bond Fund	<input type="text" value="10000"/>
ABC Bond Fund	<input type="text" value="10000"/>
Green Fund	<input type="text" value="10000"/>
Bond Index Fund	<input type="text" value="10000"/>
Smart Bond Fund	<input type="text" value="10000"/>
<b>Total</b>	<input type="text" value="100000"/>

Would you like to continue making your investments as above? ☐ Yes ☐ No

Fig. 7. High-bias treatment for ambiguity.

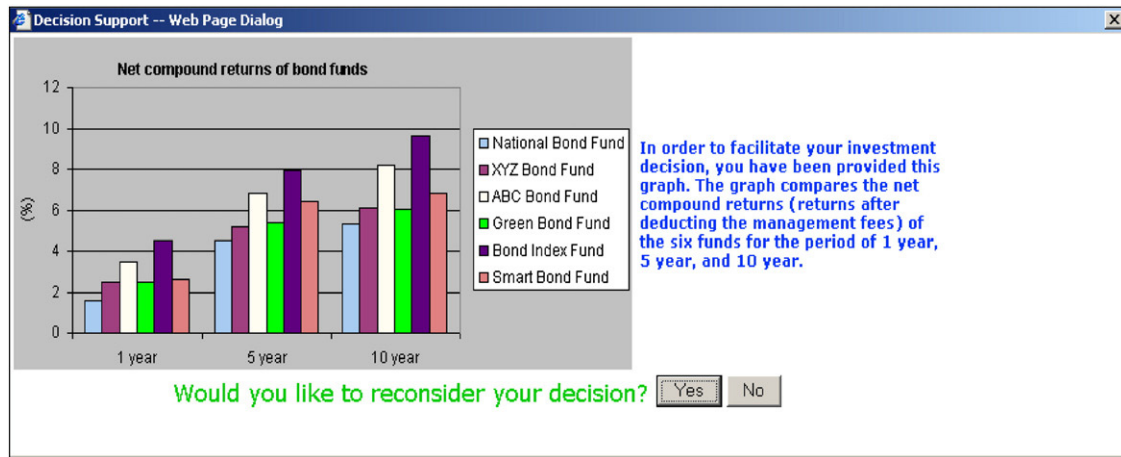


Fig. 8. Decision aid for high-bias treatment (ambiguity).

hypothesis by dividing the proposed alpha of 5% by 3. The new significance level of 1.67% was then used to assess the validity of our hypotheses. Before discussing the results pertaining to our hypotheses, we present information of the participants in our experiment.

### 5.1. Participant pool characteristics

Table 3 provides a snapshot of the participant pool obtained for this experiment. The average age of the participants was 39.9 years, and 65% of participants were female. Faculty members represented 18% of the sample while the rest were staff. As for investment experience, 25% were not currently investing. Participants had an average of 6.8 years of investment experience, with the maximum being 30 years. The investment experience distribution is skewed to the right, with about 24% participants having little or no experience. Conveniently though such a profile is what one would expect of typical individuals investing for retirement [11].

As discussed in Section 4 above, a robust measure of overconfidence combining two overconfidence metrics was used. First, overconfidence was measured by miscalibration which employed a 5-item instrument for assessing investment knowledge. In order to assess the reliability of this instrument, we computed the Cronbach alpha reliability metric. The reliability score for the 5-item instrument was initially 0.512. When the third item was dropped from the instrument, the score increased to 0.645 which is acceptable for an exploratory or social sciences study, such as this one, [55]. Based on the miscalibration test, 41.2% of the participants were overconfident in believing they obtained more correct answers than they actually did; 36.1% were correctly calibrated; and 22.7% were underconfident. Second, on the better-than-average test, the average response was 5.5 (which is exactly the midpoint on 1–10 scale). Overconfidence was not apparent for any of our participants using our robust measure, which

required individuals to be overconfident according to both metrics of *miscalibration* and *better-than-average*. Therefore, it was not used as a covariate in subsequent data analysis.

### 5.2. Results for Hypothesis 1

The data from our experiment strongly supports the usefulness of DSS in reducing all three types of biases based on the individual adjusted alpha of 1.67%. For framing and the diversification heuristic, 88 out of 119 participants were initially inconsistent in their risk-taking. Of these, after feedback, 63 moved in the correct direction, with most of the remaining participants making no change at all. The hypothesis that feedback lowers the impact of framing bias on the quality of investment decisions made by individuals could not be rejected at this level. Further evidence is shown in Table 4a. For now, just focus on the “Overall” column. Here we have defined the equity gap as the absolute difference between the objective equity and that implied by the subjective risk tolerance question. For example, say someone had allocated \$85,000 to stocks, but their subjective risk tolerance had slotted them at a 50–70% equity share. Their initial equity gap would be \$15,000 (\$85,000–\$70,000). If after feedback they had adjusted to \$75,000/\$55,000/\$45,000, then their absolute gap would be \$5000/\$0/\$5000. Table 4a shows us that the average gap dropped from \$14,170 to \$5727 after DSS support, a change of \$8443 (60%) in the right direction that is significant at the adjusted alpha level. Table 4b summarizes the asset allocation decisions by investor types before and after feedback. It is apparent from the table that the framing bias occurred to almost all types of investors as indicated by their deviation from the recommended stock allocations. Furthermore, the pairwise correlation between framing bias and investor types was 0.03 and non-significant ( $p=0.7604$ ) suggesting that individuals' risk tolerance did not influence the framing bias.

Table 3  
Summary of the participants' demographic data

Variable	
Age	Mean: 39.9 years; Min.: 22 years; Max.: 67 years
Gender	Male: 41 (34.45%), Female: 78 (65.55%)
Marital status	Married: 76 (63.87%), Single: 43 (36.13%)
Education (1—no college; 2—some college; 3—graduated; 4—PhD)	Mean: 2.98
Currently investing?	Yes: 90 (75.63%), No: 29 (24.37%)
Investment experience in years	Mean: 6.8 years; Min: 0 year; Max: 30 years
Profession	Faculty: 22 (18.49%; Staff: 97 (81.51%)
Self-rated knowledge (1—very little to 10—very much)	Mean: 5.51
Portfolio type (1—very aggressive to 6—very conservative)	Mean: 3.65



**Table 4**  
Tests of Hypotheses 1 and 2

(a) Framing and diversification heuristic (no. of participants receiving aid=88)				
	Average equity gap (in \$)		High level bias	Overall
	Low level bias			
Before support (i)	12,375		15,667	14,170
After support (ii)	5750		5708	5727
DSS benefit (i–ii)	6625		9959	8443
(b) Asset allocation decisions by investor types before and after feedback				
Investor type	Mean stock allocation under high-bias level (in \$)		Mean stock allocation under low bias level (in \$)	
	Before feedback	After feedback	Before feedback	After feedback
Very aggressive (0.8%)	100,000	100,000	–	–
Moderately aggressive (16.8%)	94,750	90,000	64,167	67,500
Growth-oriented (35.3%)	77,455	70,182	49,500	50,000
Capital preservation-oriented (23.5%)	60,818	51,727	40,294	39,118
Moderately conservative (12.6%)	51,250	34,375	38,571	27,857
Very conservative (10.9%)	34,286	22,143	16,667	13,333
(c) Representativeness heuristic (no. of participants receiving aid = 119)				
	Average diversification gap (in \$)		High level bias	Overall
	Low level bias			
Before support (i)	14,574		29,020	22,092
After support (ii)	5532		5882	5714
DSS benefit (i–ii)	9042		23,138	16,378
(d) Ambiguity aversion (no. of participants receiving aid = 119)				
	% of subjects accepting default choice		High level bias	Overall
	Low level bias			
Before support (i)	38		79	59
After support (ii)	12		25	18
DSS benefit (i–ii)	26		54	41

A very similar analysis was done for representativeness (Table 4c). A key difference to keep in mind here is that all participants received decision aid regardless of their initial decisions. We provided the unconditional graphical aids because we wanted to examine how the allocation decision of participants (whether initially biased or not) would change after receiving the decision aid. The initial allocations to winning stocks were \$40K, \$45K, \$50K, and \$55K made by 1, 2, 17, and 1 participant respectively. After the receipt of the decision aids, the allocations to winning stocks were \$45K and \$50K made by 1 and 20 participants respectively. Still it is most interesting to focus on those who initially had insufficiently diversified portfolios. Recall in our earlier discussion that it was argued that slight tilting towards the momentum stock could be justified. Based on this, we assume that an allocation towards this stock between 50% and 55% is reasonable. Those outside this range are subject to a diversification gap. There were 98 respondents originally outside this range. Of those, 78 participants moved in the right direction after receiving the decision aid. Once again this result is statistically significant at the individual adjusted alpha level. Similar evidence is available when we focus on the diversification gap reduction: the overall gap before the decision aid is \$22,092, falling to \$5714 after the support implying \$16,378 (74.1%) change in the right direction that is significant at the adjusted alpha level.

As for ambiguity aversion, the proportion of participants accepting the (inappropriate) default dropped from 59% to 18% after the decision aids kicked in (Table 4d). Once again the difference between proportions was significant at the adjusted alpha level.

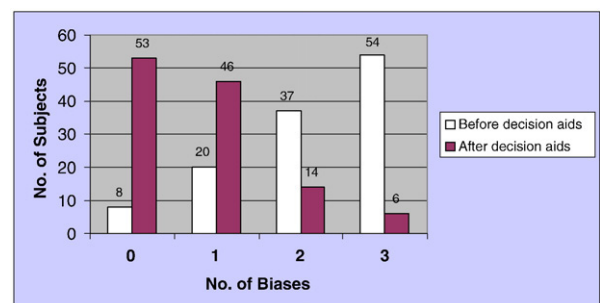
Fig. 9 depicts overall findings regarding the impact of decision aids (feedback and graphical aids) on lowering the influence of these three biases (framing, representativeness, and ambiguity). As outlined in Fig. 9, 8 participants (6.7%) were not influenced by any of these biases while 54 participants (45.4%) were influenced by all of these biases before the receipt of decision aids. After receiving decision support, 53 participants (44.5%) did not exhibit any bias at all while only 6

participants (5%) were still influenced by all of the three biases. It is evident from this figure that the number of participants influenced by the biases reduced significantly after receiving cognitive support. To conclude, the evidence is overwhelming that decision support leads to bias reduction.

In order to ensure that there was no impact of demographic factors (age, gender, education, experience) on the existence of the three biases, we ran pairwise correlations as shown in Table 5. There were no significant correlations at the 5% level except that between gender and framing. However, the significant correlation between gender and framing bias is not entirely unexpected as some previous studies also had found women to be more susceptible to framing bias than men [31].

### 5.3. Results for Hypothesis 2

Is the DSS more useful when it is most needed, that is, when the bias catalyst is set to the high level? Again, beginning with framing and the diversification heuristic, we now compare the benefit of feedback between a low bias scenario and a high-bias one. In the



**Fig. 9.** Impact of decision aids on lowering the impact of cognitive biases.

**Table 5**  
Pairwise correlation of demographic variables and the three biases

Demo. factors	Framing	Representativeness	Ambiguity
Age	0.0568 (0.5396)	0.1176 (0.2029)	0.0451 (0.6262)
Gender	0.1898 (0.0387)	−0.0591 (0.5229)	−0.1421 (0.1232)
Education	0.1149 (0.2134)	−0.0578 (0.5327)	−0.1443 (0.1174)
Experience	0.035 (0.7056)	−0.1345 (0.1449)	−0.0376 (0.6848)
Knowledge	0.0138 (0.8817)	−0.1168 (0.2058)	−0.0732 (0.4286)

Values in parentheses indicate the significance of correlations.

former case, 44% of the participants benefited from the feedback whereas in the latter case 63% benefited. The difference is significant at the adjusted alpha level thereby failing to reject Hypothesis 2 in the case of the framing bias.

A comparable benefit difference calculation is done for the representativeness bias. For the high-bias case, the diversification gap declined from \$29,020 to \$5882 for an improvement of \$23,138 (79.7%) (Table 4c). On the other hand, for the low bias case, the diversification gap declined from \$14,574 to \$5532, for an improvement of \$9042 (62%). The difference in dollar improvement averages is significant indicating strong support of this hypothesis at the adjusted alpha level.

Finally, we turn to ambiguity aversion. As shown in Table 4d, 26% of the participants benefited from the decision aid at the low-bias catalyst level, while at the high-bias catalyst level 54% of the participants benefited from the support. The difference is significant indicating strong support of this hypothesis at the adjusted alpha level.

In summary, there exists evidence that decision support matters more in environments that are more likely to facilitate bias. This has important implications for defined contribution plan sponsors. In complex environments (for example where there is a little guidance and many fund choices exist) there is likely to be a high payoff to DSS designed to ameliorate behavioral bias.

## 6. Discussion and conclusions

Using recent findings from behavioral finance, this study has demonstrated that individuals, even in simple investment decision-making tasks are adversely influenced by such cognitive biases as framing, representativeness, and ambiguity. Based on carefully designed investment scenarios and decision aids that simulated a real-world investment context, the study found that decision aids such as feedback and graphs can significantly mitigate the impact of such biases. To the best of our knowledge, no prior studies have demonstrated such a need and usefulness of a decision support system from the perspective of lowering the impact of individuals' investment-related biases. As such, we believe this study has attempted to bridge the existing gap between DSS and the psychology of investment decision making.

We conclude that decision aids such as feedback and graphs can lower the impact of investment-related cognitive biases and they are more valuable in environments where the bias level is likely to be higher. Overall, this study supports the Social–Economic–Psychological model [47] which underscores the necessity of social, economic, and psychological perspectives to understand the various needs of investors.

As with any behavioral research, this work has some potential limitations. First, the scenarios used in the experiment might appear to be simplistic and not necessarily match the complexity of the real world. It is also likely that serious investors would be able to find more detailed information while making their investment decisions from sources like the Internet compared to the limited information we provided our participants. However, such an approach is necessary as the use of scenarios provides experimental control [45]. The control of

external variables is critical for behavioral research [9]. Furthermore, many IS researchers (e.g. [2,19]) have used scenarios in their experiments in similar research areas. It should also be pointed out that the cognitive biases inherent in these scenarios are not necessarily orthogonal to each other and therefore, the possibility of some degree of confounding between these biases cannot be completely eliminated.

Second, another potential limitation is the nature of asset allocation decisions involving hypothetical money. However, several important studies in finance and information systems have asked their participants to consider imaginary situations. For example, asset allocation decisions studied by Benartzi and Thaler [7] also involved a hypothetical situation. More importantly, studies in judgment biases have found that hypothetical choices made by participants do match real-world behavior for small as well as large payoffs [48]. Cadsby and Maynes [14] provide an excellent review of laboratory experiments in corporate and investment finance outlining several studies that relied on hypothetical money for the experiment. Hence, this approach is quite acceptable. In our experiment we also provided a script to our participants in which they were asked to imagine about their pension investment. Schultz ([59], p. 226) emphasizes that such role playing increases the validity of experiment as “the intent is for the subject to directly and actively immerse him/her self in the experiment, and to conscientiously participate in the experimental task.” Furthermore, as described in an earlier section, we also used the time spent by the participants to filter out any potentially invalid responses. Specifically, three responses were not included in the analysis as we noted that three participants spent very little time on the experiment.

Third, this study uses only decision quality (reduced judgment bias) as a measure of the effectiveness of decision aids. Researchers have also suggested other criteria such as user satisfaction (e.g. [2,26]), user learning [27], and decision-making efficiency [75]. However, decision quality is the most commonly used criterion [61,75].

Finally, this study has focused on the three most commonly encountered cognitive biases of the framing and diversification heuristic; the representativeness heuristic; and ambiguity aversion. The investigation of other investment biases such as house money effect and disposition effect would require a longitudinal study of participants' investment behavior over a significant period of time which was beyond the scope of this study. As such, findings from this study are specific to studied biases and cannot be generalized to other biases without further investigation.

Future studies could extend this work by investigating the efficacy of *personalized* decision aids in combating the influence of other cognitive biases. The present study focused on asset allocation decisions only. It would be interesting to find out whether decision aids are also useful in trading decisions. Findings from such studies will have a significant impact on both the theory and the practice of investment decision making. Future studies can also investigate other measures of decision guidance effectiveness such as satisfaction, efficiency, and user learning.

We believe that this study has demonstrated that decision support systems do have a role in debiasing investors. Specifically, their presence leads to a reduction in bias and that they tend to be more valuable in environments where bias is more likely to occur and have a stronger impact. Given the worldwide trend towards defined contribution pension arrangements where individuals must make their own investment decisions, and the abundant evidence that individuals have low levels of knowledge and are subject to several biases, innovative decision support tools to debias investors should be carefully considered by plan sponsors.

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